GENERATIVE AI ADOPTION IN FACILITIES MANAGEMENT: AN EXPLORATORY STUDY OF PROFESSIONAL USES, IMPACTS, AND BARRIERS

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Abstract - *This study investigates how generative artificial intelligence (Gen AI) is being incorporated into Facilities Management (FM) practice among Brazilian professionals, providing empirical evidence in a field still dominated by conceptual and review-based studies. Survey data from 45 professionals were collected and analyzed using descriptive statistics, qualitative content analysis, and exploratory text mining to identify usage patterns, perceived impacts, and adoption barriers. Gen AI was primarily used for operational documentation, managerial support, information retrieval, and routine text processing, with ChatGPT, Microsoft Copilot, and Gemini as the most frequently reported platforms. Perceived impact was predominantly moderate to high, indicating that current applications mainly support cognitive and informational activities rather than directly transforming technical building operations. Exploratory clustering further characterized this pattern of use, with the largest cluster involving text, productivity, and operational support. Reported barriers comprised organizational governance uncertainty, technological and integration limitations, and capability-related concerns involving skills, knowledge, and training. Kruskal-Wallis tests showed the strongest unadjusted differences in perceived impact for frequency of use and organizational authorization, but these differences did not remain statistically significant after adjustment for multiple comparisons. Overall, the findings indicate that current Gen AI use in FM is concentrated in knowledge-intensive activities and is associated with reported patterns of use and organizational conditions surrounding Gen AI adoption.*

Keywords: generative artificial intelligence; facilities management; brazilian professionals; organizational readiness; technology adoption.

INTRODUCTION

Artificial intelligence has undergone a rapid transformation in recent years, evolving from narrowly specialized analytical systems toward increasingly general computational architectures capable of producing complex knowledge outputs. Advances in deep learning, large-scale datasets, and high-performance computing have enabled the development of generative artificial intelligence (Gen AI) systems capable of generating coherent text, images, code, and other structured artifacts. Architectures such as transformers and large-scale foundation models have significantly expanded the capabilities of machine intelligence, enabling systems to perform tasks traditionally associated with human cognitive work, including reasoning, information synthesis, and content generation (Vaswani et al., 2017; Brown et al., 2020; Hussain et al., 2025).

These developments mark an important shift in the role of artificial intelligence within organizational environments. Earlier AI applications were largely oriented toward predictive analytics, pattern recognition, and optimization tasks. In contrast, generative systems operate directly on unstructured knowledge domains, allowing professionals to interact with computational systems through natural language and obtain structured analytical outputs. This transition has expanded the potential of artificial intelligence beyond automation toward cognitive augmentation, in which digital systems assist professionals in managing complex informational and analytical processes.

Such capabilities are particularly relevant in domains characterized by intensive information processing and operational coordination. Facilities Management (FM) represents a multidisciplinary organizational function responsible for managing buildings, infrastructure systems, and support services that sustain organizational operations. FM activities require continuous interpretation of technical documentation, maintenance records, regulatory information, and operational reports. As digitalization expands through technologies such as Building Information Modeling, Internet of Things infrastructures, and digital building platforms, the volume and complexity of operational data in built environments have increased substantially (Volk et al., 2014; Pärn et al., 2017).

Within this context, artificial intelligence has begun to support several operational tasks in facilities operations, including predictive maintenance, energy optimization, and building performance monitoring (Zhao et al., 2019; Chen et al., 2021). However, most existing research in the built environment focuses on analytical AI techniques embedded in technical infrastructures. The emergence of generative models introduces a new category

of technological capability, oriented toward the production and interpretation of textual and knowledge-based information to support managerial and operational decision-making.

Despite the growing technological relevance of Gen AI, empirical evidence regarding its use within professional FM practice remains limited. Much of the literature emphasizes algorithmic architectures, technological potential, or conceptual applications, while relatively few studies examine how practitioners incorporate these tools into their daily workflows. Understanding how professionals integrate generative systems into operational activities is therefore essential for bridging the gap between technological innovation and real-world adoption in built environment management.

Addressing this gap, the present study investigates how FM professionals currently use generative artificial intelligence tools. Using empirical data collected through a survey of practitioners, the research identifies patterns of use, perceived operational impacts, and organizational conditions associated with early adoption. By examining practical applications in everyday professional routines, the study contributes to the emerging literature on artificial intelligence in the built environment and advances understanding of how generative technologies are reshaping knowledge-intensive activities in facilities operations.

Theoretical Background: Evolution of artificial intelligence and the emergence of Gen AI

Artificial intelligence has evolved through successive technological paradigms that progressively expanded the ability of computational systems to process information, identify patterns, and generate structured outputs. Recent advances in machine learning, deep learning, and large-scale computational infrastructures enabled the emergence of generative artificial intelligence (Gen AI) systems capable of producing text, images, code, and other forms of synthetic content (Ooi et al., 2025; Sengar et al., 2025). These developments represent an important transition from analytical systems focused primarily on prediction and optimization toward technologies capable of supporting cognitive and knowledge-intensive activities.

The contemporary evolution of AI is strongly associated with deep learning architectures and transformer-based models. Advances in neural networks and natural language processing substantially improved the capacity of computational systems to interpret context, process sequential information, and generate coherent outputs (Benbya et al., 2020; Krichen, 2023; Khan et al., 2023). The introduction of transformer architectures represented a major technological breakthrough because attention mechanisms enabled more efficient processing of long-range dependencies in textual data, significantly improving language modeling performance (Vaswani et al., 2017).

