Facilities

Detecting critical building maintenance health status through automatic performance-based assessment

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Abstract

Purpose – Large organizations receive numerous daily maintenance requests that must be assessed efficiently. Facility managers need rapid support to detect critical conditions and reduce functionality losses. A key performance indicators (KPIs)-based approach is introduced to quantify the relevance of intervention requests from a Computerized Maintenance Management System (CMMS). This work aims to develop quick metrics to help facility managers monitor relative impacts across different locations and activity types.

Design/methodology/approach – A data set of about 17,000 maintenance requests from an Italian university was analyzed. Each request was categorized by activity type (based on Omniclass classification), priority and programmability. This information is combined through the analytical hierarchy process to define a Relevance Index (RI) measuring the impact of different building clusters on the overall health status of facilities.

Findings – RI provides a rapid overview of corrective maintenance needs and performance levels. Critical conditions are identified and compared, quantifying that the larger and most crowded buildings cluster (i.e. engineering faculty buildings) has the highest impact.

Practical implications – RI can be integrated within CMMS (and customized for other large organizations) to provide facility managers with a data-driven tool for evaluating requests relevance and facilities health status, ultimately contributing to safer and more functional workplaces.

Originality/value – The proposed methodology fills the current gap in rapid metric for automatically assessing the relevance of maintenance issues across building stocks. By translating unstructured maintenance requests into a quantifiable RI, the framework strengthens facility managers decision-making and benchmarking within and between assets.

Keywords Building maintenance, Facilities management, AHP, KPI, Operational efficiency, Maintenance requests

Paper type Research paper

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1. Introduction

Facility management (FM) involves coordinating and maintaining services such as energy supply, cleaning, security, telecommunications and building repairs to ensure efficient, safe and regulation-compliant environments (Gopikrishnan and Kumar, 2019; Lok and Baldry, 2015). In large and complex organizations such as university campuses, hospital networks or corporate estates, facility managers must frequently assess the health status of multiple assets distributed across different locations (Abdeen *et al.*, 2022; Lai *et al.*, 2022; Mohammed *et al.*, 2025). This includes evaluating building systems, identifying failures and prioritizing interventions through rapid and scalable methods that can synthesize performance data across extensive building stocks (Islam *et al.*, 2021; Mohammed *et al.*, 2025). Indeed, buildings health and maintenance activities cannot be assessed independently, but in relation to their overall impact on system-wide performance and, consequently, on occupant well-being and organizational productivity (Lai and Man, 2018; Sallan *et al.*, 2025).

Traditional FM approaches often rely on static models that do not fully capture maintenance and operation variability. Recent advances in digital technologies and data science, however, enable the interpretation of buildings as dynamic systems (Grussing and Liu, 2014; Gunay *et al.*, 2019; Kim Wing *et al.*, 2016; Lu *et al.*, 2020; Wang *et al.*, 2022). User interaction with building systems has been identified as a major source of variability affecting and failures rates (Dong *et al.*, 2018). Systems such as HVAC, lighting, plumbing and elevators degrade differently depending on usage patterns, intensity and timing (D'Orazio *et al.*, 2023; Golabchi *et al.*, 2016). These patterns strongly influence corrective maintenance (Lind and Muyingo, 2012), which can vary in activity type, timing and costs, thus resulting in different levels of priority and programmability (Bortolini and Forcada, 2020; Chong *et al.*, 2018). Corrective maintenance data can therefore support not only resolution of critical failures but also preventive or predictive strategies aimed at reducing unplanned failures and breakdown (Kim Wing *et al.*, 2016; Mohammed *et al.*, 2025; Sallan *et al.*, 2025).

With the digital transition of FM, information technology (IT) systems play a central role in managing the complexity of modern building operations (Alhassan and Kidido, 2023; Fadaeefath Abadi *et al.*, 2020; Lu *et al.*, 2020). Computerized Maintenance Management Systems (CMMS), are particularly relevant for supporting corrective maintenance by providing structured access to intervention data, histories, recurrent problems, priority levels and the organizational workflow of maintenance processes (Bortolini and Forcada, 2018, 2020; D'Orazio *et al.*, 2023; Marocco and Garofolo, 2021). Other IT tools, such as mobile application and sensor-based systems, can further complement CMMS and FM decision-making (Maslesa and Jensen, 2019).

To enhance the effectiveness of these digital tools and ensure consistency in how information is structured, standardized classification systems have become increasingly relevant in FM (Royano *et al.*, 2023). They support the systematic organization of building-related data and create a shared vocabulary among stakeholders (Kula and Ergen, 2018). Several classification systems have been developed over the past decades to structure building-related knowledge and support information exchange. Between them, CI/SfB, Uniclass, MasterFormat, UniFormat and OmniClass provide structures frameworks for aligning project data, maintenance records and operational workflows, thereby facilitating better-informed decision-making in FM contexts (Royano *et al.*, 2023). Nevertheless, the adoption of a unique, universal classification remains uneven due to differences in building typologies, geographical and operational contexts (Kula and Ergen, 2018; Royano *et al.*, 2023).

While classification systems provide a structured framework for organizing building-related information, much of the operational data stored in CMMS platforms remains largely unstructured, especially when information is stored as day-to-day free-text descriptions (Aalipour *et al.*, 2018; Zangari *et al.*, 2023). Support tickets are among the most frequent systems for managing and tracking maintenance needs (Zicari *et al.*, 2021). Typically written informally by users or technicians, tickets vary widely in vocabulary and format and may be submitted through email, phone calls, web forms, live chats or social media (Zangari *et al.*, 2023). They can be generated manually or automatically (e.g. by sensor-based systems) and provide valuable insights regarding usage conditions, recurrent failures, seasonal trends and spatial clusters of anomalies, serving as a key point of interaction between end-users and FM personnel (Beneker and Gips, 2017; Ensafi *et al.*, 2023; Tolciu *et al.*, 2021).

