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Project Management Pitfalls and the Ambivalent Role of Artificial Intelligence: A Scoping Review of Bad Practices

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Systematic Review

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Abstract

Despite decades of methodological progress and widespread digital tool adoption, project management continues to suffer persistent, systemic failures. This article extends Escofet's (2016) original ten bad practices to twenty, drawn from a scoping review of source literature (2021–2026) and practitioner sources on PMO failure and AI pitfalls. The practices span four clusters: planning and estimation, resource and scope management, governance and communication, and execution and delivery. The review also examines whether artificial intelligence genuinely resolves these problems or introduces new risks. AI shows real potential for improving estimation, risk assessment, resource optimisation and performance monitoring, but uncritical adoption risks reinforcing existing bad practices through poor data quality, algorithmic bias and over-reliance on opaque models. The review concludes these failures are fundamentally organisational, behavioural and cognitive, and recommends AI be integrated as a complement to, rather than a substitute for, sound human judgement and governance.

1. Introduction

Background: Project management continues to face persistent challenges despite decades of methodological advancement and the proliferation of digital tools. This article examines twenty common bad practices that systematically undermine project success, extending and updating the ten practices originally articulated by Escofet (2016).

Objectives: The review aims to (1) identify and categorise contemporary project management practices, (2) evaluate whether artificial intelligence (AI) constitutes a genuine solution to these perennial problems or introduces new risks, and (3) provide evidence-based recommendations for integrating AI as a complementary tool rather than a substitute for sound project governance.

Eligibility criteria: Most of the sources are peer-reviewed articles published between 2021 and 2026 in Web of Science or Scopus-indexed journals, along with seminal practitioner sources addressing PMO failures and AI project pitfalls.

Sources of evidence: A comprehensive search of Scopus, Web of Science, DOAJ, OpenAlex and Google Scholar was conducted.

Charting methods: Data were extracted using a standardised form capturing author, year, methodology, key findings, and relevance to project management bad practices and AI adoption.

Results: Twenty bad practices were identified across four thematic clusters: planning and estimation failures, resource and scope management failures, governance and communication failures, and execution and delivery failures. The analysis reveals that AI offers significant potential for improving estimation, risk assessment, resource optimisation, and performance monitoring. However, its uncritical adoption may perpetuate or amplify existing bad practices through data quality issues, algorithmic bias, and over-reliance on opaque models.

Conclusions: The bad practices identified are fundamentally organisational, behavioural, and cognitive problems. AI should be adopted as a complementary tool rather than a replacement for judgment. Governance frameworks for AI adoption must address data quality, algorithmic transparency, and the distribution of decision-making authority between humans and machines.

Deployment

The project management discipline has evolved considerably over the past half-century, with the development of sophisticated methodologies, certification frameworks, and digital tools. Yet despite these advances, project failure rates remain stubbornly high. Recent large-scale analyses of over 5392 IT projects and more than 22000 capital investment projects reveal that the most significant red flag for cost blowouts is when project participants begin describing their project as ‘unique’—a cognitive signal that historical lessons and base rates are being ignored (Flyvbjerg et al., 2022). This persistent failure rate suggests that the gap between prescribed best practices and actual organisational behaviour remains wide, and that many of the problems confronting project managers today are not new but rather represent recurring patterns of error (Hubbard et al, 2025).

These bad practices—ranging from inadequate multi-project environment assessment to the destructive effects of multitasking, from the inability to say no to the tendency to deliver with unresolved items—continue to resonate with contemporary project management challenges. The persistence of these problems raises an important question: can emerging technologies, particularly artificial intelligence, help project managers overcome these perennial pitfalls, or do they risk introducing new forms of failure?

The aim of this article is threefold. First, we identify and categorise twenty bad practices through the lens of recent project management research. Second, we evaluate the potential role of AI in mitigating—or exacerbating—these problems. Third, we provide evidence-based recommendations for practitioners and researchers. In doing so, we contribute to the growing body of literature on AI in project management while maintaining a critical perspective on technological solutionism.

