Analytics Readiness for Cost-Effective Building Maintenance Decision-Making: A Conceptual Framework

Ifeoluwa Adedoyin Adeyemi[1*], Mohd Shahril Abdul Rahman[1], Adegbenga Adeyemi[2], Caleb Chidozie Chinedu[3]

[1]Real Estate Department, Faculty of Built Environment and Surveying, Universiti Teknologi Malaysia, Johor Bahru, Malaysia

[2]Department of Estate Management and Valuation, Abubakar Tafawa Balewa University, Bauchi, Nigeria

[3]Faculty of Technical and Vocational Education, Universiti Tun Hussein Onn Malaysia, Batu Pahat, Malaysia

[*]Corresponding Author

DOI: https://doi.org/10.47772/IJRISS.2026.101000290

Received: 18 October 2026; Accepted: 23 October 2026; Published: 02 November 2026

ABSTRACT

Maintenance costs rise as buildings age, and facility managers must control them without letting building performance decline. This remains challenging because maintenance decisions often still rely on intuition and experience. While these sources of knowledge are valuable, they are subjective and can lead to inconsistent decisions across managers and buildings. Data analytics offers a more evidence-based way to support maintenance decisions. However, its value depends on whether organisations have the data, skills, and systems needed to use it. Much of the building maintenance literature discusses what analytics can do, while paying less attention to whether facility managers and their organisations are ready to adopt it and how that readiness affects cost-effective decisions. This conceptual study addresses that issue. Using a document analysis of published literature, it examines the Technology-Organisation-Environment (TOE) framework, the Technology Acceptance Model (TAM), and the maintenance cost planning (MCP) framework. It groups readiness factors for maintenance analytics into resource, information systems, cultural, and organisational readiness, the external environment, and individual perceptions of usefulness and ease of use. Drawing on the MCP framework, the analysis also identifies five decision areas through which cost-effectiveness is pursued: maintenance policy, budget allocation, building condition assessment, communication protocols, and cost management strategies. Finally, the study presents an integrated framework linking analytics readiness, adoption of maintenance analytics, and cost-effective maintenance decision-making. These relationships are expressed as four hypotheses for future empirical testing, including a direct relationship between readiness and decision-making and a mediated path through adoption. The framework brings analytics readiness research into building maintenance and is intended to help maintenance stakeholders assess their readiness before investing in analytics.

Keywords*:* analytics readiness, maintenance analytics, building maintenance, cost-effectiveness, maintenance decision-making

INTRODUCTION

Buildings are among the most significant economic assets of any nation. They provide an environment for a wide range of social and economic activities (Falorca, 2021). Every building needs maintenance, regardless of its design or construction materials (Omar *et al.*, 2016). Even a new building needs maintenance to keep ownership, operation, and maintenance costs from becoming expensive (Ganisen *et al.*, 2015). As buildings

move through their life cycle, these costs tend to increase (Chong *et al.*, 2019). Operation and maintenance costs form a large share of a building's lifecycle cost, which is why maintenance planning and cost estimation have received sustained research attention (Krstić & Marenjak, 2017; Le *et al.*, 2018). Facility managers are under pressure to find maintenance strategies that remain affordable over time.

Cost-effectiveness in building maintenance refers to the value obtained from the resources used to achieve a required level of building performance (Al-Najjar & Kans, 2006). Cost can be estimated and recorded, but value is harder to define, because it depends on how well maintenance protects the function and condition of the building (Lateef, 2009; Williams, 1996). This difficulty may explain why cost-effectiveness is often treated in practice as cost minimisation (Al-Najjar & Kans, 2006). Decisions aimed only at short-term savings may defer necessary work and raise costs later (Ali, 2009). A cost-effective approach depends less on how little is spent than on how well limited funds are directed, and the way maintenance work is prioritised affects how much value a fixed budget can deliver (Purwosri *et al.*, 2025).

Maintenance decisions determine how limited resources are allocated and which tasks are prioritised, shaping the cost-effectiveness of the maintenance process (Al-Najjar & Kans, 2006; Chong *et al.*, 2019). These decisions are rarely straightforward because facility managers are constantly under pressure to reduce operating costs while keeping ageing buildings in good condition (Ensafi & Thabet, 2021). As a result, they must balance building requirements against financial limits (Chua *et al.*, 2015). Ensafi *et al.* (2023) identified inconsistent work-order prioritisation, poor data management, insufficient information, and high cognitive workload as recurring problems in user-led maintenance decision-making. Furthermore, Moghadam & Besiktepe (2025) reported that many decisions still rely on subjective judgement, which results in inconsistent and inefficient outcomes.

Effective maintenance decisions depend on accurate and timely information about the condition and performance of building components. Modern buildings generate much of this information through building automation systems, computerised maintenance management systems (CMMS), and work order records, which Gunay et al. (2019a) describe as an untapped resource for improving building operation and maintenance. Converting these data into usable evidence has proved difficult in practice. Yang and Bayapu (2020) found that inconsistent data entry, poor interoperability between software tools, and limited software training restricted the use of maintenance data in decision-making. The maintenance practice still relies largely on manual inspection and reactive repair, with weak data standards and poorly integrated systems limiting wider adoption (Zheng *et al.*, 2025).

These studies suggest that the main barrier to data-driven maintenance lies less in the analytical techniques available than in whether organisations are prepared to collect, manage, interpret, and act on maintenance data. This concern is captured by the concept of analytics readiness, which refers to an organisation's preparedness to adopt and use analytics and extends beyond the availability of technology (Auh *et al.*, 2022). Researchers have assessed readiness in sectors such as healthcare, libraries, and manufacturing, examining technological and organisational conditions alongside the wider environment in which organisations operate (Ghaleb *et al.*, 2021; Gürdür *et al.*, 2019; Kalema & Mokgadi, 2017; Salman *et al.*, 2022). Building maintenance has received far less attention in this respect, as research has focused on the potential benefits of analytics rather than the conditions needed to realise them.

The construction and building sector has also been slow to adopt Industry 4.0 technologies, partly because of its project-based structure and fragmented supply chains (Dallasega *et al.*, 2018). Building maintenance practice shows a similar pattern. Signorini and Pomè (2025) found that high costs, the need for workforce training, and immature data processing methods were the main barriers to digital twin adoption. Chui *et al.* (2025) noted that most studies come from developed countries and give limited attention to organisational change and socio-technical issues. The barriers these studies report concern people, processes, and resources as much as technology, which analytics readiness is intended to address.

This study responds to that need by developing a conceptual framework linking analytics readiness, adoption of maintenance analytics, and cost-effective maintenance decision-making. To do this, it reviews the Technology-Organisation-Environment (TOE) framework (Tornatzky & Fleischer, 1990), the Technology

Acceptance Model (TAM) (Davis, 1985), and the maintenance cost planning framework proposed (Le *et al.*, 2018).

METHODOLOGY

This conceptual study uses qualitative document analysis. Document analysis is a systematic procedure for reviewing and evaluating printed and electronic documents to extract meaning and develop understanding (Bowen, 2009). It often complements other methods, but it can also serve as a stand-alone approach when existing documents can address the research question (Ahmed, 2010; Bowen, 2009; Chinedu & Wan-Mohamed, 2017).

The documents analysed were peer-reviewed journal articles, conference papers, and books on building maintenance, maintenance decision-making, data analytics, analytics readiness, and technology adoption. Documents were selected purposively for their relevance to three guiding questions:

1. What makes cost-effective maintenance decision-making difficult?
2. How can analytics support maintenance decisions in buildings?
3. What conditions indicate an organisation's readiness to adopt analytics?

The TOE framework and TAM were examined because they are widely used to explain technology adoption at the organisational and individual levels. The maintenance cost planning framework was examined because it identifies the decision areas through which cost-effectiveness is pursued.

The analysis followed the iterative process Bowen (2009) describes, combining superficial examination, thorough reading, and interpretation. The selected documents were first screened for relevance and then read in full to identify recurring concepts. These concepts were coded and grouped into three themes, analytics readiness, maintenance analytics adoption, and cost-effective maintenance decision-making, which then informed the conceptual framework and its hypotheses. As this is a conceptual paper, the hypotheses are not tested here. Its purpose is to provide a structured basis for future empirical research.

