From Conventional to Cutting-Edge: A Comparative Study of AI-Enhanced and Traditional Management of Innovation Projects

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Abstract

Innovation projects increasingly rely on advanced technologies to remain competitive, with Artificial Intelligence (AI) emerging as a transformative tool in their management. While traditional approaches are grounded in human intuition and experience, AI offers data-driven support for tasks such as idea generation, resource allocation, and trend detection. This study aims to evaluate the impact of AI on the management of innovation projects and to compare AI-enhanced methods with traditional approaches across different project phases. A mixed-method research design was applied. First, a bibliometric analysis using the Web of Science database was conducted to identify leading research trends, institutions, and collaborations related to AI and the management of innovation projects. Second, a focused literature review of studies published between 2019 and 2024 examined how AI tools are being applied across various phases of innovation projects. The results indicate that AI significantly improves efficiency by automating processes, enabling earlier trend recognition, and supporting more accurate decision-making. However, its integration faces barriers, including technical complexity, data quality limitations, and ethical concerns. The study concludes that AI cannot fully replace human creativity and strategic thinking, but can effectively comple-

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ment them. A hybrid approach, combining AI's analytical capabilities with human judgment, is recommended for the management of innovation projects. Future research should focus on developing and testing such hybrid models, with attention to explainable AI, ethical decision-making, and the role of AI in supporting collaboration within geographically dispersed teams.

Keywords: innovation projects, artificial intelligence, project management, bibliometric analysis, comparative analysis

JEL codes: O31, O32, O33, M15, C88

Introduction

Innovation is a key area of interest for both leading researchers and consulting firms. One study found that 87% of executives consider innovation essential to their organisation's success and growth (Halme, 2023). The same study estimated that companies actively fostering a culture of innovation are 3.5 times more likely to outperform their competitors (Halme, 2023). Additionally, numerous scientific works (Đorđević-Boljanović, 2009; Hana, 2013; Dereli, 2015; Ionescu & Dumitru, 2015; Distanont, 2020) recognise innovation and innovation projects as key drivers for achieving and sustaining competitive advantage. In the business environment, innovation emerges at the intersection of creativity and improvement (Gallagher, 2015). Various models outline different phases in managing innovation projects. Organisations increasingly rely on structured approaches to manage these projects, aiming to bring new products, services, or processes to market efficiently. Effective management of innovation projects ensures optimal use of resources, mitigates risks, and aligns project outcomes with broader strategic goals.

Meanwhile, the AI market is projected to exceed 196 billion dollars in 2024, with expectations that the industry will grow more than thirteenfold over the next six years (Howarth, 2024). This rapidly evolving technology not only simplifies business processes but also encourages innovation (Garhwal, 2024), supporting the development of new products and services (Voora, 2023; GreenLeaf, 2024; Sainger, 2024).

This paper investigates how AI technologies can complement or replace traditional methods in the management of innovation projects.

The research is guided by two research questions:

- **RQ1:** How does the use of AI tools affect the management of innovation projects compared to traditional methods?
- **RQ2:** What challenges and opportunities arise when implementing AI tools in the management of innovation projects?

This exploratory study synthesises and analyses existing literature to investigate how AI enhances decision-making, efficiency, trend detection, risk management, and creativity, while addressing the limitations of AI integration. It also emphasises the continuing importance of human intuition, creativity, and ethics. The main contribution of this research is a deeper understanding of how AI can enhance the management of innovation projects without replacing the human elements critical to their success.

1. Theoretical background

The theoretical discussion that follows establishes the conceptual groundwork for examining AI's intersection with management of innovation projects. Section 1.1 addresses innovation and innovation projects themselves: what defines them, how they differ from conventional projects, and how the innovation project lifecycle unfolds. Section 1.2 then turns to AI, its nature, capabilities, and emerging applications, and examines how AI technologies map onto different phases of innovation work and different models of innovation management. Together, these sections provide an integrated foundation for analysing how AI and managerial practices co-evolve within innovation project contexts.