1.1 Rationale for a Scoping Review

A scoping review was selected as the most appropriate methodology for this study for three reasons. First, the topic of project management bad practices is broad and heterogeneous, encompassing cognitive, organisational, and technical dimensions that do not lend themselves to a narrow systematic review with a single focused question. Second, the intersection of project management bad practices and AI adoption is an emerging area of inquiry with fragmented evidence across multiple disciplines, including project management, operations research, information systems, and organisational behaviour. Third, a scoping review is particularly suited to identifying the types of available evidence, clarifying key concepts, and identifying gaps in the literature (Munn et al.,

2022). The PRISMA-ScR (Preferred Reporting Items for Systematic Reviews and Meta-Analyses extension for Scoping Reviews) framework was adopted to ensure methodological rigour and transparency (Tricco et al., 2018).

2. Methodology

2.1 Protocol and Registration

A review protocol was developed following PRISMA-ScR guidelines. The protocol was not registered, as the review was conducted as part of a broader research programme on project management practices.

2.2 Eligibility Criteria

Inclusion criteria:

- Peer-reviewed journal articles published between 2021 and 2026
- Articles indexed in Web of Science or Scopus
- Studies addressing project management bad practices, project failure, or AI in project management
- English language publications
- Seminal practitioner sources addressing PMO failures and AI project pitfalls (Blumhorst, 2010; Weiner, 2026)

Exclusion criteria:

- Conference papers, book chapters, and grey literature (except where explicitly noted as practitioner sources)
- Articles not directly addressing project management practices or outcomes
- Publications before 2021 (except for foundational works such as Escofet (2016), and Blumhorst (2010), which are cited as primary sources for the bad practices taxonomy)

2.3 Information Sources and Search Strategy

A systematic search was conducted across five databases: Scopus, Web of Science, DOAJ, OpenAlex and Google Scholar. The search strategy employed combinations of the following terms:

- ‘project management’ AND ‘bad practices’ OR ‘pitfalls’ OR ‘failure factors’
- ‘artificial intelligence’ AND ‘project management’ AND ‘systematic review’
- ‘scope creep’ AND ‘project management’
- ‘multitasking’ AND ‘project management’ AND ‘present bias’
- ‘PMO’ AND ‘failure’ AND ‘project management’
- ‘AI’ AND ‘project management’ AND ‘pitfalls’ AND ‘deployment’

The search was conducted in January-July 2026. Additional sources were identified through backward and forward citation tracking of key articles.

2.4 Selection of Sources of Evidence

Two reviewers independently screened titles and abstracts against the eligibility criteria. Disagreements were resolved through discussion. Full-text screening was conducted for articles that passed the initial screening. A total of 127 articles were identified, of which 68 met the inclusion criteria and were retained for data extraction.

2.5 Data Charting Process

A standardised data extraction form was developed, capturing the following variables: author(s), year, methodology, key findings, relevance to project management bad practices, and relevance to AI adoption. Data were charted independently by two reviewers, with discrepancies resolved through consensus.

2.6 Synthesis of Results

The extracted data were synthesised using a thematic analysis approach. Bad practices were categorised into four thematic clusters: planning and estimation failures, resource and scope management failures, governance and communication failures, and execution and delivery failures. AI-related findings were synthesised separately to assess their potential to address—or exacerbate—each category of bad practice.

3. Results

3.1 Characteristics of Sources of Evidence

A total of 68 included articles spanning a range of methodologies, including systematic literature reviews, case studies, empirical surveys, and theoretical modelling include a majority of studies (n = 42) were published between 2023 and 2026, reflecting the growing scholarly attention to both project

management failures and AI adoption. There were the final references published in journals including the *International Journal of Project Organisation and Management*, *Buildings*, *Computers*, *Manufacturing & Service Operations Management*, and *Engineering Construction and Architectural Management*. Furthermore, several studies on the topic were included (see Table 1) and twenty resilient bad practices in real-world project management were identified (see Table 2).

Table 1
presents a summary of the included studies organised by thematic focus.

Thematic focus	Number of studies	Representative sources
Project failure factors	18	Flyvbjerg (2022); Hubbard (2025); Wang and Sharma (2025); Demirkesen (2025)
Scope creep and scope management	8	Ogbuagu et al. (2025); Ajmal et al. (2022)
Multitasking and present bias	6	Li and Yu (2023); Shah et al. (2024)
AI in project management	22	Adamantiadou and Tsironis (2025); Salimimoghadam et al. (2025); Carpenter et al. (2024)
AI project pitfalls and deployment	10	Weiner (2026); Blumhorst (2010)
Planning fallacy and cognitive bias	4	Haronian and Korb (2024)
Total	**68**	

Table 2
presents the twenty bad practices identified in this review, their persistence in contemporary project management, and the potential role of AI in either mitigating or exacerbating each practice.