These advances directly contributed to the development of Large Language Models (LLMs), which constitute the technological backbone of many contemporary Gen AI systems. Trained on massive textual corpora, LLMs can perform tasks involving text generation, summarization, semantic interpretation, reasoning, and information synthesis (Brown et al., 2020; Ooi et al., 2025). Their growing accessibility via conversational interfaces has expanded the practical use of AI in organizational environments, particularly for documentation, communication, and decision support. Foundation models further expanded the flexibility of AI systems by enabling adaptation across multiple organizational tasks and application contexts (Hussain et al., 2025). Consequently, Gen AI systems increasingly operate as general computational infrastructures that support knowledge-intensive organizational activities rather than solely task-specific analytical functions.

Beyond technical innovation, Gen AI technologies are increasingly associated with cognitive augmentation processes within organizations. These systems can support document generation, information retrieval, analytical reasoning, and operational decision-making, reinforcing a broader shift from automation-centered applications toward technologies that enhance human expertise in complex informational environments. At the same time, the rapid diffusion of these systems raises important governance and ethical concerns involving misinformation, intellectual property, transparency, and algorithmic accountability (Díaz-Rodríguez et al., 2023).

Within this broader technological transformation, generative systems are beginning to influence professional domains characterized by intensive knowledge management and operational coordination. Built environment management and facilities operations are particularly relevant contexts in which such technologies may support documentation processes, technical analysis, information retrieval, and managerial decision-making.

Generative artificial intelligence and emerging applications in Facilities Management

FM is a multidisciplinary field responsible for coordinating the physical environment, infrastructure systems, and support services that sustain organizational operations. According to Amos et al. (2021), FM activities are commonly structured into two interrelated domains: hard services, including building maintenance, HVAC systems, and energy management, and soft services, such as cleaning, security, reception, and space management. These services are critical for ensuring operational continuity, building performance, and user satisfaction throughout the building lifecycle. Consequently, deficiencies in FM service quality can compromise not only technical performance but also user satisfaction and organizational outcomes.

In FM, many professional routines depend on interpreting maintenance reports, contracts, inspection records, compliance documents, technical manuals, user requests, and supplier communications. Gen AI may therefore diffuse into FM practice first through documentation support, technical consultation, and managerial coordination before becoming integrated into predictive or automated building operations. The digitalization of facilities operations through technologies such as Building Information Modeling (BIM), Internet of Things (IoT) infrastructures, and digital twins has further increased the complexity of operational environments and the demand for rapid interpretation of heterogeneous building-related information (Volk et al., 2014; Pärn et al., 2017; Memon et al., 2025).

The growing availability of building-related data has created new opportunities for applying artificial intelligence to facilities operations. Early implementations primarily focused on predictive analytics and optimization tasks, including equipment failure prediction, energy management, and space utilization. Machine learning models have demonstrated considerable potential to support maintenance planning and improve operational efficiency through data-driven decision-making (Zhao et al., 2019; Chen et al., 2021). More recently, the emergence of generative models has expanded these applications beyond predictive analytics toward cognitive and knowledge-oriented activities. Large language models, in particular, can process unstructured textual information and generate structured outputs such as reports, technical summaries, and operational recommendations. This capability is especially relevant in contexts where operational knowledge is embedded in maintenance records, technical documentation, and service reports.

These systems may support maintenance reporting, contract summarization, technical interpretation, and information retrieval across operational documentation. By reducing administrative workloads, such tools may allow professionals to devote greater attention to strategic and operational decision-making. Generative systems may also support operational decision-making by assisting managers in interpreting information derived from maintenance systems, asset management platforms, and building monitoring infrastructures (Memon et al., 2025). Such capabilities are particularly relevant in facilities operations characterized by high levels of technical coordination and regulatory complexity.

Another promising area involves the interaction between generative models and digital building systems. Recent research highlights the potential integration of these technologies with BIM environments, digital twins, and IoT infrastructures to support automated building performance analysis and operational planning. These integrations may enable natural-language interaction with building models, allowing managers to query infrastructure data, simulate operational scenarios, and generate reports directly within digital building environments (Boje et al., 2020; Van Tam, 2025).

In addition to operational efficiency, these technologies may support organizational knowledge management. Facilities operations often depend on tacit knowledge accumulated through professional experience, making FM particularly sensitive to technologies that can structure and retrieve operational information within complex service routines. Generative systems may assist in codifying such knowledge by transforming operational records into structured documentation, guidelines, and best practices, thereby supporting organizational learning and knowledge transfer. Despite these opportunities, adoption remains at an early stage. Successful implementation requires interoperability with existing operational systems, governance policies for sensitive building information, workforce familiarity with AI-assisted workflows, and organizational procedures to validate AI-generated outputs in operational environments. Studies on technology adoption in the built environment emphasize the importance of organizational alignment, digital maturity, and integration with existing operational processes (Pedral Sampaio et al., 2022). Ethical and governance considerations also remain critical. Issues related to data security, transparency of automated recommendations, and accountability for AI-assisted decisions must be carefully addressed in operational contexts where safety, infrastructure reliability, and service continuity are essential.

Research gap and conceptual positioning

Recent advances in artificial intelligence have stimulated growing academic interest in the role of generative technologies within the built environment. Existing research increasingly explores how AI techniques support operational optimization, predictive maintenance, and building performance management. However, much of this literature remains focused on analytical AI methods rather than on the emerging capabilities of generative models (Chen et al., 2021; Pedral Sampaio et al., 2022).

Large language models and multimodal generative systems have substantially expanded the potential scope of artificial intelligence in organizational contexts. These technologies can perform cognitive tasks traditionally associated with human knowledge work, including information synthesis, document generation, semantic interpretation, and decision support. Such capabilities indicate a transition from purely analytical systems toward technologies that augment human reasoning and knowledge production within complex organizational workflows (Brown et al., 2020; Hussain et al., 2025).

