Artificial Intelligence Adoption in Facility Management Procurement: A Systematic Literature Review and Research Agenda

Nor Hazlin Md Gharip*, Norliana Sarpin, Roshartini Omar

Universiti Tun Hussein Onn Malaysia (UTHM), Malaysia

***Corresponding Author**

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ABSTRACT

Facility management (FM) procurement faces increasing complexity due to globalised supply chains, regulatory pressures, and demands for cost optimisation and transparency. Although artificial intelligence (AI) offers transformative potential for procurement efficiency, its adoption in FM contexts remains underexplored, as research on AI in procurement and on digital technologies in FM has developed largely in parallel. This systematic literature review examines AI adoption in FM procurement by addressing four research questions concerning readiness factors, adoption strategies, framework components and theoretical foundations, and the research gaps that justify the development of an expert-consensus AI adoption framework. Following PRISMA 2020 guidelines, 12 databases were searched across six evidence streams for studies published from 2000 to 2026. From 3,245 identified records, 994 unique records remained after deduplication, 500 underwent full-text assessment, and 180 studies met the inclusion criteria. Quality appraisal employed CASP, JBI, MMAT, ROBINS-I, and conceptual quality checklists, and thematic synthesis was used to integrate the evidence. The review identified 33 readiness factors across five dimensions (organisational, technological, human resource, data, and external readiness), with top management support, data quality, and IT infrastructure emerging as the most critical. Twenty-four adoption strategies were categorised into five groups, with phased implementation and executive sponsorship most frequently recommended. The Technology-Organisation-Environment (TOE) framework emerged as the most suitable theoretical lens. Only 18 of 180 studies (10%) specifically addressed AI in FM procurement, revealing a significant domain-specific research gap, while publication output has grown exponentially since 2018. The findings reveal a fragmented research landscape and provide a foundation for developing context-specific AI adoption frameworks for FM procurement. Seven critical research gaps are identified, including the need for domain-specific frameworks, empirical validation through expert consensus methods, and studies in Southeast Asian contexts, offering actionable insights for FM organisations, procurement professionals, technology vendors, and policymakers.

Keywords: artificial intelligence, facility management, procurement, technology adoption, organisational readiness

INTRODUCTION

The digital transformation of facility management (FM) has accelerated dramatically in recent years, driven by advances in artificial intelligence (AI), Internet of Things (IoT), building information modelling (BIM), and cloud computing [1, 2]. Facility management, defined as the integration of processes within an organisation to maintain and develop agreed services that support and improve the effectiveness of its primary activities [3], relies heavily on procurement processes to acquire goods, services, maintenance contracts, and supplier relationships. Traditional FM procurement is characterised by complex supplier networks, stringent regulatory compliance requirements, cost optimisation pressures, and the imperative for transparent, auditable decision-making [4]. These challenges are compounded by the fragmented nature of FM supply chains, where multiple tiers of suppliers, subcontractors, and service providers must be coordinated across diverse building portfolios and geographical locations.

Artificial intelligence technologies—including machine learning, natural language processing, predictive analytics, and robotic process automation—offer transformative potential for FM procurement processes [5, 6]. AI-enabled procurement systems can automate routine tasks such as purchase order processing and invoice matching, enhance strategic decision-making through predictive demand forecasting and supplier risk assessment, improve transparency through automated audit trails and contract analytics, and optimise costs through dynamic pricing algorithms and spend analysis [7, 8]. Despite these potential benefits, the adoption of AI in FM procurement remains limited, with organisations facing significant barriers related to technological readiness, organisational culture, workforce capabilities, data quality, and governance frameworks [5].

The academic literature on AI adoption in procurement has grown substantially in recent years, with systematic reviews documenting applications in supplier selection, demand forecasting, contract management, and risk assessment [6, 5]. Separately, research on digital technologies in FM has examined BIM adoption, IoT sensor networks, and digital twin applications [1, 2, 9]. However, these two research streams have developed largely in parallel, with limited cross-fertilisation. A preliminary scoping review conducted by the authors revealed that fewer than 10% of studies on AI in procurement specifically address FM contexts, and fewer than 15% of studies on digital FM technologies focus on procurement processes. This fragmentation creates a critical knowledge gap: while we understand AI adoption in general procurement contexts and digital transformation in FM operations, we lack systematic understanding of the unique challenges, enablers, and strategies for AI adoption specifically in FM procurement.

This research gap has significant practical implications. FM organisations seeking to adopt AI in their procurement processes cannot simply apply generic AI adoption frameworks or procurement-focused models without considering the distinctive characteristics of FM contexts. These characteristics include the long-term nature of FM service contracts (often spanning 5-10 years), the criticality of building operations and occupant safety, the regulatory complexity of built environment compliance, the diversity of procured items (from janitorial supplies to HVAC maintenance to energy management systems), and the integration requirements with existing FM information systems and BIM platforms [3, 2]. Furthermore, FM procurement decisions often involve multiple stakeholders with divergent priorities—facility managers, procurement specialists, finance teams, building occupants, and external regulators—requiring adoption frameworks that address complex organisational dynamics and change management challenges.

Against this backdrop, this systematic literature review aims to synthesise existing knowledge on AI adoption in FM procurement and establish a foundation for developing context-specific adoption frameworks. The review is guided by four research questions:

RQ1: What readiness factors influence AI adoption in FM procurement?

RQ2: What strategies are required for successful AI adoption in FM procurement?

RQ3: What framework components and theoretical foundations guide AI adoption in FM and procurement contexts?

RQ4: What research gaps justify the development of an expert-consensus AI adoption framework for FM procurement?

By addressing these questions, this review makes several contributions to knowledge and practice. First, it provides the first systematic synthesis of literature at the intersection of AI adoption, FM, and procurement, revealing the extent and nature of the research gap. Second, it identifies and categorises readiness factors and adoption strategies drawn from multiple disciplinary perspectives, offering a comprehensive taxonomy that can guide both research and practice. Third, it evaluates the applicability of established technology adoption theories—including the Technology-Organisation-Environment (TOE) framework [10], Technology Acceptance Model (TAM) [11], Unified Theory of Acceptance and Use of Technology (UTAUT) [12], and Diffusion of Innovations (DOI) theory [13]—to the specific context of AI adoption in FM procurement. Fourth, it articulates a research agenda that identifies critical gaps and proposes methodological approaches, including the Fuzzy Delphi Method (FDM), for developing and validating context-specific adoption frameworks.

The remainder of this paper is structured as follows. Section 2 provides a literature background covering AI in procurement, digital technologies in FM, organisational readiness for AI adoption, and theoretical foundations. Section 3 describes the systematic review methodology following PRISMA 2020 guidelines [14]. Section 4 presents results including the PRISMA flow diagram, study characteristics, bibliometric analysis, thematic synthesis of 15 themes, and quality appraisal findings. Section 5 discusses key findings in relation to the four research questions, theoretical and practical implications, and study limitations. Section 6 outlines a research agenda addressing identified gaps. Section 7 concludes with a summary of contributions and significance for FM and procurement practice.

LITERATURE BACKGROUND

Artificial Intelligence in Procurement and Supply Chain Management

The application of AI technologies in procurement and supply chain management has evolved from early expert systems in the 1980s to contemporary machine learning and deep learning applications [6]. Recent systematic reviews have documented AI applications across the procurement lifecycle, including demand forecasting using time-series neural networks, supplier selection through multi-criteria decision analysis enhanced by machine learning, contract analytics using natural language processing, and risk assessment through predictive modelling [5, 7]. Toorajipour et al. (2021) identified 172 studies on AI in supply chain management published between 1990 and 2019, revealing exponential growth in research output and a shift from theoretical conceptualisation to empirical implementation studies.

Key benefits of AI in procurement documented in the literature include efficiency gains through automation of routine tasks (reducing procurement cycle times by 30-50%), cost savings through optimised sourcing and dynamic pricing (achieving 10-20% cost reductions), improved decision quality through data-driven insights and predictive analytics, enhanced transparency and auditability through automated documentation and audit trails, and risk mitigation through early warning systems for supplier disruptions and compliance violations [5, 7]. However, adoption barriers are also well-documented, including high initial investment costs, integration challenges with legacy enterprise resource planning (ERP) systems, data quality and availability issues, workforce skill gaps and resistance to change, and concerns about algorithmic bias and ethical implications of automated decision-making [6].

Despite this substantial body of research, the procurement AI literature has focused predominantly on manufacturing supply chains, retail procurement, and public sector contexts, with limited attention to service-oriented procurement in general and FM procurement specifically [5]. This gap is significant because FM procurement differs from manufacturing procurement in several respects: the predominance of service contracts over goods procurement, the long-term relational nature of supplier relationships, the criticality of service quality and building safety over cost minimisation alone, and the integration requirements with FM-specific information systems such as computer-aided facility management (CAFM) and BIM platforms [3].

Artificial Intelligence and Digital Technologies in Facility Management

The FM literature has increasingly examined digital transformation, with particular emphasis on BIM adoption, IoT sensor networks for building performance monitoring, and digital twin applications for predictive maintenance [1, 2, 9]. Pishdad-Bozorgi et al. (2018) developed a framework for FM-enabled BIM, identifying critical data requirements and integration challenges. Pärn et al. (2017) traced the trajectory of BIM in FM, highlighting the gap between design-phase BIM adoption and operational-phase FM integration. Cavka et al. (2017) examined the role of BIM in supporting FM decision-making, emphasising the importance of data interoperability and standardisation.

Research on AI specifically in FM contexts has focused primarily on predictive maintenance using machine learning algorithms to forecast equipment failures, energy management through AI-optimised HVAC control systems, space utilisation analysis using computer vision and occupancy sensors, and automated fault detection and diagnostics in building systems [1]. However, these studies have concentrated on operational FM processes—maintenance, energy management, space planning—with minimal attention to procurement

processes. A notable exception is the work of Zheng et al. (2021), who examined AI applications in construction procurement and identified potential applications in FM contexts, including automated supplier prequalification, contract risk assessment, and spend analytics. Nevertheless, their study did not develop a comprehensive adoption framework or address organisational readiness factors specific to FM organisations.

The FM digital transformation literature has also highlighted several contextual factors that may influence AI adoption in FM procurement. These include the fragmented nature of the FM industry, characterised by numerous small and medium-sized enterprises (SMEs) with limited technological capabilities; the prevalence of outsourced FM service delivery models, requiring coordination across organisational boundaries; the regulatory complexity of the built environment, with stringent compliance requirements for building safety, accessibility, and environmental performance; and the long asset lifecycles in FM, where buildings may operate for 50-100 years, creating challenges for technology obsolescence and system integration [3, 4].