Data-driven approaches can extract meaningful patterns from such operational data to support FM decision-making (Mawed and Aal-Hajj, 2017). Key performance indicators (KPIs) serve as quantifiable and objective metrics that translate raw data into actionable insights and benchmark current performance against measurable targets, needs and standards (Lai *et al.*, 2022; Shi *et al.*, 2021; Shohet, 2003). Several models exist across different organizational levels (operational, strategic), service phases (input, process, output), building contexts (i.e. hospitals, hotels and educational facilities) and standpoints (e.g. environmental, safety, economic and energetic perspectives) (Abdeen *et al.*, 2022; Lai *et al.*, 2022; Lai and Man, 2018; Mawed and Aal-Hajj, 2017; Shi *et al.*, 2021). However, despite this broad application, there is a lack of simple and effective KPI frameworks specifically designed for maintenance contexts to assess the overall health status of large multi-building facilities such as university campuses.

Within this context, this study defines a data-driven approach that provides facility managers with a rapid tool to assess the health status of large facilities receiving numerous daily maintenance requests. In this way, this contribution aims at providing an approach to: (1) enable a consistent interpretation and quantification of unstructured data; (2) support efficient decision-making; and (3) facilitate timely prioritization of interventions, also focusing on those which are critical to workspace quality and productivity.

The proposed assessment methodology takes advantage of a synthetic index specifically developed through a multi-criteria analysis that combines different KPIs that identify and quantify the activity type, the priority and the programmability of the interventions. Specific evaluations can be performed through aggregated classifications organized by spatial divisions, such as individual buildings or zones, allowing facility managers to drill down into detailed insights for each part of the building stock. This multiscale approach is essential to address the specific needs and characteristics of different assets within a large building complex and to optimize maintenance planning and resource allocation while satisfying occupants' needs. These research outcomes are part of the DIGITMAN project (Massafra *et al.*, 2025). DIGITMAN focuses on the digital management of building stocks and develops operational methods and easy-to-use tools to analyze data collected through typical FM workflows and inform decision-makers on current building conditions (in a continuous manner) as well as on alternative intervention scenarios (based on different resource allocations) in the context of building maintenance, operation and safety.

To demonstrate the reliability of the proposed approach, a university building stock located in Ancona, Italy, has been selected as case study in view of its relevance in the given operational context. The data set analyzed includes more than 16,000 corrective maintenance requests collected between 2018 and 2023 from 6 building clusters and 25 buildings serving educational and administrative functions, accommodating approximately 16,000 students and 1,000 staff members. The framework can guide action at both the micro (building areas) and macro (building stocks) scales and, although tailored to the Italian context, it can be adapted to other large facilities with similar maintenance systems (e.g. CMMS and ticketing platforms), supported by an extended version of the OmniClass system for classifying intervention requests.

2. Research methodology

The work is organized in three phases, as proposed in the workflow in Figure 1, applying the proposed methodology to the context of a university composed of a large building stock, as relevant case study. The first phase involves the organization of data on building stock features, their aggregation into building clusters and maintenance requests collection according to the FM (Section 2.1). In particular, basic data from requests' organization by the FM concern activity type, priority and programmability of requested interventions. The second phase concerns the definition of the methodology for aligning and categorizing data, thanks to the classification standardization of corrective maintenance activities by types, relying on the OMNIClass system, and to their relevance comparison through multicriteria analysis (subsection 2.2). Therefore, activity type-based weights are derived in this phase, to be applied in the assessment process. Finally, KPIs are defined to comprise activity types, priority and programmability, and they are combined to provide a unique metric, that is the Relevance Index (RI), for consistent and objective assessment of facility health status (subsection 2.3). To this end, the independence of KPI distributions across clusters was statistically tested before the aggregation to confirm the validity of inter-cluster comparisons. RI is calculated by building cluster, by aggregating KPIs and weighting their values by activity type-based weights.

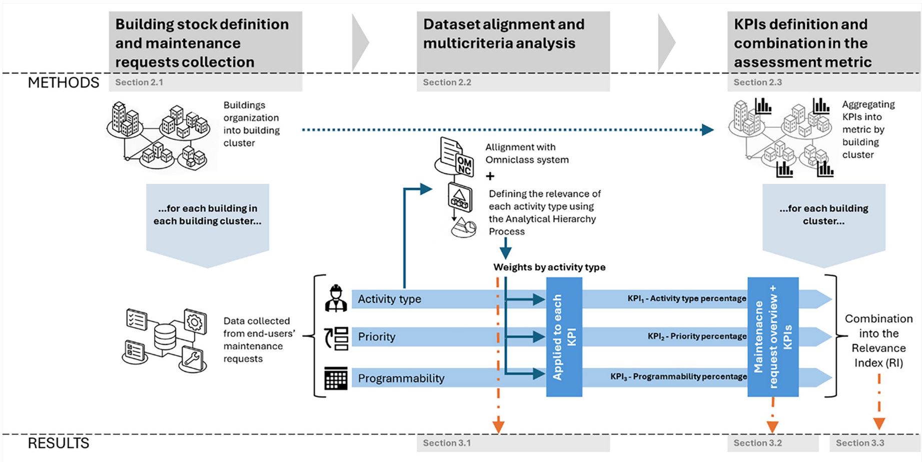

Figure 1. Research workflow, by main phases, references to the related methodological sections and results sections providing details of approach development and case-study application outcomes

Source: Authors' own work

In the sake of completeness, the list of abbreviations in this paper is reported in Supplementary Files for tables reporting both acronyms and indicators used in calculations.