Within the FM literature, however, scholarly understanding of these technologies remains limited. Recent review studies have begun to map the emerging technological landscape. For instance, Mehmood and Zafar (2025)

employed structural topic modeling to analyze the academic literature on Gen AI in FM, identifying thematic clusters related to visual applications in built environments, sustainability optimization, predictive maintenance, smart building performance, and natural language processing for automation. Despite these advances, the literature remains predominantly conceptual and technology-oriented. Most studies emphasize algorithmic architectures or potential technological applications, while empirical investigations of how practitioners use these tools remain scarce. In particular, there is limited evidence on how professionals integrate generative systems into their daily workflows and which operational activities are most affected by these technologies.

This research–practice gap reflects a broader challenge in FM's digital transformation. Although academic research highlights technological capabilities, real-world adoption depends on organizational culture, professional competencies, and operational constraints (Volk et al., 2014; Pärn et al., 2017). Therefore, understanding how emerging technologies influence operational practices requires empirical investigations of professional behavior and organizational contexts.

Unlike earlier AI applications embedded in technical infrastructure, generative tools are increasingly accessible through conversational interfaces and cloud platforms. This accessibility enables professionals to experiment with such systems in activities including report writing, document analysis, technical research, and operational planning, potentially transforming knowledge-intensive aspects of facilities work.

Against this background, an important question arises: how are these technologies currently being adopted, and which categories of tasks are most influenced by them? Understanding these usage patterns is essential for bridging the gap between technological innovation and professional practice and for advancing knowledge of the evolving role of artificial intelligence in built environment management. Accordingly, the present study adopts an empirical perspective to examine how Gen AI tools are used by professionals involved in facilities operations. Rather than focusing on algorithmic development, the study investigates practical applications within everyday professional activities, identifying the main categories of use and exploring how these technologies are beginning to reshape operational and knowledge-based tasks.

By providing empirical evidence on current Gen AI use in professional FM practice, this study contributes to the literature by distinguishing between the technically integrated applications emphasized in existing AI research and the cognitive and informational uses currently reported by practitioners. Specifically, it examines whether Gen AI is being incorporated into core technical building operations or remains concentrated in knowledge-intensive activities such as documentation, information retrieval, technical consultation, and communication. This distinction provides the basis for identifying a cognitive-oriented adoption pattern in FM and offers a practice-oriented perspective on the current gap between the technological possibilities described in the literature and their operational integration in professional settings.

RESEARCH METHODS

This study adopts an exploratory empirical design to investigate how professionals in Facilities Management (FM) currently use generative artificial intelligence (Gen AI) tools. Existing research on Gen AI in the built environment has predominantly emphasized technological architectures, conceptual applications, and review-based discussions, while empirical evidence concerning its incorporation into everyday professional practice remains limited. Under these conditions, exploratory approaches are appropriate because they let researchers identify emerging patterns and generate insights into underexplored phenomena (Creswell & Creswell, 2018). Accordingly, the methodological strategy combined descriptive survey analysis, qualitative content analysis, and exploratory text mining to examine both structural patterns of technology use and contextualized descriptions of professional practice.

Data collection was conducted through a structured online questionnaire administered to professionals engaged in Facilities Management activities in Brazil. The dataset contains 45 responses collected between 6 and 11 March 2026. The questionnaire included questions on professional profile, organizational characteristics, frequency of GenAI use, perceived operational impact, organizational authorization, practical applications, and barriers to adoption. Perceived operational impact was measured using a five-category ordinal scale: “No impact,” “Low impact,” “Moderate impact,” “High impact,” and “Very high impact.” The questionnaire also included an open-ended question asking respondents to describe the main practical uses of Generative AI in their Facilities Management activities and a separate open-ended question asking: “What are the main barriers to the use of Generative AI in your work environment?” The questionnaire was administered electronically using Microsoft Forms, and responses were collected anonymously. Survey methods are widely used in information systems and organizational research because they enable the collection of empirical evidence directly from practitioners operating in real-world contexts (Pinsonneault & Kraemer, 1993). Open-ended questions further contribute to interpretative depth by allowing participants to contextualize their experiences and perceptions regarding emerging technological practices (Hadler, 2025).

Participants were recruited through a non-probabilistic convenience sampling strategy. This approach is commonly employed in exploratory investigations involving professional populations where access depends on voluntary participation and professional networks (Etikan et al., 2016). The dataset comprised 45 responses. Because some variables contained missing responses, the number of valid observations varied across analyses. The perceived operational impact variable, which served as the dependent variable in the Kruskal-Wallis analyses, had 43 valid responses. The open-ended question concerning practical uses of GenAI had 42 valid textual responses, while the question concerning barriers to GenAI adoption had 43 valid textual responses. Given the non-probabilistic recruitment strategy and the limited sample size, the study was designed to identify exploratory patterns rather than estimate population parameters or test population-level relationships. The statistical analyses should therefore be interpreted as descriptive and exploratory evidence within the observed sample. In particular, non-significant group comparisons cannot be interpreted as evidence that professional or organizational characteristics are unrelated to perceived Gen AI impact, because the limited number of observations within some subgroups reduces the ability to detect differences that may exist in the broader FM professional population.

The total population of FM professionals in Brazil could not be reliably determined because FM constitutes a multidisciplinary professional field encompassing practitioners with heterogeneous occupational titles, educational backgrounds, and organizational roles. Consequently, no comprehensive national sampling frame was available from which a population-based response rate could be calculated. Participants were therefore recruited through professional networks using non-probabilistic convenience sampling. The resulting sample should not be interpreted as statistically representative of the Brazilian FM professional population. Consequently, the results should be interpreted cautiously regarding external validity and broader sectoral generalization.

The analytical procedure was organized into two complementary stages. First, descriptive statistics were used to characterize the respondents and identify general patterns in the use of Gen AI tools within professional contexts. Descriptive statistical procedures are frequently adopted in exploratory survey research because they provide a structured overview of distributions, tendencies, and organizational characteristics within the dataset (Field, 2018). This stage enabled the identification of preliminary patterns across organizational context, professional profile, frequency of technological use, and perceived operational impact.

