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DRIVERS AND BARRIERS TO ADOPTING ARTIFICIAL INTELLIGENCE PRACTICES IN MANAGING PROJECTS: A SYSTEMATIC LITERATURE REVIEW THROUGH THE TOE FRAMEWORK

Abstract

This study examines the main drivers and barriers influencing the adoption of artificial intelligence (AI) in project management, with a specific focus on emerging market conditions. The research is based on a systematic literature review conducted in accordance with the PRISMA 2020 guidelines. The final sample included 41 peer-reviewed articles and conference papers retrieved from the Scopus database for the period 2016–2025. The identified adoption factors were coded and grouped using the Technology–Organisation–Environment (TOE) framework. As a result, twenty-one driver categories and twenty barrier categories were identified. The findings show that AI adoption in project management is not limited to the availability of advanced tools. Organisations are often interested in AI because of its potential to improve project performance, yet practical implementation is constrained by weak data infrastructure, limited technical maturity, shortage of qualified specialists, and unclear regulatory conditions. This gap is particularly visible in emerging markets, where environmental factors such as digital infrastructure, regulation, standards, and institutional support often determine whether firm-level adoption is possible at all. The study argues that AI adoption strategies should therefore be adapted to the maturity of the local context. For emerging markets, this means that policy and organisational efforts should not begin only with firm-level training or software implementation, but also with the development of basic digital, regulatory, and institutional conditions that make sustainable AI adoption feasible.

Keywords: Artificial intelligence; Barriers; Drivers; Emerging markets; Project management; Systematic literature review; TOE framework.

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Introduction

Artificial intelligence (AI) has emerged as one of the most influential technological developments of the modern digital economy, fundamentally transforming how organizations operate, make decisions, and manage complex processes. In the field of project management (PM), AI technologies are increasingly integrated into core managerial processes, including project planning, scheduling, cost estimation, risk management, and stakeholder communication. Empirical evidence suggests that AI-driven tools improve forecasting accuracy, enhance risk identification, and support proactive decision-making, contributing to improved project performance and reduced failure rates [1, 2].

However, despite its demonstrated potential, the adoption of AI in project management remains uneven across organisations and regions. Existing research indicates that while some organisations successfully integrate AI into their project processes, others face persistent challenges related to data infrastructure, technical expertise, and organisational readiness. This uneven adoption is particularly evident when comparing developed and emerging market contexts. In developed economies, AI adoption is typically constrained by organisational and technological considerations, such as integration complexity and change management. In contrast, in emerging markets, the adoption challenge is structurally different. It is shaped by limited digital infrastructure, shortages of skilled personnel, high implementation costs relative to organisational capacity, weak or evolving regulatory frameworks, and lower levels of digital maturity across firms. These conditions suggest that AI adoption in project management cannot be understood as a uniform process across contexts.

A persistent gap exists between the demonstrated capabilities of AI technologies and their effective integration into organisational project environments. This gap reflects a misalignment between what AI systems can theoretically deliver and the conditions required for their successful deployment in practice. Existing research attributes this discrepancy to a complex interplay of technological, organisational, and human-related factors [3].

Although the use of artificial intelligence in project management has received growing scholarly attention, the existing literature still leaves several important issues unresolved. Many studies examine AI mainly through its practical applications, such as scheduling, cost estimation, risk analysis, or decision support, and therefore tend to emphasise performance outcomes rather than the conditions that make adoption possible in the first place. As a result, the mechanisms through which organisations accept, integrate, and sustain AI-based tools remain less clearly explained. Another limitation is that the literature remains relatively fragmented, as technological, organisational, and human-related factors are often discussed separately, while their interaction within the adoption process is not examined in sufficient depth. In addition, despite the growing number of studies on AI in project management, there is still limited systematic synthesis of the factors influencing AI adoption across technological, organisational, and environmental dimensions. A further research gap concerns the limited attention given to emerging market contexts. Much of the existing literature is based on developed economies, where digital infrastructure, institutional support, and access to specialised expertise are relatively more advanced. Consequently, there remains comparatively limited evidence on how AI adoption is influenced in emerging markets, where organisations may face additional structural challenges, including infrastructure limitations, shortages of skilled personnel, regulatory uncertainty, and financial constraints. Although prior studies occasionally acknowledge these issues, they are still not sufficiently integrated into existing analytical frameworks or systematically examined within the context of project management.

In response to these limitations, this study applies a systematic literature review approach, using PRISMA-based procedures for article selection. The purpose is not simply to summarise how AI is applied in project management, but to examine the drivers and barriers that shape its adoption. The reviewed literature is analysed through thematic coding and then structured using the Technology–Organisation–Environment framework . This allows the study to consider adoption as a process influenced by technological conditions, organisational capacity, and the external environment. The contribution of this study is threefold. It shifts attention from the performance effects of AI to the adoption factors that enable or constrain its use in project management. It also brings together previously scattered findings by comparing drivers and barriers across technological, organisational, and environmental dimensions. Finally, the study gives particular attention to emerging markets and argues that these contexts should not be treated simply as delayed versions of developed economies.

The primary aim of this study is to systematically examine the drivers and barriers influencing the adoption of artificial intelligence in project management.

To achieve this aim, the study addresses the following research questions:

RQ1: What are the key barriers to AI implementation in project management?

RQ2: What are the key drivers of AI implementation in project management?

RQ3: What strategies can support successful AI implementation in project management?

