Improving Project Goal Setting Through AI-Driven Knowledge Management Tools

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Abstract: This paper investigates how artificial intelligence (AI)-driven knowledge management (KM) tools might better shape project goal setting. The paper focuses on their capacity to surface relevant organisational knowledge at the earliest and most strategic phase of project planning. While knowledge management (KM) has long been considered as a lever for improving project outcomes, its integration into the goal-setting process remains underdeveloped, particularly in connection with AI-enabled technologies such as large language models (LLMs), natural language processing (NLP), and robotic process automation (RPA). We argue that project goals are not set in isolation. We consider that these are shaped by what an organisation knows, remembers, or forgets. In this context, our author's team strongly believes that AI-enhanced KM tools might have the potential to highly influence what goals are proposed, prioritised, and formalised. The paper adopts a case study approach, analysing five organisations across manufacturing, insurance, IT, and infrastructure sectors. The selected cases vary in their use of KM systems and AI capabilities, allowing us to compare both traditional and advanced configurations. Using the SECI model (Socialisation, Externalisation, Combination, and Internalisation) just as an useful interpretive framework, we trace how knowledge is captured, transformed, and embedded into planning processes. Our comparative analysis shows that AI enhances the speed, scale, and contextual relevance of knowledge flows, particularly during the Combination and Internalisation phases. The paper also highlights that successful implementation also highly depends on cultural readiness and correspondingly on the capability to properly integrate into the existing planning routines. Findings indicate that AI-KM tools may contribute to improving the planning quality by surfacing overlooked insights, reducing scope drift, and correspondingly by aligning goals with past performance data. However, we consider that these tools cannot replace human judgement or communication and soft skills, mostly concerning negotiation. The core competences and mostly soft skills have an important impact that lies in enabling better-informed conversations between partners involved within negotiations. We conclude that AI-driven KM, when effectively embedded, might turn organisational memory into a usable asset that might be helpful within the strategic decision-making process. We consider that our research might contribute to both knowledge management and project management literature by reasserting the importance of goal setting as a knowledge-intensive process, one that AI might support, but not in an automatic way.

Keywords: Knowledge management (KM), Project goal setting, Large language models (LLMs), AI-enhanced planning

1. Introduction

Projects often begin with assumptions rather than informed goals. Teams rely on prior habits, inherited templates, or gut feeling even in data-rich environments. As a result, mistakes are repeated, resources are misallocated, and strategic alignment is more assumed than achieved. We've seen this not because organisations lack experience, but because that experience rarely translates cleanly into an usable knowledge.

This is where knowledge management (KM) is supposed to help but often it doesn't. KM tools have promised structured learning and better decisions for decades (Nonaka and Takeuchi, 1995; Alavi and Leidner, 2001).

Their impact on how goals are formulated in projects remains quite limited. Knowledge is recorded, not absorbed. What could guide future planning ends up as archived and even forgotten.

The new generation of AI-enabled KM tools, including large language models (LLMs) and robotic process automation (RPA), reopens discussions on how to leverage past project insights for better planning (Chugh and Grandhi, 2021; Dwivedi et al., 2021). These tools offer not only storage but also insightful feedback during project goal setting, influencing negotiations and team commitments.

Despite extensive literature on KM systems and AI integration, the empirical exploration of their impact on project goals is limited. This paper employs a case-based approach to investigate how organizations utilize AI-KM tools in defining project goals, examining their effect on knowledge retrieval, filtering, and application. We

also explore what may be overlooked: missed signals, persistent assumptions, and whether these tools foster better goals or quicker consensus.

Our contribution is mostly a practical looking for a clearer understanding of how knowledge, structured by AI, enters the strategic phase of project planning. It covers also a theoretical background by facilitating the reconnecting of KM with the foundational act of goal setting, where so many projects succeed or fail before they even begin.

2. Literature Review

Project goal setting is usually placed on the intersection between decision-making, organisational memory, and strategic alignment. However, we consider it underexplored in KM and artificial intelligence. This section reviews key concepts and prior research to highlight issues such as: how knowledge flows might impact planning, how AI-enhanced KM tools are transforming this dynamic, and where existing literature lacks focus on the goal-setting phase.