#	Bad practice	Cluster	AI potential to mitigate	AI risk of exacerbation
1	Incorrect estimation and planning	Planning	High: LLMs improve estimation accuracy (Carpenter et al., 2024)	High: AI perpetuates historical estimation bias
2	Unrealistic promises without accounting for variability	Planning	Medium: probabilistic models can model variability	Low: AI cannot override political pressure
3	Ignoring statistical nature of project networks	Planning	Medium: network analysis can identify dependencies	Low
4	Planning fallacy and optimism bias	Planning	Low: cognitive bias resists technical solutions	Low: AI may create new forms of 'magical thinking'
5	Sunk cost fallacy	Planning	Medium: objective data on project viability	Medium: data can be selectively deployed
6	Inadequate multi-project environment assessment	Resource	High: portfolio optimisation algorithms	Medium: governance gaps limit effectiveness
7	Inappropriate role assignment	Resource	Medium: skill-matching algorithms	Low
8	Resource underutilisation	Resource	Medium: resource optimisation tools	Low
9	Overutilisation and burnout of best resources	Resource	Medium: workload balancing	High: AI may maximise utilisation without regard for human limits
10	Maintaining original scope when conditions change	Scope	Medium: scenario analysis	Medium
11	Accepting scope changes without impact analysis	Scope	High: automated impact analysis	Medium: results may be used to justify predetermined conclusions
12	Assuming rather than contrasting	Governance	Medium: data-driven verification	Medium: AI insights may become new assumptions
13	Planning without all responsible parties	Governance	Low: collaboration platforms can help	Low
14	Insufficient dependency identification	Governance	High: automated dependency mapping	Medium: tacit dependencies may be neglected
15	Fragmented project focus	Governance	Low: dashboards provide integrated visibility	Medium: fragmented reporting may reinforce silos
16	Lack of communication	Governance	Medium: automated translation and summarisation	Medium: illusion of engagement
17	Inability to say no	Governance	Low: AI cannot make judgment calls	High: pressure for rapid, data-driven decisions
18	Excessive inflexibility and micromanagement	Governance	Low	Low
19	Delivering with pending items	Execution	Medium: tracking and prediction tools	Low
20	Multitasking	Execution	Medium: visibility into resource utilisation	High: AI-optimised allocation may increase multitasking

3.2 Table 1: **Summary of Included Studies by Thematic Focus**

3.3 Table 2: **Twenty Bad Practices, Their Persistence, and AI Implications**

3.4 Planning and Estimation Failures

Incorrect estimation and planning. The most common error in project management involves several interconnected factors: clients without clear objectives, overly changing requirements, and the setting of excessively optimistic goals. A particularly damaging pattern occurs when an initial estimate—produced under pressure and with limited information—becomes the final commitment for the client. Carpenter et al. (2024) demonstrated that large language models can achieve estimation accuracy superior to several baseline machine learning methods, with a mean absolute error of 2,398.2 on the ISBSG dataset. However, if historical data reflects systematic underestimation, AI models will perpetuate this bias.

The planning fallacy and optimism bias. Haronian and Korb (2024) describe the planning fallacy as a form of 'magical thinking' where planners convince themselves that their project will be different (and better) than others. Their case study of a Pumped Hydroelectric Energy Storage facility demonstrates how the Choosing by Advantages method can serve as an antidote to optimism bias by engaging 'slow thinking' at the organisational level.

The sunk cost fallacy. Demirkesen (2025) identified emotional investment, internal politics, and fear of reputational damage as key contributing factors to the sunk cost fallacy in mega construction projects. The ability to recognise misalignment and act decisively is described as 'strategic maturity' rather than weakness. AI can provide objective data on project viability, but it cannot override the political and emotional factors that sustain failing projects.

3.5 Resource and Scope Management Failures

Multi-project environment assessment. Wang and Sharma (2025) conducted a systematic literature review of project failure factors in complex infrastructure projects in the Netherlands, identifying 'scope changes', 'coordination and communication problems', and 'poor project structure and scheduling problems' as the main factors leading to project failure. An et al. (2025) emphasise the need for decision support systems that help managers balance resource allocation and resolve conflicts in multi-project parallel environments.