The study contributes on two levels. Theoretically, it provides a structured mapping of AI adoption factors within the TOE framework, moving beyond the fragmented treatment of drivers and barriers in prior work to examine their interdependencies across technological, organisational, and environmental dimensions. Practically, the findings are most directly relevant for organisations and policymakers navigating AI implementation in contexts with significant structural constraints. The explicit attention to emerging markets is intended to support more realistic and targeted strategies than those derived from developed-economy evidence alone.

Materials and methods

Artificial Intelligence as a Transforming Force Across Industries

Artificial intelligence (AI) is increasingly conceptualized in the literature as a set of data-driven methods that enable the formalization and partial automation of decision-making processes. It encompasses a range of techniques, including machine learning (ML), natural language processing (NLP), and neural network-based models, which are designed to identify patterns in large datasets and generate predictive or prescriptive outputs [4]. Beyond standalone AI applications, recent research on hybrid modelling in social-ecological systems suggests that incorporating machine learning into system dynamics and agent-based models could further enhance their capacity to represent adaptive behaviors and optimize long-term planning and decision-making in areas such as natural resource and environmental management [5]. Empirical and review-based studies indicate that AI applications are most effective in environments characterized by high complexity, interdependence, and variability. Within this broader context, project management emerges as a domain where the application of AI is both relevant and challenging. Project environments are defined by time constraints, resource limitations, and the need to coordinate multiple stakeholders, often under conditions of uncertainty. Empirical evidence from large-scale infrastructure projects illustrates this challenge: technical complexity and project-specific characteristics have been shown to be significant determinants of schedule delays and cost overruns, even in the absence of AI-based interventions [6]. These characteristics increase the demand for timely and well-founded decisions while simultaneously complicating the decision-making process. Consequently, AI-based tools are increasingly examined in the literature as a means of improving planning accuracy, monitoring project progress, and supporting adaptive responses to emerging risks.

Artificial Intelligence in Project Management: State of the Field

The application of AI to project management has gained considerable scholarly attention over the past decade. [1] provided a comprehensive systematic literature review mapping AI applications, methodologies, and outcomes in project management, identifying forecasting accuracy, risk mitigation, and stakeholder collaboration as key impact areas. [2] subsequently consolidated this evidence base through a systematic review explicitly examining opportunities, enablers, and barriers to AI adoption in project management. [7] further demonstrated that AI-driven optimization yields measurable improvements in efficiency, resource allocation, and project delivery. Recent studies have continued to consolidate evidence on AI applications in project management and adjacent fields, including trend analysis [8], AIdriven practice transformation [9], and a mixed-methods examination of AI-related benefits and challenges across the procurement process [10].

Drivers and Barriers in AI Adoption: A Fragmented Picture

Despite the growing body of research, the understanding of factors influencing AI adoption remains fragmented. A tertiary review by [3], synthesising findings from multiple systematic reviews, concludes that economic motivations consistently emerge as primary drivers, while barriers are predominantly associated with technical and social constraints. However, when compared with studies conducted within project management contexts, organisational factors, particularly top management support, strategic alignment, and organisational readiness, are often found to play a more decisive role. At the same time, inconsistencies are evident: some studies emphasise technological barriers (data quality, integration), while others highlight human-related obstacles (skills shortages, resistance to change). These differences are not merely empirical but reflect underlying contextual divergences. Studies in technologically advanced environments tend to emphasise integration and data-related challenges, whereas research in less digitally mature contexts more frequently identifies organisational capacity and human capital as primary constraints.

Consequently, while the categories of drivers and barriers are relatively well established, their relative importance, interdependencies, and context-specific variations remain insufficiently explored in a systematic manner. This lack of integrative and context-sensitive analysis represents a key limitation of the existing literature.

The Present Study: Systematic Perspective on AI Adoption in Project Management

These limitations are particularly pronounced when considering emerging markets. Most existing studies are grounded in developed economy contexts, whereas emerging markets are characterised by additional structural constraints, including limited digital infrastructure, skills shortages, regulatory uncertainty, and financial limitations. These factors fundamentally shape the conditions under which AI can be implemented, yet they are rarely systematically incorporated into existing analytical approaches.

To address these gaps, this study adopts a systematic literature review (SLR) approach guided by PRISMA-based article selection procedures. The study focuses explicitly on the identification and analysis of drivers and barriers of AI adoption in project management, treating them as the primary unit of analysis. The analytical framework is organised using the Technology–Organisation–Environment (TOE) perspective, allowing for the classification of drivers and barriers across multiple dimensions and examination of their interdependencies. By combining a systematic review methodology with a structured analytical framework, this study aims to move beyond descriptive synthesis toward a more comprehensive and context-sensitive understanding of AI adoption in project management.

This study adopts a systematic literature review (SLR) as the primary research methodology to examine the drivers and barriers of artificial intelligence adoption in project management. The selection of SLR is justified by the fragmented nature of existing research, where relevant findings are dispersed across different contexts, industries, and methodological approaches. To ensure methodological rigor and transparency, this study follows the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) 2020 guidelines [11].

Search Strategy

The search was executed in the Scopus database on 14 March 2026. The exact query applied was: TITLE-ABS-KEY((“driver” OR “enabler” OR “success factor” OR “barrier” OR “challenge” OR “risk” OR “obstacle*”) AND (“artificial intelligence” OR “ai”) AND (“project management”)). The search was limited to titles, abstracts, and keywords, and filtered by document type (Article, Conference Paper), language (English), and publication years (2016–2025). Duplicate records were identified through matching DOI and title followed by manual verification and were removed prior to title and abstract screening.