Second, qualitative content analysis was applied to the open-ended responses describing how professionals employ Gen AI systems in their operational routines. Content analysis provides a systematic approach for identifying recurring themes and patterns within textual material through structured coding procedures (Krippendorff, 2018). This method is particularly suitable for qualitative survey responses because it enables unstructured textual information to be transformed into analytically meaningful categories. The coding process followed an inductive logic in which categories emerged from the empirical material rather than being defined a priori. Inductive coding is especially appropriate in exploratory investigations involving emerging technologies because it allows patterns of meaning to arise directly from practitioners' descriptions of their experiences (Hsieh & Shannon, 2005).

Each response was examined and classified based on the primary professional activity it supported using Gen AI tools. Through iterative comparison and thematic aggregation, responses were grouped into broader analytical categories associated with managerial support, documentation, information retrieval, operational consultation, and routine productivity activities. This process enabled the identification of recurring domains of Gen AI applications within FM practice.

To support thematic interpretation, the 42 valid textual responses concerning practical uses were additionally subjected to exploratory text mining procedures. Responses were preprocessed by converting to lowercase, removing punctuation and stopwords, and tokenizing. The resulting corpus was converted into a document-term matrix weighted using the Term Frequency–Inverse Document Frequency (TF-IDF) approach, which increases the analytical relevance of terms that occur frequently within individual responses but less frequently across the corpus as a whole. The document-term matrix was subsequently analyzed using the K-means clustering algorithm to identify recurring lexical patterns among responses. The three-cluster solution was selected because it yielded the most interpretable configuration in terms of semantic coherence and cluster-size distribution. Following clustering, responses were manually reviewed to verify semantic consistency within clusters and to avoid overinterpreting mechanically generated groupings. The text mining procedure was therefore used as an exploratory support to thematic interpretation rather than as a standalone predictive analytical model.

To strengthen analytical rigor, the coding process followed systematic procedures for category development, review, and verification (Figure 1). Content analysis emphasizes transparency and replicability through explicit coding rules and conceptual boundaries between categories (Krippendorff, 2018). During the analytical process, responses were repeatedly reviewed to ensure internal consistency and reduce interpretative bias. The integration of qualitative coding, descriptive statistics, and exploratory text mining provided methodological complementarity by combining interpretative analysis with structured empirical evidence. Such triangulation is widely recommended in exploratory investigations involving complex organizational phenomena and emerging technological practices (Tashakkori & Teddlie, 2010).

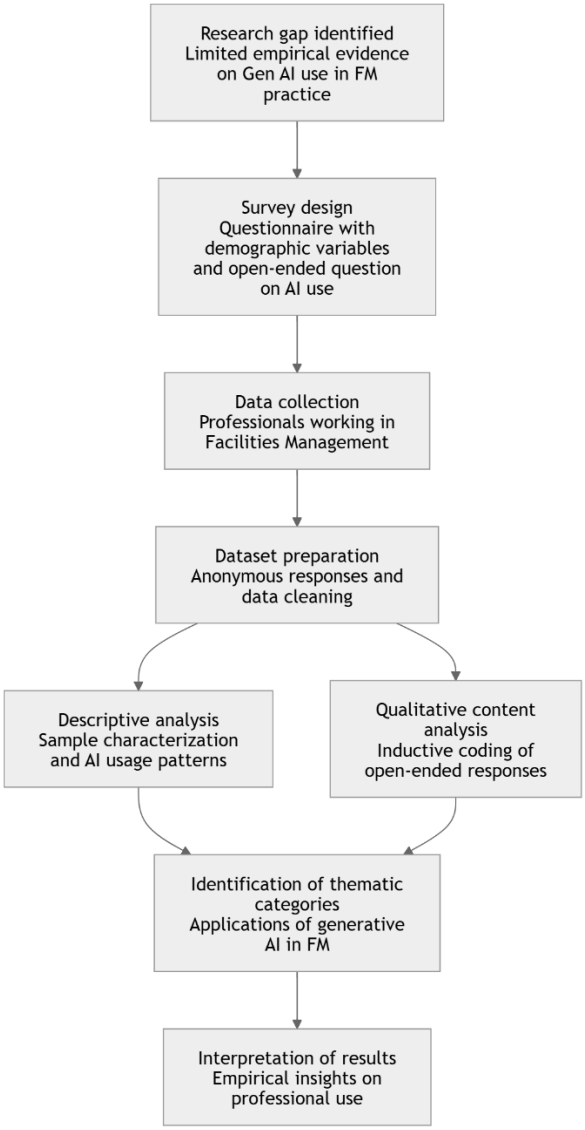


Figure 1

Research procedure illustrating the methodological steps followed to identify patterns of generative artificial intelligence use in FM practice.

Source: Authors' elaboration (2026)

Differences in perceived operational impact across professional and organizational groups were examined using Kruskal-Wallis tests. Because the dependent variable was ordinal and the sample size relatively small, this nonparametric procedure was considered appropriate for exploratory group comparisons. Eight exploratory group comparisons were conducted. To account for multiple testing, Holm-adjusted p-values were calculated. Nevertheless, the results were interpreted conservatively. Non-significant findings were not treated as evidence of the absence of an association, but rather as the absence of statistically detectable differences within the dataset. Some subgroup comparisons may therefore present limited statistical power, particularly where categories contain relatively few observations.

Participants were fully anonymized during data collection and analysis to ensure confidentiality and protect individual identities. No personally identifiable information was collected at any stage of the research process. Responses were analyzed exclusively in aggregated and anonymized form, preventing the identification of specific individuals or organizations. The survey instrument informed participants about the voluntary nature of participation and the confidentiality of the information provided. Such procedures are consistent with established ethical standards for research involving human participants and are commonly adopted in survey-based organizational studies (Creswell & Creswell, 2018).