Scope creep. Ogbuagu et al. (2025) found that real-time tracking and management of scope changes resulted in a 25% increase in on-time completion, a 20% improvement in budget adherence, and a 30% reduction in scope change frequency. Ajmal et al. (2022) examined project scope creep factors in the construction industry, highlighting the role of stakeholder perspectives in driving undocumented changes.

Multitasking and present bias. Li and Yu (2023) provide a rigorous theoretical analysis of multitasking in the context of present-biased preferences. Their model demonstrates that multitasking is more likely when projects have low start-up costs but high finishing costs, and that adding carefully chosen projects to the portfolio can prevent both naïve and sophisticated agents from multitasking. Shah et al. (2024) found that multitasking is mediated by exhaustion and work overload, with implications for employee retention.

3.6 Governance and Communication Failures

PMO worst practices. Blumhorst (2010) identified ten common PMO worst practices, including: the PMO playing 'methodology cop', implementing a methodology without a framework, not matching demand to supply, not logging time, gathering unnecessary information, keeping an ad-hoc project request process, lack of executive support, implementing a tool without a process, and implementing a process without a tool. These practices resonate with contemporary research on PMO failure. Project One (2026) identified excessive bureaucracy, an obsession with reporting, lack of authority, and disconnection from delivery as common causes of PMO failure. Effective governance should support delivery rather than obstruct it, and a PMO should provide insight that enables better decisions rather than simply collecting information.

Communication and stakeholder engagement. Research on construction project failures has identified 'poor communication' and 'limited stakeholder engagement during project lifecycles' as critical dysfunctionalities. Wang and Sharma (2025) found that 'coordination and communication problems' were among the main factors leading to project failure in infrastructure projects.

The inability to say no. Escofet (2016) describes the inability to say no as a personal trait that can 'drag down the rest of the team'. Saying no does not mean being negative; it means recognising that under specific conditions and requirements, what is being asked cannot be delivered on time and in form. Recent research on project governance supports this position: the ability to resist pressure for premature commitment is a mark of project management maturity.

3.7 Execution and Delivery Failures

Delivering with pending items. The practice of delivering at intermediate or final points while leaving elements unfinished is described by Escofet (2016) as counterproductive. The 2026 analysis of 'zombie projects' found that 44% of organisations entered the year weighed down by initiatives that had not moved in weeks. AI can assist in tracking pending items and predicting the likelihood of timely completion, but the discipline to close projects properly is a governance and leadership issue that AI cannot address (Almalki, 2025).

Multitasking. Escofet (2016) identified multitasking as a fundamental problem that impacts project duration when resources are expected to perform tasks from different projects in overlapping timeframes. The original recommendations—reducing work in progress by 25–50% in cases of proven unproductivity, preferring to close or pause some projects rather than keep several open, and using quantitative planning and control methods—remain relevant. Li and Yu (2023) provide strong theoretical support for these recommendations.

3.8 AI in Project Management: Opportunities and Risks

Opportunities. Adamantiadou and Tsironis (2025) synthesised 97 peer-reviewed studies and found that AI techniques such as machine learning, deep learning, and hybrid models have exhibited transformative effects on forecasting accuracy, risk mitigation, stakeholder collaboration, and safety management. Salimimoghadam et al. (2025) identified three key themes: the knowledge ecosystem in project management in the era of AI, the intersection of AI and humanity, and integrating AI into project management. Yamuna and Nighojkar (2026) reviewed 354 publications and found that deep learning and machine learning models demonstrated prediction accuracies of 92% and 80% reduction in errors compared to conventional methods.

Risks and barriers. Despite these advances, scholars have raised concerns about the socio-technical risks associated with AI adoption. Salimimoghadam et al. (2025) identified high implementation and maintenance costs, lack of top-down support, shortage of skilled employees trained in AI, and organisational resistance as primary barriers to adoption. Weiner (2026) documents five common pitfalls that prevent AI and data science projects from reaching deployment: the scope of the project is too big, scope creep, the model couldn't be explained, the model was too complex, and the project solved the wrong problem. Weiner (2026) reports that 87% of AI and Big Data projects fail by never reaching deployment, indicating a systematic problem rather than something specific to a particular project.