Relevant Article Selection Process

The selection of relevant studies followed the PRISMA 2020 four-phase framework. After removing 3 records with incomplete bibliographic information, 328 records were screened by title and abstract. Studies were excluded if they did not address both AI and project management. Subsequently, 179 full texts were assessed. At the full-text screening stage, studies were excluded for the following reasons: articles did not report drivers of AI adoption and did not report barriers of AI adoption, addressed AI outside a project management context, and lacked sufficient methodological detail to support data extraction. This process yielded a final sample of 41 studies. The final inclusion criteria required that studies address both drivers and barriers of AI adoption within a project management context. After this assessment, 41 studies were included in the final dataset. The complete selection process is shown in Figure 1 (PRISMA flowchart).

The coding scheme for driver and barrier categories was developed jointly by two researchers, who divided the 41 included studies between them, with each researcher responsible for coding their assigned portion of the sample. Throughout the process, the two researchers coordinated closely, regularly comparing emerging categories to ensure consistent labelling and grouping of drivers and barriers across both portions of the dataset. Where a factor could not be clearly classified. For instance, because it plausibly belonged to more than one TOE dimension, such as data quality, explainability, or resistance to change, the case was flagged and referred to a third researcher, whose input was used to reach a final classification decision. In such instances, factors were assigned to the context in which they were most directly framed within the original source (e.g., a driver described primarily in terms of organizational capability was coded as organizational, even where it carried secondary technological implications). This combination of divided responsibility, ongoing coordination, and third-party review of ambiguous cases was applied consistently across the dataset to ensure coherent and reliable classification of all categories.

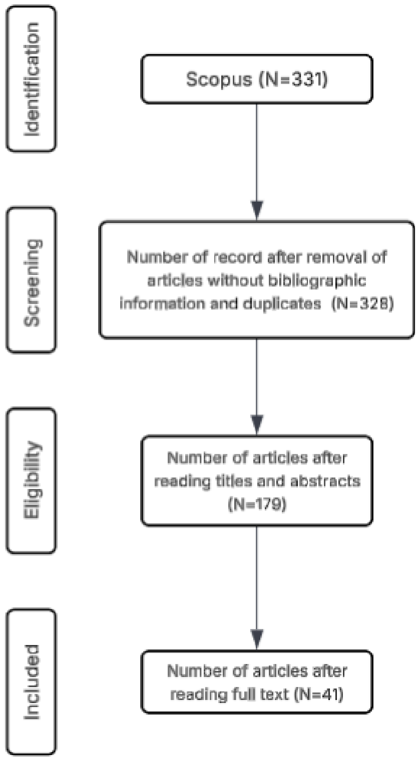

Figure 1 – PRISMA flowchart of selected articles

Structural Dimensions and Analytical Categories

To classify and analyse the reviewed literature, both inductive and deductive approaches were applied [12]. Inductive subject-specific dimensions included: drivers of AI adoption, barriers of AI adoption, AI techniques and tools, and project industry. The 21 driver categories and 20 barrier categories presented in Table 1 were derived inductively through open coding of the 41 included studies.

Deductively, drawing on the PMBOK Guide [13], the project management knowledge area was used as a dimension. Additionally, the Technology–Organisation–Environment (TOE) framework [14] was applied to structure three analytical dimensions: technological context, organisational context, and environmental context. The full framework of structural dimensions and analytical categories is presented in Table 1. Together, these dimensions provide the analytical framework through which drivers, barriers, and contextual conditions of AI adoption are examined.

Table 1 — Structural dimensions and their analytical categories

Methods	Structural dimensions	Analytical categories
Inductive, based on the literature being reviewed	Drivers of AI adoption	Predictive capability, Automation; Realtime monitoring; Decision support; Data quality and analysis; Usability and ease of use; Trust and transparency; Bias reduction; Efficiency and Productivity increase; Cost reduction; Risk reduction and management; Resource optimisation; Collaboration and communication; HumanAI collaboration; Innovation and digital transformation; Quality improvement; Strategic alignment; Safety; Competitive advantage; Sustainability; Regulatory compliance.
	Barriers of AI adoption	Data quality and availability issues; System integration difficulties; AI output inaccuracy and bias; Lack of contextual and domainspecific understanding; Lack of explainability; High computational and resource requirements; Limited AI capability and tool immaturity; Limited real world implementation and maturity; Lack of sufficient and historical data; Lack of AI expertise and literacy; High investment cost; Resistance to change; Need for human oversight; Lack of trust in AI outputs; Organisational misalignment and lack of strategy; Ethical concerns; Data privacy and security concerns; Regulatory and legal barriers; Lack of technical infrastructure; Lack of standardization.
	AI techniques / tools	Machine learning; Deep learning; Natural language processing (NLP) and generative AI; Computer vision; Integrated intelligent systems.
	Project industry	Construction; Construction/ Infrastructure; Construction/ Safety Management; Education; IT/Information systems; Oil&gas industry; Supply chain.
Deductive, related to PM	Project management knowledge area	Scope Management; Schedule (Time) Management Cost Management; Resource Management; Risk Management Quality Management; Stakeholder Management; Procurement Management; Integration Management.
Deductive, related to AI adoption	Technological context	Data infrastructure maturity; Data quality and availability; Algorithm performance; System integration capability; Explainability and transparency
	Organizational context	Skill availability; Organizational readiness; Management support; Resource availability; Change management capability
	Environmental context	Regulatory environment; Industry competition; Market demand; Institutional support; External pressure
Source: compiled by the authors based on existing data		

Results and discussion

Drivers of AI adoption

The review of 41 publications yielded 21 driver categories, presented in Table 3. Citation frequency across the included studies provided the basis for ranking. The three most prominently cited drivers were efficiency and productivity increase, decision support, and risk reduction and management.