2. Innovation and innovation projects

An increasing number of organisations are structuring their operations through project-based approaches, and the domain of innovation is no exception. Innovation has been defined from diverse perspectives: economic, managerial, engineering, social, and legal. Despite these varied viewpoints, common elements include the nature of change, its scale, source, and impact (Stošić & Milutinović, 2022). One of the earliest and most influential contributors to this field is Schumpeter, who emphasised the centrality of entrepreneurial innovation in driving economic development (Sweezy, 1943; Śledzik, 2013; Milutinović, 2020; Ziemnowicz, 2020; Stošić & Milutinović, 2022).

In this paper, innovation is defined as the process of creating value by applying knowledge and resources to transform an idea into a new or improved product, process, or practice (Artto et al., 2008; Varadarajan, 2018), or simply as turning an idea into practical use (Stošić & Milutinović, 2022). It can be understood as a result, a process, and a mindset (Kahn, 2018), where outcomes stem from thought-driven activities.

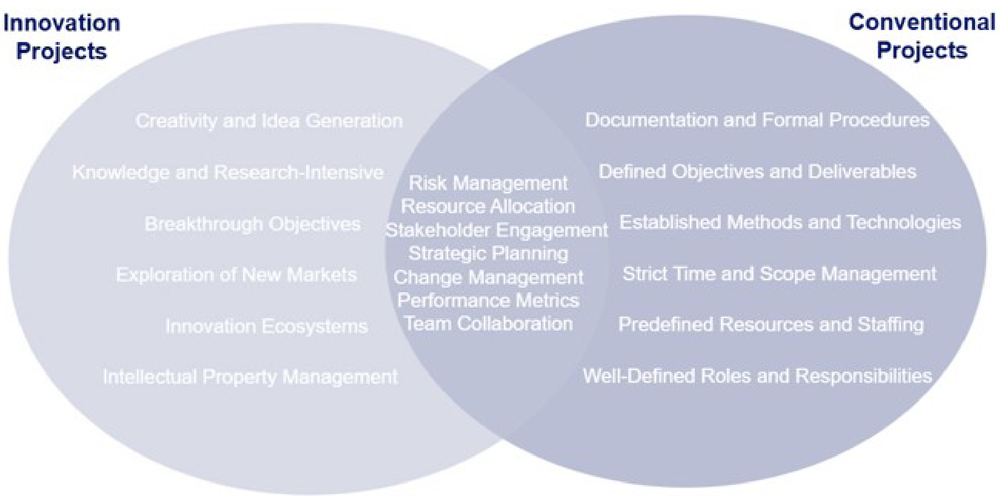
Framing innovation as a sequence of interconnected activities has led to the concept of innovation projects (Milutinović, 2020). Kerzner (2022) asserts that creative ideas must be realised through projects and their specific management frameworks. In practice, project management has proven to be the most effective way to manage innovation efforts (Stošić & Milutinović, 2017).

Innovation projects emerge from combining the concepts of "innovation" and "project." Drucker (1998) defines innovation as a discipline that converts ideas into value for organisations and society. A project, meanwhile, is a unique endeavour aimed at achieving defined goals within constraints of time, budget, scope, and quality (Petrović et al., 2010). Innovation projects are distinct in that their goals and costs are often undefined at the outset and evolve over time (Milutinović, 2020; Stošić & Milutinović, 2022). They typically involve experimental and research-oriented methods (Stošić & Milutinović, 2022; Dektyareva, 2023) and require higher team engagement in risk management due to potentially greater consequences of failure (Bowers & Khorakian, 2014; Stošić & Milutinović, 2022).

Although innovation and project management are closely connected in practice, their relationship was initially underrepresented in academic literature (Brady & Hobday, 2012; Milutinović, 2020). The two disciplines evolved largely independently (Filippov & Mooi, 2009; Stošić & Milutinović, 2017, 2022), with their interrelation remaining mostly implicit (Filippov & Mooi, 2009). Furthermore, while modern organisations often excel in project management, the management of innovation projects remains insufficiently defined and underexplored (Yordanova, 2018).

Although innovation projects share certain features with conventional projects, such as defined objectives, resource constraints, and team-based execution, they differ in fundamental ways that shape how management practices apply. Innovation projects typically involve higher uncertainty, goals that evolve as learning occurs, experimental rather than routine methods, and greater consequences of failure (Milutinović, 2020; Stošić & Milutinović, 2022). Figure 1. captures these distinctions and overlaps through a Venn diagram that synthesizes key characteristics from the literature. This conceptual clarification matters because AI tools may enhance or constrain different aspects of project management depending on whether uncertainty, experimentation, and learning are central, as they are in innovation contexts, or peripheral. The framework thus provides necessary context for understanding the phase-specific and model-dependent patterns of AI integration explored in Tables 1 and 2.