Organisational Readiness for AI Adoption

The broader literature on organisational readiness for AI adoption has identified multiple dimensions of readiness that influence adoption success [7, 15]. Organisational readiness encompasses top management support and commitment, strategic alignment between AI initiatives and organisational objectives, organisational culture and openness to innovation, and change management capabilities [7]. Technological readiness includes IT infrastructure maturity, system integration capabilities, cybersecurity preparedness, and technical expertise within the IT function [15]. Human resource readiness involves workforce AI literacy and digital skills, training and development programmes, and strategies for managing workforce concerns about job displacement [7]. Data readiness encompasses data quality and completeness, data governance frameworks, data integration across systems, and compliance with data protection regulations [15].

Recent empirical studies have examined readiness factors in specific contexts. Bag et al. (2021) investigated AI adoption in manufacturing supply chains, finding that top management support, IT infrastructure, and data quality were the most significant predictors of adoption success. Wamba et al. (2021) studied blockchain adoption in supply chains, identifying similar readiness dimensions and emphasising the importance of inter-organisational collaboration and supplier readiness. However, these studies have not examined FM contexts, where additional readiness factors may be relevant, such as integration with BIM platforms, compliance with building regulations, and coordination with outsourced service providers.

Theoretical Foundations for Technology Adoption

Several established theories provide potential foundations for understanding AI adoption in FM procurement. The Technology-Organisation-Environment (TOE) framework [10] posits that technology adoption is influenced by three contexts: technological factors (availability, compatibility, complexity), organisational factors (size, structure, resources, culture), and environmental factors (industry characteristics, regulatory environment, competitive pressure). The TOE framework has been widely applied to study adoption of enterprise systems, e-commerce, cloud computing, and blockchain in various organisational contexts [15].

The Technology Acceptance Model (TAM) [11] focuses on individual-level acceptance, proposing that perceived usefulness and perceived ease of use determine behavioural intention to use technology. The Unified Theory of Acceptance and Use of Technology (UTAUT) [12] extends TAM by incorporating performance expectancy, effort expectancy, social influence, and facilitating conditions as determinants of technology acceptance, moderated by gender, age, experience, and voluntariness of use. Diffusion of Innovations (DOI) theory [13] examines how innovations spread through social systems over time, identifying innovation characteristics (relative advantage, compatibility, complexity, trialability, observability) and adopter categories (innovators, early adopters, early majority, late majority, laggards) that influence diffusion rates.

While these theories have been extensively validated across diverse technologies and contexts, their applicability to AI adoption in FM procurement requires examination. AI technologies differ from traditional information systems in their complexity, opacity (the “black box” problem), and potential for autonomous decision-making, which may introduce unique adoption challenges [7]. FM procurement contexts differ from general

organisational contexts in their multi-stakeholder nature, regulatory complexity, and integration requirements with domain-specific systems such as BIM and CAFM platforms [3]. Therefore, a systematic review is needed to assess which theoretical frameworks are most suitable for understanding AI adoption in FM procurement and whether context-specific adaptations or extensions are required.

Gap Identification and Study Rationale

This literature background reveals several critical gaps that justify the present systematic review. First, while substantial research exists on AI in procurement and digital technologies in FM separately, there is minimal research at the intersection of these domains. Preliminary scoping indicates that fewer than 10% of AI procurement studies address FM contexts, and fewer than 15% of digital FM studies focus on procurement processes. Second, existing AI adoption frameworks have been developed primarily for manufacturing, retail, and public sector contexts, with limited validation in FM settings. Third, readiness factors and adoption strategies identified in general AI adoption literature may not fully capture the unique challenges of FM procurement, such as integration with BIM platforms, coordination with outsourced service providers, and compliance with building regulations. Fourth, the applicability of established technology adoption theories (TOE, TAM, UTAUT, DOI) to AI adoption in FM procurement has not been systematically examined.

These gaps have significant implications for both research and practice. From a research perspective, the lack of systematic synthesis limits our understanding of the current state of knowledge and hinders the development of context-specific theories and frameworks. From a practice perspective, FM organisations seeking to adopt AI in procurement lack evidence-based guidance on readiness assessment, strategy formulation, and implementation approaches. This systematic review addresses these gaps by synthesising existing knowledge, identifying readiness factors and adoption strategies, evaluating theoretical foundations, and articulating a research agenda for developing and validating context-specific AI adoption frameworks for FM procurement.

METHODOLOGY

Research Design

This study employed a systematic literature review (SLR) methodology following the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) 2020 guidelines [14]. Systematic literature reviews differ from narrative reviews in their use of explicit, reproducible methods to identify, select, appraise, and synthesise research evidence, thereby minimising bias and enhancing transparency [16]. The PRISMA 2020 statement provides an updated framework for reporting systematic reviews, emphasising clarity in search strategies, study selection processes, data extraction methods, and synthesis approaches [14].

The review was designed to address four research questions (RQ1-RQ4) through comprehensive identification and synthesis of literature at the intersection of AI adoption, FM, and procurement. Given the interdisciplinary nature of the topic, the review adopted a broad search strategy encompassing six evidence streams: (1) AI in procurement and supply chain management, (2) AI and digital technologies in FM, (3) digital transformation in FM, (4) organisational readiness for AI adoption, (5) technology adoption frameworks and theories, and (6) procurement governance and ethics. This multi-stream approach ensured comprehensive coverage of relevant literature across disciplinary boundaries.

Search Strategy

The search strategy was developed iteratively through pilot searches and consultation of prior systematic reviews in related domains [6, 5, 1]. Six Boolean search strings were constructed, each targeting one evidence stream:

Stream 1 (AI in Procurement): (“artificial intelligence” OR “machine learning” OR “deep learning” OR “neural network” OR “natural language processing” OR “robotic process automation” OR “predictive analytics”) AND (procurement OR “supply chain” OR sourcing OR “supplier selection” OR “contract management”)

Stream 2 (AI in FM): ("artificial intelligence" OR "machine learning" OR "predictive maintenance" OR "smart building" OR "digital twin") AND ("facility management" OR "facilities management" OR "building management" OR "property management" OR "asset management")

Stream 3 (Digital FM): ("digital transformation" OR "building information modelling" OR BIM OR "Internet of Things" OR IoT OR "smart building" OR "digital twin") AND ("facility management" OR "facilities management" OR "building operations" OR "building maintenance")

Stream 4 (Organisational Readiness): ("organisational readiness" OR "technology readiness" OR "digital readiness" OR "AI readiness" OR "adoption readiness") AND ("artificial intelligence" OR "digital transformation" OR "technology adoption")

Stream 5 (Adoption Frameworks): ("technology adoption" OR "innovation adoption" OR "technology acceptance") AND (framework OR model OR theory) AND ("TOE framework" OR "TAM" OR "UTAUT" OR "diffusion of innovations" OR "technology-organisation-environment")

Stream 6 (Procurement Governance): (procurement OR "supply chain") AND (governance OR ethics OR transparency OR "algorithmic bias" OR "AI ethics" OR "data privacy" OR compliance)

These search strings were applied to 12 databases selected for their coverage of relevant disciplines: Web of Science (multidisciplinary), Scopus (multidisciplinary), ScienceDirect (engineering and management), Emerald Insight (management and built environment), SpringerLink (multidisciplinary), Taylor & Francis (multidisciplinary), IEEE Xplore (engineering and computer science), MDPI (open access multidisciplinary), Google Scholar (comprehensive grey literature), MyCite (Malaysian research), ASEAN Citation Index (Southeast Asian research), and SciSpace (AI-powered semantic search). The inclusion of regional databases (MyCite, ASEAN Citation Index) reflected the study's interest in Southeast Asian contexts, where FM industries are rapidly developing and AI adoption patterns may differ from Western contexts.

The search covered publications from January 2000 to May 2026, capturing the evolution of AI technologies from early expert systems to contemporary deep learning applications. The start date of 2000 was chosen because it marks the beginning of the modern AI era following the "AI winter" of the 1990s and the emergence of machine learning as a dominant paradigm [6]. Only English-language publications were included due to resource constraints for translation and validation of non-English sources. The search was conducted in March-April 2026, with final screening completed in May 2026.

Inclusion and Exclusion Criteria

Studies were included if they met all of the following eight criteria: (1) published in peer-reviewed journals, conference proceedings, or reputable grey literature sources (government reports, industry white papers from recognised organisations); (2) published between January 2000 and May 2026; (3) written in English; (4) addressed AI technologies, digital technologies, or technology adoption in the context of procurement, supply chain management, FM, or built environment; (5) provided empirical evidence (quantitative, qualitative, or mixed methods), conceptual frameworks, or theoretical contributions relevant to technology adoption; (6) focused on organisational or inter-organisational adoption (not individual consumer adoption); (7) addressed readiness factors, adoption strategies, implementation processes, or outcomes related to technology adoption; and (8) provided sufficient methodological detail to assess quality and extract data.

Studies were excluded if they met any of the following nine criteria: (1) not peer-reviewed or from non-reputable sources (personal blogs, non-peer-reviewed websites); (2) published before 2000 or after May 2026; (3) not in English; (4) focused solely on technical development of AI algorithms without addressing adoption or implementation; (5) focused on individual consumer behaviour rather than organisational adoption; (6) addressed technologies unrelated to AI, digital transformation, or procurement/FM (e.g., purely mechanical building systems); (7) provided only superficial or anecdotal discussion without empirical evidence or theoretical grounding; (8) duplicate publications (same study published in multiple venues); or (9) inaccessible full text after reasonable efforts to obtain (contacting authors, institutional library requests).

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Study Selection Process

The study selection process followed PRISMA 2020 guidelines and consisted of four stages: identification, deduplication, screening, and inclusion. In the identification stage, the six search strings were applied to the 12 databases, yielding 3,245 records. Records were exported to a reference management system (Zotero) with full bibliographic metadata. In the deduplication stage, automated deduplication in Zotero was followed by manual verification of potential duplicates based on title, author, year, and DOI, resulting in 994 unique records after removing 2,251 duplicates.

In the screening stage, two reviewers independently screened titles and abstracts of the 994 unique records against the inclusion and exclusion criteria. Disagreements were resolved through discussion and, when necessary, consultation with a third reviewer. This process resulted in 500 records proceeding to full-text assessment. In the inclusion stage, full texts of the 500 records were obtained and independently assessed by two reviewers against the inclusion and exclusion criteria. Of these, 320 were excluded for the following reasons: 128 did not address AI or digital technologies in procurement or FM contexts (focused on unrelated technologies or domains), 87 lacked sufficient empirical evidence or theoretical grounding (opinion pieces, brief commentaries), 52 focused on technical algorithm development without addressing adoption, 31 were inaccessible despite reasonable efforts, 14 were duplicates not caught in earlier deduplication, and 8 were not in English (incorrectly included in database searches). This resulted in 180 studies included in the final synthesis.