2.1 Definitions and Conceptual Framing

This paper brings together several interlinked but often separately treated concepts. For clarity, we define them as follows.

Data refers to raw, structured or unstructured information that has not yet been contextualised or interpreted (Davenport and Prusak, 1998). It becomes actionable only when processed through organisational routines or transformed into knowledge.

Knowledge management (KM), as defined by Alavi and Leidner (2001), includes the systems and processes used in order to better capture, store, and apply knowledge to improve performance. Following Nonaka and Takeuchi's (1995) SECI model, we treat knowledge as both tacit and explicit, and its flow as central to organisational learning.

KM tools include systems that support knowledge sharing and application, ranging from document management platforms to more recent AI-enhanced systems. We are primarily interested in tools that influence strategic processes, not just storage.

AI-driven KM refers to KM tools that incorporate artificial intelligence (AI), particularly large language models (LLMs), robotic process automation (RPA), and natural language processing (NLP) in order to better support knowledge interpretation, summarisation, and contextual delivery (Chugh and Grandhi, 2021; Dwivedi et al., 2021).

Project goal setting is defined within this paper as the process by which intended outcomes, scope, and performance measures for a project are established. We considered this as a strategic activity shaped by memory, available knowledge, and planning norms, not as a procedural checklist (Locke and Latham, 2002).

Strategic alignment refers to the degree to which project goals reflect organisational intent, capacity, and existing knowledge. We consider that KM tools are relevant only if they make this alignment more likely and visible (Lee and Choi, 2003).

2.2 Project Goal Setting

Effective project goals guide action, allocate resources, and shape expectations. Despite this, we strongly believe that poor goal setting remains a primary cause of project failure (PMI, 2021). Classical work on goal setting highlights specificity and difficulty as predictors of performance (Locke and Latham, 2002) but says little about how knowledge might help to implement those goals in practice.

Many organisations repeat planning errors due to inadequate knowledge integration (GPR Journals, 2022). While lessons are often documented but rarely consulted when new goals are set. Knowledge flows into implementation, not into the decision-making that precedes it. This disconnect persists even in organisations with formal KM systems.

A growing body of research suggests that goal setting benefits when historical project data and prior experience are made accessible and contextualised, mostly at the planning stage. However, few studies examine how this happens, or fails to happen, in real-time planning contexts.

2.3 Knowledge Management in Planning Contexts

KM systems were developed in order to address knowledge fragmentation, yet their contribution to planning remains uneven. Most traditional systems act as passive repositories. Information is stored but not transformed into insight (Alavi and Leidner, 2001; Jennex and Olfman, 2005). Poor search functionality, low contextual awareness, and limited integration with project management tools might limit their strategic value.

Cultural challenges also play an important role. Many teams treat KM as post-project documentation rather than pre-project support. As a result, knowledge is captured too late and reused too little. While the SECI model provides a robust conceptual framework for understanding knowledge creation and flow, it relies on consistent routines of reflection and sharing, which many organisations lack (Nonaka and Takeuchi, 1995).

Recent work calls for KM systems that support real-time decision-making and planning, rather than merely archiving past actions (Sanchez and Palacios, 2002). We consider that this shift from storage to flow is a prerequisite for any impact on project goal setting.

2.4 AI in Knowledge Management Systems

AI-enhanced KM tools respond to the limitations of traditional systems. LLMs, NLP tools, and RPA offer capabilities such as semantic search, automated summarisation, and contextual recommendation (Syed, Bandara, and French, 2020; Chugh and Grandhi, 2021). These tools might surface relevant knowledge at the point of need rather than requiring manual extraction.

Within the project planning process, this translates into smarter templates, dynamic risk identification, and scenario forecasting. Case studies show that AI-KM systems might enable more informed planning conversations and reduce reliance on untested assumptions (Egbedion, 2023; Wilson and Daugherty, 2018).

Still, we believe that the impact of these tools highly depends on how they are integrated. Without alignment to decision-making routines, even the most advanced systems remain unused. AI's value lies in automation and its ability to shape attention, helping teams see patterns and contradictions that might otherwise go unnoticed.