Figure 1. Key Similarities and Differences Between Innovation and Conventional Projects



Source: Edited by the author

2.1. AI and innovation

Innovation projects are no longer isolated efforts but operate within broader ecosystems of stakeholders, including customers, partners, and competitors. This interconnected nature contributes to the growing complexity of project management. Among emerging technologies, AI offers promising solutions to support and streamline the management of such projects.

AI plays a vital role across industries. The Oxford definition describes it as the theory and development of computer systems capable of performing tasks that typically require human intelligence, such as visual perception, speech recognition, decision-making, and language translation (Barredo et al., 2019). Functionally, AI can be understood as software that executes algorithm-based tasks intelligently (Neştian et al., 2020), simulating or even surpassing human cognitive abilities. Stošić and Milutinović (2022) categorise AI into three types: weak AI, designed for specific tasks; strong AI, comparable to human intelligence; and super AI, which exceeds human capacity (Radojković et al., 2021; Stošić & Milutinović, 2022).

According to Cooper and McCausland (2024), AI serves as a prediction technology that reduces forecasting costs. A central goal in AI development is creating systems that operate autonomously, adapt to new situations, and improve over time without reprogramming (Cooper, 2024). AI-based innovation is evident across business domains such as marketing, sales, procurement, and production (Radojković et al., 2021). Its use in managing innovation projects has gained increasing interest from both business and academia. Researchers highlight AI's potential to support key phases of innovation, from problem analysis to solution development (Kakatkar et al., 2020). Kakatkar et al. (2020) also identify key resources for innovation practitioners, including online courses, readings, tools, demos, and sample code. Additionally, Füller et al. (2022) propose four organisational profiles for AI integration in innovation management: (1) AI Frontrunners, (2) AI Practitioners, (3) AI Occasional Innovators, and (4) Innovators not yet adopting AI.

The innovation project life cycle, as defined by Kerzner and further elaborated by Stošić and Milutinović (2022), comprises four main phases: early, product design, implementation, and commercialisation. The early stage includes activities preceding final development, such as idea generation, initial research, concept validation, and specification definition. The product design phase focuses on transforming user requirements into detailed design parameters, covering both engineering and industrial aspects while considering technical and resource constraints. The implementation phase encompasses activities following detailed design, including development, execution, and testing. Finally, the commercialisation phase involves market entry and post-launch feedback activities aimed at ensuring the innovation's sustained success and continuous improvement. Each phase offers distinct opportunities for applying specific AI technologies that enhance analytical precision, decision-making efficiency, and innovation outcomes. Table 1 provides an overview of applicable AI tools across these phases, their primary functions, and associated benefits.

Table 1. AI applications in the management of innovation projects: Phases, technologies, and benefits

Innovation phase	AI application	Function	Key benefits
Early stages (idea generation, research, validation)	Natural language processing	Analyses datasets, identifies trends, and gathers user feedback (Just, 2024; Deekshith, 2024)	Faster idea generation; market-driven insights
	Machine learning & predictive analytics	Validates concepts and forecasts success using historical data (Ongsulee, 2018; Sarker, 2021; Albérico & Joana, 2023)	Improved decision-making; enhanced prediction accuracy
	Idea generation tools	Supports ideation and concept screening with domain data (Ivcevic & Grandinetti, 2024; Joosten et al., 2024)	Broader idea exploration; efficient concept filtering
	Knowledge graphs	Integrates technical, regulatory, and market information (Schramm et al., 2023)	Comprehensive information synthesis
Product design (detailed design and prototyping)	Generative design tools	Explores design alternatives based on constraints (Shrestha et al., 2021; Barbieri & Muzzupappa, 2024)	Shortened design cycles; cost reduction
	Collaborative AI tools	Facilitates cross-functional communication (Gong et al., 2024; Malakar & Leeladharan, 2024)	Improved interdisciplinary collaboration
	Simulation & testing	Enables virtual experimentation before prototyping (Ören, 1987; Bojić et al., 2024)	Early risk detection; error reduction
Implementation (development and execution)	Robotics & automation	Increases manufacturing precision and consistency (Nishar, 2023)	Reduced production errors; higher quality
	AI-enhanced project management	Tracks progress, forecasts delays, and optimises resources (Barcaui & Monat, 2023; Shamim, 2024; Zahaib, 2024)	Improved timeline adherence; resource efficiency
	Supply chain optimisation	Applies ML algorithms to logistics and delivery (Pasupuleti et al., 2024)	Timely delivery; reduced logistics costs