2.1 Building stock definition and maintenance requests collection

The data set used as a case study consists of end-user requests collected from the building stock of the University "Politecnica delle Marche" (UNIVPM), shown in Table 1 and Figure 2. UNIVPM building stock is mainly located in Ancona, Italy, and composed of 25 buildings, built/renovated in different years and being characterized by different sized in terms of gross floor area (GFA – [m^2]) and floors number. These buildings are indeed organized into 6 main buildings clusters. In each building, the assets targeted by maintenance activities include building components, systems and equipment characterized by a good degree of homogeneity, supported by continuous maintenance interventions and systematic replacement of faulty components. For instance, the HVAC systems include centralized heating, fan coil units and an independent ventilation network, while no mechanical cooling systems are installed. Maintenance activities are systematically carried out and managed through a CMMS operated by an external contractor, who provides both regular predictive maintenance (e.g. scheduled component replacements before the expected end-of-life) and on-demand corrective maintenance (e.g. repairs or replacements following faults reported by end-users via email).

Table 1. List of buildings organized by cluster. Each cluster corresponds to different areas in the municipality of Ancona, Italy. YoC/R stands for year of construction or rehabilitation; GFA stands for gross floor area

Cluster (ID code)	Building code	YoC/R	GFA [m^2]	Floors
Engineering (ED)	ED1	1990	7870	6
	ED1BIS	1990	3175	3
	ED2	1990	14340	3
	ED3A	1990	6540	3
	ED3B	1990	6035	4
	ED4	1990	12360	3
	ED5	1990	11825	3
	EDAM	1990	2605	1
	EDPMS	1990	4110	4
	EDTOR	1990	4375	11
	EDBAS	2005	14670	3
Science (SC)	SC1	1997	3645	3
	SC2	2004	3510	3
	SC3	2008	4010	3
Agricultural science (AG)	AG1	1982	9430	4
	AG2	1982	5990	2
	AG3	2002	955	1
Economics (EC)	EC1	1996	31240	4
	EC2	1996	565	2
Medicine (MED)	MED1	1995	26305	7
	MED2	2008	10280	6
Administration (AM)	AM1	1976	3060	5
	AM2	1976	1620	3
	AM3	1976	3140	3
	AM4	1976	2350	6

Source(s): Authors' own work

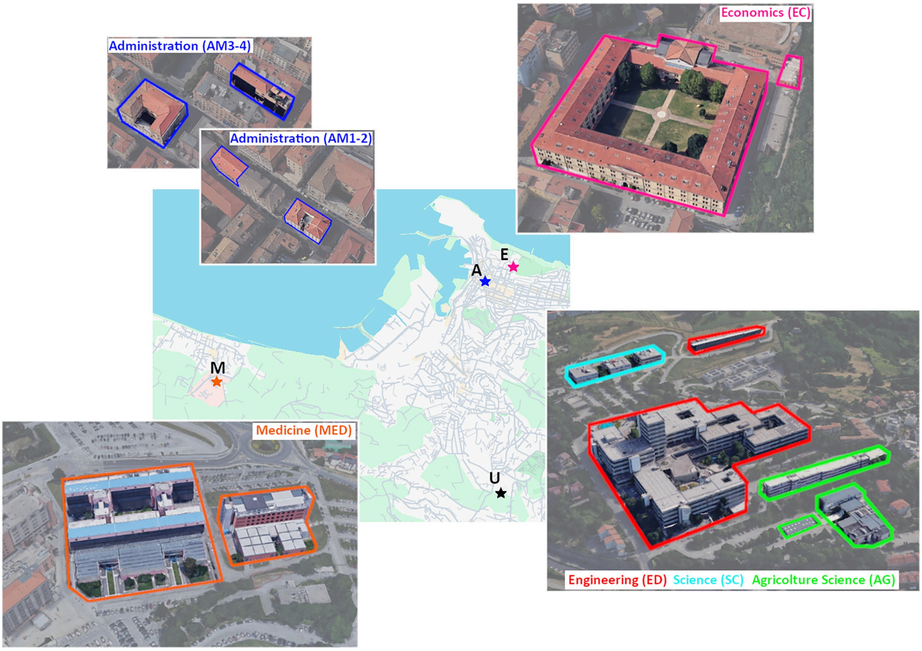

Figure 2. General map of Ancona (Italy) showing each cluster location, with corresponding aerial views (source: Google Maps). Legend: orange indicates Medicine (m); blue indicates Administration (a); magenta indicates Economics (e), while U includes the other clusters: Engineering in red, Science in cyan and Agricultural Science in green

Source: Authors' own work

End-users typically submit maintenance requests via support tickets (i.e. email, phone calls, service forms) which are then processed within the CMMS to organize the interventions. In particular, each request is translated by the technical staff into a work order that categorizes technical information, including:

- the original, unstructured end-user's communication;
- the intervention object, by defining the maintenance activity according to the operational organization of the external contractor (Elevators; Electrical; Fire alarm; General Building Components, such as Walls, stairs, floors, ceilings; HVAC, including heating, ventilation, cooling units; Openings; Plumbing; Utilities, by mainly focusing on sewer systems);
- dates (i.e. request arrival, opening, closing, inspection);
- priority, as the urgency of a maintenance issue, divided into three main categories: P1 high, P2 medium and P3 low; and
- and programmability, as the flexibility to schedule it without immediate action, divided in four main categories: U undeferrable, ST short-term, MT medium-term and LT long-term.

This study considers 16,790 work orders collected in UNIVPM between 2018 and 2023, which also roughly corresponds to the contract period of the external contractor, thus depicting the building stock health status in an operationally homogenous period in terms of FM. Furthermore, a discussion with decision-makers in the case study has been also performed at the end of the monitoring period, once data were assessed according to the methodology analysis, to point out possible reasons for indicators' status in the different clusters. This supports the reliability analysis of the proposed assessment method.