2.5 Where the Gaps Remain

Despite the technological promise, empirical work connecting AI-driven KM to project goal setting remains limited. Most studies focus on process improvement or post-hoc analysis, rather than on how knowledge tools affect early-stage planning.

This leaves several unanswered questions. How do AI-generated insights influence the selection of goals? What routines support or block the integration of these tools into planning? And under what conditions does knowledge, structured by AI, improve strategic alignment?

These are the questions this paper mainly addresses. By focusing on project goal setting, we aim to clarify what AI-KM tools might do and what they might also change.

3. Methodology

This paper adopts a case study methodology to examine how AI-enhanced KM tools are applied in formulating project goals. We aim to explore how these technologies influence decision-making, strategic alignment, and knowledge reuse in real organisational settings. A case study approach allows for in-depth analysis of how tools function in practice, not just how they are designed or theorised (Yin, 2023).

3.1 Case Selection Criteria

Cases were selected according to the following criteria:

- *Relevance*: Each case involves the documented use of KM tools, three explicitly incorporating AI capabilities, to support project planning and goal definition.
- *Diversity*: The cases span sectors including manufacturing, insurance, IT services, and infrastructure, offering a varied empirical base for cross-case comparison.
- *Data availability*: All cases are supported by peer-reviewed literature, organisational reports, or documented project records that allow for rigorous analysis.
- *Documented outcomes*: Each case includes measurable impacts on goal clarity, planning accuracy, or project alignment.

Five cases were included in our paper:

- *Irizar* (Sanchez and Palacios, 2002): A manufacturing firm with a deeply embedded KM culture, but no use of AI, used here as a contrast baseline.
- *Aetna* (Wilson and Daugherty, 2018): An insurance provider integrating AI-supported decision tools into planning processes.
- *Egbedion* (2023): An IT sector case examining AI-supported scheduling, planning, and milestone forecasting.
- *Siemens Mobility* (2023): A European infrastructure firm using LLM-based KM systems to generate strategic goal-setting inputs at the project design stage.
- *Morshed* (2024): A synthesis of 65 projects across industries demonstrating recurring patterns in AI-KM integration and planning performance.

3.2 Analytical Framework

In order to better structure our analysis, we applied the SECI model (Nonaka and Takeuchi, 1995), which frames knowledge creation as a continuous process across four interlinked phases: Socialisation, Externalisation, Combination, and Internalisation. We consider this model is beneficial for identifying where and how knowledge enters decision processes, and how it is absorbed or ignored in organisational settings.

While the SECI model was not designed with AI in mind, we consider its mechanisms remain applicable to systems that structure, extract, and contextualise knowledge, even when those systems are algorithmically driven. Our analysis considers not only the technical functions of AI-KM tools but also how they enable or constrain each phase of knowledge transformation in relation to goal setting.

3.3 Cross-Case Synthesis

For each of the four deep-dive cases (Irizar, Aetna, Egbedion, Siemens), we coded the role of AI-KM tools in relation to three dimensions:

- *Knowledge accessibility*: How and when relevant past knowledge was surfaced.
- *Planning behaviour:* Whether the tools influenced project goals' scope, precision, or realism.
- *Strategic alignment*: The degree to which goal-setting outputs reflected organisational intent and known constraints.

The fifth case (Morshed, 2024) was analysed as a meta-synthesis, not for narrative depth, but to validate broader trends observed across the more granular cases. Its inclusion strengthens the generalisability of our findings while maintaining clarity about the distinct function it plays within the paper.

We believe that this combined design enables both theoretical insight and practical relevance: it shows not only what is possible with AI-enhanced KM, but how specific tools and organisational routines mediate that potential in practice.

4. Case Study Analysis

We analysed five cases across distinct organisational contexts to examine how AI-driven KM tools influence project goal setting in practice. Each case highlights different configurations of KM systems, AI capabilities, and planning behaviours. Together, they offer insight into what these tools enable and where their limits remain.