Generative AI-specific pitfalls. Weiner (2026) identifies four additional pitfalls specific to generative AI projects: not accounting for security and intellectual property, creating redundant solutions for the same problem, building solutions that don't scale, and not taking cost into consideration. The cost of training foundation models is on the order of $50–$100 million, making it not cost-effective for a single enterprise to build large language models of the size of those behind ChatGPT or Microsoft Copilot. Pre-trained models and retrieval augmented generation offer more practical alternatives for most enterprise applications.

4. Discussion

4.1 The Persistence of Bad Practices

The findings of this scoping review confirm that the bad practices identified by Escofet (2016) and Blumhorst (2010) remain pervasive in contemporary project management. Despite decades of methodological advancement and the proliferation of digital tools, the fundamental categories of failure—planning and estimation, resource and scope management, governance and communication, and execution and delivery—remain stable. This suggests that the persistence of bad practices is not primarily a knowledge problem. Project managers and organisations know what they should do; the challenge is doing it.

Cognitive biases such as the planning fallacy, sunk cost fallacy, and optimism bias are deeply embedded in human decision-making and resist purely technical solutions. Haronian and Korb (2024) demonstrate that methodical approaches like Choosing by Advantages can serve as an antidote, but these require organisational commitment and cultural change. Li and Yu (2023) show that present bias causes three behavioural anomalies in project scheduling: procrastination, multitasking, and suboptimal sequencing. Remedies include adding carefully chosen projects to the portfolio and increasing awareness of self-control problems.

4.2 The Ambivalent Role of AI

Our analysis reveals that AI offers genuine potential to address many of the bad practices identified in this study, particularly in areas such as estimation, risk assessment, resource optimisation, performance monitoring, and scope tracking. Carpenter et al. (2024) demonstrated that large language models can provide accurate estimates even with minimal data, making them a practical tool for early-stage project planning. Yamuna and Nighojkar (2026) found that deep learning and machine learning models demonstrated prediction accuracies of 92% and 80% reduction in errors compared to conventional methods. Adamantiadou and Tsironis (2025) identified hybrid AI models that enhance risk assessment, duration forecasting, and cost estimation.

However, several caveats are in order. First, the effectiveness of AI depends on the quality and completeness of organisational data. Salimimoghadam et al. (2025) identified 'data quality issues' as a primary barrier to AI adoption, along with 'integration with legacy systems' and 'resistance to change'. Carpenter et al. (2024) encountered significant challenges related to data completeness, with only 35 out of 7,518 entries in the ISBSG dataset having no missing values across their selected features.

Second, AI tools introduce new risks that must be managed. These include algorithmic bias, which can perpetuate or amplify existing inequalities; data privacy and security concerns; the erosion of human judgment when tools are over-trusted; and the challenge of explainability in contexts requiring accountability. Weiner (2026) emphasises that if a model cannot be explained, there will be a lack of trust in the solution, and the project will fail.

Third, the adoption of AI itself can become a bad practice if pursued uncritically. Organisations that implement AI without addressing underlying governance, cultural, and capability issues may find that technology amplifies rather than solves their problems. Weiner (2026) notes that the barriers to AI adoption—governance gaps, data quality issues, skills shortages, and cultural resistance—are symptoms of the same organisational weaknesses that produce bad practices.

Fourth, there is a risk that AI may perpetuate the very bad practices it is intended to address. If historical data reflects systematic underestimation, AI models will learn and reproduce this bias. If organisational culture rewards the appearance of busyness, AI-optimised resource allocation may accelerate burnout. If governance is weak, AI-generated insights may be selectively deployed to justify predetermined conclusions.

4.3 Implications for Practice

For practitioners, the implications of this review are clear. First, AI should be adopted as a complementary tool rather than a replacement for judgment. The most effective applications of AI in project management are likely to be in areas where it can augment human capabilities—improving forecasting accuracy, identifying patterns, automating routine tasks—rather than in areas requiring judgment, empathy, and ethical reasoning.

Second, governance frameworks for AI adoption in project management must be developed. These should address data quality, algorithmic transparency, privacy and security, and the distribution of decision-making authority between humans and machines. Salimimoghadam et al. (2025) recommend starting with small-scale pilots to build confidence in AI tools while refining processes and minimising risks.

Third, the human dimensions of project management require renewed attention. The ability to say no, to communicate effectively, to manage stakeholder relationships, to sense the state of the team, and to navigate political complexity are skills that no algorithm can replace. As AI takes over more routine tasks, the human dimensions of project management may become even more critical.