Before analysis, the dataset was screened for response completeness and consistency. Records were reviewed for missing or unusable responses in the variables required for the descriptive and inferential analyses. The full dataset comprised 45 responses, while the number of valid observations varied according to the variable analyzed. For the

inferential analyses of perceived operational impact, 43 valid responses were available. For the text-mining analysis of practical uses, 42 valid textual responses were analyzed. For the qualitative categorization of barriers, 43 valid responses were available. Text preprocessing for the practical-use corpus involved conversion to lowercase, removal of punctuation and stopwords, and tokenization before construction of the TF-IDF document-term matrix.

RESULTS AND DISCUSSIONS

The empirical dataset comprises 45 professionals engaged in FM across organizations of varying sizes, sectors, and hierarchical structures. Three responses were excluded from the clustering stage because they were blank, incomplete, or lacked sufficient textual content for thematic classification. The descriptive profile indicates that the respondents largely represent experienced practitioners working in structured corporate environments where digital transformation initiatives are more likely to occur.

Professional tenure in the field is relatively high. More than half of the participants (51.1%) reported over 10 years of experience, 31.1% reported 6–10 years, and 17.8% reported up to 5 years of professional practice. The hierarchical distribution also reflects mature operational positions. Managers, coordinators, and supervisors represent the largest group (48.9%), followed by analysts, engineers, and technical specialists (35.6%). Assistant-level functions account for 11.1%, while executive roles, such as directors or CEOs, account for 2.2%, and other roles account for 2.2%. Educational attainment is also notably elevated, with 82.2% of respondents holding postgraduate degrees.

The organizational context reinforces this professional profile. National companies represent 62.2% of the respondents' organizations, whereas multinational firms account for 37.8%. Service-oriented organizations constitute the largest sectoral group (46.7%), followed by industry (22.2%), commerce (11.1%), and other sectors (17.8%). The public sector accounts for 2.2% of the sample. In terms of organizational size, companies with 500 or more employees account for 73.3% of the sample. These characteristics suggest that the observations originate primarily from complex corporate environments in which advanced digital infrastructure and data-driven operational practices are increasingly prevalent. Such environments have been identified as particularly conducive to the introduction of artificial intelligence technologies into built-environment operations (Volk et al., 2014; Pärn et al., 2017).

In these contexts, generative artificial intelligence already appears in professional routines, though at varying levels of intensity. 46.7% of respondents reported frequent use of Gen AI tools, while 15.6% reported very frequent use. Occasional use appears in 20.0% of responses, whereas 13.3% reported rare use and 4.4% indicated no use in their professional activities. These results indicate that Gen AI is already present in the professional workflows of most respondents, although with varying levels of use.

The platforms most frequently mentioned reflect the current Gen AI ecosystem. ChatGPT (OpenAI) emerged as the dominant system, reported by 44.2% of valid respondents, followed by Microsoft Copilot (30.2%) and Gemini (Google) (16.3%). Other systems were mentioned by 9.3% of participants. The predominance of large language model platforms suggests that early adoption occurs primarily through text-based interfaces that support knowledge-intensive activities. This pattern is consistent with the expanding role of large language models in organizational environments, where they facilitate tasks such as information synthesis, document production, and analytical interpretation (Brown et al., 2020; Hussain et al., 2025).

Institutional governance surrounding the use of these technologies is heterogeneous. Approximately 44.2% of respondents indicated that their organizations explicitly authorize and encourage the use of Gen AI tools, while 27.9% reported conditional authorization subject to internal guidelines. A relevant proportion of participants (23.3%) expressed uncertainty regarding the existence of formal policies regulating these technologies, whereas 4.7% reported complete prohibition. These findings suggest that organizational governance mechanisms for Gen AI remain uneven, reflecting the broader transitional phase associated with emerging digital technologies.

Participants were also asked to evaluate the perceived operational impact of Gen AI within their professional activities. Among the 43 respondents who provided a valid assessment, moderate impact represents the most frequent evaluation (41.9%), followed by high impact (34.9%). Very high impact was reported by 11.6% of respondents, while 9.3% perceived low impact and 2.3% reported no observable effect. The predominance of moderate assessments indicates that respondents generally perceive Gen AI as having a noticeable, but not yet extensive, influence on their professional activities. Rather than directly transforming operational processes, these systems appear to complement existing workflows by supporting information processing, documentation, and analytical reasoning.

To explore how Gen AI is used in practice, the 42 non-missing open-ended responses describing specific applications were analyzed using the exploratory text-mining procedures previously described in the Methods section. The textual corpus was processed using TF-IDF weighting and K-means clustering. Evaluation of semantic coherence and cluster size distribution indicated that a three-cluster solution provided the most interpretable

configuration. The results reveal three dominant patterns of Gen AI use. The first cluster, comprising nine responses (21.4%), corresponds to document, contract, and data analysis support, including activities such as report preparation, contract analysis, proposal comparison, document management, data analysis, and management support. The second and largest cluster, comprising 28 responses (66.7%), reflects text, productivity, and operational support, including text revision, summaries, spreadsheets, presentations, emails, procedures, action plans, routine organization, and content generation. The third cluster, comprising five responses (11.9%), corresponds to information search and technical consultation, including research on market practices, technical information, standards, legislation, and sector-specific issues.

Table 1
Dominant patterns of Gen AI use

Cluster	Dominant usage pattern	Frequency	Percentage
C1	Document, contract, and data analysis support	9	21.4%
C2	Text, productivity, and operational support	28	66.7%
C3	Information search and technical consultation	5	11.9%
Total		42	100.0

Source: Authors' elaboration (2026)

The clustering results indicate that Gen AI use in the observed sample is predominantly concentrated in cognitive, informational, and productivity-oriented activities. The largest cluster reflects routine text and productivity support, while document and data analysis and information search constitute additional application domains. These findings suggest that Gen AI is currently being used primarily to augment knowledge-intensive and information-processing activities rather than directly automate technical building operations. This pattern aligns with the knowledge-intensive nature of operational coordination in FM, where documentation, analytical interpretation, information retrieval, and communication constitute core professional activities.