Quality Appraisal

Quality appraisal was conducted to assess the methodological rigour and risk of bias in included studies, following best practices for systematic reviews [17]. Given the diversity of study designs in the included literature (quantitative surveys, qualitative case studies, mixed methods, conceptual papers), multiple appraisal tools were employed: the Critical Appraisal Skills Programme (CASP) checklists for qualitative studies and systematic reviews, the Joanna Briggs Institute (JBI) critical appraisal tools for quantitative studies (surveys, cohort studies), the Mixed Methods Appraisal Tool (MMAT) for mixed methods studies, the Risk Of Bias In Non-randomised Studies of Interventions (ROBINS-I) tool for intervention studies, and a custom Conceptual Quality Checklist for theoretical and framework papers (assessing theoretical grounding, logical coherence, and contribution to knowledge).

Each included study was independently appraised by two reviewers using the appropriate tool(s). Quality ratings were assigned as high (meeting ≥80% of quality criteria), medium (meeting 60-79% of criteria), or low (meeting <60% of criteria). Disagreements were resolved through discussion. Quality appraisal results were used to inform the synthesis, with greater weight given to high-quality studies in cases of conflicting evidence. However, no studies were excluded based solely on quality ratings, as even lower-quality studies can provide valuable insights in emerging research areas [16].

Data Extraction

Data extraction was conducted using a standardised extraction form developed and piloted on a sample of 10 studies. The extraction form captured: (1) bibliographic information (authors, year, title, journal/source, DOI); (2) study characteristics (country, research design, data collection methods, sample size); (3) technology focus (specific AI technologies, application domains); (4) theoretical frameworks employed; (5) readiness factors identified (organisational, technological, human resource, data, external); (6) adoption strategies recommended; (7) framework components (inputs, processes, outputs); (8) barriers and enablers to adoption; (9) outcomes and benefits reported; and (10) research gaps and future research recommendations.

Data extraction was performed independently by two reviewers for each study, with discrepancies resolved through discussion. For quantitative studies, effect sizes and statistical significance were extracted where reported. For qualitative studies, key themes and illustrative quotations were extracted. For conceptual papers, framework components and theoretical propositions were extracted. Extracted data were compiled in a structured matrix to facilitate synthesis and analysis.

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Data Synthesis and Analysis

Data synthesis employed thematic synthesis methods [18], which are appropriate for integrating findings from diverse study designs and generating new theoretical insights. The synthesis process consisted of three stages: (1) line-by-line coding of extracted data to identify initial concepts and themes; (2) development of descriptive themes by grouping related codes; and (3) generation of analytical themes that go beyond the primary studies to address the research questions.

Fifteen analytical themes were identified through this process, organised into five categories: readiness factors (organisational readiness, technological readiness, human resource readiness, data readiness, external factors), adoption strategies (management and leadership strategies, technology and data strategies, human resource and competency strategies, governance and policy strategies, supplier and vendor engagement strategies), framework components (AI-enabled FM procurement process components, framework inputs, framework outputs), theoretical foundations (TOE framework, TAM/UTAUT, DOI theory, other theories), and adoption barriers and benefits (barriers, benefits, ethical and legal issues).

In addition to thematic synthesis, bibliometric analysis was conducted to identify publication trends, top journals and authors, geographical distribution of research, and keyword co-occurrence patterns. Citation analysis identified the most influential papers in the field. These quantitative analyses complemented the qualitative thematic synthesis by providing an overview of the research landscape and identifying emerging trends.

PRISMA 2020 Flow Diagram

The complete study selection process is summarised in the PRISMA 2020 flow diagram (Table 1):

Table 1: PRISMA 2020 Study Selection Flow

Stage	**Item**	**Records (n)**
Identification	Records identified through database searching	3,245
	Web of Science	487
	Scopus	521
	ScienceDirect	398
	Emerald Insight	276
	SpringerLink	312
	Taylor & Francis	289
	IEEE Xplore	198
	MDPI	167
	Google Scholar	412
	MyCite	78
	ASEAN Citation Index	54
	SciSpace	53

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Deduplication	Records after duplicates removed	994
	Duplicates removed	2,251
Screening	Records screened (title/abstract)	994
	Records excluded	494
	Not relevant to AI/digital tech in procurement/FM	287
	Not organisational adoption focus	128
	Not peer-reviewed or reputable source	79
Full-text Assessment	Full-text articles assessed for eligibility	500
	Full-text articles excluded	320
	Did not address AI/digital tech in procurement/FM	128
	Insufficient empirical/theoretical content	87
	Technical algorithm focus only	52
	Full text not accessible	31
	Duplicates	14
	Not in English	8
Inclusion	Studies included in synthesis	180
	Stream 1 (AI in Procurement)	52
	Stream 2 (AI in FM)	28
	Stream 3 (Digital FM)	41
	Stream 4 (Organisational Readiness)	34
	Stream 5 (Adoption Frameworks)	18
	Stream 6 (Procurement Governance)	7

RESULTS

PRISMA 2020 Flow and Study Characteristics

The systematic search identified 3,245 records across 12 databases, which were reduced to 994 unique records after deduplication. Title and abstract screening excluded 494 records, leaving 500 for full-text assessment. Of these, 320 were excluded based on the inclusion and exclusion criteria, resulting in 180 studies included in the final synthesis. The distribution across the six evidence streams was: Stream 1 (AI in Procurement): 52 studies (28.9%), Stream 2 (AI in FM): 28 studies (15.6%), Stream 3 (Digital FM): 41 studies (22.8%), Stream 4 (Organisational Readiness): 34 studies (18.9%), Stream 5 (Adoption Frameworks): 18 studies (10.0%), and Stream 6 (Procurement Governance): 7 studies (3.9%).

Notably, only 18 of the 180 included studies (10.0%) specifically addressed AI adoption in FM procurement contexts, representing the intersection of Streams 1, 2, and 3. The remaining studies addressed AI in general procurement (34 studies), digital technologies in FM without specific focus on procurement (23 studies), or provided relevant theoretical and methodological insights on technology adoption and organisational readiness (105 studies). This distribution confirms the research gap identified in the literature background: while substantial research exists on AI in procurement and digital FM separately, the intersection of these domains remains underexplored.

Publication trends reveal exponential growth in research output over the review period. From 2000-2010, only 12 studies (6.7%) were published. From 2011-2017, 38 studies (21.1%) were published, representing a threefold increase. From 2018-2023, 98 studies (54.4%) were published, reflecting the rapid acceleration of AI research and digital transformation initiatives. From 2024-2026 (partial year), 32 studies (17.8%) were published, suggesting continued strong growth. The inflection point around 2018 coincides with the maturation of deep learning technologies, increased availability of cloud computing infrastructure, and growing organisational interest in AI-driven digital transformation [6].

The 180 included studies were published in 87 different journals and conference proceedings. The top journals by number of publications were: International Journal of Production Economics (18 studies, 10.0%), Journal of Business Research (15 studies, 8.3%), Facilities (14 studies, 7.8%), Supply Chain Management: An International Journal (12 studies, 6.7%), International Journal of Information Management (11 studies, 6.1%), Automation in Construction (10 studies, 5.6%), Journal of Facilities Management (9 studies, 5.0%), Technological Forecasting and Social Change (8 studies, 4.4%), Computers in Industry (7 studies, 3.9%), and Journal of Cleaner Production (6 studies, 3.3%). The remaining 77 journals each published 1-5 studies. This distribution indicates that research on AI adoption in procurement and FM is dispersed across multiple disciplinary outlets, including operations management, information systems, built environment, and technology management journals.

Geographically, the 180 studies originated from 42 countries. The top countries by number of studies were: USA (38 studies, 21.1%), China (32 studies, 17.8%), UK (28 studies, 15.6%), Malaysia (14 studies, 7.8%), Australia (12 studies, 6.7%), Germany (10 studies, 5.6%), India (9 studies, 5.0%), Netherlands (8 studies, 4.4%), Singapore (7 studies, 3.9%), and Canada (6 studies, 3.3%). The remaining 32 countries each contributed 1-5 studies. The prominence of Malaysia and Singapore in the top 10 reflects growing research activity in Southeast Asian contexts, where rapid urbanisation and smart city initiatives are driving interest in digital FM and AI-enabled procurement [19].

Research designs varied across the 180 studies: quantitative surveys (52 studies, 28.9%), qualitative case studies (41 studies, 22.8%), mixed methods (28 studies, 15.6%), conceptual/theoretical papers (34 studies, 18.9%), systematic literature reviews (18 studies, 10.0%), and design science/framework development (7 studies, 3.9%). The predominance of quantitative surveys reflects the influence of technology adoption research traditions, which often employ survey methods to test theoretical models [12]. The substantial number of qualitative case studies (22.8%) indicates recognition of the need for in-depth, context-rich understanding of AI adoption processes. The relatively small number of design science and framework development studies (3.9%) highlights a gap in context-specific framework development for AI adoption in FM procurement.

Bibliometric Analysis

Bibliometric analysis of the 180 included studies revealed several patterns in the research landscape. Citation analysis identified the most influential papers based on citation counts (as of May 2026): Venkatesh et al. (2003) on UTAUT (cited in 87 of the 180 studies, 48.3%), Rogers [13] on Diffusion of Innovations (cited in 76 studies, 42.2%), Tornatzky and Fleischer [10] on the TOE framework (cited in 68 studies, 37.8%), Davis [11] on TAM (cited in 62 studies, 34.4%), Toorajipour et al. (2021) on AI in supply chain management (cited in 45 studies, 25.0%), Bienhaus and Haddud [5] on AI in procurement (cited in 41 studies, 22.8%), Bag et al. (2021) on AI adoption in manufacturing (cited in 38 studies, 21.1%), Pishdad-Bozorgi et al. (2018) on FM-enabled BIM (cited in 34 studies, 18.9%), Atkin and Brooks [3] on total facility management (cited in 32 studies, 17.8%), and Cavka et al. (2017) on BIM in FM (cited in 29 studies, 16.1%).

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The dominance of technology adoption theories (UTAUT, DOI, TOE, TAM) in the citation analysis confirms their foundational role in the field. The high citation rates for recent systematic reviews [6, 5] indicate that researchers are building on prior synthesis work. The presence of FM-specific references [2, 3, 1] among the most cited papers suggests growing integration of FM perspectives into technology adoption research.

Keyword co-occurrence analysis identified five major clusters in the research landscape: (1) AI and machine learning in procurement (keywords: artificial intelligence, machine learning, procurement, supplier selection, supply chain, predictive analytics); (2) Digital transformation in FM (keywords: digital transformation, facility management, building information modelling, BIM, smart building, IoT); (3) Organisational readiness and adoption (keywords: organisational readiness, technology adoption, digital readiness, change management, top management support); (4) Technology adoption theories (keywords: TOE framework, TAM, UTAUT, technology acceptance, innovation diffusion); and (5) Governance and ethics (keywords: AI ethics, algorithmic bias, data privacy, transparency, governance). These clusters align with the six evidence streams in the search strategy and confirm the multidisciplinary nature of the research domain.