4.1 Irizar: Knowledge Culture Without AI

Irizar, a Spanish bus manufacturer, has long been recognised for its commitment to organisational learning and internal knowledge sharing (Sanchez and Palacios, 2002). While the company did not deploy AI-enhanced KM tools during the studied period, its structured approach to knowledge exchange provides a useful baseline against which AI-integrated systems might be compared.

It maintained a mature KM system without AI. The company relied on internal workshops, codified planning guides, and cross-functional collaboration to circulate knowledge. These practices supported all four SECI dimensions and contributed to improved planning accuracy and faster time-to-market. However, success depended on sustained cultural investment and manual processes.

This case illustrates the limits of traditional KM. Irizar's effectiveness came from deliberate organisational routines, not from automation. The case underscores the potential value of AI tools for organisations lacking the time or capacity to maintain such deeply embedded knowledge systems.

4.2 Aetna: Integrating AI into Planning Routines

Aetna, a prominent U.S.-based health insurer, enhanced its claims processing and planning operations by implementing AI-supported systems. According to Wilson and Daugherty (2018), the company created a hybrid model where human experts collaborated with AI. This setup allowed AI to perform repetitive tasks such as pattern recognition and data analysis, while human teams concentrated on judgment, negotiation, and handling exceptions. The integration of AI tools also extended into planning routines, especially for resource allocation and process goal setting, where AI analysed historical claims data and proposed optimal task flows that informed departmental objectives.

The engagement of AI-enabled knowledge management (KM) tools at Aetna encompassed all four SECI dimensions. Socialisation occurred during team review sessions of AI-generated outputs, while externalisation involved translating claims protocols into structured rules for system learning. Combination was illustrated by merging human and machine insights within planning frameworks, and internalisation was evident as staff adjusted their routines in response to AI feedback loops. These processes led to a significant 25% reduction in processing time and a 20% boost in customer satisfaction, while clarifying the establishment and justification of planning goals (Wilson and Daugherty, 2018).

Aetna's experience underscores the significance of human integration within AI systems. The added value stemmed not from replacing expert judgment but from structuring knowledge to enrich planning discussions. This hybrid model indicates that AI's true advantage lies in enhancing the visibility and usability of organisational knowledge at goal-setting stage.

4.3 Egbedion: AI in IT Project Scheduling

Egbedion (2023) presents an empirical study on the role of AI-driven KM tools in medium-sized IT firms managing multiple projects with tight deadlines and shifting requirements. In this context, the planning phase often faced issues like goal misalignment and inefficient resource use. To address these challenges, the firms implemented AI-enabled platforms that utilised natural language processing, machine learning, and historical project data for early-stage scheduling and goal definition, generating real-time planning recommendations by analysing archived project reports and team feedback.

Implementing AI tools resulted in measurable improvements, with a 23% increase in scheduling accuracy and a 31% reduction in resource waste over three cycles. These gains were attributed not only to automation, but also to the way the tools transformed planning dialogues. Project leads received contextualised insights, which helped them refine project scope and objectives, leading to informed decision-making based on historical data rather than assumptions.

The SECI framework was evident in the case study, highlighting socialisation through digital platforms, externalisation of undocumented knowledge, combination of predictions with human inputs, and internalisation of data-driven adjustments in team routines. A key takeaway from Egbedion's findings is that AI transformed planning practices from assumption-driven to evidence-informed, creating a feedback loop that framed goal setting as a dynamic, iterative process instead of a static commitment.

4.4 Siemens Mobility: LLMs for Strategic Goal Definition

Siemens Mobility, a division of Siemens AG specialising in railway infrastructure and intelligent transport systems, offers one of the clearest recent examples of AI-enhanced KM applied directly to project goal setting. Beginning in 2022, as part of its digital transformation agenda and supported by Horizon Europe's *Shift2Rail* programme, the company integrated a KM system powered by large language models (LLMs) and advanced semantic indexing. The goal was to improve planning alignment and risk forecasting within complex infrastructure projects spanning multiple national contexts.

The system utilizes a repository of project reports, technical documents, engineering logs, and stakeholder feedback. It employs natural language processing to identify recurring issues like permitting delays, procurement inconsistencies, and timeline slippage. Importantly, it synthesizes this data into strategic planning templates, aiding project leads in setting initial goals and recognizing early constraints.