The survey also investigated perceived barriers to the adoption of Gen AI. Of the 45 respondents, 43 provided valid responses to the open-ended question concerning barriers. The responses were analyzed through qualitative categorization supported by exploratory text analysis. Four patterns were identified, as presented in Table 2. The largest category, comprising 16 responses (37.2%), concerns skills, knowledge, training, and user capability limitations, including lack of familiarity with Gen AI tools, limited training, difficulties in prompt engineering, and uncertainty about how to apply the technology to routine activities. The second category, comprising 10 responses (23.3%), concerns technological, infrastructure, access, and reliability limitations, including implementation costs, access to paid platforms, hardware requirements, integration difficulties, information leakage, and concerns regarding the accuracy of generated outputs. The third category, comprising seven responses (16.3%), reflects organizational culture, governance, and implementation uncertainty, including internal policies, organizational culture, limited incentives, engagement, and the absence of structured implementation plans. Finally, 10 respondents (23.3%) explicitly reported no significant barriers to the use of Gen AI in their work environment.

Table 2
Principal categories of constraints

Cluster	Barrier category	Frequency	Percentage
C1	Skills, knowledge, training, and user capability limitations	16	37.2%
C2	Technological, infrastructure, access, and reliability limitations	10	23.3%
C3	Organizational culture, governance, and implementation uncertainty	7	16.3%
C4	No significant barriers reported	10	23.3%
Total		43	100.0%

Source: Authors' elaboration (2026)

These findings indicate that the most frequently reported barriers are related to professional capabilities and knowledge required to use Gen AI effectively, followed by technological and infrastructure limitations. Organizational culture and governance also emerge as relevant, although less frequently reported. At the same time, nearly one-quarter of respondents explicitly reported no significant barriers, suggesting heterogeneous levels of perceived constraint across the organizations represented in the sample.

Finally, differences in perceived operational impact across professional and organizational characteristics were examined using Kruskal-Wallis tests, as shown in Table 3. Because the dependent variable is ordinal and the sample size is relatively small, this nonparametric method provides a suitable approach for evaluating group differences.

Most structural variables did not produce statistically significant differences. The Kruskal-Wallis tests did not identify statistically significant differences in perceived GenAI impact after Holm adjustment for multiple comparisons. Frequency of GenAI use showed the strongest unadjusted association with perceived impact (H =

11.495, raw p = 0.009), followed by organizational authorization (H = 8.475, raw p = 0.037). However, neither association remained statistically significant after Holm adjustment (p = 0.075 and p = 0.260, respectively). These results should therefore be interpreted as exploratory signals rather than confirmatory evidence of group differences. Given the limited sample size and the small number of observations in some subgroups, these non-significant results should not be interpreted as evidence that such characteristics have no relationship with perceived Gen AI impact.

Table 3

Differences in Perceived Operational Impact Across Professional and Organizational Characteristics

Variable	Category	n	Median	H	Raw p	Holm p
Professional experience	0–5 years	8	2.0	1.224	0.542	1.000
	6–10 years	13	2.0			
	More than 10 years	22	2.5			
Organizational role	Analyst/Engineer/Technician	16	2.0	4.368	0.359	1.000
	Assistant/Administrative Support	5	3.0			
	Management/Coordination/Supervision	20	2.5			
	Other	1	2.0			
	President/Director/CEO	1	4.0			
Company origin	Multinational/Foreign	15	2.0	0.373	0.542	1.000
	Domestic	28	2.0			
Educational level	Undergraduate degree	8	2.5	0.040	0.842	1.000
	Postgraduate degree	35	2.0			
Company sector	Commerce	4	2.5	1.959	0.743	1.000
	Industry	10	3.0			
	Other	8	2.0			
	Services	20	2.0			
	Public sector	1	2.0			
Company size	Large: 500 or more employees	31	3.0	2.475	0.480	1.000
	Micro: up to 19 employees	3	1.0			
	Medium: 100–499 employees	6	2.0			
	Small: 20–99 employees	3	2.0			
Frequency of GenAI use	Rarely use	6	2.0	11.495	0.009	0.075
	Frequently use	21	2.0			
	Very frequently use	7	3.0			
	Occasionally use	9	2.0			
Organizational authorization	Authorized with restrictions or guidelines	12	3.0	8.475	0.037	0.260
	Do not know	10	2.0			
	Fully authorized and encouraged	19	2.0			
	Fully prohibited	2	0.5			

Note. *n* indicates the number of valid observations in each category. Perceived GenAI impact was measured on a five-category ordinal scale ranging from 0 = no impact to 4 = very high impact. *H* represents the Kruskal-Wallis test statistic. Raw *p*-values are unadjusted. Holm *p*-values were calculated to account for the eight exploratory comparisons. Due to missing responses, the number of valid observations varies across analyses.

Source: Authors' elaboration (2026)

Taken together, the results suggest that perceived GenAI impact was not clearly differentiated by the demographic and structural characteristics examined, whereas the strongest unadjusted differences were observed for frequency of use and organizational authorization. However, these associations did not remain statistically significant after Holm adjustment. From a broader exploratory perspective, the findings highlight the relevance of organizational conditions and opportunities for practical engagement with emerging digital technologies.

The Brazilian sample provides an empirical setting in which organizations differ in sector, size, organizational origin, and approaches to Gen AI authorization. Within this heterogeneous sample, accessible platforms such as ChatGPT, Copilot, and Gemini were reported more frequently than applications involving direct integration with building management or operational infrastructure. This pattern may partly reflect the lower integration requirements of conversational Gen AI tools, which can be incorporated into documentation, information retrieval, and technical consultation without direct connection to building management systems, IoT infrastructures, or enterprise asset-management platforms. The findings should therefore be interpreted as evidence from the Brazilian FM context rather than as representative of national adoption patterns or of emerging economies more

broadly. Because the questionnaire did not directly assess BIM, IoT, digital twins, or building management system integration, the findings cannot establish the absence of these applications in FM practice.