Search Procedure

Relevant literature was identified through searches from Scopus, Web of Science, and Google Scholar. The search terms were grouped according to the three guiding questions. For the use of analytics in maintenance, terms such as *"data analytics"*, *"big data"*, *"machine learning"*, and *"predictive maintenance"* were combined with *"building maintenance"*, *"facility management"*, and *"facilities management"*. For readiness and adoption, the searches combined *"analytics readiness"*, *"data readiness"*, and *"digital readiness"* with *"technology adoption"*, *"technology acceptance"*, and *"technology-organisation-environment"*. For maintenance decision-making, the searches combined *"maintenance cost"*, *"cost-effective maintenance"*, *"maintenance planning"*, and *"maintenance decision-making"* with *"building"* and *"facility"*. The searches focused on literature published between 2006 and 2026, but retained earlier works that were foundational to the theories used, such as Simon (1960), Davis (1989), and Tornatzky and Fleischer (1990). Peer-reviewed journal articles, conference papers, and books published in English were included. Titles and abstracts were screened first, and the full texts of potentially relevant documents were then assessed against the three guiding questions. Studies that mentioned analytics or maintenance only in passing were excluded. The reference lists of key studies were also checked to identify further relevant sources. Since the aim was to build a conceptual framework rather than map the entire field, the selection was purposive and not a systematic review.

LITERATURE REVIEW

The Challenge of Cost-Effective Building Maintenance

The building industry has paid more attention to reducing construction costs than to the cost of maintaining buildings once they were in use (Marenjak *et al.*, 2002). Maintenance management largely depends on facility

managers' knowledge and experience to decide what work is needed and when (Al-Najjar & Kans, 2006; Lateef, 2009). That approach has proven harder to sustain today. Building services have become more technically complex, maintenance budgets remain under pressure, and owners increasingly expect maintenance to support energy and sustainability targets while keeping buildings functional (Moghadam & Besiktepe, 2025; Zheng *et al.*, 2025).

Cost-effective maintenance involves more than reducing immediate spending, as decisions must balance current costs against the condition, service life, and building performance (Ali, 2009; Lateef, 2009). Studies of maintenance practice suggest that this balance is often lost at the point of decision. Palis and Misnan (2018) identified reactive maintenance among the factors that raise maintenance costs in university buildings, and Islam *et al.* (2019) found that planning and management factors shape FM cost performance more broadly.

Existing studies have identified fund allocation as a particular weakness. In interviews with 20 maintenance experts in Malaysia, Hauashdh *et al.* (2022) found that organisations responsible for several buildings often exhausted their budgets early because they did not allocate funds systematically to each building, and they recommended systematic budget setting and long-term budget planning as part of a strategy for more effective maintenance. This implies that how priorities are set matters as much as how much is available. In school maintenance, Purwosri *et al.* (2025) observed that ranking schools by structural damage alone funded 27 schools serving 2,442 students. In contrast, a method combining damage severity, cost, and the number of students affected funded 33 schools serving 2,957 students within the same budget. Many of these weaknesses trace back to the information available to decision-makers. Ensafi and Thabet (2021) reported that weak use of maintenance data remains a persistent gap in facility maintenance practice. These studies suggest that cost problems in maintenance are often decision problems.

The Limitations of Intuition-Based Decision-Making

Decision-making theory distinguishes between two broad modes of choice. Intuitive decisions are fast, automatic, and based on experience and judgement, and people tend to use them when no established procedure exists for the problem at hand (Bazerman & Moore, 2012). Deliberate decisions are slower and more explicit, drawing on information, analysis, and structured procedures to compare alternatives (Hastie & Dawes, 2010). Building maintenance has traditionally relied on the first mode, with facility managers drawing on accumulated experience to judge which work to carry out and when (Al-Najjar & Kans, 2006; Lateef, 2009).

Depending on intuition carries risks, because personal judgement shaped by experience is vulnerable to bias. Decision-makers may prefer familiar solutions even when other options would serve the building better (Lateef, 2009). Different individuals facing similar problems may reach different conclusions, making it difficult to standardise maintenance decisions across a portfolio (Ali, 2009).

Another limitation is that intuition relies on the information available to an individual at a given moment. Maintenance decisions often require technical, financial, condition, and safety information simultaneously. Besiktepe *et al.* (2020) found that facility managers consider several criteria in maintenance decisions, including health and safety, code compliance, and condition, and that cost is not always the most important. Consistently bringing these criteria together is difficult without structured information.

Moghadam and Besiktepe (2025) reviewed 107 studies on multi-criteria decision-making in FM and building maintenance. The study found that subjectivity, uncertainty, and expert qualifications remain persistent problems, even when structured decision methods are used. The review also identified integrating technology into decision-making as an unresolved issue. This suggests that structured, data-supported decisions are needed, but the conditions for using data in practice are not yet well understood.

The Role of Analytics in Building Maintenance

Analytics in building maintenance refers to using data from building systems, sensors, maintenance records, and work orders to support decisions. Gunay *et al.* (2019a) reviewed the use of data analytics in building

operation and maintenance and found that existing data sources were rarely used to their full potential. Ahmed *et al.* (2017) reported that industry stakeholders saw value in big data for FM but recognised an imbalance between data capture and data analysis, and a need for guidance and leadership.

Several digital technologies support maintenance decisions. Sensor data from Internet of Things (IoT) devices can support condition monitoring and predictive maintenance for systems such as heating, ventilation, and air conditioning, electrical equipment, and elevators (Daissaoui *et al.*, 2020). Work order data can be analysed to produce maintenance performance metrics (Dutta *et al.*, 2020) and estimate component fault frequency (Gunay *et al.*, 2019b). Condition-assessment data can support defect-based building evaluation (Faqih & Zayed, 2021), and historical cost data can support cost prediction and budget planning (Au-Yong *et al.*, 2013; Li & Guo, 2012). A review of maintenance analytics studies by Adeyemi *et al.* (2022) found that data sources from both legacy and emerging technologies such as CMMS, building automation systems, building information modelling (BIM), and IoT shaped the choice of analytical technique. More recently, researchers have proposed digital twins as a way to integrate these data sources (Signorini & Pomè, 2025; Nageeb *et al.*, 2026).

Evidence on the outcomes of analytics in maintenance is more limited than its promise. Many studies demonstrate technical methods in single buildings or case studies, while limited data and models that generalise poorly to other buildings constrain large-scale deployment (Zheng *et al.*, 2025). A systematic review of data-driven building management systems found that building device data are often heterogeneous, incomplete, and inconsistent, limiting their usefulness for decision-making (Taboada-Orozco *et al.*, 2024). A more recent review of 238 studies on predictive maintenance in building energy systems reported similar constraints, including fragmented data, limited interoperability, high implementation costs, a shortage of skilled workers, and insufficient validation in real buildings (Boukaf *et al.*, 2026). Therefore, the potential of analytics is well described, but organisations have paid far less attention to what they need in place before analytics can support everyday maintenance decisions.

Analytics Readiness

The concept of readiness addresses what organisations need in place. Studies have examined readiness at both the individual and organisational levels. At the individual level, Parasuraman (2000) described technology readiness as the tendency of individuals to embrace and use new technologies, shaped by optimism, innovativeness, discomfort, and insecurity. Flavián *et al. (*2022) found that technology readiness was associated with intention to use analytical artificial intelligence in services. Technology readiness describes a general disposition towards technology rather than beliefs about a particular system. Because this study is concerned with how facility managers view analytics specifically, individual readiness is examined through perceived usefulness and perceived ease of use from TAM (Davis, 1989). At the organisational level, analytics readiness refers to how prepared an organisation is to adopt and use analytics (Auh *et al.*, 2022). It covers the infrastructure for storing and processing data, the procedures for collecting, cleaning, and preparing data, and the skills needed to analyse it (Gürdür *et al.*, 2019).

Interest in readiness grew partly because the early promise of big data was not always realised in practice, as the initial expectations in many organisations exceeded what was delivered (Grover *et al.*, 2018). Grover *et al.* (2018) argued that value from big data analytics depends on developing the organisational capabilities that support it, not on the technology alone. A similar position appears in research on developing countries, where Kalema and Mokgadi (2017) examined readiness for big data analytics in terms of organisational as well as technological conditions. These studies suggest that acquiring analytics tools does not in itself make an organisation ready to use them.