Table 2 – Ranked Driver Categories and TOE framework classification

№	Driver categories	Count	Articles	TOE framework
1	Efficiency and Productivity increase	34	1, 2, 3, 4, 5, 6, 7, 9, 10, 11, 12, 13, 15, 17, 19, 20, 21, 23, 24, 25, 26, 27, 28, 29, 30, 31, 32, 33, 34, 35, 38, 39, 40, 41	Organization
2	Decision support	24	1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 13, 19, 21, 23, 24, 25, 26, 30, 31, 32, 33, 36, 41	Technology
3	Risk reduction and management	18	3, 4, 5, 7, 8, 9, 15, 21, 23, 24, 27, 28, 29, 33, 34, 37, 38, 40	Organization
4	Resource optimization	16	1, 4, 5, 9, 13, 15, 16, 22, 24, 27, 28, 29, 31, 37, 40, 41	Organization
5	Collaboration and communication	16	5, 9, 12, 13, 14, 15, 17, 18, 25, 26, 28, 29, 33, 37, 38, 40	Organization
6	Realtime monitoring	15	1, 10, 13, 14, 15, 19, 23, 27, 28, 29, 31, 32, 34, 38, 40	Technology
7	Data quality and analysis	14	1, 4, 7, 8, 10, 12, 13, 17, 18, 20, 21, 26, 31, 37	Technology
8	Automation	14	2, 3, 6, 11, 15, 18, 21, 25, 26, 27, 34, 35, 36, 40	Technology
9	Innovation and digital transformation	14	2, 3, 11, 12, 13, 14, 16, 17, 18, 19, 22, 26, 31, 39	Organization
10	HumanAI collaboration	13	2, 6, 14, 16, 17, 18, 19, 22, 24, 26, 31, 38, 39	Organization
11	Cost reduction	12	1, 5, 7, 15, 16, 19, 25, 30, 31, 32, 33, 35	Organization
12	Predictive capability	12	1, 2, 3, 5, 11, 13, 15, 18, 19, 27, 32, 40	Technology
13	Trust and transparency	6	8, 10, 12, 16, 18, 28	Technology
14	Regulatory compliance	6	12, 14, 16, 19, 33, 40,	Environment
15	Usability and ease of use	5	1, 17, 19, 22, 38	Technology
16	Sustainability	5	2, 11, 15, 23, 35	Environment
17	Safety	5	15, 25, 27, 34, 40	Organization
18	Quality improvement	4	6, 15, 27, 35	Organization
19	Strategic alignment	4	11, 12, 18, 24	Organization
20	Competitive advantage	4	10, 12, 25	Environment
21	Bias reduction	3	18, 20, 38	Technology
Source: compiled by the author based on existing data				

Efficiency and productivity increase (D1)

With 34 references, efficiency and productivity increase is the most consistently cited motivation for AI adoption across the reviewed literature. Organisations pursue AI primarily because it accelerates work processes and reduces operational costs; strategic vision is rarely the lead justification. This may reflect where the technology currently stands, capable enough to demonstrate efficiency gains, but is not yet sufficiently developed to carry out deeper organizational transformations. It also raises a question that is largely ignored in the literature: whether an exclusive focus on efficiency risks narrowing AI's perceived value, leaving longer-term strategic benefits underexplored.

Decision support (D2)

Decision support ranked second among the identified drivers. Project managers routinely work under conditions of uncertainty, incomplete information, and time pressure, circumstances that make unaided human judgment both cognitively demanding and error-prone. AI addresses this through data-driven insights and predictive capabilities that augment rather than supplant managerial reasoning [1]. Across the reviewed literature, the relationship between AI and decision-making is consistently framed as complementary: AI improves the speed, quality, and consistency of decisions, and in doing so contributes to better project outcomes overall.

Risk reduction and management (D3)

Risk management is one of the most consistently cited motivations for AI adoption. What the literature points to is not simply that AI improves risk management, but that it changes its fundamental logic: rather than retrospective assessment after problems arise, AI enables continuous anticipation and dynamic response [2, 15]. Probabilistic risk estimation on the basis of large, multidimensional datasets allows early warning where conventional methods would not yet register a signal, and the integration of AI with sensor-based monitoring extends this capability into real time. The frequency with which risk reduction appears as a driver reflects how much organisations value the capacity to stabilise project outcomes in uncertain environments, not only the efficiency gains that tend to dominate the discussion.

Barriers of AI adoption

The review identified 20 barrier categories, presented in Table 4. The three most frequently cited were lack of AI expertise and skilled personnel, data quality and availability issues, and high implementation and investment cost.

Table 3 – Ranked Barrier Categories and TOE framework classification

№	Barrier categories	Count	Articles	TOE framework
1	Lack of AI expertise and literacy	22	2, 3, 5, 6, 7, 8, 9, 10, 11, 13, 16, 17, 18, 24, 25, 28, 29, 32, 35, 37, 40, 41	Organization
2	Data quality and availability issues	15	1, 2, 5, 7, 8, 11, 13, 14, 25, 26, 28, 29, 31, 32, 34	Technology
3	High investment cost	15	2, 7, 9, 10, 11,16, 17, 19, 25, 27, 31, 32, 35, 36, 40	Organization
4	Resistance to change	15	6, 10, 11, 13, 15, 16, 17, 18, 19, 22, 31, 32, 35, 40, 41	Organization
5	Ethical concerns	14	9, 13, 14, 18, 19, 20, 24, 26, 30, 32, 38	Environment
6	System integration difficulties	13	1, 3, 7, 11, 13, 14, 17, 19, 28, 29, 33, 35, 41	Technology
7	AI output inaccuracy and bias	12	4, 5, 6, 15, 17, 18, 20, 21, 23, 26, 34, 38	Technology
8	Data privacy and security concerns	11	9, 13, 16, 17, 18, 19, 26, 30, 32, 35, 38	Environment
9	Regulatory and legal	10	2, 11, 13, 15, 16, 17, 22, 27, 30, 40	Environment
10	Lack of technical infrastructure	10	1, 10, 16, 27, 31, 33	Environment
11	Lack of contextual and domainspecific understanding	10	4, 5, 19, 20, 21, 23, 26, 34, 38, 39	Technology
12	Need for human oversight	9	4, 20, 21, 23, 26, 34, 36, 38, 39	Organization
13	Lack of trust in AI outputs	7	7, 15, 17, 28, 23, 25, 30	Organization
14	Lack of explainability	5	2, 8, 13, 18, 30	Technology
15	Organizational misalignment and lack of strategy	5	2, 11, 18, 24, 33	Organization
16	High computational and resource requirements	5	8, 17, 19, 28, 29	Technology