2.2 Data set alignment and multicriteria analysis

To support the systematic analysis and interpretation of data through the KPIs, maintenance requests were categorized by converting work orders into a standardized classification framework, by mainly acting on the definition of maintenance activity per intervention object (Royano *et al.*, 2023). For this purpose, the OmniClass structure was adopted as a common reference and subsequently adapted to reflect the operational and technological characteristics of the selected case study (CSI, 2019). In particular, the classification is based on the structure of Table 2 (Work Results), considering the first hierarchical level, which pertains to the general structural domain of the intervention. This process enabled the consistent identification and grouping of maintenance activity types into a unified set of categories. The final data set comprises eight distinct activity types, summarized in Table 2.

To complete this procedure, the original data set of UNIVPM maintenance requests was analyzed using the Python programming language (version 3.11.7) within the DataSpell 2023.3.4 (JetBrains) IDE, selected for its user-friendly interface and suitability for efficient data analysis procedures. All the original number of requests (16,790) was re-classified.

Since maintenance activity types are characterized by different impacts on asset performance, it is essential to differentiate their relative significance when assessing building conditions (Shohet, 2003). To this end, a multicriteria analysis was performed using the Analytic Hierarchy Process (AHP) to assign weights to each activity type and reflect their relative importance within the analysis framework (Saaty, 1980), which has been previously applied also in the context of facilities performance (Lai *et al.*, 2022; Shi *et al.*, 2021). In particular, a panel of 7 domain experts within the DIGITMAN project was consulted. The experts were facility managers, technical staff and academic researchers with proven expertise in building maintenance, asset management and facility performance assessment.

Table 2. List of maintenance activity types aligning the omniclass system to the UNIVPM data set activities, by including both the omniclass – table 22 code and the identification code (ID) used in this work (last column)

Omniclass activity	Omniclass code	UNIVPM classification	UNIVPM ID used in this work
Conveying equipment	14	Elevators	1
Electrical	26	Electrical: Lighting, power systems	2
Electronic safety and security	28	Fire alarm: Alarms, video surveillance	3
General building components	09	General building components: Walls, stairs, floors, ceilings	4
HVAC	23	HVAC: Heating, ventilation, cooling units…	5
Openings	08	Openings: Doors and windows	6
Plumbing	22	Plumbing: Plumbing and sanitary systems	7
Utilities	33	Utilities: Sewer systems	8

Source(s): Authors' own work

Their background ensured a comprehensive understanding of the maintenance activities considered, enabling them to reliably perform pairwise comparisons between the activity types. The comparisons considered a linear scale from 1 (equal importance) to 9 (maximum importance of one factor over another), and individual evaluations were collected using a freeware AHP Excel template (Goepel, 2018) [https://bpmsg.com/new-ahp-excel-template-with-multiple-inputs/]. The final weights were computed by aggregating the experts' judgments using the row geometric mean method (RGMM), ensuring that the resulting priority values for each KPI were summed to one. Consistency of individual judgments was verified to ensure that the Consistency Ratio (CR) remained below the 10% threshold. Subsequently, a consensus matrix was generated by synthesizing the inputs of all experts, and the same RGMM method was applied to derive group priorities. The level of agreement among experts was assessed using the AHP consensus indicator S*, a homogeneity measure based on Shannon entropy (Goepel, 2018). S* values close to 100% indicate a strong consensus, while values near 0% suggest divergence in expert opinions.

2.3 Key performance indicator definition and combination in the assessment metric

KPIs were defined according to the SMART assessment framework, which introduces the following criteria (Doran, 1981):

- Specific – KPIs are designed to address clearly defined maintenance issues pertinent to buildings, encompassing all elements within the building stock, and following established classification systems, such as those based on the Omniclass taxonomy.
- Measurable – KPIs quantify the maintenance needs of buildings to be comparable across data outputs.
- Assignable – KPIs are associated with specific building components/systems or, at a minimum, with defined spatial areas or units within a larger building stock. This association provides insights for decision-makers about the impact of building current conditions.
- Realistic – KPIs are based on the practical context of large organizations. They consider input from end-users and are guided by decisions made at a higher management level, supporting the optimization of maintenance strategies according to realistic constraints and priorities.
- Time-related – KPIs are designed to support rapid assessments, focusing on timely analysis of building maintenance conditions. They enable decision-makers to quickly evaluate requests (e.g. by type, severity or spatial location), thereby minimizing delays and reducing the effort for manual data processing.

A set of KPIs has been defined to assess the current health status of buildings by applying data mining techniques to maintenance records. These indicators, resumed in Table 3, vary within a range from 0 (minimum impact) to 100 (maximum impact), ensuring consistency and comparability across different spatial and functional contexts. The KPIs are designed to measure the impact of each activity type j (see Table 2) on specific locations k (see Table 1), allowing spatial comparisons within the data set. In particular, for cluster evaluations ($k = C$), KPIs are calculated with respect to the total number of requests of the same activity type within the entire data set, while for single building evaluations ($k = b$), they can be calculated with respect to the total number of requests of the same activity type within the corresponding cluster.