Readiness is also assessed at the building level. The European Union's Smart Readiness Indicator evaluates how far a building's services can support smart operation. In a review of smart building services, Jørgensen *et al.* (2026) found that monitoring and control function as a cross-cutting layer through which many higher-order capabilities, including maintenance awareness, are expressed. Building-level smart readiness concerns the technical services a building provides, whereas this study focuses on the readiness of the organisation that manages it. The two are related, as an organisation's ability to use analytics depends partly on the monitoring and data infrastructure available in its buildings.

Several readiness models set out what an organisation needs in place, and they show considerable agreement. Schuh *et al.* (2017), in the Industrie 4.0 Maturity Index, grouped organisational capabilities into four structural areas: resources, information systems, culture, and organisational structure. Sulistyowati *et al.* (2021) arrived at the same four dimensions when developing a data analytics readiness model for Indonesian government agencies through a literature review, expert verification, and a survey. Gürdür *et al.* (2019) used a comparable set of indicators to assess data analytics readiness in Swedish industry. Other studies have approached readiness through the TOE framework, examining big data readiness in healthcare (Ghaleb *et al.*, 2021) and in Malaysian libraries (Salman *et al.*, 2022). This paper draws on the four-dimension structure, developed and tested across sectors, to identify four readiness capabilities relevant to maintenance analytics.

Resource readiness refers to the physical and human resources needed to carry out analytics. This includes hardware, software, and storage to support data collection and analysis, along with staff skilled in using them (Gürdür *et al.*, 2019; Schuh *et al.*, 2017). Both elements appear in the broader big data literature, where technological and people-related factors are identified as critical success factors for big data projects (Al-Sai *et al.*, 2020), and employee knowledge and skills are treated as part of organisational readiness to adopt big data (Olszak & Mach-Król, 2018). In FM, a lack of training and specialist expertise is a major barrier to digital adoption (Chui *et al.*, 2025; Signorini & Pomè, 2025).

Information systems readiness concerns the availability, accessibility, and quality of data, and the policies that govern how data are defined, collected, and used (Sulistyowati *et al.*, 2021). Analytics depends on accurate, consistent, and complete data (Ijab *et al.*, 2019), which makes this capability particularly relevant to maintenance. Inconsistent data entry, poorly structured records, and data spread across separate systems have been reported as barriers to data-driven building management and FM (Taboada-Orozco *et al.*, 2024; Yang & Bayapu, 2020).

Cultural readiness refers to whether an organisation values data-based decisions over intuition- or routine-driven ones, and whether it is willing to act on the insights analysis produces (Gürdür *et al.*, 2019; Schuh *et al.*, 2017). This capability matters in building maintenance, where reliance on experience is long established (Lateef, 2009). An organisation with adequate data and tools may still make decisions in familiar ways if its culture does not support a shift toward evidence-based practice.

Organisational readiness concerns structure, strategy, and management support. It includes a clear vision for using analytics, leadership commitment, and funding for technology and training (Schuh *et al.*, 2017; Sulistyowati *et al.*, 2021). Schuh *et al.* (2017) distinguished this capability from culture, explaining that organisational structure sets the formal rules for how work and collaboration are organised. In contrast, culture describes the values that shape behaviour. Studies using the TOE framework have also found top management support to be associated with technology adoption (Ghaleb *et al.*, 2021; Oliveira *et al.*, 2014). In FM, Signorini and Pomè (2025) found that implementing digital twins required a clearly defined client purpose and an investor-facing driver, suggesting that strategic direction may matter as much as technical capacity.

These four capabilities describe organisational-level readiness. Individual perceptions, particularly whether facility managers and technicians see analytics as useful and easy to use, add a further layer (Davis, 1989). External conditions, such as regulations and client expectations, may also play a role in readiness (Oliveira *et al.*, 2014).

Maintenance Analytics Readiness

Maintenance analytics applies analytical techniques specifically to maintenance data. Karim *et al.* (2016) describe it as progressing through descriptive, diagnostic, predictive, and prescriptive stages, moving from explaining what happened to recommending what to do. Each stage places greater demands on the organisation, as predictive and prescriptive analytics require more complete historical data and more specialised skills than descriptive reporting.

Maintenance analytics depends on data captured and stored in a usable form. CMMS provide a central place to record assets, schedule work, and track maintenance history, and can be linked with building information

modelling (Ismail *et al.*, 2020). In practice, these systems are often used mainly for recording work orders, and their analytical potential is underused (Zheng *et al.*, 2025). The problem worsens when maintenance information is spread across many systems. In their case study of a university campus, Yang and Bayapu (2020) identified 36 separate digital tools used to manage facilities, making it difficult to consolidate maintenance data for decision-making.

A recent study has suggested that readiness does not necessarily depend on advanced sensor networks. Nageeb *et al.* (2026) developed a BIM-integrated framework for an educational building in Egypt that combined condition assessment with Markov-based deterioration prediction, allowing proactive maintenance planning without real-time IoT data. The authors presented it as a practical route for buildings with limited digital infrastructure, but they validated it in a single case study. This suggests that information systems readiness may begin with well-structured condition and asset data rather than with large technology investments.

Evidence from Malaysia points to the same pattern. Maintenance decisions have long focused on immediate costs and relied on the judgement of individual managers (Ali, 2009; Lateef, 2009), and more recent work found they often rely on the latest inspection without considering trends in past data (Adeyemi *et al.*, 2022). In a review of Malaysian studies published between 2009 and 2019, Hauashdh *et al.* (2020) identified effective management, technical capability, human resource development, and cost optimisation as key areas for improvement, which closely align with the readiness capabilities discussed above. Razali *et al.* (2020) analysed maintenance data for government buildings in Putrajaya and concluded that big data analytics was needed to support predictive maintenance management. Studies of analytics in Malaysian maintenance have concentrated on public buildings, and evidence from privately managed buildings remains limited.

In summary, the literature suggests that maintenance analytics readiness involves more than acquiring software. Organisations need reliable and accessible maintenance data, staff who can interpret it, a culture willing to act on it, and management that supports and funds its use. Much of the evidence for these conditions comes from case studies, reviews, and research outside building maintenance, and empirical studies that measure maintenance analytics readiness directly remain scarce.

Data-Driven Decision-Making and Cost-Effectiveness

The argument for data-driven maintenance decisions draws on the wider case for evidence-based management. Pfeffer and Sutton (2006) observed that managers often base decisions on outdated information, personal experience, or instinct rather than the best available evidence. Rousseau and McCarthy (2007) described evidence-based management as the conscientious use of such evidence to inform decisions, so that choices can be justified and their outcomes evaluated. In building maintenance, this means drawing on condition, cost, and performance data rather than relying on judgement alone.

In maintenance, data-driven decisions are expected to reduce subjectivity in this way. Ensafi *et al.* (2023) found that facility managers prioritising work orders faced inconsistent criteria, poor data, and heavy cognitive workload, suggesting that better information could support more consistent decisions. Moghadam and Besiktepe (2025) also identified integrating data and technology as a way to reduce subjectivity in maintenance decision-making.

Evidence from outside building maintenance indicates that the benefit of analytics depends on how it is used. Ghasemaghaei (2019) examined whether data analytics improved firms' decision-making quality and found that the relationship depended on knowledge sharing and data analytics competency. This finding matters for this study, as it suggests analytics may improve decisions only when an organisation has the competencies to use it, which relates to readiness.

In building maintenance, the link between analytics and cost-effectiveness is often assumed rather than tested. Studies have shown that analytics can identify fault patterns (Gunay *et al.*, 2019b), produce performance metrics from work order data (Dutta *et al.*, 2020), and support condition assessment (Faqih & Zayed, 2021). Few of the studies reviewed here trace these outputs through to lower maintenance costs or better value for

money at the organisational level. For this reason, this study presents the proposed relationships as hypotheses to be tested rather than established findings.

Summary of Gaps in the Literature

Four gaps emerge from this study. First, the building maintenance literature has focused more on what analytics can do than on whether organisations are ready to use it. Studies of predictive maintenance, fault detection, and work order analysis mostly demonstrate techniques in single buildings or case studies (Zheng *et al.*, 2025), and insufficient validation in real buildings remains a recognised limitation (Boukaf *et al.*, 2026). The organisational conditions needed to use these techniques in everyday practice have received less attention.

Second, analytics readiness has been studied mainly outside building maintenance, in sectors such as healthcare, libraries, government, and industry (Ghaleb *et al.*, 2021; Gürdür *et al.*, 2019; Salman *et al.*, 2022; Sulistyowati *et al.*, 2021). Whether the same readiness capabilities apply to maintenance organisations, and in the same way, remains unclear.