Continuation of Table 3

17	Limited AI capability and tool immaturity	2	7, 8	Technology
18	Limited realworld implementation and maturity	1	3	Technology
19	Lack of sufficient and historical data	1	5	Technology
20	Lack of standardization	1	32	Environment
Source: compiled by the authors based on existing data				

Lack of AI expertise and skilled personnel (B1)

Cited by 22 studies, the absence of adequate AI expertise is the most frequently identified barrier. The reviewed studies illustrate different dimensions of this constraint: strategic (organisations cannot plan AI adoption without people who understand it), operational (teams cannot use tools they do not understand), and financial (the cost of closing the gap is itself a barrier). Where AI-capable personnel are unavailable or unaffordable, organisations cannot build reliable data pipelines, meaningfully evaluate model outputs, or develop the institutional trust that sustained adoption requires. This makes the expertise gap more than a standalone obstacle: it amplifies several other barriers and in that sense operates as a foundational constraint.

Data quality and availability issues (B2)

Cited jointly second with 15 references, data quality and availability issues reflect a structural problem inherent to most project environments: project data is often incomplete, unstandardised, or simply not collected in forms that AI systems can use. Unreliable inputs produce unreliable outputs, and unreliable outputs erode confidence in AI tools, which in turn discourages the investment in data governance that would address the problem. Breaking this cycle requires deliberate upfront commitment to data infrastructure before AI deployment begins.

High implementation and investment cost (B3)

Also cited by 15 studies, implementation cost extends well beyond software licensing to cover system integration, staff training, ongoing maintenance, and specialist recruitment. This financial burden is particularly consequential because it overlaps directly with the expertise barrier: hiring AI-capable personnel is among the most significant cost items, so the two constraints reinforce each other. Smaller organisations and those operating in resource-constrained environments bear this compounding effect most acutely.

Analytical interpretation of TOE framework results

The 21 driver categories and 20 barrier categories were mapped to the three TOE contexts following [14]. The framework has gained traction in AI adoption research within construction and project management, including recent work on carbon-neutral buildings [16], and proved well-suited to capturing the multi-dimensional character of adoption factors identified here.

Cross-context analysis

Analyzing the relative distribution and interrelationships across TOE contexts, rather than treating each in isolation, reveals two structural problems shaping the current AI implementation landscape.

First, drivers and barriers are unevenly distributed: organizational factors dominate the drivers (10 of 21 categories), while technological factors dominate the barriers (9 of 20 categories), exposing a readiness gap in which firms are strategically motivated and organizationally prepared to adopt AI, yet available technologies often lack the maturity to reliably deliver on ambitions such as productivity gains, risk management, and cost optimization, suggesting that technological development, rather than organizational change management alone, should be a primary focus of intervention.

Second, these contexts are deeply interdependent rather than independent. Organizational barriers such as low trust and resistance to change are frequently rooted in technological shortcomings, particularly inaccurate outputs and insufficient explainability, meaning that stakeholders grow cautious when AI systems fail to justify their outputs transparently or perform unreliably; consequently, technological improvements can simultaneously resolve multiple organizational obstacles. Similarly, environmental constraints such as inadequate infrastructure and low standardization not only impede implementation directly but also determine whether technological solutions can function at all, since AI systems depend fundamentally on data availability, computing resources, connectivity, and compatible platforms; conversely, stronger environmental conditions can enable coordination mechanisms that extend adoption beyond isolated organizational efforts.

Taken together, these cross-context interactions indicate that AI adoption in project management requires a multi-layered strategy, combining advances in data infrastructure, model reliability, explainability, and system integration with improvements in regulatory transparency, standardization, and digital infrastructure investment, since organizational willingness to adopt AI already exists at a high level, but the necessary technological and institutional conditions remain insufficient to convert that intent into sustainable adoption.

Emerging markets: a distinct adoption context

One of the central findings of this study is that AI adoption in emerging markets should not be understood as a delayed replication of the process observed in advanced economies. The evidence instead points to a more complex and structurally distinct pattern.

To distinguish between developed and emerging market contexts, countries represented in the reviewed studies were classified according to the International Monetary Fund (IMF) classification of Advanced Economies and Emerging Market and Developing Economies. This classification served purely as a descriptive filter for organizing the sample and had no bearing on the formal inclusion criteria for the review; all extracted data and generalizations were subsequently checked to ensure that country-level grouping accurately reflected the adoption conditions described in each study.