The independence of KPI distributions across clusters was verified through chi-square tests applied to contingency tables of activity types versus clusters, to ensure that inter-

Table 3. List of KPI to be combined into the RI. Percentages are calculated with respect to the total number of requests for that same activity type within the corresponding specific area (that is the entire campus for building cluster analyses, and building clusters for single building analyses)

KPI_i	Name	Formula	Explanation
KPI_1	Intervention percentage by activity type	$KPI_{1,j,k} = \frac{S_{j,k}}{S_j} \cdot 100$	Percentage of maintenance requests *S* of a specific activity type *j* in a specific location *k*. Evaluates how relevant a location is for a specific type of maintenance activity
KPI_2	Priority percentage by activity type	$KPI_{2,j,k} = \frac{S_{j,k}^{(P1)}}{S_j^{(P1)}} \cdot 100$	Percentage of maintenance requests *S* classified under the highest priority category (within a Three levels priority scale: P1 high, P2 medium and P3 low) of a specific activity type *j* in a specific location *k* Evaluates which location concentrates the most urgent interventions for a given maintenance activity
KPI_3	Programmability percentage by activity type	$KPI_{3,j,k} = \frac{S_{j,k}^{(U)}}{S_j^{(U)}} \cdot 100$	Percentage of maintenance requests *S* classified under the highest programmability category (within a Four-level scale: U undeferrable, ST short-term, MT medium-term and LT long-term) of a specific activity type *j* in a specific location *k* Evaluates the level of planning flexibility in a given location for a given maintenance activity

Source(s): Authors' own work

cluster variations reflected genuine structural differences rather than random effects (Gravetter and Wallnau, 2013). All three KPIs showed statistically significant differences ($p < 0.05$), confirming that maintenance patterns vary meaningfully across clusters.

It is important to note that all KPIs offer complementary perspectives into urgency and planning implications of reported maintenance issues:

- KPI_1 considers the distribution of maintenance requests by activity type across locations, that are specified by the end-users at the time of request submission;
- KPI_2 considers the priority classification, that is directly defined by the end-users when submitting the request (based on their perception of how quickly the intervention is needed), and
- KPI_3 considers the programmability assessment, that is defined by the maintenance technicians after an on-site inspection, and it is then grounded in technical assessments of feasibility and urgency.

In this sense, programmability can be influenced by practical and logistical considerations (e.g. the availability of replacement components or scheduling constraints) that may lead to postponement, while the same issues are not known by end-users, possibly implying misalignment between operational schedules and end-users' desires.

In view of the above, KPIs in Table 3 help hence decision-makers to characterize not only the volume, but also the urgency and scheduling constraints associated with maintenance needs across the facilities, providing a solid basis for a data-driven assessment of the health status of the buildings.

Finally, to ease and speed up decision-making, the three KPIs are aggregated into a single Relevance Index (RI_k), which quantifies the overall maintenance impact on building health. This index is computed as the Euclidean norm of a vector in a three-dimensional KPI space (k = 3), with the resulting value also ranging from 0 to 100. In this formulation, summarized in equation (1), each KPI is considered equally relevant in terms of its contribution to the overall impact assessment, ensuring a balanced and objective representation of the combined effect of maintenance object, priority and programmability with respect to the whole system conditions. In particular, prior to aggregation, each KPI is weighted depending on the activity type involved, through the same AHP multicriteria analyses introduced in subsection 2.2, and then the weighted values are summed and squared. The final RI is calculated as the square root of the mean of these squared sums, as shown in equation (1). This approach ensures that KPIs remain directly comparable across the assessment space while also incorporating the relative importance of the underlying activities, thereby aligning both the analytical structure and the operational relevance of the results:

$$RI_k = \sqrt{\frac{\sum_{i=1}^{3}\left(\sum_{j=1}^{8} W_j \cdot KPI_{ijk}\right)^2}{3}}$$

where:

- $i \in \{1, 2, 3\}$ represents the three KPIs (e.g. activity type, priority, programmability);
- $j \in \{1, \ldots, 8\}$ represents the eight categories of activity type;
- k represents the location (i.e. the cluster or the building);
- W_j is the weight associated with activity type j, obtained through the AHP multicriteria analysis (see Section 2.2);
- KPI_{ijk} is the value of KPI i for activity j for location k;
- The inner sum applies weights to the KPIs per activity type; and
- The outer sum aggregates the weighted KPIs.

3. Findings

This section presents this work's results, structured in three main parts. Subsection 3.1 discusses the AHP outcomes, providing the weighting factors associated with the different maintenance activity types. Subsection 3.2 analyzes the KPIs outcomes broken down by activity type and by cluster. In this process, KPIs can be customized to different spatial scales (i.e. location *k*, as shown in equation (1)); this study, however, focuses on the cluster level to ensure clarity and conciseness. Finally, in subsection 3.3, the three KPIs are aggregated into the RI, which synthesizes the multidomain information into a single metric supporting the overall assessment of building health.

3.1 Analytic hierarchy process results

The multicriteria analysis carried out through the AHP provided a robust framework for quantifying the relative impact of the different maintenance activity types. The results shown in Figure 3 reveal huge variability in perceived impact across categories. Fire Alarm systems received the highest weight (26.41%), indicating their central role in ensuring occupant safety and compliance with regulations. Electrical systems followed with a substantial weight (19.32%), reflecting their critical contribution to operational continuity. Openings ranked third (13.86%), underscoring their importance in maintaining accessibility and usability of environments. Elevators and Plumbing interventions were also regarded as significant, while General Building Components, HVAC systems and Utilities were assigned

	1-elevators	2-electrical	3-fire alarm	4-GBC	5-HVAC	6-openings	7-plumbing	8-utilities
1-elevators	1.00	0.42	0.36	3.31	2.60	0.54	0.53	2.08
2-electrical	2.39	1.00	0.66	2.69	3.06	1.18	2.23	3.44
3-fire alarm	2.77	1.51	1.00	3.54	3.14	2.58	2.95	3.83
4-GBC	0.30	0.37	0.28	1.00	0.98	0.37	0.53	1.40
5-HVAC	0.38	0.33	0.32	1.02	1.00	0.48	0.73	1.42
6-openings	1.85	0.85	0.39	2.67	2.10	1.00	1.18	1.93
7-plumbing	1.87	0.45	0.34	1.87	1.37	0.85	1.00	2.95
8-utilities	0.48	0.29	0.26	0.71	0.70	0.52	0.34	1.00

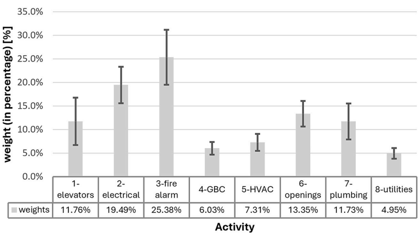

Figure 3. Results of the AHP process and the consensus group tasks. On the left, summary of the final comparison matrix; on the right, activity types and related weights, associated with vertical bars, that show the weights uncertainties

Source: Authors' own work

lower weights, suggesting a relatively limited impact on perceived building health within the context. Overall, this hierarchy suggests that maintenance activities exert their greatest influence where they directly affect safety-related functions, followed by interventions that ensure the usability and accessibility of facilities and finally by activities primarily associated with user comfort and environmental quality. The resulting weighting factors are integrated into the RI to deliver more rapid and comprehensive insights into the health status of building systems.