Third, the contribution of analytics to cost-effective maintenance decisions has received little direct examination. Adeyemi *et al.* (2022) found that maintenance analytics studies had concentrated on building performance and operation, end-user complaints, and work orders, and identified cost-effective decision-making as an under-examined application. Studies describe the potential for lower costs and better prioritisation, but few of those reviewed here measure whether organisations that use analytics make more cost-effective decisions.

Fourth, technology adoption, readiness, and maintenance cost planning have largely been studied as separate strands. The TOE framework and TAM explain adoption, and the MCP framework describes how maintenance costs are planned. However, no framework identified in this study has brought them together to explain how readiness and adoption relate to maintenance decision outcomes. The framework developed in the following section aims to address this gap and provide a basis for empirically examining the others.

THEORETICAL BACKGROUND AND CONCEPTUAL FRAMEWORK

Technology-Organisation-Environment Framework

Tornatzky and Fleischer (1990) developed the TOE framework to explain how organisations adopt technological innovations. It proposes that three contexts shape adoption: the technological context, the organisational context, and the external environment. The framework has been widely used to study the adoption of cloud computing and big data (Low *et al.*, 2011; Lutfi *et al.*, 2022; Oliveira *et al.*, 2014) and to assess analytics readiness (Ghaleb *et al.*, 2021; Salman *et al.*, 2022).

The technological context concerns the characteristics of the technology and the organisation's existing technical resources. Compatibility, complexity, infrastructure, data management, and security have been associated with adoption decisions (Ghaleb *et al.*, 2021; Lutfi *et al.*, 2022). For maintenance analytics, this context would cover whether the organisation has the systems and data needed to support analysis.

The organisational context concerns features such as size, resources, structure, and management support. In a study of cloud computing adoption, Oliveira *et al.* (2014) found that top management support and firm size were associated with adoption. In maintenance, this context includes leadership commitment, staff skills, and whether the organisational culture supports using data in decision-making.

The environmental context concerns external conditions such as competition, regulation, and pressure from clients or industry partners. Zorn *et al.* (2011) found that institutional pressures were associated with the adoption and use of information and communication technology in nonprofit organisations. For building maintenance, relevant external factors may include regulatory requirements, client expectations, and data protection rules. The TOE framework is useful in this study because it considers adoption in organisational and

environmental conditions, as well as in the technology itself. This matches the study's view that readiness involves more than owning technology.

Technology Acceptance Model

Davis (1985, 1989) proposed TAM, which draws on the Theory of Reasoned Action (Ajzen & Fishbein, 1980). It explains individual acceptance of technology through two beliefs: perceived usefulness and perceived ease of use. Perceived usefulness is the degree to which a person believes that using a technology will improve their job performance. Perceived ease of use is the degree to which a person believes that using it will be free of effort (Davis, 1989). Both beliefs are expected to influence the intention to use a technology, which in turn influences actual use. Ease of use also affects perceived usefulness, because a system that is easier to use is more likely to be seen as useful.

TAM has been applied in many settings, including smart home technologies (Nikou, 2019; Shin et al., 2018). It has also been extended to include social influence and cognitive factors such as job relevance and output quality (Venkatesh & Davis, 2000). TAM complements the TOE framework in this study. TOE operates at the organisational level, but individuals use analytics. Facility managers who do not see analytics as useful, or who find it difficult to use, may continue to rely on intuition even when the technology is available. In this study, perceived usefulness and perceived ease of use are treated as the individual components of analytics readiness, and intention to adopt is treated as part of adoption.

Maintenance Cost Planning Framework

The third perspective is the maintenance cost planning (MCP) framework proposed by Le *et al.* (2018). The framework was developed from a review of maintenance cost prediction and estimation models, including those of Krstić and Marenjak (2017), Li and Guo (2012), and Au-Yong *et al.* (2013). Le *et al.* (2018) observed that these models did not account for how the maintenance strategy adopted affects cost-effectiveness, and that maintenance decisions tend to be more intuitive than rational.

The MCP framework treats maintenance cost planning as an activity that transforms inputs into outputs under specific controls and through specific mechanisms (Le *et al.*, 2018). Inputs include maintenance policy, budget availability, organisational goals, and building conditions. Controls include communication, maintenance strategy, the maintenance process, and the budget monitoring system. The mechanisms are data collection and management, building inspection, and decision-making. The outputs are cost estimates, cost management, and funding requirements.

This study draws five decision areas from this structure to describe cost-effective maintenance decision-making. Maintenance policy, budget allocation, and building condition assessment come from the framework's inputs, communication protocols from its controls, and cost management strategies from its outputs. Maintenance policy concerns the choice between planned, preventive, condition-based, and corrective approaches, and the criteria used to prioritise work (Besiktepe *et al.*, 2020; Chong *et al.*, 2019). Budget allocation concerns how limited funds are distributed across buildings, systems, and time periods (Au-Yong *et al.*, 2013; Li & Guo, 2012). Building condition assessment provides the information that informs priorities and budgets (Faqih & Zayed, 2021). Communication protocols concern how building owners, facility managers, and maintenance contractors exchange information, which has been associated with maintenance outcomes (Au-Yong *et al.*, 2017; Hua *et al.*, 2005). Cost management strategies concern how costs are monitored, predicted, and controlled, including the use of performance indicators and cost models (Ali, 2009; Krstić & Marenjak, 2017).

Each area depends on information, and analytics can support it by providing condition data, cost histories, and performance indicators. Recent work has applied machine learning to cost management. Mohamed *et al.* (2024) combined semantic web technologies with an artificial neural network to predict maintenance costs for building services, using six years of historical maintenance data from a financial services firm in Egypt. The model predicted costs with high accuracy, but the authors noted that this depended on the firm's data being well structured and complete, and that the approach required specialist technical expertise. Both conditions

concern readiness rather than the analytical technique itself. Whether analytics supports maintenance decisions in practice is therefore likely to depend on the readiness factors discussed above.

The MCP framework has two limitations for this study. It does not consider the external environment, and although it identifies data collection and management as a mechanism, it does not examine whether organisations are ready to adopt the technologies needed to capture and analyse maintenance data. These gaps are the reason it is combined here with TOE and TAM.

Integrating the Three Perspectives

Each perspective explains part of the problem. TOE describes the technological, organisational, and environmental conditions under which organisations adopt new technology. TAM describes the individual beliefs that influence whether people use it. The MCP framework describes the cost planning decisions that analytics may support. None of the three is sufficient on its own. TOE does not explain whether individuals will use analytics, and TAM does not account for organisational or environmental conditions. Additionally, neither describes the maintenance decisions analytics is meant to support, as the MCP framework does. As noted in the previous section, researchers have largely studied these strands separately, and no framework in this analysis links readiness, adoption, and maintenance decision outcomes.

The framework proposed in this study combines the three perspectives. Analytics readiness draws on TOE, TAM, and the readiness models discussed earlier. Resource readiness and information systems readiness reflect the technological context, cultural readiness and organisational readiness reflect the organisational context, and the external environment reflects the environmental context. Perceived usefulness and perceived ease of use represent the individual conditions drawn from TAM. Maintenance analytics adoption refers to the intention to adopt analytics and its actual use in maintenance work. Intention to adopt and actual use are treated as two distinct stages of adoption and are defined separately in Table 1. The framework describes cost-effective maintenance decision-making through five decision areas drawn from the MCP framework.

Table 1 defines the components of analytics readiness and maintenance analytics adoption and proposes example indicators for each. The indicators are not validated measures. They are intended as a starting point for developing survey items in future empirical work. Intention to adopt and actual use are treated as distinct stages of adoption because an organisation may intend to use analytics without doing so, and they should be measured separately.