Of the 41 articles reviewed, 13 were conducted in emerging market contexts, spanning the UAE (Articles 11, 15), Indonesia (Article 14), Ghana (Article 16), China (Articles 19, 22, 34, 36, 41), Ukraine (Article 27), Saudi Arabia (Articles 29, 32), and South Africa (Article 31). Although this sub-sample is small, it spans a broad range of regional and sectoral settings. The results should therefore be treated as suggestive rather than statistically generalizable. Nonetheless, the consistency of certain patterns within this sub-sample offers a useful foundation for examining how AI adoption in emerging markets differs from the global picture.

Table 4 – Top-3 AI adoption drivers in emerging market studies (n = 13)

№	Driver category	Count	Articles	TOE framework
1	Efficiency and productivity increase	9	11, 15, 19, 27, 29, 31, 32, 34, 41	Organization
2	Real-time monitoring	8	14, 15, 19, 27, 29, 31, 32, 34	Technology
3	Resource optimisation	7	15, 16, 22, 27, 29, 31, 41	Organization
Source: compiled by the authors based on existing data				

As shown in Table 4, efficiency and productivity gains emerge as the most frequently cited driver in the emerging market sub-sample, a ranking that mirrors the global dataset, where this driver also holds the top position. This consistency reflects a shared underlying logic: organizations turn to AI primarily to reduce manual work, accelerate decision-making, and optimize resource use in order to improve operational performance.

Beyond this shared top driver, however, the emerging market profile diverges markedly from the global pattern. Real-time monitoring ranks second in the sub-sample, appearing in 8 of 13 studies. a striking contrast to its sixth-place ranking globally. In emerging markets, real-time monitoring appears to serve a more foundational role than simply adding value to an already information-rich environment. It enables continuous tracking of project progress, early detection of deviations from planned schedules, and more responsive project control capabilities that are especially critical where planning and execution conditions are less predictable.

Resource optimization ranks third, reflects the practical value of AI in contexts where project resources are constrained by cost pressures, limited personnel availability, fragmented supply chains, and schedule uncertainty. Here, AI functions less as an abstract technological advance and more as a pragmatic tool for allocating labor, equipment, time, and capital more effectively.

Table 5 – Top-3 AI adoption barriers in emerging market studies (n = 13)

№	Barrier category	Count	Articles	TOE framework
1	Resistance to change	8	11, 15, 16, 19, 22, 31, 32, 41	Organisation
2	High investment cost	7	11, 16, 19, 27, 31, 32, 36	Organisation
3	Data quality and availability	6	11, 14, 29, 31, 32, 34	Technology
Source: compiled by the authors based on existing data				

The comparison of barriers, summarized in Table 5, reveals an even sharper divergence. Resistance to change is the most frequently cited barrier in the emerging market sub-sample, whereas globally the top barrier is a lack of AI knowledge and literacy. This difference is telling: it suggests that adoption barriers in emerging markets are not purely technical but are equally behavioral, organizational, and cultural in nature. Even where the potential benefits of AI are recognized, entrenched routines, reliance on established work practices, and managerial reluctance to embrace unfamiliar technologies can impede adoption (Article 16).

The second barrier extends beyond software licensing costs to encompass equipment, data preparation, system integration, staff training, infrastructure upgrades, and the development of custom AI solutions, a cost structure identified as the most significant constraint on AI adoption in Ghana's construction sector (Article 16).

Data quality and availability barrier, confirms that data constraints remain a persistent obstacle in emerging market settings. Importantly, this barrier is not simply a matter of data scarcity; it also reflects deeper structural issues, including data fragmentation, low standardization, heterogeneous formats, poor interoperability, and insufficient integration with existing project information systems.

Recommendations

Addressing RQ3, what strategies can support successful AI implementation, the evidence points to differentiated responses depending on context. For organisations, the clearest implication of the readiness gap is that internal capability must precede tool deployment. Committing to an AI system before the data infrastructure, skills base, and change management processes are in place typically produces underperformance that discourages further adoption. Practically, this means prioritising data governance as a strategic rather than technical function: establishing data collection standards, cleaning historical records, and assigning ownership of data quality before procurement decisions are made. It also means framing AI as a decision-support layer rather than an autonomous replacement for project managers. The literature is consistent on this point: resistance is lower and performance outcomes are better when human-AI collaboration is the explicit model. Adoption that begins with lower-risk, well-defined tasks such as schedule monitoring or cost variance detection, allows organisations to build trust in AI outputs before extending reliance to more complex or consequential decisions.

For policymakers in emerging markets, the analysis identifies a sequencing problem that shapes the entire adoption challenge. Environmental preconditions, reliable digital infrastructure, data protection legislation, industry-level data standards, and accessible financing mechanisms, must be addressed before firm-level capability-building efforts can gain traction. The evidence from Ghana, Saudi Arabia, and South Africa in the reviewed sample consistently shows that where these conditions are absent, even willing and strategically motivated organisations cannot sustain AI adoption. A practical policy agenda therefore has two tracks: the first establishes the enabling environment through infrastructure investment, regulatory development, standardisation, and instruments such as public-private partnerships that reduce upfront cost barriers; the second supports organisational capability through training programmes, AI literacy initiatives, and procurement guidelines. The sequencing matters: the first track must be underway before the second can achieve its objectives.

For the research community, the geographic concentration of existing studies is a limitation that future work should address directly. Most reviewed articles originate from developed economies or a narrow range of emerging market countries in the Gulf, China, and select African contexts. Latin America, South and Southeast Asia, and Sub-Saharan Africa remain substantially underrepresented despite being regions where infrastructure investment needs are acute and where AI adoption in project management could have considerable impact. In addition to geography, longitudinal and experimental developments would be useful in this area. Cross-sectional studies can identify existing barriers and driving forces; they are less suitable for explaining how implementation occurs over time or which interventions actually affect outcomes. Comparative studies combining the contexts of developed and emerging markets within the same type of project or sector would also help to distinguish general conclusions from specific ones more clearly than the available data allow.