The consistency ratio obtained during the AHP process is equal to 2.5%, which is below the 10% recommended threshold and ensures the reliability of the pairwise comparisons. Furthermore, the consensus indicator (S*=0.83) demonstrated a high degree of agreement among experts, supporting the credibility of the aggregated values (values higher than 0.80 guarantee strong consistency).

3.2 Key performance indicators results

The analysis of the single KPIs provides a detailed overview of the maintenance needs across the different building clusters. Indeed, by examining the three perspectives of overall intervention requests (KPI_1), priority perception by users (KPI_2) and assigned programmability by technicians (KPI_3), it is possible to identify distinctive maintenance patterns and critical areas requiring attention.

Regarding KPI_1, which measures the relative relevance of each activity type within a specific location, Figure 4 points out the heterogeneity among the building clusters and the distinct operational profiles and pattern of use.

The Engineering cluster clearly stands out as the primary driver of maintenance requests across the campus, encompassing a broad spectrum of systems. The most affected activity types include Elevators, Plumbing, General Building Components and Utilities, that reach values exceeding 40%. This widespread distribution indicates an intensive use of facilities also characterized by huge technical complexities. The presence of elevated values across several categories suggests that failures or malfunctions are not confined to a single system but rather dispersed across different functional domains.

The Medicine cluster follows this trend, with high maintenance demand especially for Openings, HVAC, Electrical systems and Fire Alarms. This pattern aligns with the operational stress typical of health-care and laboratory environments, where comfort and safety systems must sustain continuous operation under stringent conditions. The

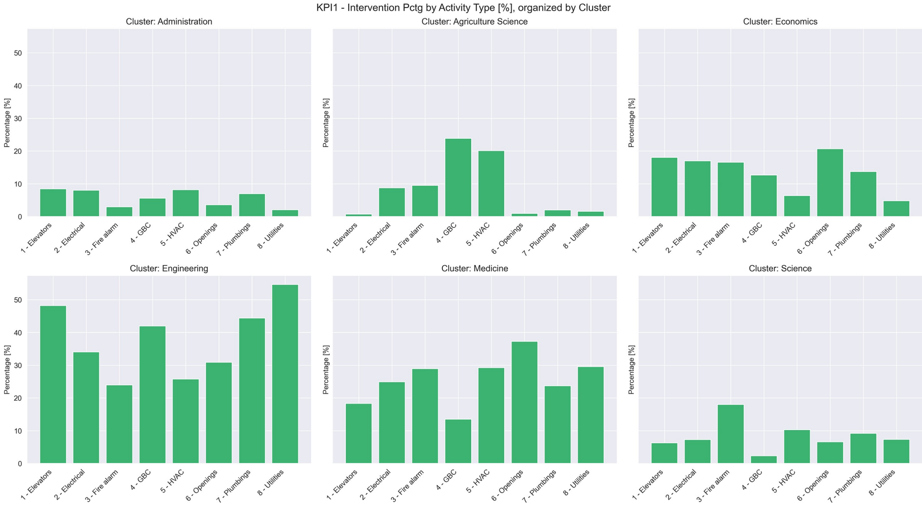

Figure 4. Intervention percentage by activity type (KPI_1) organized by Cluster. GBC stands for General Building Components, HVAC stands for Heat, Ventilation and Air Conditioning

Source: Authors' own work

combination of high values in both HVAC and Fire Alarm categories suggests an environment highly sensitive to thermal comfort and safety reliability.

In the Economics cluster, the distribution of requests is more balanced but still highlights substantial requests in Elevators, Electrical, Fire Alarms and Openings. The prevalence of these categories reflects the predominance of office-type environments, where accessibility and day-to-day usability issues generate recurring maintenance needs rather than system-critical failures.

The Agricultural Sciences cluster presents peaks of requests for HVAC and General Building Components, while other systems remain below 10%. This indicates that maintenance demand in these facilities is concentrated on environmental control and structural aspects, reflecting significant users' flow and interactions in respect to indoor comfort, but also consistent with the presence of spaces where temperature is critical for research activities.

The Science cluster displays moderate activity levels, with a small peak in Fire Alarms and modest values in other systems. This distribution can be attributed to the presence of laboratory layouts and controlled environments, where safety systems play a central role in maintenance operations. However, a discussion with facility managers of the case study underlined that some criticalities in this activity type were pointed out during the monitoring period, requiring additional verifications and updating of the whole system. In this sense, the proposed methodology can timely underline critical operational conditions, boosting decision-making support by early detection tasks.

The Administration cluster records generally lower and more evenly distributed maintenance requests across all categories, mainly due to the limited technical complexity of these building systems and facilities.