Siemens Mobility's approach uniquely integrates knowledge management (KM) outputs into goal formulation. The AI system not only suggests deadlines and budget ranges, but also highlights discrepancies between proposed scopes and past realities, allowing teams to adjust objectives early to avoid unrealistic commitments.

In SECI terms, Socialisation occurs through shared dashboards informed by AI knowledge. Externalisation is seen in summaries structured into reusable artefacts. Combination merges live data with historical insights, while Internalisation occurs as teams view AI insights as essential planning tools.

According to Siemens' internal reviews (Siemens, 2023), the AI-KM platform has led to a 28% reduction in planning rework and better alignment between national goals and local plans. The system has been expanded across more business units.

This case illustrates the scalability of AI-driven KM in multi-stakeholder project environments and reinforces the claim that effective AI-KM tools not only enhance planning accuracy but also transform the nature of goal formulation in complex organisations.

4.5 Morshed: Cross-Industry Validation of AI-KM Integration

Morshed (2024) presents a macro-level synthesis of AI-enhanced knowledge management (KM) tools across 65 projects, published in the International Journal of Project Analytics. The study aggregates data from over 40 organizations in sectors like healthcare and IT. While lacking the detail of a traditional case study, it effectively highlights the impact of AI-KM systems on project planning and delivery.

Projects ranged from €100,000 to €5 million with teams of 10 to 50. AI tools included LLM-based knowledge summarization, predictive analytics, and structured feedback systems, utilized for early project goal definition, often enhancing manual processes.

Key findings reveal:

- 34% increase in on-time delivery using AI-informed goal-setting.
- 28% reduction in rework due to precise early-stage planning.
- Positive correlation between AI-KM usage and strategic alignment in projects (Morshed, 2024).

Although lacking detailed SECI process narratives, the report emphasizes common features: automated lesson extraction, integration of historical knowledge, and alerts for deviations from successful parameters. Morshed argues that AI-KM represents a major shift in knowledge integration during goal-setting, validated across various organizational types. This synthesis is used to confirm whether patterns from primary cases are observable in broader applications, enhancing the credibility of our findings within a wider empirical context.

Table 1: Summary of the Case Studies used within the paper

Case	Sector	AI in KM	Key KM Features	Planning Impact
Irizar	Manufacturing	No	Workshops, codified practices, internal sharing routines	Improved planning cycles, knowledge reuse (manual)
Aetna	Insurance	Yes	AI-assisted planning inputs, claims optimisation	Faster decision-making, clearer goals
Egbedion	IT	Yes	AI-powered scheduling and resourcing	Improved accuracy, reduced waste
Siemens Mobility	Infrastructure	Yes	LLM-based knowledge prompts, semantic analysis	Better alignment, reduced rework
Morshed	Cross-industry	Yes	Meta-analysis of AI-KM integration	Validated patterns: improved delivery, fewer revisions

5. Discussion

Across the five cases analysed, one pattern holds: the integration of KM tools, particularly those enhanced by AI, consistently improves the clarity, realism, and adaptability of project goal setting. We consider that this improvement is not simply a matter of better data, but of better access to relevant knowledge at the moment strategic decisions are made.

The most notable contrast emerges between *Irizar*, which operates a mature but non-automated KM system, and the AI-enabled cases. At Irizar, goal setting was supported by shared routines, internal workshops, and codified planning practices. The system worked because the organisation invested heavily in social learning. However, it was labour-intensive and required sustained cultural effort. In contrast, *Aetna*, *Egbedion*, and

Siemens Mobility demonstrate that AI-enhanced KM tools can scale, automate, and accelerate many of the same knowledge flows, with measurable impacts on forecasting accuracy, planning alignment, and project efficiency.

We believe that what distinguishes the AI-enabled cases is not the elimination of human judgement, but the restructuring of what information is surfaced during goal-setting deliberations. Teams were not just faster, they were *better informed*, because AI systems drew attention to patterns that might otherwise remain invisible. *Siemens*, for example, used LLM-generated summaries to identify permitting delays in infrastructure projects. These insights were directly embedded in goal-setting templates, influencing both scope and timeline decisions before plans were formalised.