Conclusion

A systematic review of 41 peer-reviewed articles, structured around the Technology–Organisation–Environment framework, identified 21 driver categories and 20 barrier categories shaping AI adoption in project management. The dominant driver pattern is internal and operational: organisations are motivated by efficiency gains, decision support, and risk management capabilities that AI can provide within their own project environments. The dominant barrier is technological rather than organisational: data quality problems, infrastructure deficits, and the absence of mature, reliable AI tools constrain adoption in ways that organisational willingness alone cannot overcome. Taken together, these two patterns define what the review identifies as the central structural challenge, a readiness gap in which motivation and capability are misaligned. The TOE framework illuminates this well, though the review also reveals a limitation in how the framework is conventionally applied: it treats technological, organisational, and environmental contexts as parallel conditions, whereas the evidence, particularly from emerging market studies, suggests that environmental factors often operate as gateway conditions that must be met before the other two dimensions become effective.

Several limitations bear acknowledgement. The evidence base is heterogeneous in methodology and context, and the findings naturally reflect the state of the literature at the time of review. The emerging market analysis, while analytically meaningful, draws on thirteen studies concentrated in a narrow geographic range; broader coverage would strengthen the contextual conclusions. Notwithstanding these constraints, the review makes three contributions. It provides a structured mapping of drivers and barriers across the TOE framework, moving beyond lists to a cross-context analysis that surfaces the readiness gap as the field's central structural challenge. It offers an original characterisation of emerging market adoption as structurally distinct rather than simply delayed. And by synthesising adoption factors as the primary object of analysis, rather than as secondary findings within application-focused studies, it gives researchers and practitioners a basis for more targeted strategy development as AI tools continue to mature and embed themselves in project management practice.

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Appendix A. Screened articles (N=41)

#	Authors	Title
1	Elghaish et al.	Predictive digital monitoring of construction resources: an integrated digital twin solution
2	Hughes et al.	Impact of artificial intelligence on project management (PM): Multi-expert perspectives toward PM2030
3	Garcia et al.	Project control and computational intelligence: Trends and challenges
4	Nyqvist et al.	Can ChatGPT exceed humans in construction project risk management?
5	Fridgeirsson et al.	A Qualitative Study on AI and Its Impact on the Project Schedule, Cost and Risk Management in PMBOK
6	Hettrich et al.	Bridging the Expertise Gap: The Role of Generative AI in Supporting Project Planning Tasks
7	Wachnik B.	Analysis of the use of AI in the management of Industry 4.0 projects: perspective of Polish industry
8	Chen et al.	Transparent and reliable construction cost prediction using advanced ML and explainable AI

Continuation

9	Alqudah et al.	Developing an Intelligent Model for Construction PM Using AI and Big Data Analysis
10	Bozorgzadeh & Umar	Automated progress measurement using computer vision technology in UK construction
11*	Al Sulaity et al.	Driving digital transformation in the oil and gas sector: unlocking AI potential in the UAE
12	Merhi & Harfouche	Enablers of artificial intelligence adoption and implementation in production systems
13	Torres et al.	Enhancing construction PM competencies with AI-driven assistants: dual perspective from academia and industry
14*	Waqar et al.	Evaluation of success factors of utilizing AI in digital transformation of H&S management systems in construction
15*	Alketbi et al.	The Role of Artificial Intelligence in Aviation Construction Projects in the United Arab Emirates
16*	Acheampong et al.	Evaluating the factors influencing AI technology uptake in health and safety management in Ghanaian construction
17	Skuridin & Wynn	Chatbot Design and Implementation: Towards an Operational Model for Chatbots
18	Tursunbayeva & Chalutz-Ben Gal	Adoption of artificial intelligence: A TOP framework-based checklist for digital leaders
19*	Ma et al.	Adopting Large Language Models in the Construction Industry: Drivers, Barriers, and Strategic Implications from China
20	Aljaz T.	Leveraging ChatGPT for Enhanced Logical Analysis in the Theory of Constraints Thinking Process
21	Barcaui & Monat	Who is better in project planning? Generative artificial intelligence or project managers?
22*	Zhang et al.	Enhancing construction workers health and safety: mechanisms for implementing Construction 4.0 technologies
23	Aladag H.	Assessing the Accuracy of ChatGPT Use for Risk Management in Construction Projects
24	Serikbay et al.	When Machines Manage: How AI Is Reshaping Project Management Practices
25	Jallow et al.	Artificial Intelligence and the UK Construction Industry - Empirical Study
26	Nikolic & Bjelica	Digital product success under the microscope: When artificial intelligence in projects helps and when it hurts
27*	Sobchenko et al.	Artificial Intelligence for Enhancing Engineering Project Management During Emergencies: Perception-based Analysis
28	Almalki S.S.	AI-Driven Decision Support Systems in Agile Software Project Management
29*	Alnaser & Elmousalami	Exploring Critical Success Factors of AI-Integrated Digital Twins on Saudi Construction Project Deliverables
30	Georgiev et al.	The role of artificial intelligence in project management: a supply chain perspective
31*	Bikwa & Bond-Barnard	Exploring the Challenges and Opportunities of AI in Decision-Making in Construction Project Management
32*	Alnaser & Elmousalami	Benefits and Challenges of AI-Based Digital Twin Integration in the Saudi Arabian Construction Industry
33	Tominc et al.	Statistically Significant Differences in AI Support Levels for Project Management between SMEs and Large Enterprises
34*	Kamran et al.	Generative AI and Prompt Engineering: Transforming Rockburst Prediction in Underground Construction
35	Nyqvist et al.	Artificial intelligence driven platforms in the construction industry: implications for companies business models
36*	Jiang et al.	Automatic daily salary settlement for construction workers in photovoltaic engineering using lean construction and AIoT
37	Bockova et al.	The Role of Artificial Intelligence in Managing Scientific Research Projects Funded by KEGA and VEGA grant schemes