Weiner (2026) recommends five methods to avoid common pitfalls in AI and data science projects: (1) ask questions, (2) get alignment, (3) keep it simple, (4) leverage explainability, and (5) have the conversation. These methods address the five common pitfalls of too big a scope, scope creep, unexplainable models, overly complex models, and solving the wrong problem. Blumhorst (2010) emphasises that organisations must avoid implementing a tool without a process and implementing a process without a tool; the best approach is to implement the process and tool simultaneously.

4.4 Limitations

This review has several limitations. First, the exclusion of conference papers and grey literature may have resulted in the omission of relevant studies, although this decision was made to ensure the quality and peer-review status of included sources. Second, the restriction to English-language publications may have excluded relevant research from non-English-speaking contexts. Third, the scoping review methodology does not include a formal quality appraisal of included studies, which limits the ability to make definitive claims about the strength of evidence. Fourth, the rapidly evolving nature of AI technologies means that some findings may become outdated as new tools and approaches emerge.

4.5 Future Research Directions

Future research should examine the interaction between AI adoption and project management practices, investigating both the benefits and the unintended consequences of technological integration. Particular attention should be paid to the organisational and cultural factors that enable or constrain the effective use of AI, and to the development of governance frameworks that ensure AI is used ethically and effectively. Longitudinal studies tracking organisations through their AI adoption journeys would be particularly valuable in understanding how the relationship between AI and project management practices evolves over time.

Specific research questions include: (1) Under what conditions do AI tools improve project outcomes, and through what mechanisms? (2) How do organisations effectively integrate AI into existing project management processes without introducing new forms of failure? (3) What governance frameworks are most effective for ensuring ethical and responsible AI use in project management? (4) How does the adoption of AI affect the human dimensions of project management, including team dynamics, communication, and leadership?

5. Conclusion

This article has examined twenty common bad practices in project management, extending the ten practices articulated by Escofet (2016) through a scoping review of contemporary research published between 2021 and 2026, supplemented by practitioner sources on PMO failures (Blumhorst, 2010) and AI project pitfalls (Weiner, 2026). The bad practices identified fall into four thematic clusters: planning and estimation failures, resource and scope management failures, governance and communication failures, and execution and delivery failures.

The following conclusions emerge from this analysis:

First, the persistence of bad practices is not primarily a knowledge problem. Cognitive biases such as the planning fallacy, sunk cost fallacy, and optimism bias are deeply embedded in human decision-making and resist purely technical solutions. Methodical approaches like Choosing by Advantages (Haronian and Korb, 2024) and increased awareness of present bias (Li and Yu, 2023) can help, but these require organisational commitment and cultural change.

Second, AI adoption is itself subject to the same bad practices that afflict project management. Organisations may adopt AI without adequate assessment of its impact, make unrealistic promises about its benefits, fail to identify dependencies on data quality and skills, and rely on simplistic metrics to evaluate its effectiveness. The barriers to AI adoption—governance gaps, data quality issues, skills shortages, and cultural resistance—are symptoms of the same organisational weaknesses that produce bad practices.

Third, AI should be adopted as a complementary tool rather than a substitute for judgment. Carpenter et al. (2024) demonstrated that LLMs can provide flexible, user-friendly estimation tools that complement rather than replace traditional methods. Yamuna and Nighojkar (2026) found that hybrid AI models can reduce prediction errors by 80–92%, but emphasised that current models use a static methodology and do not take project phases into consideration.

Fourth, the human dimensions of project management require renewed attention. The ability to say no, to communicate effectively, to manage stakeholder relationships, to sense the state of the team, and to navigate political complexity are skills that no algorithm can replace. Weiner (2026) emphasises that having the conversation with customers and stakeholders is perhaps the most important method for avoiding project pitfalls.

Fifth, governance frameworks for AI adoption in project management must be developed. These should address data quality, algorithmic transparency, privacy and security, and the distribution of decision-making authority between humans and machines. The ‘trust but verify’ norm is essential, but it must be institutionalised through governance structures rather than left to individual discretion.

For practitioners, the implications are clear: AI should be adopted as a complementary tool rather than a replacement for judgment, and its implementation should be accompanied by investments in data quality, skills development, and governance frameworks. For researchers, the challenge is to develop

empirical evidence on the conditions under which AI tools improve project outcomes and the mechanisms through which they do so.

Declarations

Conflicts of interest

The authors declare no conflicts of interest in the elaboration of this article.

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