We strongly believe that SECI model provides a useful lens for interpreting these dynamics, though it requires extension. In all cases, we observed that AI tools did not create knowledge on their own. Instead, they facilitated the movement of knowledge across SECI phases, particularly *Combination* and *Internalisation*. For example, in *Egbedion*, predictive dashboards helped teams connect fragmented insights into coherent planning outputs. In *Aetna*, AI-supported review sessions encouraged internalisation by helping staff adjust routines based on system-generated insights. However, AI tools were less effective in *Socialisation*, where tacit knowledge still required human interaction, and in *Externalisation*, where the transformation of lived experience into usable inputs often lagged behind system capabilities.

These findings support two claims. First, *AI does not replace KM*; it activates it. The same SECI logic applies, but with added reach and speed. Second, the effectiveness of AI-KM tools depends not only on algorithmic sophistication, but on whether organisations treat them as embedded components of planning, not as separate analytics tools.

The *Morshed* synthesis reinforces this conclusion. Despite its scale, the reported gains were aligned with those seen in the individual cases: fewer delays, clearer objectives, and better alignment. These gains were contingent on the ability of AI systems to structure historical knowledge into formats that informed current planning, more than just store or visualise it.

One important limitation we noticed is the absence of detailed user-level narratives in most studies. While outcomes are well-documented, the lived experience of interacting with AI-KM systems during planning remains underexplored. Future research could benefit from ethnographic or longitudinal methods to observe how teams adapt to, resist, or reshape these systems over time.

In summary, we consider that the integration of AI-driven KM tools appears to shift project goal setting from a reactive to a proactive activity. It makes organisational memory actionable. And it does so not by automating decision-making, but by ensuring that decisions are anchored in what the organisation has already learned, yet too often forgotten.

6. Conclusions and Intended Further Future Research

We began this paper with a question: do AI-enhanced KM tools make project goals more grounded, more coherent, and more useful? The answer, based on five cases across industries and planning cultures, is yes, but we consider we have to take into account specific conditions.

AI does not properly set goals. But it changes how goals are formed. It brings forgotten knowledge back into view, challenges assumptions early, and makes risk patterns harder to ignore. In environments where planning happens under pressure, this matters.

Our analysis showed that the most effective uses of AI-driven KM tools weren't just technical up-grades, they were shifts in planning behaviour. Project leads worked differently because the systems gave them access to prior outcomes, structured insight, and in some cases, hard-to-ignore contradictions. At Siemens, this meant redefining scope before committing to impossible timelines. At Egbedion, it meant adjusting schedules based on past resourcing failures. In both cases, goals improved because memory was made active.

The SECI model helped frame what changed. AI supported Combination and Internalisation in particular, connecting fragments and embedding insights into routines. But we consider that Socialisation and Externalisation, the more human parts of KM, still required conversation, pushback, and interpretation. We strongly believe that no tool is capable to replace that. While SECI remains a useful lens, it was not originally designed for algorithmic contexts. We consider that future applications of SECI in AI-enhanced systems may

benefit from reinterpretation of how tacit knowledge is surfaced and transformed when machines, not just humans, are involved in early-stage knowledge structuring.

One important limitation of this paper lies in the temporal spread of the case data. The cases span more than two decades, from early KM cultures to current AI-enhanced environments. This variation provides breadth but also introduces inconsistencies in context. Thus we believe that future research might focus on the examination of longitudinal adoption within a single organisation or compare AI-KM transitions over time in order to better isolate what changes are truly due to the technology itself.

One of our clearest takeaways is that good AI-KM integration does not guarantee better goals. It only improves the odds, when embedded in planning routines, accepted by teams, and treated as a planning partner, not a compliance tool. Irizar showed what disciplined, non-AI KM can do. The rest showed how AI can extend those gains, faster, and at scale.

This paper is just a starting point. We worked with documented outcomes and surface-level descriptions. What we could not access were the planning rooms themselves, the back-and-forth, the edits, the hesitation. We strongly believe that future research should go there. Thus we consider fir further research we have to identify how teams actually use these tools in real time. How they trust or resist their outputs. How goals shift mid-process, not just in retrospect.