Continuation

38	Martin et al.	Exploring Large Language Model AI tools in Construction Project Risk Assessment: ChatGPT Limitations
39	Catta-Preta et al.	Innovation Flow: A Human-AI Collaborative Framework for Managing Innovation with Generative Artificial Intelligence
40	Wong et al.	Towards Digital Transformation in Building Maintenance and Renovation: Integrating BIM and AI in Practice
41*	Chong et al.	BIM and AI Integration for Dynamic Schedule Management: A Practical Framework and Case Study

*=Emerging Market Study

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ДАМУШЫ НАРЫҚТАРДА ЖАСАНДЫ ИНТЕЛЛЕКТ ТӘЖІРИБЕСІН ЕНГІЗУДІҢ ҚОЗҒАУШЫ КҮШТЕРІ МЕН КЕДЕРГІЛЕРІ

Аңдатпа

Зерттеу дамушы нарық жағдайларына ерекше назар аудара отырып, жобаларды басқаруда жасанды интеллектті (ЖИ) енгізуге әсер ететін негізгі факторлар мен кедергілерді зерттейді. Зерттеу PRISMA 2020 нұсқауларына сәйкес жүргізілген әдебиеттерді жүйелі шолуға негізделген. Қорытынды үлгіге 2016–2025 жж. аралығында Scopus дерекқорынан алынған 41 рецензияланған мақала кірді. ЖИ енгізуге әсер ететін факторлар кодталып, Technology–Organisation–Environment (TOE) моделі негізінде топтастырылды. Нәтижесінде қозғаушы факторлардың жиырма бір санаты және кедергілердің жиырма санаты анықталды. Зерттеу нәтижелері жобаларды басқаруда ЖИ енгізу тек озық құралдардың қолжетімділігімен шектелмейтінін көрсетеді. Ұйымдар ЖИ-ге жобалардың тиімділігін арттыру әлеуетіне байланысты қызығушылық танытады, алайда тәжірибелік енгізу әлсіз деректер инфрақұрылымы, техникалық жетілудің төмен деңгейі, білікті мамандардың жетіспеушілігі және нормативтік талаптардың айқын болмауымен шектеледі. Бұл айырмашылық әсіресе дамушы нарықтарда анық байқалады, өйткені цифрлық инфрақұрылым, реттеу, стандарттар және институционалдық қолдау сияқты сыртқы орта факторлары ұйым деңгейінде ЖИ енгізудің мүмкіндігін айқындайды. Зерттеу ЖИ енгізу стратегиялары жергілікті контекстің жетілу деңгейіне бейімделуі тиіс деген қорытынды жасайды. Дамушы нарықтар үшін бұл мемлекеттік және ұйымдық күш-жігер тек қызметкерлерді оқытудан немесе бағдарламалық қамтамасыз етуді енгізуден басталмай, сонымен қатар ЖИ-ді тұрақты түрде енгізуге мүмкіндік беретін базалық цифрлық, нормативтік және институционалдық жағдайларды дамытуға бағытталуы қажет екенін білдіреді.

Түйін сөздер: жасанды интеллект, кедергілер, қозғаушы факторлар, дамушы нарықтар, жобаларды басқару, жүйелі әдебиет шолуы, TOE framework.

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ДВИЖУЩИЕ СИЛЫ И БАРЬЕРЫ ВНЕДРЕНИЯ ПРАКТИК ИСКУССТВЕННОГО ИНТЕЛЛЕКТА НА РАЗВИВАЮЩИХСЯ РЫНКАХ

Аннотация

Данное исследование рассматривает основные драйверы и барьеры, влияющие на внедрение искусственного интеллекта (ИИ) в управление проектами, с особым акцентом на условия развивающихся рынков. Исследование основано на систематическом обзоре литературы, проведенном в соответствии с руководством PRISMA 2020. Итоговая выборка включала 41 рецензируемую статью, полученную из базы данных Scopus за период 2016–2025 гг. Выявленные факторы внедрения были закодированы и сгруппированы с использованием модели Technology–Organisation–Environment (TOE). В результате была определена 21 категория движущихся сил и 20 категорий барьеров. Результаты исследования показывают, что внедрение ИИ в управление проектами не ограничивается наличием передовых инструментов. Организации часто проявляют интерес к ИИ из-за его потенциала для повышения эффективности проектов, однако практическое внедрение сдерживается слабой инфраструктурой обработки данных, недостаточной технической зрелостью, нехваткой квалифицированных специалистов и неясными нормативными условиями. Этот разрыв особенно заметен на развивающихся рынках, где такие факторы окружающей среды, как цифровая инфраструктура, регулирование, стандарты и институциональная поддержка, часто определяют, возможно ли вообще внедрение на уровне компаний. В исследовании утверждается, что стратегии внедрения ИИ должны быть адаптированы к местным условиям. Для развивающихся рынков это означает, что организационные усилия должны начинаться не только с обучения на уровне фирмы или внедрения программного обеспечения, но и с разработки базовых цифровых, институциональных условий, которые делают возможным устойчивое внедрение ИИ.

Ключевые слова: искусственный интеллект, барьеры, движущие силы, развивающиеся рынки, управление проектами, систематический обзор литературы, TOE framework.