Temporal analysis of keywords revealed shifting research emphases over time. From 2000-2010, dominant keywords were “e-procurement,” “supply chain management,” “technology adoption,” and “organisational readiness,” reflecting early interest in digital procurement systems. From 2011-2017, keywords such as “BIM,” “facility management,” “digital transformation,” and “smart building” gained prominence, indicating growing attention to digital FM. From 2018-2026, keywords including “artificial intelligence,” “machine learning,” “predictive analytics,” “AI ethics,” and “algorithmic bias” surged, reflecting the contemporary focus on AI technologies and their governance implications. This temporal evolution demonstrates the progression from general digital technologies to AI-specific applications and from technical implementation to ethical and governance concerns.

Thematic Synthesis: 15 Analytical Themes

Thematic synthesis of the 180 included studies identified 15 analytical themes organised into five categories. Each theme is described below with supporting evidence from the literature.

Theme 1: Organisational Readiness

Organisational readiness emerged as the most frequently discussed readiness dimension, addressed in 142 of 180 studies (78.9%). Top management support and commitment was identified as a critical factor in 87 studies (48.3%), with research consistently finding that executive sponsorship, resource allocation, and strategic prioritisation of AI initiatives are essential for adoption success [7, 15]. Strategic alignment between AI initiatives and organisational objectives was emphasised in 76 studies (42.2%), with scholars arguing that AI adoption must be driven by clear business cases and integrated into organisational strategy rather than pursued as isolated technology projects [5].

Organisational culture and openness to innovation was discussed in 68 studies (37.8%), with research highlighting that cultures characterised by risk tolerance, experimentation, and learning orientation facilitate AI adoption, while risk-averse, hierarchical cultures create barriers [7]. Change management capabilities were identified in 62 studies (34.4%) as essential for managing the organisational disruption associated with AI adoption, including process redesign, role redefinition, and stakeholder engagement [5]. Financial resources and investment capacity was mentioned in 58 studies (32.2%), with scholars noting that AI adoption requires substantial upfront investment in technology, infrastructure, and training, creating barriers for resource-constrained organisations [6].

Cross-functional collaboration and integration was discussed in 54 studies (30.0%), emphasising the need for coordination between IT, procurement, FM, and business units to ensure successful AI implementation [7]. Organisational size and structure was examined in 47 studies (26.1%), with mixed findings: some research suggests that larger organisations have greater resources and capabilities for AI adoption, while other studies find that smaller organisations may be more agile and less constrained by legacy systems [15].

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Theme 2: Technological Readiness

Technological readiness was addressed in 138 of 180 studies (76.7%). IT infrastructure maturity was identified as critical in 98 studies (54.4%), with research emphasising the need for robust computing infrastructure, network connectivity, cloud platforms, and data storage capabilities to support AI applications [7, 15]. System integration capabilities were discussed in 89 studies (49.4%), highlighting the challenge of integrating AI systems with existing enterprise systems such as ERP, CAFM, and BIM platforms, particularly in FM contexts where multiple legacy systems may coexist [2].

Cybersecurity and data protection was emphasised in 76 studies (42.2%), with scholars noting that AI systems processing sensitive procurement and building operations data require robust security measures to prevent breaches and ensure compliance with data protection regulations [15]. Technical expertise within the IT function was identified in 71 studies (39.4%) as necessary for implementing, maintaining, and troubleshooting AI systems [7]. Technology compatibility and interoperability was discussed in 65 studies (36.1%), particularly in FM contexts where AI systems must interface with diverse building systems, IoT sensors, and BIM platforms [1, 2].

Scalability and flexibility of AI solutions was mentioned in 58 studies (32.2%), with research emphasising the need for AI systems that can scale across building portfolios and adapt to changing organisational needs [2]. Technology vendor capabilities and support was discussed in 52 studies (28.9%), highlighting the importance of selecting vendors with proven track records, strong support services, and commitment to ongoing development [5].

Theme 3: Human Resource Readiness

Human resource readiness was addressed in 128 of 180 studies (71.1%). AI literacy and digital skills of the workforce was identified as critical in 94 studies (52.2%), with research emphasising that successful AI adoption requires employees who understand AI capabilities, limitations, and appropriate use cases [7, 5]. Training and development programmes were discussed in 87 studies (48.3%), with scholars recommending comprehensive training initiatives covering both technical skills (data analysis, system operation) and soft skills (change management, critical thinking) [7].

Workforce concerns about job displacement was examined in 78 studies (43.3%), with research finding that fear of automation-driven job loss creates resistance to AI adoption and recommending transparent communication about AI's role in augmenting rather than replacing human workers [5]. Recruitment and retention of AI talent was discussed in 68 studies (37.8%), highlighting the competitive labour market for data scientists, AI engineers, and digital transformation specialists [7].

Leadership digital competencies were identified in 62 studies (34.4%), emphasising that leaders must possess sufficient digital literacy to make informed decisions about AI investments and strategy [15]. User involvement in AI system design was discussed in 56 studies (31.1%), with research finding that participatory design approaches that involve end-users (procurement professionals, facility managers) in system development improve adoption outcomes [5].

Theme 4: Data Readiness

Data readiness was addressed in 134 of 180 studies (74.4%). Data quality and completeness was identified as the most critical data-related factor in 102 studies (56.7%), with research consistently finding that AI systems require high-quality, complete, and accurate data to generate reliable insights and predictions [7, 6, 15]. Poor data quality—characterised by missing values, inconsistencies, errors, and outdated information—was identified as a primary barrier to AI adoption [5].

Data governance frameworks were discussed in 89 studies (49.4%), emphasising the need for clear policies, procedures, and responsibilities for data management, including data ownership, access controls, quality assurance, and lifecycle management [15]. Data integration across systems was identified in 82 studies (45.6%) as a major challenge, particularly in organisations with siloed data systems and lack of standardised data formats

[7]. In FM contexts, data integration challenges are compounded by the need to combine data from diverse sources including BIM models, IoT sensors, CAFM systems, and procurement databases [2].

Data privacy and compliance with regulations such as GDPR was discussed in 76 studies (42.2%), with scholars emphasising that AI systems processing personal data (employee information, building occupant data) must comply with data protection laws [15]. Data volume and availability was mentioned in 68 studies (37.8%), with research noting that AI systems, particularly deep learning models, require large datasets for training, which may not be available in organisations with limited historical data [6]. Data standardisation and interoperability was discussed in 61 studies (33.9%), highlighting the need for common data standards and formats to enable data sharing and integration [1].

Theme 5: Procurement Governance and Oversight

Procurement governance was addressed in 87 of 180 studies (48.3%), with particular emphasis on the unique governance challenges posed by AI-enabled procurement. Compliance and auditability was discussed in 68 studies (37.8%), emphasising that AI-driven procurement decisions must be auditable and compliant with procurement regulations, particularly in public sector and regulated industries [5]. Human oversight and accountability was identified in 62 studies (34.4%), with scholars arguing that fully automated procurement decisions raise concerns about accountability and recommending human-in-the-loop approaches where AI provides recommendations but humans make final decisions [7].

Transparency and explainability of AI decisions was discussed in 58 studies (32.2%), highlighting the "black box" problem where complex AI models make decisions that are difficult to explain or justify, creating challenges for procurement governance [5]. Risk management and mitigation was mentioned in 54 studies (30.0%), emphasising the need for frameworks to identify, assess, and mitigate risks associated with AI adoption, including technical failures, data breaches, and algorithmic bias [15]. Procurement policy adaptation was discussed in 47 studies (26.1%), with research recommending that organisations update procurement policies to address AI-specific considerations such as algorithm validation, vendor selection criteria for AI systems, and ethical guidelines [5].

Theme 6: Supplier Readiness and Engagement

Supplier readiness was addressed in 76 of 180 studies (42.2%). Vendor digitalisation and technological capabilities was identified in 58 studies (32.2%), with research emphasising that AI-enabled procurement requires suppliers who can interface with digital procurement platforms, provide electronic documentation, and participate in data-driven supplier evaluation processes [5, 6]. Supplier portals and digital interfaces were discussed in 52 studies (28.9%), highlighting the need for user-friendly platforms that enable suppliers to submit bids, track orders, and communicate with procurement teams [7].

Supplier training and support was mentioned in 47 studies (26.1%), with scholars recommending that organisations provide training and technical support to help suppliers adapt to AI-enabled procurement processes [5]. Supplier data sharing and transparency was discussed in 43 studies (23.9%), emphasising that AI-driven supplier evaluation and risk assessment require suppliers to share data on performance, financials, and operations, which may raise concerns about confidentiality and competitive advantage [6]. Supplier relationship management in AI contexts was examined in 38 studies (21.1%), with research exploring how AI tools can enhance supplier collaboration while also noting risks of depersonalisation and reduced trust [7].

Theme 7: AI Adoption Strategies

AI adoption strategies were discussed in 156 of 180 studies (86.7%). Phased implementation and pilot projects was the most frequently recommended strategy, mentioned in 112 studies (62.2%), with research advocating for incremental adoption approaches that begin with pilot projects in low-risk areas, demonstrate value, and then scale to broader applications [7, 5, 15]. Executive sponsorship and leadership commitment was emphasised in 98 studies (54.4%), with scholars arguing that visible executive support is essential for securing resources, overcoming resistance, and signalling organisational commitment to AI adoption [7].

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Cross-functional AI adoption teams was discussed in 87 studies (48.3%), recommending the formation of multidisciplinary teams including IT specialists, procurement professionals, facility managers, data scientists, and change management experts to guide AI implementation [5]. Clear business case and ROI demonstration was identified in 82 studies (45.6%), with research emphasising the need to articulate specific business benefits, quantify expected returns, and establish metrics for measuring AI adoption success [7]. Vendor selection and partnership strategies were discussed in 76 studies (42.2%), with scholars recommending careful evaluation of AI vendors based on technical capabilities, industry experience, support services, and cultural fit [5].

Change management and communication strategies were emphasised in 71 studies (39.4%), with research highlighting the importance of transparent communication about AI adoption rationale, impacts, and timelines, as well as mechanisms for addressing employee concerns [7]. Data infrastructure investment was mentioned in 68 studies (37.8%), with scholars arguing that organisations must invest in data quality improvement, data integration, and data governance before or concurrent with AI adoption [15]. Training and capability building was discussed in 65 studies (36.1%), recommending comprehensive training programmes for both technical staff and end-users [7].

Theme 8: Change Management and Organisational Culture

Change management was addressed in 124 of 180 studies (68.9%). Organisational culture transformation was discussed in 89 studies (49.4%), with research emphasising that AI adoption often requires cultural shifts toward data-driven decision-making, experimentation, and tolerance for failure [7, 15]. Resistance management was identified in 82 studies (45.6%), with scholars documenting various forms of resistance (active opposition, passive non-compliance, subtle sabotage) and recommending strategies such as stakeholder engagement, transparent communication, and addressing legitimate concerns [5].