Table 1. Definitions and proposed indicators for analytics readiness and maintenance analytics adoption

Construct	Component	Conceptual Definition	Proposed Indicators	Source
Analytics readiness	Resource readiness	The extent to which the organisation has the financial, technological, and human resources needed to implement and run maintenance analytics	Budget allocated to analytics tools; availability of suitable software and hardware; staff with data analysis skills; access to technical support	Schuh *et al.* (2017); Sulistyowati et al. (2021)
	Information systems readiness	The extent to which maintenance data and information systems are complete, consistent, accessible, and integrated enough to support analysis	Completeness of work order and asset records; consistency of recording formats; integration between CMMS, building automation, and other systems; access to data for decision-makers	Schuh *et al.* (2017); Sulistyowati *et al.* (2021)
	Cultural readiness	The extent to which staff and management value data and evidence in maintenance decisions	Data routinely consulted before decisions; willingness to change established practices; openness to sharing data across teams	Schuh *et al.* (2017); Sulistyowati *et al*. (2021)
	Organisational	The extent to which	Top management support;	Schuh *et al.*

	readiness	leadership, strategy, structures, and procedures support the use of analytics	analytics included in maintenance strategy; defined responsibility for data; procedures for acting on analytics outputs	(2017); Sulistyowati *et al.* (2021)
	External environment	External conditions that encourage or constrain the use of analytics in maintenance	Regulatory and compliance reporting requirements; client expectations for performance reporting; data protection rules; availability of external vendors and technical support	Tornatzky and Fleischer (1990)
	Perceived usefulness	The degree to which facility managers believe that using analytics would improve their maintenance job performance	Analytics would improve the accuracy of maintenance decisions; help prioritise work; make planning more efficient	Davis (1989)
	Perceived ease of use	The degree to which facility managers believe that using analytics would be free of effort	Analytics is easy to learn; outputs are easy to interpret; easy to fit into daily maintenance work	Davis (1989)
Maintenance analytics adoption	Intention to adopt	The planned willingness of the organisation and its facility managers to use analytics in maintenance within a defined period	Plans to use analytics within the next 12 months; intention to extend use to further maintenance tasks; willingness to invest	Davis (1989); Venkatesh and Davis (2000)
	Actual use	The extent and frequency with which analytics is currently used in maintenance work	Frequency of use; range of tasks supported, such as condition monitoring, work order analysis, and cost forecasting; share of maintenance decisions informed by analytics	Davis (1989)

Table 2 sets out the five decision areas and proposes outcome indicators for each. Since cost-effectiveness concerns the value obtained for the money spent rather than cost reduction alone, cost indicators should be read together with indicators of condition, downtime, and service performance.

Table 2. Definitions and proposed indicators for decision-making for cost-effective maintenance.

Decision Area	Conceptual Definition	Proposed Indicators	Source
Maintenance policy	The choice and balance between planned, preventive, condition-based, and corrective maintenance, and the criteria used to prioritise work	Ratio of planned to unplanned maintenance; share of corrective work orders; downtime of critical building systems	Besiktepe *et al.* (2020); Chong *et al.* (2019); Le *et al.* (2018)
Budget allocation	The distribution of limited maintenance funds across buildings, systems, and time periods	Budget utilisation (actual against planned spending); maintenance expenditure relative to asset condition; frequency of budget overruns	Au-Yong *et al.* (2013); Li and Guo (2012); Le *et al.* (2018)
Building condition assessment	The systematic evaluation of the condition of building elements to inform priorities and budgets	Coverage and frequency of condition surveys; how current condition records are; trend in condition ratings over time	Faqih and Zayed (2021); Le *et al.* (2018)

Communication protocols	The exchange of maintenance information between building owners, facility managers, and contractors	Time from fault report to work order completion; occupant complaints; rework caused by miscommunication	Au-Yong *et al.* (2017); Hua *et al.* (2005); Le *et al.* (2018)
Cost management strategies	The monitoring, prediction, and control of maintenance costs, including the use of performance indicators and cost models	Unplanned repair costs as a share of total maintenance cost; accuracy of cost forecasts; maintenance cost per square metre	Ali (2009); Krstić and Marenjak (2017); Le *et al.* (2018)

Figure 1 presents the proposed framework. Analytics readiness appears at the base of the framework, with its components grouped according to the theory from which they are drawn: technological, organisational, and environmental conditions from TOE, and individual perceptions from TAM. Maintenance analytics adoption, comprising intention to adopt and actual use, links readiness to cost-effective maintenance decision-making, which the five decision areas from the MCP framework describe. The arrows show the four proposed relationships. H1 links readiness to adoption, H2 links adoption to decision-making, and H3 represents a direct relationship between readiness and decision-making. H4 proposes that adoption mediates the relationship between readiness and decision-making. The framework does not specify the strength of these relationships, which is left to future empirical testing.

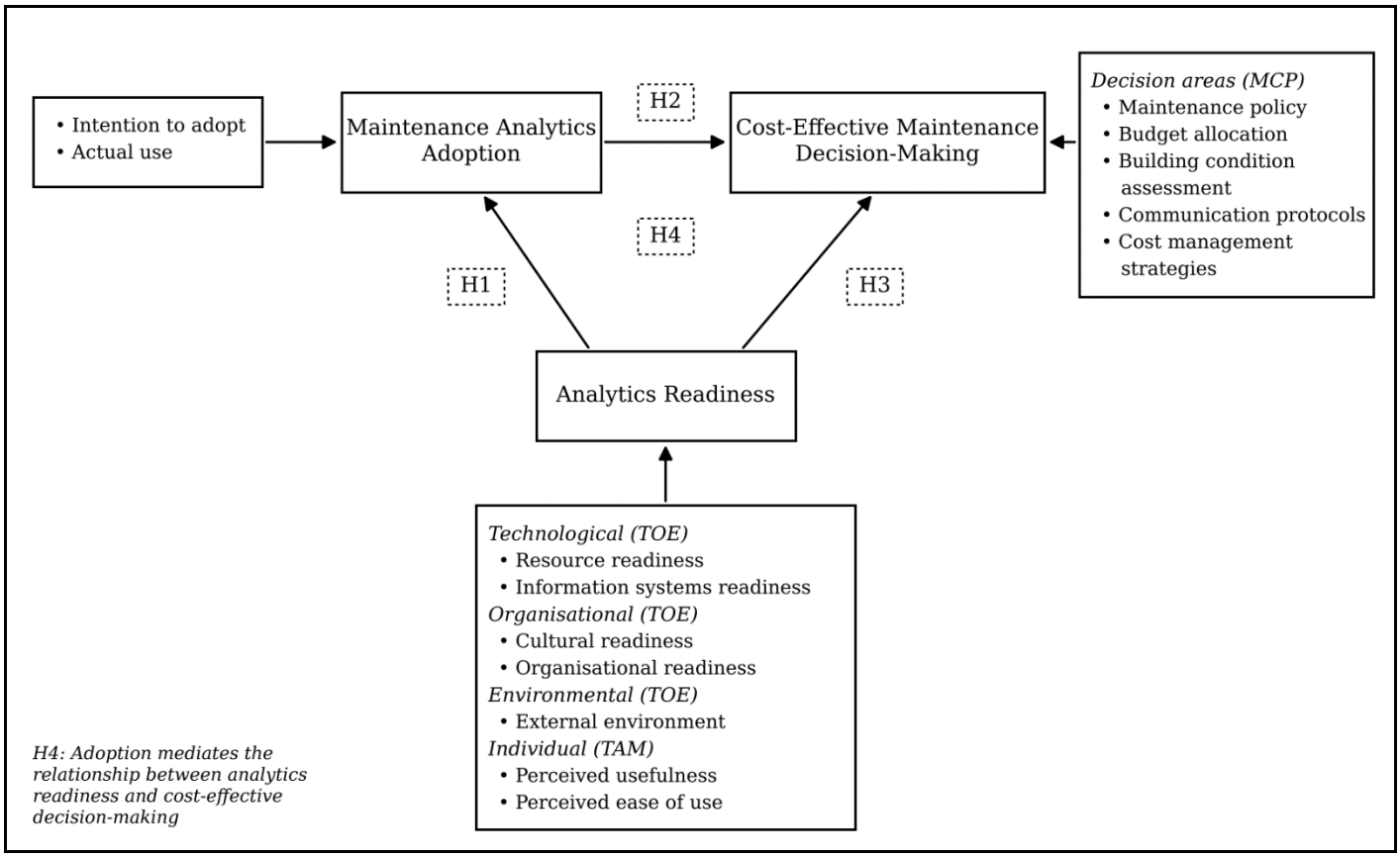

Fig. 1 Conceptual framework of analytics readiness, maintenance analytics adoption, and cost-effective maintenance decision-making

Hypotheses

The framework proposes four hypotheses. As this is a conceptual study, the hypotheses are not tested here. They are developed from the literature reviewed above and are intended for empirical testing in future research. All three direct relationships are expected to be positive, and adoption is expected to mediate the relationship between readiness and decision-making partially.