Figure 5 displays KPI_2 (priority percentage, in red) and KPI_3 (programmability percentage, in yellow), offering a joint overview of user-perceived urgency and the

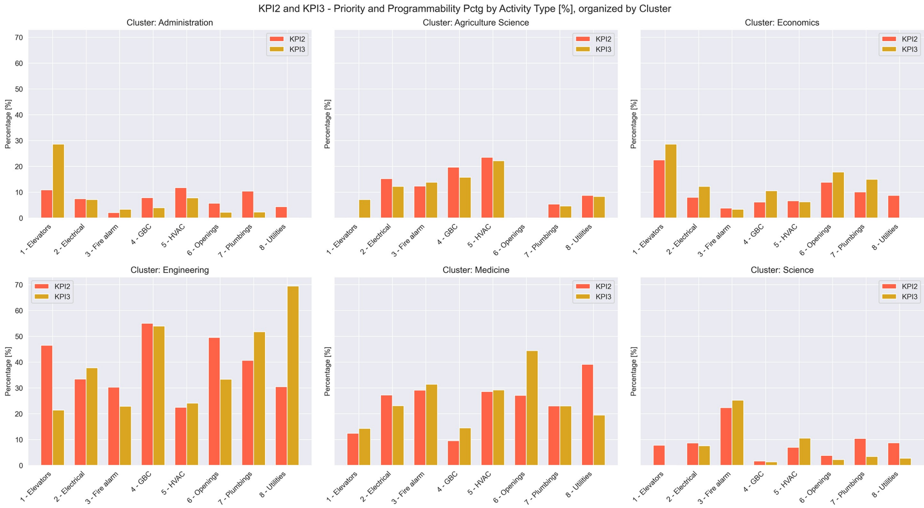

Figure 5. Priority percentage (KPI_2, in red) and programmability percentage by activity type (KPI_3, in yellow) organized by Cluster. GBC stands for general building components, HVAC stands for heat, ventilation and air conditioning

Source: Authors' own work

technicians' post-inspection evaluations. Taken together, both indicators confirm that Engineering and Medicine clusters represent the most operationally demanding environments, combining high perceived urgency with limited scheduling flexibility across multiple domains. On the other hand, some clusters display more specialized urgency patterns, characterized by lower priority levels and greater programmability margins, reflecting contexts where targeted maintenance activities can be planned more efficiently. Beyond these overall trends, the comparison between KPI_2 and KPI_3 allows identifying specific activity types where perceived urgency and actual technical indications diverge. In particular:

Engineering stands out as the most maintenance-intensive cluster across both indicators. High values of KPI_2 and KPI_3 are recorded for General Building Components, Utilities, Plumbing and Electrical systems, revealing strong convergence between user-perceived urgency and the technicians' assessment of undeferrability. This distribution is consistent with environments characterized by intensive uses and complex equipment, where rapid interventions are required across several subsystems rather than specific single categories. Medicine also displays high consistency between KPI_2 and KPI_3, with Fire Alarms, HVAC, Openings, Plumbing and Utilities as recurrent criticalities. This reinforces the critical role of environmental control and service continuity in health-care and laboratory contexts, where system reliability is essential. Economics and Administration present lower and balanced distributions, reflecting less critical (and complex) maintenance environments. In both cases, most requests concentrate in Elevators, indicating that in this clusters main criticalities are linked to accessibility and usability, rather than to technical systems. Science reveals some discrepancy between KPI_2 and KPI_3. While Fire Alarms maintain high values, other systems such as Plumbing, Utilities and Elevators resulted less critical from a technical standpoint, suggesting that some interventions can be planned with more flexibility. Agricultural

Sciences shows good agreement between requests with high levels of priority and programmability, mostly registered for HVAC and General Building Components, confirming trends observed also by KPI_1 on environmental and structural aspects.

3.3 Relevance Index results

The RI offers a synthetic measure of maintenance impact, combing activity relevance and frequency, user-perceived urgency and technical programmability into a single value through a multicriteria approach. By integrating weighted contributions into a single value, RI allows direct comparisons of maintenance requests across clusters and supports data-driven prioritization of interventions. The resulting distribution shown in Figure 6 reveals a marked variability between clusters, with values ranging from 3.30% to 20.67%.

In particular, the Engineering cluster records the highest RI (35.68%), confirming its role as the most maintenance-intensive context within the university campus. This outcome aligns with the high volume of urgent and undeferrable requests associated with multiple activity types, as well as with the dimension and complexity of its spaces. Medicine follows with a RI of 26.32%, reflecting the combined effect of a substantial number of requests and a high proportion of urgent and undeferrable activities. Such outcomes also align with the huge variety of functions herein performed, including operational and educational activities. The Economics cluster marks a clear gap from the first two clusters (12.43%), showing that a large building and a high volume of requests do not automatically result in a high RI, as low incidence of urgent or high-priority activities moderates the overall score. The Science cluster, with an RI of 10.35%, shows a smaller share of total requests but a relatively high proportion of urgent and undeferrable maintenance requests in high-impact system such as Fire Alarms. This concentration contributes to raise RI despite the lower request volume, suggesting a maintenance profile characterized by targeted interventions rather than generalized. The Agricultural Sciences follows with an RI of 9.33%, reflecting the lower impact of HVAC and General Building Components activities and, similarly to Science, the need for localized interventions. Finally, the Administration cluster registers the lowest RI (6.32%), resulting the least demanding cluster in maintenance terms. This outcome is consistent with the small sample of requests and the absence of criticalities in crucial activity types. The absence of complex infrastructure and equipment contributes to its low operational impact overall.