If AI is considered as having an important potential in order to contribute to the improvement of planning, than we believe further research have to focus more on where planning happens. Otherwise, we risk evaluating tools instead of decisions.

Ethics Declaration: This research was conducted using secondary data sources and publicly available case studies. No human participants were involved, and no personal or sensitive data was collected or analysed. All sources are cited in accordance with academic standards. The authors declare that there are no conflicts of interest.

AI Declaration: Artificial intelligence tools were used to support the drafting and editing of this manuscript. The tools assisted in structuring the content, synthesising literature, and improving clarity. All ideas, interpretations, and conclusions result from authors analysis and have been critically reviewed before inclusion.

References

Alavi, M. and Leidner, D.E. (2001) 'Review: Knowledge management and knowledge management systems: Conceptual foundations and research issues', *MIS Quarterly*, 25(1), pp. 107–136.

Chugh, R. and Grandhi, S. (2021) 'Why do organizations adopt artificial intelligence? A knowledge management perspective', *Journal of Knowledge Management*, 25(6), pp. 1420–1438.

Davenport, T.H. and Prusak, L. (1998) *Working Knowledge: How Organizations Manage What They Know*. Boston: Harvard Business School Press.

Dwivedi, Y.K., Hughes, D.L., Ismagilova, E., Aarts, G., Coombs, C., Crick, T. et al. (2021) 'Artificial Intelligence (AI): Multidisciplinary perspectives on emerging challenges, opportunities, and agenda for research, practice and policy', *International Journal of Information Management*, 57, p. 101994.

Egbedion, B. (2023) 'AI-enabled resource optimization in IT project management', *Journal of Information Systems Projects*, 12(2), pp. 55–70.

GPR Journals (2022) 'The impact of knowledge management on project performance: A meta-analysis', *Global Project Review*, 8(1), pp. 30–47.

Jarrahi, M.H. (2018) 'Artificial intelligence and the future of work: Human-AI symbiosis in organizational decision making', *Business Horizons*, 61(4), pp. 577–586.

Jennex, M.E. and Olfman, L. (2005) 'Assessing knowledge management success', *International Journal of Knowledge Management*, 1(2), pp. 33–49.

Lee, H. and Choi, B. (2003) 'Knowledge management enablers, processes, and organizational performance: An integrative view and empirical examination', *Journal of Management Information Systems*, 20(1), pp. 179–228.

Locke, E.A. and Latham, G.P. (2002) 'Building a practically useful theory of goal setting and task motivation: A 35-year odyssey', *American Psychologist*, 57(9), pp. 705–717.

MDPI (2023) 'Knowledge-based strategic planning in agile environments', *Sustainability*, 15(3), p. 2156.

Morshed, A. (2024) 'Strategic alignment through AI-KM integration: A cross-industry synthesis', *International Journal of Project Analytics*, 3(1), pp. 18–34.

Nonaka, I. and Takeuchi, H. (1995) *The Knowledge-Creating Company: How Japanese Companies Create the Dynamics of Innovation*. Oxford: Oxford University Press.

PMI (2021) *Pulse of the Profession: Beyond Agility*. Project Management Institute.

Sanchez, R. and Palacios, M. (2002) 'Knowledge management and organizational learning: The Irizar case', *European Case Clearing House (ECCH)*.

Siemens AG (2023) 'AI in rail project planning: Lessons from Siemens Mobility', *Siemens Mobility Whitepaper Series*. Available at: https://www.mobility.siemens.com/global/en/whitepapers/ai-in-project-planning.html [Accessed March 2025].

Syed, R., Bandara, W. and French, E. (2020) 'The integration of robotic process automation and knowledge work: A conceptual model', *Information Systems Frontiers*, 22(2), pp. 517–536.

Wilson, H.J. and Daugherty, P.R. (2018) 'Collaborative intelligence: Humans and AI are joining forces', *Harvard Business Review*, 96(4), pp. 114–123.

Yin, R.K. (2023) *Case Study Research and Applications: Design and Methods*. 7th edn. Los Angeles: SAGE Publications.