TOE treats technological, organisational, and environmental conditions as determinants of adoption, and TAM treats individual beliefs as antecedents of the intention to use a technology. Studies using TOE have associated technological readiness and top management support with adoption (Oliveira *et al.*, 2014), and readiness assessments have identified infrastructure, data management, and skills as conditions for analytics use (Ghaleb *et al.*, 2021). At the individual level, perceived usefulness and perceived ease of use have been associated with the intention to use a technology (Davis, 1989). Evidence from FM is consistent with this. In a survey of Italian FM operators, Signorini and Pomè (2025) found that high investment costs, a lack of effective data-processing methods, and the need for workforce training were the most significant barriers to adopting digital technologies, and Yang and Bayapu (2020) reported similar barriers. On this basis, the following hypothesis is proposed:

The four readiness capabilities provide a more specific basis for this hypothesis. Without resource readiness, an organisation lacks the tools and skills to run analytics. Without information systems readiness, the data are too incomplete or inconsistent to analyse. Without cultural and organisational readiness, organisations may acquire analytics but not use it in decisions. Each capability can be expected to support adoption, although the strength of each relationship may differ between organisations.

H1: Analytics readiness is positively associated with maintenance analytics adoption.

Analytics can extract operational information from data that facility managers already collect, such as building automation records, work orders, and tenant feedback (Dutta *et al.*, 2020; Gunay *et al.*, 2019a). In principle, this information could support more consistent prioritisation and better-targeted budgets. Few of the studies examined here measure whether adoption is associated with more cost-effective decisions at the organisational level, and most work in this area consists of technical case studies (Zheng *et al.*, 2025). This relationship requires empirical testing.

H2: Maintenance analytics adoption is positively associated with cost-effective maintenance decision-making.

Readiness may also relate directly to decision-making. Organisations with good data, clear procedures, and skilled staff may make more consistent decisions even before they adopt advanced analytics. Well-managed condition records, for example, can support prioritisation without predictive tools (Faqih & Zayed, 2021). Auh *et al.* (2022) found that analytics readiness was linked to service firm performance, which suggests that readiness may matter in its own right.

H3: Analytics readiness is positively associated with cost-effective maintenance decision-making.

If readiness supports adoption, and adoption supports better decisions, then part of the effect of readiness on decision-making may operate through adoption. In a survey of 133 US firms, Ghasemaghaei (2019) found that the effect of data analytics use on decision quality operated through knowledge sharing, and that this effect was not significant where data analytics competency was low. Competency in that study covered data quality, analytical skills, and tool sophistication, which are close to the resource and information systems readiness capabilities in this framework. This suggests that readiness and use work together rather than separately. Since H3 allows for a direct relationship, the mediation proposed here is partial rather than full. The final hypothesis is:

H4: Maintenance analytics adoption mediates the relationship between analytics readiness and cost-effective maintenance decision-making.

Theoretical Implications

The framework contributes to the literature in three ways. First, it brings the analytics readiness literature into building maintenance, where readiness has received little attention compared with the technical capabilities of analytics. Second, it combines organisational and environmental readiness conditions, drawn from TOE and readiness models, with individual acceptance, drawn from TAM. This recognises that the use of analytics in maintenance may depend on both the organisation and the people who make maintenance decisions. Third, it

links readiness and adoption to specific maintenance decision areas derived from the MCP framework (Le *et al.*, 2018). This gives cost-effective decision-making a clearer definition than general claims about lower costs.

The hypotheses also clarify the order of the relationships. Readiness is treated as an antecedent of adoption, which is consistent with both TOE and TAM. Adoption is treated as a mechanism through which readiness may relate to decision outcomes, drawing on the MCP framework and evidence that analytics use is associated with decision quality (Ghasemaghaei, 2019). The framework also retains a direct relationship between readiness and decision-making, which allows future studies to examine whether adoption fully or partially explains the effect of readiness. These relationships can be tested with structural equation modelling once suitable measures are developed.

Practical Implications

For facility managers and building owners, the framework suggests assessing readiness before investing in analytics. An organisation can review whether it has suitable systems and skills, whether its maintenance data are complete and consistent, whether its staff value data-based decisions, and whether management will support and fund the change. It can also consider external requirements, such as client expectations and data protection rules, that may shape how analytics is used. Weaknesses in any of these areas may limit the return on an analytics investment.

The framework also suggests where improvement efforts could start. Standardising how work orders and inspection results are recorded may be a practical starting point for improving information systems readiness. Nageeb *et al.* (2026) reported that structured condition data combined with BIM can support predictive planning even where real-time sensing is not available. Training facility managers to interpret maintenance data may strengthen both resource readiness and perceived usefulness. Agreeing on how information is shared among management, facility managers, and contractors would strengthen the communication protocols the MCP framework treats as a control on cost planning and help analytics outputs reach the people who act on them.

CONCLUSION

This study examined how analytics may support cost-effective building maintenance decisions and argued that the readiness of organisations and individuals deserves more attention than it has received. The literature suggests that analytics can support condition monitoring, prioritisation, and cost planning. It also indicates that data quality, system integration, skills, cost, and organisational support continue to limit its use in FM practice.

Drawing on the TOE framework, TAM, and the MCP framework, the study proposed a framework linking analytics readiness, maintenance analytics adoption, and cost-effective maintenance decision-making. These relationships were expressed as four hypotheses, including a partially mediated path from readiness to decision-making through adoption.

The study has a few limitations. It is conceptual and based on document analysis, so the hypotheses have not been tested. Although the literature was identified through a structured search, the final selection was purposive, and other relevant studies may have been missed. Much of the readiness literature comes from sectors other than building maintenance, and it is uncertain how well its findings transfer to maintenance practice. The Malaysian studies reviewed also focus mainly on public buildings. Future research should develop measures for each construct, refine them through a pilot study, and then test the hypotheses with survey data from facility managers and maintenance decision-makers, including whether adoption fully or partially explains the relationship between readiness and decision-making. Such studies will also need to account for the different levels at which readiness and individual perceptions are measured. Studies across different building types, ownership arrangements, and countries would help establish how far the framework applies beyond the contexts reviewed here.

FUNDING

This study was partially funded by the International Doctoral Fellowship, sponsored by Universiti Teknologi

Malaysia.

Conflict of Interest

The authors declare that they have no relevant financial or non-financial interests to disclose.

Ethical Approval

Ethical approval was not required for this study, as it is a conceptual study based on published literature and did not involve human participants or animals.

Data Availability

No new data were created or analysed in this study. All sources analysed are published and cited in the reference list.

Author Contributions

Ifeoluwa Adedoyin Adeyemi, Mohd Shahril Abdul Rahman, Adegbenga Adeyemi, and Caleb Chidozie Chinedu: literature review, conceptualisation, writing, and editing. Mohd Shahril Abdul Rahman and Ifeoluwa Adedoyin Adeyemi: reviewed the article to ensure integrity.

REFERENCES

1. Adeyemi, I. A., Rahman, M. S. A., & Adeyemi, A. (2022). Maintenance analytics for building decision making: A literature review. *Journal of Information System and Technology Management, 7(25)*, 127–138. https://doi.org/10.35631/JISTM.725010
2. Ahmed, J. U. (2010). Documentary research method: New dimensions. *Indus Journal of Management & Social Sciences, 4*, 1–14.
3. Ahmed, V., Tezel, A., Aziz, Z., & Sibley, M. (2017). The future of big data in facilities management: Opportunities and challenges. *Facilities, 35(13/14)*, 725–745. https://doi.org/10.1108/F-06-2016-0064
4. Ajzen, I., & Fishbein, M. (1980). *Understanding attitudes and predicting social behavior*. Prentice-Hall.
5. Al-Najjar, B., & Kans, M. (2006). A model to identify relevant data for problem tracing and maintenance cost-effective decisions: A case study. *International Journal of Productivity and Performance Management, 55*, 616–637. https://doi.org/10.1108/17410400610710170
6. Al-Sai, Z. A., Abdullah, R., & Husin, M. H. (2020). Critical success factors for big data: A systematic literature review. *IEEE Access, 8*, 118940–118956.
7. Ali, A. S. (2009). Cost decision-making in building maintenance practice in Malaysia. *Journal of Facilities Management, 7*, 298–306. https://doi.org/10.1108/14725960910990044
8. Anbari Moghadam, M., & Besiktepe, D. (2025). Synthesis of multi-criteria decision-making applications in facilities management and building maintenance: Trends, methods, and future research directions. *Buildings, 15(18)*, 3258. https://doi.org/10.3390/buildings15183258
9. Au-Yong, C. P., Ali, A. S., & Ahmad, F. (2013). Office building maintenance: Cost prediction model. *Građevinar, 65*, 803–809. https://doi.org/10.14256/JCE.677.2012
10. Au-Yong, C. P., Ali, A. S., Ahmad, F., & Chua, S. J. L. (2017). Influences of key stakeholders' involvement in maintenance management. *Property Management, 35*, 217–231. https://doi.org/10.1108/PM-01-2016-0004
11. Auh, S., Menguc, B., Sainam, P., & Jung, Y. S. (2022). The missing link between analytics readiness and service firm performance. *The Service Industries Journal, 42*, 148–177. https://doi.org/10.1080/02642069.2021.1998461
12. Bazerman, M. H., & Moore, D. A. (2012). *Judgment in managerial decision making (8th ed.)*. John Wiley & Sons.
13. Besiktepe, D., Ozbek, M. E., & Atadero, R. A. (2020). Identification of the criteria for building maintenance decisions in facility management: First step to developing a multi-criteria decision-making approach. *Buildings, 10(9)*, 166. https://doi.org/10.3390/buildings10090166