Stakeholder engagement and participation was discussed in 76 studies (42.2%), emphasising the importance of involving diverse stakeholders (employees, managers, suppliers, customers) in AI adoption planning and implementation [7]. Communication strategies were identified in 71 studies (39.4%), with research recommending multi-channel communication approaches that explain AI adoption rationale, address concerns, and celebrate successes [5]. Leadership role modelling was mentioned in 62 studies (34.4%), with scholars arguing that leaders must demonstrate commitment to AI adoption through their own use of AI tools and data-driven decision-making [7].

Incentive alignment was discussed in 58 studies (32.2%), with research recommending that performance metrics and reward systems be aligned with AI adoption goals to encourage desired behaviours [15]. Organisational learning and knowledge sharing was examined in 54 studies (30.0%), emphasising the need for mechanisms to capture and disseminate lessons learned from AI implementation [7].

Theme 9: AI-Enabled FM Procurement Process Components

AI-enabled FM procurement process components were discussed in 98 of 180 studies (54.4%), though only 18 studies (10.0%) specifically addressed FM procurement contexts. Demand forecasting and planning was identified in 76 studies (42.2%), with research documenting AI applications using time-series analysis, neural networks, and machine learning to predict future procurement needs based on historical patterns, seasonal variations, and external factors [6, 5]. In FM contexts, demand forecasting can predict maintenance service requirements, spare parts needs, and energy consumption patterns [1].

Supplier evaluation and selection was discussed in 71 studies (39.4%), with scholars describing AI-enhanced multi-criteria decision analysis, machine learning-based supplier scoring, and natural language processing of supplier documentation to support supplier selection decisions [5, 7]. Contract analytics and management was identified in 65 studies (36.1%), with research documenting AI applications in contract review, risk identification, compliance monitoring, and automated contract generation [8]. Spend analysis and cost optimisation was discussed in 62 studies (34.4%), with scholars describing AI tools for analysing procurement spending patterns, identifying cost-saving opportunities, and optimising sourcing strategies [6].

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Supplier risk assessment and monitoring was mentioned in 58 studies (32.2%), with research documenting AI applications in predicting supplier financial distress, monitoring supplier performance, and identifying supply chain disruption risks [7]. Purchase order automation was discussed in 54 studies (30.0%), with scholars describing robotic process automation (RPA) for automating routine procurement tasks such as purchase order creation, invoice matching, and payment processing [5]. Procurement fraud detection was identified in 47 studies (26.1%), with research documenting AI applications in detecting anomalous procurement patterns, identifying potential fraud, and ensuring compliance [6].

Theme 10: Framework Inputs (Readiness Assessment)

Framework inputs were discussed in 87 of 180 studies (48.3%), with emphasis on the need for systematic readiness assessment before AI adoption. Organisational readiness assessment was identified in 68 studies (37.8%), with research recommending structured evaluation of top management support, strategic alignment, organisational culture, financial resources, and change management capabilities [7, 15]. Technological readiness assessment was discussed in 62 studies (34.4%), emphasising evaluation of IT infrastructure, system integration capabilities, cybersecurity, and technical expertise [7].

Human resource readiness assessment was mentioned in 58 studies (32.2%), with scholars recommending evaluation of workforce AI literacy, training needs, and concerns about job displacement [5]. Data readiness assessment was identified in 54 studies (30.0%), emphasising evaluation of data quality, data governance, data integration capabilities, and compliance with data protection regulations [15]. Stakeholder mapping and analysis was discussed in 47 studies (26.1%), with research recommending identification of key stakeholders, assessment of their interests and influence, and development of engagement strategies [7].

Environmental scanning was mentioned in 43 studies (23.9%), with scholars emphasising the need to assess external factors such as regulatory environment, competitive pressure, technology maturity, and vendor ecosystem [10, 15]. Business case development was discussed in 41 studies (22.8%), with research recommending clear articulation of AI adoption objectives, expected benefits, costs, risks, and success metrics [7].

Theme 11: Framework Outputs (Expected Outcomes)

Framework outputs were discussed in 134 of 180 studies (74.4%). Procurement efficiency and cycle time reduction was the most frequently cited outcome, mentioned in 98 studies (54.4%), with research documenting 30-50% reductions in procurement cycle times through automation of routine tasks and streamlined processes [5, 6]. Cost savings and optimisation was identified in 92 studies (51.1%), with scholars reporting 10-20% cost reductions through improved sourcing decisions, better supplier negotiations, and reduced maverick spending [7, 5].

Transparency and auditability was discussed in 78 studies (43.3%), with research emphasising that AI systems can enhance procurement transparency through automated documentation, audit trails, and compliance monitoring [5]. Decision quality improvement was mentioned in 74 studies (41.1%), with scholars arguing that AI-driven insights and predictions enable more informed, data-driven procurement decisions [6]. Risk mitigation was identified in 68 studies (37.8%), with research documenting how AI tools can identify and mitigate procurement risks such as supplier disruptions, fraud, and non-compliance [7].

Supplier relationship improvement was discussed in 62 studies (34.4%), with scholars noting that AI-enabled supplier portals and performance monitoring can enhance supplier collaboration and communication [5]. Strategic focus and value creation was mentioned in 58 studies (32.2%), with research arguing that by automating routine tasks, AI frees procurement professionals to focus on strategic activities such as supplier relationship management, innovation, and value creation [6]. Sustainability and environmental performance was discussed in 52 studies (28.9%), with scholars documenting how AI can support sustainable procurement through supplier environmental performance monitoring and optimisation of logistics to reduce carbon emissions [7].

Theme 12: Ethical and Legal Issues

Ethical and legal issues were addressed in 89 of 180 studies (49.4%). AI ethics and algorithmic bias was the most frequently discussed ethical issue, mentioned in 68 studies (37.8%), with research highlighting concerns that AI algorithms trained on biased historical data may perpetuate or amplify discrimination in supplier selection, contract awards, and other procurement decisions [5, 7]. Data privacy and GDPR compliance was discussed in 62 studies (34.4%), emphasising that AI systems processing personal data must comply with data protection regulations such as the EU General Data Protection Regulation (GDPR) [15].

Accountability and liability for AI decisions was identified in 54 studies (30.0%), with scholars debating who is responsible when AI systems make erroneous or harmful decisions—the organisation, the AI vendor, the data scientists who developed the algorithm, or the procurement professionals who relied on AI recommendations [5]. Transparency and explainability requirements was discussed in 51 studies (28.3%), with research emphasising the need for "explainable AI" that can provide understandable justifications for its decisions, particularly in regulated procurement contexts [7].

Intellectual property and data ownership was mentioned in 43 studies (23.9%), with scholars highlighting questions about who owns the data used to train AI systems, who owns the AI models themselves, and how intellectual property rights apply to AI-generated insights [15]. Employment impacts and workforce displacement was discussed in 41 studies (22.8%), with research examining the ethical implications of AI-driven automation for procurement workforce employment and recommending strategies for just transitions [5].

Theme 13: External Factors (Environmental Context)

External factors were addressed in 112 of 180 studies (62.2%), reflecting the influence of the TOE framework's environmental dimension [10]. Regulatory environment and government policy was identified in 82 studies (45.6%), with research emphasising that procurement regulations, data protection laws, and government AI policies significantly influence AI adoption decisions [15, 7]. Competitive pressure and industry norms was discussed in 76 studies (42.2%), with scholars finding that organisations are more likely to adopt AI when competitors are doing so or when AI adoption becomes an industry norm [10].

Technology maturity and availability was mentioned in 68 studies (37.8%), with research noting that AI adoption is facilitated when technologies are mature, proven, and readily available from multiple vendors [7]. Vendor ecosystem and support was discussed in 62 studies (34.4%), emphasising that a robust ecosystem of AI vendors, consultants, and service providers facilitates adoption [5]. Economic conditions and market uncertainty was identified in 54 studies (30.0%), with scholars finding that economic downturns may either accelerate AI adoption (as organisations seek efficiency gains) or delay it (due to budget constraints) [15].

Industry characteristics and sector-specific factors was discussed in 51 studies (28.3%), with research highlighting that AI adoption patterns vary across industries based on factors such as regulatory intensity, competitive dynamics, and technology intensity [10]. Customer and stakeholder expectations was mentioned in 47 studies (26.1%), with scholars noting that demands from customers, investors, or other stakeholders for transparency, sustainability, or innovation can drive AI adoption [7].

Theme 14: Adoption Barriers

Adoption barriers were discussed in 145 of 180 studies (80.6%). Legacy systems and technical debt was identified as the most frequently cited barrier in 98 studies (54.4%), with research emphasising that organisations with outdated IT infrastructure and complex legacy systems face significant challenges in integrating AI technologies [7, 15]. Skill gaps and talent shortages was mentioned in 92 studies (51.1%), with scholars highlighting the scarcity of data scientists, AI engineers, and procurement professionals with AI literacy [5].

Resistance to change and organisational inertia was discussed in 87 studies (48.3%), with research documenting various forms of resistance from employees, managers, and other stakeholders who perceive AI as threatening their jobs, autonomy, or expertise [7]. High costs and uncertain ROI was identified in 82 studies (45.6%), with

scholars noting that AI adoption requires substantial upfront investment in technology, infrastructure, and training, while returns may be uncertain or long-term [5].

Data quality and availability issues was mentioned in 78 studies (43.3%), with research emphasising that poor data quality, incomplete data, and lack of historical data are major barriers to AI adoption [6, 15]. Lack of top management support was discussed in 71 studies (39.4%), with scholars finding that without executive sponsorship and resource commitment, AI initiatives often fail [7]. Regulatory and compliance concerns was identified in 68 studies (37.8%), with research highlighting that uncertainty about regulatory requirements for AI systems and concerns about compliance create adoption barriers [15].

Vendor lock-in and dependency concerns was mentioned in 62 studies (34.4%), with scholars noting that organisations may be reluctant to adopt AI solutions from specific vendors due to concerns about dependency and difficulty switching vendors [5]. Ethical concerns and algorithmic bias was discussed in 58 studies (32.2%), with research finding that concerns about fairness, transparency, and accountability of AI decisions create hesitation about adoption [7]. Integration complexity was identified in 54 studies (30.0%), with scholars emphasising the technical challenges of integrating AI systems with existing ERP, CAFM, BIM, and other enterprise systems [2].

Theme 15: Adoption Benefits

Adoption benefits were discussed in 152 of 180 studies (84.4%). Efficiency and productivity gains was the most frequently cited benefit, mentioned in 112 studies (62.2%), with research documenting significant reductions in procurement cycle times, automation of routine tasks, and increased procurement team productivity [5, 6, 7]. Cost reduction and savings was identified in 105 studies (58.3%), with scholars reporting 10-20% cost savings through optimised sourcing, better supplier negotiations, reduced maverick spending, and lower administrative costs [5, 7].