The findings should be interpreted in light of several limitations. First, the study is based on a non-probabilistic sample of 45 respondents, with fewer valid observations available for some variables because of missing responses. Second, the sample is concentrated among highly educated professionals, with 82.2% reporting postgraduate education, and professionals working in large organizations, with 73.3% employed by organizations with 500 or more employees. These characteristics limit the transferability of the findings to smaller organizations and other professional populations. Third, perceived operational impact was measured using a subjective ordinal scale rather than objective performance indicators. Fourth, the exploratory text-mining analysis was based on 42 textual responses, which limits the stability and generalizability of the identified clusters.

Theoretical Implications

Existing AI research in FM has predominantly emphasized technically embedded applications, including predictive maintenance, BIM-supported analytics, building performance optimization, and digitally integrated operational systems (Chen et al., 2021; Pedral Sampaio et al., 2022). More recent studies on Gen AI have expanded this technological landscape toward generative and knowledge-oriented applications, including natural-language processing, information synthesis, decision support, and interaction with digital building environments (Mehmood & Zafar, 2025; Memon et al., 2025). The present findings extend this literature by showing that current practitioner adoption does not yet correspond to the level of technical integration emphasized in much of the research. Instead, Gen AI use is concentrated in documentation, information retrieval, technical consultation, communication, and routine text processing.

This difference between the technological possibilities described in the literature and observed professional use supports the identification of a cognitive and informational adoption pattern in FM. In the present sample, Gen AI use is concentrated in knowledge-intensive activities requiring limited integration with building systems, whereas technically embedded applications were not directly assessed by the questionnaire and therefore cannot be considered absent from professional practice. The contribution therefore lies less in demonstrating that Gen AI can support FM activities and more in identifying a practice-based distinction between cognitive and informational uses and the technically integrated applications emphasized in the literature. This finding suggests that the informational layer represents an important locus of Gen AI use in the observed FM sample. However, the cross-sectional design does not allow conclusions about whether such use subsequently progresses toward deeper operational integration.

The results concerning perceived operational impact provide an additional organizational dimension to this interpretation. No statistically detectable differences were observed across professional experience, hierarchical position, educational attainment, organizational sector, company size, or organizational origin within the present sample. Given the limited sample size and the number of observations within some subgroups, these findings should not be interpreted as evidence that such characteristics are unrelated to Gen AI adoption or impact. Frequency of use and organizational authorization showed the strongest unadjusted differences in perceived operational impact, but neither remained statistically significant after Holm adjustment for multiple comparisons. These results should therefore be interpreted as exploratory signals rather than confirmatory evidence of group differences. This pattern is consistent with socio-technical perspectives in which the effects of emerging technologies depend on the interaction between technological capabilities, organizational conditions, and opportunities for practical use rather than on technology availability alone.

Organizational authorization is particularly relevant because Gen AI adoption introduces governance requirements associated with data security, accountability, transparency, and validation of generated outputs, concerns also identified in the responsible AI literature (Díaz-Rodríguez et al., 2023). Similarly, the exploratory signal associated with recurrent use is consistent with research emphasizing organizational alignment, digital maturity, and integration of digital technologies into operational processes as conditions for technology assimilation in FM (Pedral Sampaio et al., 2022). Figure 2 provides a conceptual summary of the findings by positioning usage patterns and adoption barriers as contextual dimensions relevant to professional interaction with Gen AI and perceived operational impact. These dimensions should not be interpreted as empirically established causal relationships, given the exploratory design and the absence of direct statistical testing of the relationships between specific barriers and perceived impact.