14. Boukaf, M., Fadli, F., & Meskin, N. (2026). Enabling predictive maintenance in smart buildings: A review of AI approaches, digital integration, and system challenges. *IEEE Access, 14*, 63012–63049. https://doi.org/10.1109/ACCESS.2026.3686217
15. Bowen, G. A. (2009). Document analysis as a qualitative research method. *Qualitative Research Journal, 9(2)*, 27–40. https://doi.org/10.3316/QRJ0902027
16. Chinedu, C. C., & Wan-Mohamed, W. A. (2017). A document analysis of the visibility of sustainability in TVE teacher education program: The case of a Malaysian HEI. *Pertanika Journal of Social Sciences & Humanities, 25(S)*, 201–216.
17. Chong, A. K. W., Mohammed, A. H., Abdullah, M. N., & Rahman, M. S. A. (2019). Maintenance prioritization: A review on factors and methods. *Journal of Facilities Management, 17*, 18–39. https://doi.org/10.1108/JFM-11-2017-0058
18. Chua, S. J. L., Ali, A. S., & Alias, A. B. (2015). Implementation of analytic hierarchy process (AHP) decision making framework for building maintenance procurement selection: Case study of Malaysian public universities. *Eksploatacja i Niezawodność, 17*(1).
19. Chui, C. Y. S., Zayed, T., Xing, J., & Ma, S. (2025). Emerging digitalization in property/facility management: A state-of-the-art review and future directions. *Intelligent Infrastructure and Construction, 1(2)*, 7. https://doi.org/10.3390/iic1020007
20. Daissaoui, A., Boulmakoul, A., Karim, L., & Lbath, A. (2020). IoT and big data analytics for smart buildings: A survey. *Procedia Computer Science, 170*, 161–168. https://doi.org/10.1016/j.procs.2020.03.021
21. Dallasega, P., Rauch, E., & Linder, C. (2018). Industry 4.0 as an enabler of proximity for construction supply chains: A systematic literature review. *Computers in Industry, 99*, 205–225. https://doi.org/10.1016/j.compind.2018.03.039
22. Davis, F. D. (1985). *A technology acceptance model for empirically testing new end-user information systems: Theory and results [Doctoral dissertation, Massachusetts Institute of Technology]*.
23. Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly, 13(3)*, 319–340. https://doi.org/10.2307/249008
24. Dutta, S., Gunay, H. B., & Bucking, S. (2020). A method for extracting performance metrics using work-order data. *Science and Technology for the Built Environment, 26*, 414–425. https://doi.org/10.1080/23744731.2019.1693208
25. Ensafi, M., & Thabet, W. (2021). Challenges and gaps in facility maintenance practices. *EPiC Series in Built Environment, 2*, 237–245.
26. Ensafi, M., Thabet, W., Afsari, K., & Yang, E. (2023). Challenges and gaps with user-led decision-making for prioritizing maintenance work orders. *Journal of Building Engineering, 66*, 105840. https://doi.org/10.1016/j.jobe.2023.105840
27. Falorca, J. G. F. (2021). *Building maintenance management: Development of an integrated model of procedures* [Doctoral thesis, University of Coimbra].
28. Faqih, F., & Zayed, T. (2021). Defect-based building condition assessment. *Building and Environment, 191*, 107575. https://doi.org/10.1016/j.buildenv.2020.107575
29. Flavián, C., Pérez-Rueda, A., Belanche, D., & Casaló, L. V. (2022). Intention to use analytical artificial intelligence (AI) in services: The effect of technology readiness and awareness. *Journal of Service Management, 33(2)*, 293–320. https://doi.org/10.1108/JOSM-10-2020-0378
30. Ganisen, S., Mohammad, I. S., Nesan, L. J., Mohammed, A. H., & Kanniyapan, G. (2015). The identification of design for maintainability imperatives to achieve cost effective building maintenance: A Delphi study. *Jurnal Teknologi, 77*(30).
31. Ghaleb, E. A., Dominic, P. D. D., Fati, S. M., Muneer, A., & Ali, R. F. (2021). The assessment of big data adoption readiness with a technology–organization–environment framework: A perspective towards healthcare employees. *Sustainability, 13*, 8379. https://doi.org/10.3390/su13158379
32. Ghasemaghaei, M. (2019). Does data analytics use improve firm decision-making quality? The role of knowledge sharing and data analytics competency. *Decision Support Systems, 120*, 14–24. https://doi.org/10.1016/j.dss.2019.03.004
33. Grover, V., Chiang, R. H. L., Liang, T.-P., & Zhang, D. (2018). Creating strategic business value from big data analytics: A research framework. *Journal of Management Information Systems, 35(2)*, 388–423.