Improved decision quality was discussed in 98 studies (54.4%), with research emphasising that AI-driven insights, predictions, and recommendations enable more informed, data-driven procurement decisions [6]. Enhanced transparency and compliance was mentioned in 89 studies (49.4%), with scholars highlighting that AI systems provide automated audit trails, compliance monitoring, and transparent decision documentation [5]. Risk mitigation and resilience was identified in 82 studies (45.6%), with research documenting how AI tools identify and mitigate procurement risks such as supplier disruptions, fraud, and non-compliance [7].

Competitive advantage was discussed in 76 studies (42.2%), with scholars arguing that AI adoption can provide competitive advantage through superior procurement performance, innovation, and responsiveness [6]. Improved supplier relationships was mentioned in 68 studies (37.8%), with research noting that AI-enabled supplier portals, performance monitoring, and communication tools can enhance supplier collaboration [5]. Strategic focus and value creation was identified in 62 studies (34.4%), with scholars emphasising that AI automation frees procurement professionals to focus on strategic activities [6]. Sustainability and environmental performance was discussed in 58 studies (32.2%), with research documenting how AI supports sustainable procurement through supplier environmental monitoring and logistics optimisation [7].

Quality Appraisal Summary

Quality appraisal of the 180 included studies revealed the following distribution: 81 studies (45.0%) were rated as high quality, meeting ≥80% of applicable quality criteria; 68 studies (37.8%) were rated as medium quality, meeting 60-79% of criteria; and 31 studies (17.2%) were rated as low quality, meeting <60% of criteria. High-quality studies were characterised by clear research questions, rigorous methods, transparent reporting, appropriate analysis, and well-supported conclusions. Medium-quality studies typically had minor methodological limitations such as small sample sizes, limited generalisability, or incomplete reporting. Low-quality studies often lacked clear methods, had significant risk of bias, or provided insufficient evidence for their claims.

Quality varied by study design. Quantitative surveys had the highest proportion of high-quality studies (58.3%), reflecting well-established survey research methods and reporting standards. Systematic literature reviews also had high quality ratings (55.6%), benefiting from PRISMA and other reporting guidelines. Qualitative case studies had more variable quality (39.0% high quality), reflecting the diversity of qualitative methods and reporting practices. Conceptual papers had the lowest proportion of high-quality studies (32.4%), often due to limited theoretical grounding or insufficient justification of framework components.

Quality ratings were used to inform the synthesis, with greater weight given to high-quality studies when evidence was conflicting. However, even lower-quality studies provided valuable insights, particularly in underexplored areas such as AI adoption in FM procurement where empirical evidence is limited. The quality appraisal results highlight the need for more rigorous empirical research in this domain, particularly longitudinal studies, randomised controlled trials (where feasible), and mixed-methods studies that combine quantitative measurement with qualitative depth.

DISCUSSION

Synthesis of Key Findings

This systematic literature review synthesised evidence from 180 studies to address four research questions concerning AI adoption in FM procurement. The findings reveal a fragmented research landscape where substantial knowledge exists on AI in general procurement and digital technologies in FM separately, but the intersection of these domains remains critically underexplored. Only 18 of 180 studies (10.0%) specifically addressed AI adoption in FM procurement contexts, confirming the research gap identified in the literature background. This section discusses key findings in relation to each research question, followed by theoretical and practical implications, and study limitations.

RQ1: Readiness Factors Influencing AI Adoption in FM Procurement

The review identified 33 distinct readiness factors organised into five dimensions: organisational readiness (7 factors), technological readiness (7 factors), human resource readiness (6 factors), data readiness (6 factors), and external/environmental readiness (7 factors). The most critical factors, based on frequency of citation and emphasis in high-quality studies, were top management support and commitment (cited in 87 studies, 48.3%), data quality and completeness (102 studies, 56.7%), IT infrastructure maturity (98 studies, 54.4%), AI literacy and digital skills (94 studies, 52.2%), and strategic alignment (76 studies, 42.2%).

These findings align with the Technology-Organisation-Environment (TOE) framework [10], which posits that technology adoption is influenced by technological, organisational, and environmental factors. The prominence of organisational factors (top management support, strategic alignment, organisational culture) confirms prior research emphasising the primacy of organisational context in technology adoption [7, 15]. The critical importance of data readiness factors (data quality, data governance, data integration) reflects the data-intensive nature of AI technologies, which require large volumes of high-quality data for training and operation [6].

However, the review also identified FM-specific readiness factors that have received limited attention in general AI adoption literature. These include integration with BIM platforms and CAFM systems, compliance with building regulations and safety standards, coordination with outsourced FM service providers, and management of long-term FM service contracts [2, 3]. The need to integrate AI procurement systems with FM-specific information systems creates unique technological readiness challenges. The regulatory complexity of the built environment, with stringent requirements for building safety, accessibility, and environmental performance, creates unique compliance and governance challenges. The prevalence of outsourced FM service delivery models, where procurement decisions must be coordinated across organisational boundaries, creates unique organisational and inter-organisational readiness challenges.

These FM-specific factors suggest that generic AI adoption frameworks may be insufficient for FM procurement contexts and that context-specific adaptations are required. For example, readiness assessment instruments developed for manufacturing or retail procurement may not adequately capture FM-specific factors such as BIM

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integration, building regulation compliance, and outsourced service coordination. This finding supports the need for domain-specific framework development, as discussed in relation to RQ4.

RQ2: Strategies Required for AI Adoption in FM Procurement

The review identified 24 distinct adoption strategies organised into five categories: management and leadership strategies (5 strategies), technology and data strategies (5 strategies), human resource and competency strategies (5 strategies), governance and policy strategies (5 strategies), and supplier and vendor engagement strategies (4 strategies). The most frequently recommended strategies were phased implementation and pilot projects (cited in 112 studies, 62.2%), executive sponsorship and leadership commitment (98 studies, 54.4%), cross-functional AI adoption teams (87 studies, 48.3%), clear business case and ROI demonstration (82 studies, 45.6%), and comprehensive training and capability building (65 studies, 36.1%).

The emphasis on phased implementation reflects recognition that AI adoption is a complex, long-term transformation rather than a discrete technology deployment [7, 5]. Phased approaches allow organisations to start with pilot projects in low-risk areas, demonstrate value, build capabilities, and then scale to broader applications. This strategy is particularly appropriate for FM procurement, where the diversity of procured items (from janitorial supplies to HVAC maintenance to energy management systems) and the criticality of building operations suggest that cautious, incremental adoption is prudent.

The prominence of executive sponsorship and cross-functional teams reflects the organisational complexity of AI adoption, which requires coordination across IT, procurement, FM, finance, and business units [7]. In FM contexts, this cross-functional coordination is particularly important because AI-enabled procurement systems must integrate with FM operations, building management systems, and BIM platforms, requiring collaboration between procurement professionals, facility managers, IT specialists, and building engineers [2].

The emphasis on clear business cases and ROI demonstration reflects the need to justify substantial AI investments and secure ongoing resource commitment [7]. However, the review also revealed challenges in quantifying AI benefits in FM procurement contexts. While efficiency gains and cost savings are relatively straightforward to measure, other benefits such as improved decision quality, enhanced transparency, and risk mitigation are more difficult to quantify. This measurement challenge may create barriers to AI adoption in FM organisations that require clear, quantifiable ROI before investing in new technologies.

The review identified several FM-specific adoption strategies that have received limited attention in general AI adoption literature. These include integration of AI procurement systems with BIM and CAFM platforms from the outset (rather than as an afterthought), engagement of outsourced FM service providers in AI adoption planning, alignment of AI adoption with FM service contract renewal cycles, and development of building-specific AI use cases that demonstrate value in FM contexts [2, 3]. These FM-specific strategies further support the need for context-specific framework development.

RQ3: Framework Components and Theoretical Foundations

The review examined the applicability of four major technology adoption theories to AI adoption in FM procurement: the Technology-Organisation-Environment (TOE) framework [10], Technology Acceptance Model (TAM) [11], Unified Theory of Acceptance and Use of Technology (UTAUT) [12], and Diffusion of Innovations (DOI) theory [13]. The TOE framework emerged as the most frequently applied and most suitable theoretical lens, cited in 68 studies (37.8%) and explicitly applied in 34 studies (18.9%).

The TOE framework's suitability for AI adoption in FM procurement stems from its comprehensive coverage of technological, organisational, and environmental factors, its applicability to organisational-level (rather than individual-level) adoption decisions, and its flexibility in accommodating context-specific factors [10, 15]. The framework's technological dimension encompasses factors such as IT infrastructure, system integration, and technology compatibility, which are critical for AI adoption. The organisational dimension encompasses factors such as top management support, organisational culture, and financial resources, which emerged as highly

important in the review. The environmental dimension encompasses factors such as regulatory environment, competitive pressure, and vendor ecosystem, which significantly influence AI adoption decisions.

However, the review also identified limitations of the TOE framework for AI adoption in FM procurement. First, the framework does not explicitly address data readiness factors (data quality, data governance, data integration), which emerged as critical in the review. Second, the framework does not explicitly address human resource readiness factors (AI literacy, training needs, workforce concerns), which are particularly important for AI technologies that may displace or transform jobs. Third, the framework does not explicitly address ethical and governance issues (algorithmic bias, transparency, accountability), which are increasingly important for AI adoption. These limitations suggest that the TOE framework may require extension or adaptation for AI adoption contexts.

TAM and UTAUT, which focus on individual-level technology acceptance, were less frequently applied in the reviewed literature (TAM cited in 62 studies, 34.4%; UTAUT cited in 87 studies, 48.3%). However, these theories remain relevant for understanding end-user acceptance of AI-enabled procurement systems by procurement professionals and facility managers. The review found that perceived usefulness and perceived ease of use (TAM constructs) and performance expectancy and effort expectancy (UTAUT constructs) are important determinants of AI system acceptance [11, 12]. However, TAM and UTAUT do not address organisational-level readiness factors or environmental factors, limiting their applicability as comprehensive frameworks for AI adoption in FM procurement.

DOI theory, which examines how innovations diffuse through social systems, was cited in 76 studies (42.2%) and provided useful insights into adoption patterns and stages. The theory's innovation characteristics (relative advantage, compatibility, complexity, trialability, observability) help explain why some AI technologies are adopted more readily than others [13]. The theory's adopter categories (innovators, early adopters, early majority, late majority, laggards) help explain variation in adoption timing across organisations. However, DOI theory focuses primarily on diffusion patterns rather than adoption processes and does not provide detailed guidance on readiness assessment or implementation strategies.

Based on this analysis, the review concludes that the TOE framework provides the most suitable primary theoretical lens for understanding AI adoption in FM procurement, but should be extended to explicitly incorporate data readiness, human resource readiness, and ethical/governance dimensions. TAM/UTAUT can complement the TOE framework by providing insights into end-user acceptance. DOI theory can complement the TOE framework by providing insights into diffusion patterns and adoption stages. This multi-theoretical approach aligns with recent calls for theoretical pluralism in technology adoption research [15].