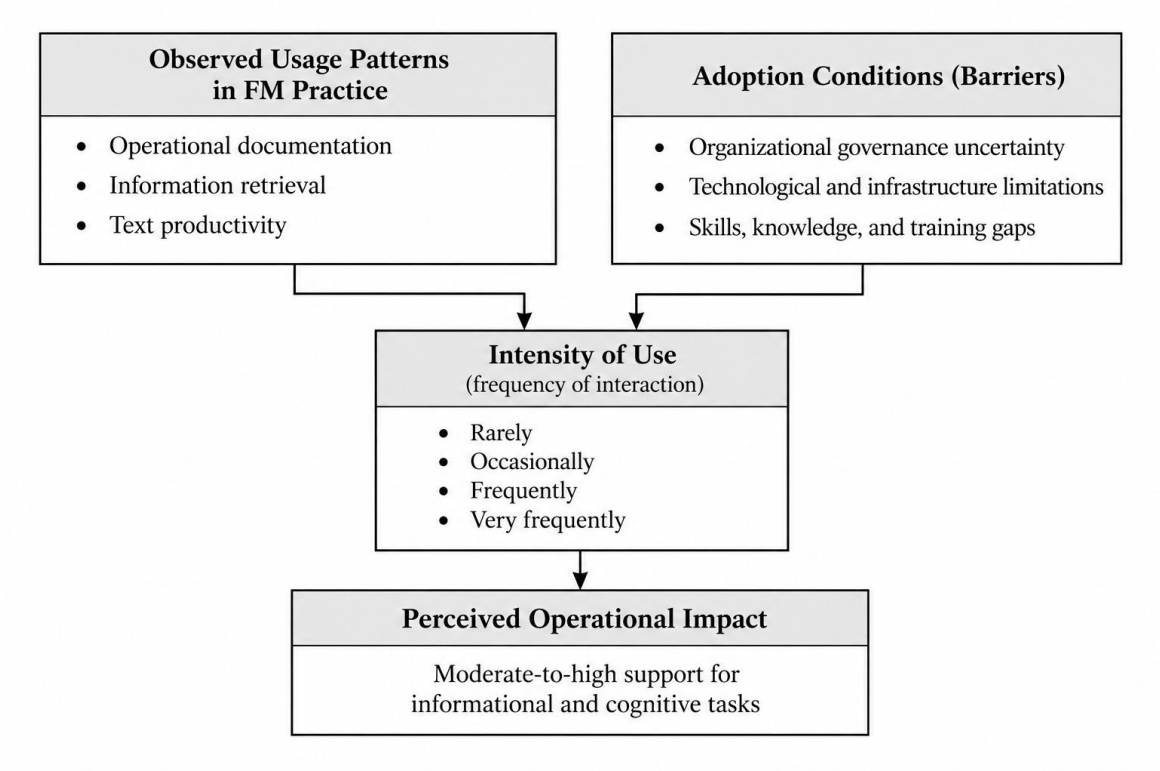


Figure 2
Conceptual summary of the relationships between Gen AI usage patterns, adoption barriers, and perceived operational impact in FM practice
Source: Authors' elaboration (2026)

The clustering results further refine this theoretical interpretation. The concentration of responses in managerial documentation, information search, technical consultation, and routine productivity indicates that Gen AI is currently functioning primarily as a cognitive augmentation technology within the observed FM sample rather than as a mechanism for direct automation of building operations. This empirical pattern provides a practice-based distinction between generative AI use and earlier forms of AI embedded in predictive, monitoring, and optimization systems, contributing to a more specific conceptualization of how generative technologies are being incorporated into facilities operations.

Managerial Implications

The findings suggest that organizations considering Gen AI adoption in FM can initially focus on knowledge-intensive activities that require limited integration with critical building systems. Documentation, report preparation, information retrieval, technical consultation, and text processing represented the predominant applications observed in the sample. These activities may therefore constitute practical entry points for organizational experimentation because they allow Gen AI capabilities to be evaluated within existing workflows before implementation is considered for applications involving operational infrastructure, building automation, or integrated asset-management systems. This approach is consistent with research indicating that digital transformation in FM depends on organizational alignment and compatibility with existing processes and technological infrastructures (Pedral Sampaio et al., 2022).

The observed exploratory differences across organizational-authorization categories, together with the prominence of governance-related barriers in the qualitative findings, indicate that formal governance deserves particular attention when implementing Gen AI. Responsible use policies should specify which data may be processed by Gen AI systems, which applications are permitted, how generated outputs must be validated, and where human accountability remains mandatory. These requirements are particularly relevant in FM because operational records, maintenance information, contracts, supplier data, technical documentation, and building-related information may involve confidentiality, regulatory compliance, safety, or infrastructure reliability. The need for such governance is consistent with broader responsible AI research emphasizing transparency, accountability, data protection, and human oversight as conditions for organizational deployment of AI systems (Díaz-Rodríguez et al., 2023).

The exploratory difference associated with frequency of use and perceived operational impact further suggests that organizational value is unlikely to emerge solely from providing access to Gen AI platforms. Professionals require opportunities to test these systems in recurrent work activities and to develop criteria for evaluating the reliability and appropriateness of generated outputs. Structured training, controlled experimentation, and internal knowledge-sharing

mechanisms may support this process. This interpretation is consistent with studies of digital transformation in FM that emphasize organizational readiness and the development of capabilities required to integrate emerging technologies into established operational processes (Pedral Sampaio et al., 2022).

At the same time, the present findings do not provide empirical evidence to assess the immediate expansion of Gen AI into safety-critical or highly automated building operations. The observed use pattern remains concentrated in cognitive and informational activities, whereas the literature describes more advanced possibilities involving BIM, digital twins, building monitoring, and integrated operational systems (Memon et al., 2025). For FM managers, this distinction suggests that implementation decisions should differentiate between low-integration knowledge applications and technically embedded applications requiring stronger controls, system interoperability, validated data sources, and explicit responsibility for AI-assisted decisions. The managerial implication is therefore not a prescriptive sequence of adoption stages, but the need to align governance, professional capability, and technological integration with the specific risk and complexity of each Gen AI application.

CONCLUSIONS

This study examined how Gen AI is currently incorporated into FM professional practice using exploratory evidence from Brazilian practitioners. The findings show that reported use is concentrated primarily in knowledge-intensive activities, including operational documentation, information retrieval, technical consultation, communication, and routine text processing. Direct integration with technical building operations was comparatively less evident in respondents' descriptions.

This concentration supports the identification of a cognitive-oriented adoption pattern in the observed FM context. Rather than demonstrating a temporal sequence of technological adoption, the pattern distinguishes current cognitive and informational applications from the technically embedded AI applications more frequently emphasized in the FM literature. In this respect, the study contributes empirical evidence on the gap between the technological possibilities associated with Gen AI and its current incorporation into professional practice.

Exploratory group comparisons showed the strongest unadjusted differences in perceived operational impact for frequency of use and organizational authorization, but these differences did not remain statistically significant after adjustment for multiple comparisons. These results should be interpreted cautiously given the sample size, convenience sampling strategy, and subgroup distributions. The qualitative findings nevertheless reinforce the relevance of organizational conditions, particularly governance uncertainty, technological integration, and professional capabilities, as barriers to adoption.

The study is limited by its relatively small, non-probabilistic sample, subjective measurement of perceived impact, and the limited textual corpus used for exploratory clustering. Consequently, the findings are not intended to represent the Brazilian FM population or establish causal relationships. Future research should test the cognitive-oriented adoption pattern using larger and more diverse samples, longitudinal designs, and objective indicators of operational performance. Longitudinal research would be particularly valuable for determining whether cognitive and informational uses subsequently evolve toward deeper integration with building systems and operational infrastructures.

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