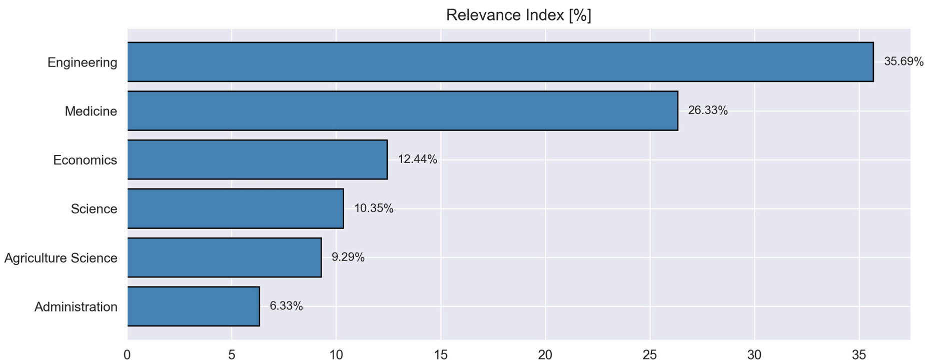

Figure 6. RI evaluated at cluster-scale
Source: Authors' own work

Overall, the RI confirms and complements the insights derived from the individual KPIs. While KPIs allowed for distinguishing the contributions of activity type frequency, user-defined priority and technical programmability, the RI provides an integrated perspective that highlights areas where maintenance requests have the greatest impact on building health, also accounting for activity relevance through the applied weighting method. In this sense, Engineering and Medicine emerge as the most critical clusters, while Economics, Science, Agricultural Sciences and Administration appear comparatively less affected.

4. Conclusions

This study presents a KPI-based approach for analyzing maintenance request actions from a Computerized Maintenance Management System (CMMS), with the aim of supporting data-driven decision-making in FM. Maintenance activities are first standardized through the Omniclass classification to improve data consistency, and then they are weighed through the Analytical Hierarchy Process (AHP) to balance the impact of different activities and ensure a comparable structure across the data set. Finally, by integrating three core indicators that quantify activity types, priority and programmability distributions, the research introduces a RI capable of synthesizing maintenance requests into a single performance-based metric that reflects the overall health status of buildings.

The application to the case study of the Università Politecnica delle Marche campus demonstrates that the proposed tool can identify the most critical clusters (in this case, Engineering and Medicine, where both the volume and criticality of requests are highest) and highlights significant differences between them and the other clusters. For instance, Economics has large surface areas but moderate impacts, while Science and Agricultural Science have smaller clusters with more urgencies in some selected systems. Furthermore, a clear and rapid overview of criticalities in maintenance is provided, particularly those related to safety systems (Fire Alarms) and technical installations (Electrical, HVAC, Plumbing).

In view of the definition of the RI, it is worth noting that:

- the percentage of requests, priority and programmability have the same relevance into the RI calculation, and the weighting process is only applied to activity types;
- RI enable cross-location comparisons by highlighting the overall maintenance demand per area, yet it can also be disaggregated to provide more detailed insights at the activity-type level; and
- the methodology adopts a multiscale perspective, allowing application not only at the cluster level but also, where data granularity allows, at finer spatial resolutions such as individual buildings or rooms.

Therefore, the proposed methodology first supports internal benchmarking for the facility managers, allowing direct comparison of maintenance performance for different clusters (from rooms to building clusters) within the same buildings stock. Nevertheless, the methodology can be easily extended to external benchmarking, enabling comparisons across different assets or buildings stocks. In fact, consistent data structures and classification schemes could be assumed by slightly adapting those from different assets thanks to the easy-to-implement data set alignment process. At the same time, the KPIs and RI normalization ensure comparability among different cases, potentially not only related to educational contexts (as in this work) but also to other single and multiple building functions.

From a practical perspective, RI represents a flexible and easily integrable within CMMS platforms. From a scientific standpoint, this work contributes to filling the methodological gap concerning simple, comparable and automatable metrics for assessing the health of complex building portfolios, showing how heterogeneous and unstructured data can be converted into actionable insights. Beyond its technical relevance, the proposed framework could also have positive social implications, contributing to safer and more functional working and learning environments. In this sense, this work represents a first step toward reliable and rapid data-informed decision-making, supporting the broader objectives of the DIGITMAN project (Massafra *et al.*, 2025).

At the same time, further efforts should be addressed at overcoming current limitations that could affect the reliability of the RI. For instance, data consistency should rely on the rapid and systematic collection of requests and their full integration within CMMS platforms. In this work, the assessment covered the entire monitoring period, which roughly corresponds to the external contractor's working cycle. Under these conditions, the RI can serve as a control tool for building owners, providing a comprehensive overview of operational performance over the contract duration. On the other hand, contractors could exploit the same framework by defining internal reporting periods and maintenance targets, using RI outputs to adjust operational strategies based on the spatiotemporal distribution of needs. Such an approach supports resource optimization and improve intervention programmability, as it enables a clearer understating of how maintenance request evolves over space and time. Moreover, the analysis of single KPI complements this perspective by evaluating the consistency between user-perceived and technical urgency, emphasizing the importance of integrating user feedback with expert evaluation.

To support these tasks, future developments should promote standardized classification systems aligned with the international maintenance frameworks, ensuring comparability and objectivity. Other multicriterial methods can be also compared to the proposed AHP-based one, including both alternatives in weights definition (e.g. Fuzzification logics combined with AHP) and sensitivity analysis (Chen *et al.*, 2018; Jin *et al.*, 2021). The absence of economic and temporal data currently limits the evaluation of maintenance performance in sustainability and economic terms. To this end, future developments could involve the integration of indicators describing user presence, dynamics and typologies, thereby allowing a more accurate correlation between RI trends, operational costs and the impact on building occupants. Combining these data with user satisfaction assessments would also enable a deeper understanding of how maintenance strategies affect both service performance and the overall experience of contractors, end-users and building owners. Finally, the application of the proposed framework to different context could be also considered (e.g. hospitals, corporate estates, public administrations), as well as the integration of predictive analytics through machine learning and data mining techniques (Adhikari *et al.*, 2025). In particular, predictive models help automate the assignment of priority and programmability labels, reducing subjectivity and ensuring more consistent categorization across activity types.

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Supplementary material

The supplementary material for this article can be found online.

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