34. Gunay, H. B., Shen, W., & Newsham, G. (2019a). Data analytics to improve building performance: A critical review. *Automation in Construction, 97*, 96–109. https://doi.org/10.1016/j.autcon.2018.10.020https://doi.org/10.1016/j.autcon.2018.10.020
35. Gunay, H. B., Shen, W., & Yang, C. (2019b). Text-mining building maintenance work orders for component fault frequency. *Building Research & Information, 47*, 518–533. https://doi.org/10.1080/09613218.2018.1459004https://doi.org/10.1080/09613218.2018.1459004
36. Gürdür, D., El-Khoury, J., & Törngren, M. (2019). Digitalizing Swedish industry: What is next? Data analytics readiness assessment of Swedish industry, according to survey results. *Computers in Industry, 105*, 153–163. https://doi.org/10.1016/j.compind.2018.12.011
37. Hastie, R., & Dawes, R. M. (2010). *Rational choice in an uncertain world: The psychology of judgment and decision making*. Sage.
38. Hauashdh, A., Jailani, J., Rahman, I. A., & Al-fadhali, N. (2020). Building maintenance practices in Malaysia: A systematic review of issues, effects and the way forward. *International Journal of Building Pathology and Adaptation, 38(5)*, 653–672. https://doi.org/10.1108/IJBPA-10-2019-0093
39. Hauashdh, A., Jailani, J., Rahman, I. A., & Al-fadhali, N. (2022). Strategic approaches towards achieving sustainable and effective building maintenance practices in maintenance-managed buildings: A combination of expert interviews and a literature review. *Journal of Building Engineering, 45*, 103490. https://doi.org/10.1016/j.jobe.2021.103490
40. Hua, G. C., Sher, W., & Pheng, L. S. (2005). Factors affecting effective communication between building clients and maintenance contractors. *Corporate Communications: An International Journal, 10*, 240–251. https://doi.org/10.1108/13563280510614492
41. Ijab, M. T., Surin, E. S. M., & Nayan, N. M. (2019). Conceptualizing a big data quality framework from a systematic literature review perspective. *Malaysian Journal of Computer Science, Special* Issue 1, 25–37. https://doi.org/10.22452/mjcs.sp2019no1.2
42. Islam, R., Nazifa, T. H., & Mohamed, S. F. (2019). Factors influencing facilities management cost performance in building projects. *Journal of Performance of Constructed Facilities, 33*, 04019036.
43. Ismail, Z. A., Rahim, M. A., & Ghazaly, Z. M. (2020). BIM and CMMS for IBS building maintenance in Malaysia. *IOP Conference Series: Earth and Environmental Science, 476*, 012012. https://doi.org/10.1088/1755-1315/476/1/012012
44. Jørgensen, B. N., Staugaard, B. E., Madsen, S. S., & Ma, Z. G. (2026). A review informed translation framework for mapping smart building services into smart readiness indicator aligned assessment. *Buildings, 16(10)*, 1998. https://doi.org/10.3390/buildings16101998
45. Kalema, B. M., & Mokgadi, M. (2017). Developing countries organizations' readiness for big data analytics. *Problems and Perspectives in Management, 15(1-1)*, 260–270. https://doi.org/10.21511/ppm.15(1-1.2017.13)
46. Karim, R., Westerberg, J., Galar, D., & Kumar, U. (2016). Maintenance analytics: The new know in maintenance. *IFAC-PapersOnLine, 49(28)*, 214–219.
47. Krstić, H., & Marenjak, S. (2017). Maintenance and operation costs model for university buildings. *Tehnički Vjesnik, 24*, 193–200. https://doi.org/10.17559/TV-20140606093626
48. Lateef, O. A. (2009). Building maintenance management in Malaysia. *Journal of Building Appraisal, 4*, 207–214. https://doi.org/10.1057/jba.2008.27
49. Le, A. T. H., Domingo, N., Rasheed, E., & Park, K. S. (2018). Building maintenance cost planning and estimating: A literature review. In Proceedings of the 34th Annual ARCOM Conference (pp. 697–706). Association of Researchers in Construction Management.
50. Li, C. S., & Guo, S. J. (2012). Life cycle cost analysis of maintenance costs and budgets for university buildings in Taiwan. *Journal of Asian Architecture and Building Engineering, 11*, 87–94. https://doi.org/10.3130/jaabe.11.87
51. Low, C., Chen, Y., & Wu, M. (2011). Understanding the determinants of cloud computing adoption. *Industrial Management & Data Systems, 111*, 1006–1023. https://doi.org/10.1108/02635571111161262
52. Lutfi, A., Alshira'h, A. F., Alshirah, M. H., Al-Okaily, M., Alqudah, H., Saad, M., Ibrahim, N., & Abdelmaksoud, O. (2022). Antecedents and impacts of enterprise resource planning system adoption among Jordanian SMEs. *Sustainability, 14*, 3508. https://doi.org/10.3390/su14063508
53. Marenjak, S., El-Haram, M. A., & Horner, R. M. W. (2002). Analysis of overall project costs for the building industry. *Građevinar, 54*(7), 393–401.

54. Mohamed, A. G., Ghaly, J. E., & Marzouk, M. (2024). Revolutionizing semantic integration of maintenance cost prediction for building systems using artificial neural networks. *Journal of Building Engineering, 96*, 110416. https://doi.org/10.1016/j.jobe.2024.110416
55. Nageeb, A., Elyamany, A., Elbehairy, H., & Alhady, A. (2026). A BIM-integrated eco-digital framework for Markov-based predictive maintenance and sustainability assessment in educational buildings towards digital twin readiness. *Sustainability, 18(14)*, 7133. https://doi.org/10.3390/su18147133
56. Nikou, S. (2019). Factors driving the adoption of smart home technology: An empirical assessment. *Telematics and Informatics, 45*, 101283. https://doi.org/10.1016/j.tele.2019.101283
57. Oliveira, T., Thomas, M., & Espadanal, M. (2014). Assessing the determinants of cloud computing adoption: An analysis of the manufacturing and services sectors. *Information & Management, 51*, 497–510. https://doi.org/10.1016/j.im.2014.03.006
58. Olszak, C. M., & Mach-Król, M. (2018). A conceptual framework for assessing an organization's readiness to adopt big data. *Sustainability, 10(10)*, 3734.
59. Omar, M. F., Ibrahim, F. A., & Omar, W. M. S. W. (2016). An assessment of the maintenance management effectiveness of public hospital building through key performance indicators. *Sains Humanika, 8*(4-2).
60. Palis, P., & Misnan, M. S. (2018). A review of key factors that affect university building maintenance costs. *International Journal of Engineering & Technology, 7*, 32–34.
61. Parasuraman, A. (2000). Technology Readiness Index (TRI): A multiple-item scale to measure readiness to embrace new technologies. *Journal of Service Research, 2(4)*, 307–320. https://doi.org/10.1177/109467050024001
62. Pfeffer, J., & Sutton, R. I. (2006). *Hard facts, dangerous half-truths, and total nonsense: Profiting from evidence-based management*. Harvard Business Press.
63. Purwosri, V. P., Prasetyo, H., Solikin, M., Harnaeni, S. R., & Sunarjono, S. (2025). Designing school building maintenance priorities using the cost-user effectiveness ratio. *ComTech: Computer, Mathematics* and Engineering Applications, 16(1), 67–79. https://doi.org/10.21512/comtech.v16i1.12385
64. Razali, M. N., Jamaluddin, A. F., Jalil, R. A., & Nguyen, T. K. (2020). Big data analytics for predictive maintenance in maintenance management. *Property Management, 38(4)*, 513–529. https://doi.org/10.1108/PM-12-2019-0070
65. Rousseau, D. M., & McCarthy, S. (2007). Educating managers from an evidence-based perspective. *Academy of Management Learning & Education, 6*(1), 84–101.
66. Salman, M. S., Sani, M. K. J. A., & Sahid, N. Z. (2022). Assessing the big data analytics readiness based on Technology-Organization-Environment (TOE) framework of Malaysian libraries: Descriptive analysis. *International Journal of Academic Research in Progressive Education and Development, 11(2)*, 1465–1484. https://doi.org/10.6007/IJARPED/v11-i2/13903
67. Schuh, G., Anderl, R., Gausemeier, J., ten Hompel, M., & Wahlster, W. (Eds.). (2017). *Industrie 4.0 Maturity Index: Managing the digital transformation of companies (acatech STUDY)*. Herbert Utz Verlag.
68. Shin, J., Park, Y., & Lee, D. (2018). Who will be smart home users? An analysis of adoption and diffusion of smart homes. *Technological Forecasting and Social Change, 134*, 246–253. https://doi.org/10.1016/j.techfore.2018.06.029
69. Signorini, M., & Pomè, A. P. (2025). Shaping the future of facility management: Market and literature insights on digital twin adoption. *Facilities, 43(11/12)*, 818–834. https://doi.org/10.1108/F-02-2025-0029
70. Simon, H. A. (1960). *The new science of management decision*. Harper & Brothers.
71. Sulistyowati, I., Fransisca, D., & Ruldeviyani, Y. (2021). Data analytics readiness model in Indonesian government. In Proceedings of the 6th International Conference on Sustainable Information Engineering and Technology (pp. 100–105). Association for Computing Machinery. https://doi.org/10.1145/3479645.3479669
72. Taboada-Orozco, A., Yetongnon, K., & Nicolle, C. (2024). Smart buildings: A comprehensive systematic literature review on data-driven building management systems. *Sensors, 24(13)*, 4405. https://doi.org/10.3390/s24134405

73. Tornatzky, L. G., & Fleischer, M. (1990). *The processes of technological innovation*. Lexington Books.
74. Venkatesh, V., & Davis, F. D. (2000). A theoretical extension of the technology acceptance model: Four longitudinal field studies. *Management Science, 46(2)*, 186–204. https://doi.org/10.1287/mnsc.46.2.186.11926
75. Williams, B. (1996). Cost-effective facilities management: A practical approach. *Facilities, 14*, 26–38. https://doi.org/10.1108/02632779610117107
76. Yang, E., & Bayapu, I. (2020). Big Data analytics and facilities management: A case study. *Facilities, 38(3/4)*, 268–281. https://doi.org/10.1108/F-01-2019-0007
77. Zheng, Y., Sun, B., Guan, Y., & Yang, Y. (2025). Artificial intelligence empowering the transformation of building maintenance: Current state of research and knowledge. *Buildings, 15(22)*, 4118. https://doi.org/10.3390/buildings15224118
78. Zorn, T. E., Flanagin, A. J., & Shoham, M. D. (2011). Institutional and noninstitutional influences on information and communication technology adoption and use among nonprofit organizations. *Human Communication Research, 37*, 1–33. https://doi.org/10.1111/j.1468-2958.2010.01387