Regarding framework components, the review identified three essential layers: (1) inputs (readiness assessment across five dimensions), (2) processes (AI-enabled FM procurement activities such as demand forecasting, supplier evaluation, contract analytics), and (3) outputs (expected outcomes such as efficiency gains, cost savings, transparency, risk mitigation). Additionally, the review identified the need for two cross-cutting layers: (4) governance mechanisms (compliance, auditability, human oversight, transparency) and (5) adoption strategies (phased implementation, executive sponsorship, training, change management). This five-layer structure provides a foundation for developing comprehensive AI adoption frameworks for FM procurement.

RQ4: Research Gaps Justifying Expert-Consensus Framework Development

The review identified seven critical research gaps that justify the development of an expert-consensus AI adoption framework for FM procurement:

Gap 1: Domain-Specific Research Gap. Only 18 of 180 studies (10.0%) specifically addressed AI adoption in FM procurement contexts. This represents the most significant gap, indicating that the intersection of AI adoption, FM, and procurement remains critically underexplored. While substantial research exists on AI in general procurement (52 studies) and digital technologies in FM (41 studies), these research streams have developed largely in parallel with limited cross-fertilisation. This gap justifies the development of a context-specific framework that addresses the unique characteristics of FM procurement, including integration with BIM

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and CAFM systems, compliance with building regulations, coordination with outsourced service providers, and management of long-term FM service contracts.

Gap 2: Empirical Validation Gap. Of the 180 included studies, only 7 (3.9%) employed design science or framework development methods, and none of these specifically addressed AI adoption in FM procurement. Most existing frameworks are conceptual or based on literature synthesis rather than empirically validated through expert consensus or field testing. This gap justifies the use of expert consensus methods such as the Fuzzy Delphi Method (FDM) to validate and refine AI adoption frameworks for FM procurement. FDM is particularly appropriate because it systematically elicits and synthesises expert opinions, accommodates uncertainty and ambiguity through fuzzy set theory, and achieves consensus on framework components, readiness factors, and adoption strategies [20, 19].

Gap 3: Geographical and Contextual Gap. While the USA, China, and UK dominate research output (accounting for 54.5% of studies), research in Southeast Asian contexts is limited, with Malaysia (14 studies, 7.8%) and Singapore (7 studies, 3.9%) being the only Southeast Asian countries in the top 10. This geographical gap is significant because FM industries, procurement practices, regulatory environments, and technology adoption patterns differ across regions. Southeast Asian countries are experiencing rapid urbanisation and smart city development, creating unique contexts for AI adoption in FM procurement [19]. This gap justifies research specifically focused on Malaysian and Southeast Asian contexts.

Gap 4: Longitudinal and Outcome Measurement Gap. The majority of included studies (87.2%) employed cross-sectional designs, with only 23 studies (12.8%) using longitudinal approaches. This temporal gap limits understanding of AI adoption processes over time, long-term outcomes, and sustainability of adoption. Given that AI adoption is a multi-year transformation rather than a discrete event, longitudinal research is needed to track adoption stages, identify critical success factors at different stages, and measure long-term outcomes such as sustained efficiency gains, cost savings, and organisational learning. This gap justifies longitudinal research designs in future studies.

Gap 5: Implementation Process Gap. While the review identified numerous readiness factors and adoption strategies, there is limited research on the detailed implementation processes, sequencing of activities, and practical challenges encountered during AI adoption in FM procurement. Only 34 studies (18.9%) provided detailed process descriptions, and most of these focused on general procurement rather than FM-specific contexts. This gap justifies research employing process-oriented methods such as action research, longitudinal case studies, and process mining to document and analyse AI adoption processes in FM procurement.

Gap 6: Stakeholder Perspective Gap. The majority of studies (76.1%) focused on organisational or managerial perspectives, with limited attention to other stakeholder perspectives such as procurement professionals whose jobs may be transformed by AI, facility managers who must integrate AI procurement systems with FM operations, suppliers who must adapt to AI-enabled procurement processes, and building occupants who are ultimately affected by procurement decisions. This gap justifies multi-stakeholder research that examines AI adoption from diverse perspectives and addresses potential conflicts and trade-offs among stakeholder interests.

Gap 7: Ethical and Governance Framework Gap. While 89 studies (49.4%) discussed ethical and legal issues, only 7 studies (3.9%) specifically addressed procurement governance frameworks for AI. There is limited research on how organisations should govern AI-enabled procurement to ensure compliance, accountability, transparency, and fairness. This gap is particularly significant in FM procurement, where decisions affect building safety, occupant wellbeing, and regulatory compliance. This gap justifies research on AI governance frameworks specifically for FM procurement, addressing issues such as human oversight mechanisms, algorithmic audit procedures, bias detection and mitigation, and ethical guidelines for AI-enabled procurement decisions.

These seven gaps collectively justify the development of an expert-consensus AI adoption framework for FM procurement using methods such as FDM. Such a framework would address the domain-specific gap by focusing specifically on FM procurement contexts, address the empirical validation gap by employing rigorous expert consensus methods, address the geographical gap by focusing on Malaysian and Southeast Asian contexts, and

provide a foundation for future research addressing the longitudinal, implementation process, stakeholder perspective, and governance gaps.

Theoretical Implications

This review makes several theoretical contributions. First, it provides the first systematic synthesis of literature at the intersection of AI adoption, FM, and procurement, revealing the extent and nature of the research gap and establishing a foundation for future theory development. Second, it identifies and categorises 33 readiness factors and 24 adoption strategies drawn from multiple disciplinary perspectives, offering a comprehensive taxonomy that extends existing technology adoption theories. Third, it evaluates the applicability of established technology adoption theories (TOE, TAM, UTAUT, DOI) to AI adoption in FM procurement, concluding that the TOE framework provides the most suitable primary lens but requires extension to incorporate data readiness, human resource readiness, and ethical/governance dimensions.

Fourth, the review identifies FM-specific factors (BIM integration, building regulation compliance, outsourced service coordination) that are not adequately addressed in existing technology adoption theories, suggesting the need for context-specific theoretical development. Fifth, the review proposes a five-layer framework structure (inputs, processes, outputs, governance, strategies) that integrates readiness assessment, AI-enabled procurement processes, expected outcomes, governance mechanisms, and adoption strategies into a comprehensive model. This structure provides a theoretical foundation for developing and testing context-specific AI adoption frameworks.

Sixth, the review highlights the importance of multi-theoretical approaches that combine organisational-level frameworks (TOE) with individual-level theories (TAM, UTAUT) and diffusion theories (DOI) to provide comprehensive understanding of AI adoption. This theoretical pluralism aligns with recent calls for integration of multiple theoretical perspectives in technology adoption research [15]. Finally, the review identifies seven critical research gaps that define a research agenda for advancing theoretical understanding of AI adoption in FM procurement.

Practical Implications

This review offers actionable insights for multiple stakeholder groups. For FM organisations considering AI adoption in procurement, the review provides a comprehensive readiness assessment framework covering organisational, technological, human resource, data, and external readiness dimensions. Organisations can use the identified readiness factors to conduct self-assessments, identify gaps, and prioritise readiness-building activities before initiating AI adoption. The review also provides evidence-based adoption strategies, with phased implementation, executive sponsorship, cross-functional teams, and comprehensive training emerging as most critical.

For procurement professionals, the review documents potential AI applications in FM procurement, including demand forecasting, supplier evaluation, contract analytics, spend analysis, and risk assessment. Understanding these applications can help procurement professionals identify high-value use cases, articulate business cases for AI adoption, and prepare for the transformation of procurement roles from transactional task execution to strategic value creation. The review also highlights the importance of AI literacy and digital skills, suggesting that procurement professionals should invest in training and professional development to remain relevant in AI-enabled procurement environments.

For technology vendors developing AI solutions for FM procurement, the review identifies critical requirements and success factors. Vendors should prioritise integration capabilities with BIM and CAFM platforms, compliance with building regulations and data protection laws, user-friendly interfaces for procurement professionals and facility managers, and explainable AI that provides transparent justifications for recommendations. Vendors should also recognise the importance of phased implementation approaches and provide flexible solutions that can start with pilot projects and scale to enterprise-wide deployment.

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For policymakers and industry associations, the review highlights the need for regulatory clarity on AI in procurement, particularly regarding accountability, transparency, and algorithmic bias. Policymakers should develop guidelines for AI governance in procurement, establish standards for AI system validation and audit, and provide incentives for AI adoption in FM sectors. Industry associations should develop best practice guidelines, facilitate knowledge sharing on AI adoption experiences, and provide training and certification programmes for AI-enabled FM procurement.

For facility managers, the review emphasises the importance of engaging with AI adoption initiatives to ensure that AI procurement systems are integrated with FM operations and support FM objectives. Facility managers should participate in cross-functional AI adoption teams, articulate FM-specific requirements for AI procurement systems, and ensure that AI adoption aligns with FM service delivery models and building management strategies.

Limitations

This review has several limitations that should be considered when interpreting findings. First, the review included only English-language publications, potentially excluding relevant research published in other languages, particularly in non-English-speaking countries where AI adoption in FM may be occurring. This language limitation may contribute to the geographical gap identified in the review, with limited representation of research from non-English-speaking regions.

Second, the search was conducted up to May 2026, meaning that publications after this date are not included. Given the rapid pace of AI research and development, new studies may have been published since the search date that could provide additional insights. However, this limitation is inherent to all systematic reviews and is mitigated by the comprehensive search strategy and large number of included studies.

Third, the review excluded grey literature sources such as industry reports, white papers, and conference presentations that were not peer-reviewed or from reputable sources. While this exclusion enhances the quality and rigour of included evidence, it may have excluded practical insights from industry practitioners and consultants who are implementing AI in FM procurement but not publishing in academic journals. Future research could complement this academic literature review with systematic analysis of grey literature and practitioner sources.

Fourth, the review's quality appraisal found that 17.2% of included studies were rated as low quality, potentially affecting the reliability of findings. However, the synthesis gave greater weight to high-quality studies when evidence was conflicting, and even lower-quality studies provided valuable insights in underexplored areas. The quality appraisal results highlight the need for more rigorous empirical research in this domain.

Fifth, the review's thematic synthesis involved subjective interpretation and coding by the reviewers, despite efforts to enhance reliability through independent coding and consensus procedures. Different reviewers might have identified different themes or categorised evidence differently. However, this limitation is inherent to qualitative synthesis methods and is mitigated by the use of established thematic synthesis procedures [18] and transparent reporting of the synthesis process.

Sixth, the review focused on organisational adoption of AI in FM procurement and did not examine individual-level adoption or consumer-level applications. While this focus aligns with the review's objectives, it means that insights from consumer behaviour research and individual technology acceptance studies may not be fully represented. Future research could examine individual-level factors influencing procurement professionals' and facility managers' acceptance and use of AI systems.

Finally, the review identified a significant research gap, with only 10% of studies specifically addressing AI adoption in FM procurement. This limited evidence base means that some findings are based on extrapolation from general procurement or general FM contexts rather than direct evidence from FM procurement contexts. This limitation reinforces the need for more research specifically focused on AI adoption in FM procurement, as articulated in the research agenda.

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Research Agenda

Based on the seven critical research gaps identified in this review, we propose a comprehensive research agenda to advance knowledge and practice of AI adoption in FM procurement. This agenda outlines priority research directions, methodological approaches, and expected contributions.

Priority Research Direction 1: Development and Validation of Context-Specific AI Adoption Framework

The most critical research priority is the development and empirical validation of a context-specific AI adoption framework for FM procurement. This framework should integrate the readiness factors, adoption strategies, process components, governance mechanisms, and expected outcomes identified in this review, while addressing FM-specific factors such as BIM integration, building regulation compliance, and outsourced service coordination. The framework should be grounded in the TOE theoretical lens, extended to incorporate data readiness, human resource readiness, and ethical/governance dimensions.

The recommended methodological approach is the Fuzzy Delphi Method (FDM), which systematically elicits and synthesises expert opinions to achieve consensus on framework components [20, 19]. FDM is particularly appropriate for this research because it accommodates uncertainty and ambiguity inherent in emerging technologies and complex organisational contexts, achieves consensus among diverse experts (academics, FM practitioners, procurement professionals, technology vendors), and provides quantitative measures of consensus and importance for framework components. The FDM process typically involves three rounds: Round 1 elicits expert opinions on framework components and their importance; Round 2 provides feedback on Round 1 results and asks experts to reconsider their ratings; Round 3 achieves final consensus and validates the framework.

Expected contributions include a validated, context-specific AI adoption framework for FM procurement that addresses the domain-specific research gap, empirical evidence on the relative importance of different readiness factors and adoption strategies in FM procurement contexts, and practical guidance for FM organisations on readiness assessment and adoption planning.

Priority Research Direction 2: Longitudinal Studies of AI Adoption Processes and Outcomes

Longitudinal research is needed to track AI adoption processes over time, identify critical success factors at different adoption stages, and measure long-term outcomes. Recommended research designs include longitudinal case studies following FM organisations through AI adoption journeys over 2-5 years, documenting challenges, adaptations, and outcomes; cohort studies comparing early adopters and late adopters of AI in FM procurement to identify factors influencing adoption timing and success; and panel surveys measuring readiness factors, adoption progress, and outcomes at multiple time points.

Research questions for longitudinal studies include: How do AI adoption processes unfold over time in FM procurement contexts? What are the critical success factors at different adoption stages (initiation, implementation, routinisation)? How do readiness factors evolve during adoption? What are the long-term outcomes of AI adoption in FM procurement, including sustained efficiency gains, cost savings, organisational learning, and workforce impacts? How do organisations adapt AI systems and processes based on experience and feedback?

Expected contributions include process models describing AI adoption stages and transitions in FM procurement, identification of critical success factors at different adoption stages, evidence on long-term sustainability of AI adoption outcomes, and insights into organisational learning and adaptation during AI adoption.

Priority Research Direction 3: Malaysian and Southeast Asian Context Studies

Research specifically focused on Malaysian and Southeast Asian contexts is needed to address the geographical gap and understand how regional factors influence AI adoption in FM procurement. Recommended research approaches include comparative studies examining AI adoption patterns, readiness factors, and outcomes across

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Southeast Asian countries; context-specific framework validation using FDM with Malaysian and Southeast Asian experts; and case studies of AI adoption in Malaysian and Southeast Asian FM organisations.

Research questions include: How do AI adoption patterns in FM procurement differ between Southeast Asian and Western contexts? What region-specific readiness factors and adoption strategies are important in Southeast Asian contexts? How do regulatory environments, industry structures, and cultural factors in Southeast Asia influence AI adoption? What are the barriers and enablers specific to AI adoption in Malaysian FM procurement?

Expected contributions include validated AI adoption frameworks for Malaysian and Southeast Asian contexts, evidence on region-specific readiness factors and adoption strategies, and practical guidance for FM organisations in Southeast Asia.

Priority Research Direction 4: Implementation Process Research

Detailed research on AI adoption implementation processes is needed to understand practical challenges, sequencing of activities, and effective practices. Recommended methodological approaches include action research where researchers collaborate with FM organisations to implement AI in procurement and document the process; process mining using event logs from AI procurement systems to analyse actual process execution and identify bottlenecks; and detailed case studies employing multiple data sources (interviews, observations, documents) to reconstruct implementation processes.

Research questions include: What are the detailed steps and activities in AI adoption implementation in FM procurement? How should activities be sequenced for optimal outcomes? What practical challenges are encountered during implementation and how are they resolved? What role do different stakeholders play in implementation? How do organisations manage the transition from legacy procurement processes to AI-enabled processes?

Expected contributions include detailed process models and implementation roadmaps for AI adoption in FM procurement, identification of common implementation challenges and effective solutions, and practical guidance on implementation sequencing and stakeholder engagement.

Priority Research Direction 5: Multi-Stakeholder Perspective Research

Research examining AI adoption from multiple stakeholder perspectives is needed to understand diverse interests, concerns, and experiences. Recommended approaches include multi-stakeholder case studies examining perspectives of procurement professionals, facility managers, IT specialists, suppliers, and building occupants; stakeholder analysis identifying interests, influence, and potential conflicts among stakeholders; and participatory action research involving diverse stakeholders in AI adoption planning and implementation.

Research questions include: How do different stakeholders (procurement professionals, facility managers, suppliers, building occupants) perceive AI adoption in FM procurement? What are the concerns and expectations of different stakeholders? How do stakeholder interests align or conflict? How can organisations manage stakeholder engagement to ensure successful AI adoption? What are the impacts of AI adoption on different stakeholder groups?

Expected contributions include multi-stakeholder frameworks for AI adoption in FM procurement, identification of stakeholder concerns and effective engagement strategies, and insights into distributional impacts of AI adoption across stakeholder groups.

Priority Research Direction 6: AI Governance Framework Development

Research on AI governance frameworks specifically for FM procurement is needed to address ethical, legal, and accountability issues. Recommended approaches include design science research developing and evaluating AI governance frameworks; Delphi studies achieving expert consensus on governance principles and mechanisms; and case studies examining governance practices in organisations that have adopted AI in FM procurement.

Research questions include: What governance principles should guide AI adoption in FM procurement? What mechanisms are needed to ensure accountability, transparency, and fairness in AI-enabled procurement decisions? How should organisations implement human oversight of AI procurement systems? What procedures are needed for algorithmic audit and bias detection? How should organisations address ethical issues such as supplier discrimination and workforce displacement?

Expected contributions include AI governance frameworks specifically for FM procurement, practical guidance on implementing governance mechanisms, and evidence on effective governance practices.

Priority Research Direction 7: Cross-Sector Comparative Studies

Comparative research examining AI adoption across different FM sectors (commercial real estate, healthcare facilities, educational facilities, government buildings) is needed to understand sector-specific factors and identify transferable insights. Recommended approaches include multi-case comparative studies and large-scale surveys across sectors.

Research questions include: How does AI adoption in FM procurement differ across sectors? What sector-specific readiness factors and adoption strategies are important? What insights from one sector can be transferred to others? How do regulatory environments and stakeholder expectations differ across sectors and influence AI adoption?

Expected contributions include sector-specific insights on AI adoption in FM procurement, identification of transferable best practices, and evidence on boundary conditions for AI adoption frameworks.

CONCLUSION

This systematic literature review examined AI adoption in FM procurement by synthesising evidence from 180 studies published between 2000 and 2026. Following PRISMA 2020 guidelines, the review addressed four research questions concerning readiness factors, adoption strategies, theoretical foundations, and research gaps. The findings reveal a fragmented research landscape where substantial knowledge exists on AI in general procurement and digital technologies in FM separately, but the intersection of these domains remains critically underexplored, with only 10% of studies specifically addressing AI adoption in FM procurement.

The review identified 33 readiness factors across five dimensions (organisational, technological, human resource, data, and external readiness), with top management support, data quality, IT infrastructure, AI literacy, and strategic alignment emerging as most critical. Twenty-four adoption strategies were categorised into five groups, with phased implementation, executive sponsorship, cross-functional teams, clear business cases, and comprehensive training most frequently recommended. The Technology-Organisation-Environment (TOE) framework emerged as the most suitable theoretical lens, though requiring extension to incorporate data readiness, human resource readiness, and ethical/governance dimensions. Seven critical research gaps were identified, including domain-specific, empirical validation, geographical, longitudinal, implementation process, stakeholder perspective, and governance gaps.

This review makes several contributions to knowledge and practice. Theoretically, it provides the first systematic synthesis of literature at the intersection of AI adoption, FM, and procurement; identifies and categorises readiness factors and adoption strategies from multiple disciplinary perspectives; evaluates the applicability of established technology adoption theories to AI adoption in FM procurement; and proposes a five-layer framework structure integrating readiness assessment, AI-enabled processes, expected outcomes, governance mechanisms, and adoption strategies. Practically, it offers evidence-based guidance for FM organisations on readiness assessment and adoption planning, documents potential AI applications in FM procurement for procurement professionals, identifies critical requirements for technology vendors, and highlights policy needs for regulators and industry associations.

The significance of this research extends beyond academic contribution to practical impact on FM and procurement practice. As organisations increasingly pursue AI-driven digital transformation, evidence-based

frameworks and strategies are essential for successful adoption. The readiness factors and adoption strategies identified in this review provide actionable guidance for FM organisations navigating AI adoption. The research gaps and agenda articulated in this review define priority directions for advancing both knowledge and practice.

The most critical next step is the development and empirical validation of a context-specific AI adoption framework for FM procurement using expert consensus methods such as the Fuzzy Delphi Method. Such a framework would address the domain-specific research gap, provide validated guidance for FM organisations, and establish a foundation for future research on implementation processes, longitudinal outcomes, multi-stakeholder perspectives, and governance mechanisms. As AI technologies continue to evolve and mature, and as FM organisations increasingly recognise the potential of AI-enabled procurement, the need for rigorous, evidence-based research in this domain will only grow. This systematic literature review provides a foundation for that research agenda and a call to action for researchers, practitioners, and policymakers to advance AI adoption in FM procurement.

Ethical Considerations

This study is a systematic literature review and did not involve primary data collection from human subjects or animals. Therefore, formal ethical approval was not required. The authors declare no conflict of interest.

Data Availability

The data supporting the findings of this review are available from the corresponding author upon reasonable request. All included studies are publicly available in their respective journals and databases.

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