Table 1 continued

Commercialisation (market entry and feedback)	Customer insight analytics	Extracts insights from user data and sentiment (Albérico & Joana, 2023; Santoro et al., 2024)	Data-informed marketing; better customer understanding
	Sales forecasting & demand prediction	Anticipates adoption rates and market response (Santoro et al., 2024)	Accurate demand planning; reduced inventory risk
	Personalised marketing	Delivers tailored promotional strategies (Albérico & Joana, 2023; Santoro et al., 2024)	Higher user engagement; improved conversion rates
	Post-launch analytics	Monitors product performance for iterative improvement (Santoro et al., 2024)	Continuous enhancement; Product-market fit refinement

Source: Edited by the author

In addition to the defined phases of managing innovation projects, various models and frameworks have been developed to support the effective management of innovation and innovation projects. Numerous studies trace the chronological evolution of innovation models (Pohlmann, 2005; Stošić & Milutinović, 2014, 2022; Barbieri & Álvares, 2016; Silva et al., 2016; Cohendet & Simon, 2017), highlighting the diversity among them due to the lack of consensus on the structure of the innovation process and the differing objectives behind each model (Eveleens, 2010). These models assist organisations in fostering creativity, structuring innovation efforts, and aligning outcomes with strategic goals (Tidd, 2006). For the purposes of this paper, several contemporary innovation models are further elaborated, as presented by Stošić and Milutinović (2022): the Innovation Diamond Model (Cooper et al., 2002, 2003), Stage-Gate (Cooper & Kleinschmidt, 1993), Open Innovation (Chesbrough, 2003), Agile (Beck et al., 2001), and Design Thinking (Simon, 1996). Table 2 provides brief descriptions of these models along with examples of human-driven and potential AI-supported roles.

Table 2. Innovation management models: a comparison of potential human and AI roles

Innovation model	Core focus	Primary human roles	AI-supported functions
Innovation diamond model (Cooper & Mills, 2005)	Integrates four core dimensions of innovation management: strategy, portfolio management, idea generation, and innovation culture.	Strategic decision-making, portfolio oversight, innovation leadership	Data-driven portfolio analysis, automated idea screening and evaluation
Stage-gate model (Cooper, 1990; Stošić & Milutinović, 2022)	Divides innovation projects into sequential phases separated by structured gate reviews for decision-making.	Project oversight, gate evaluation, cross-functional coordination	Predictive analytics for gate reviews, data-supported decision-making
Open innovation (Chesbrough, 2014; Radziwon et al., 2023)	Promotes collaboration and knowledge exchange across organisational boundaries.	Partnership management, co-creation, IP governance	AI-based collaboration platforms, automated technology scouting

Table 2 continued

Agile framework (Stošić & Milutinović, 2022)	Iterative development approach emphasising flexibility, continuous feedback, and stakeholder involvement.	Sprint leadership, backlog management, feedback facilitation	Predictive sprint planning, feedback analysis, workflow optimisation
Design thinking (Goel, 2024)	Human-centred methodology focusing on empathy, ideation, prototyping, and iterative testing.	User research, ideation, prototyping, user evaluation	Behavioural analytics, automated prototype testing, sentiment analysis

Source: Edited by the author

Table 2 demonstrates that human-AI collaboration in innovation management follows distinct patterns across different frameworks. Across all models examined, humans retain responsibility for strategic decision-making, stakeholder coordination, and judgment in ambiguous contexts, while AI contributes through enhanced analytical capacity, predictive modelling, and process automation. However, integration approaches vary by model characteristics: structured, process-oriented frameworks such as Stage-Gate and Agile show different integration patterns compared to human-centred approaches like Design Thinking, where preserving empathy and creativity remains essential (Goel, 2024). AI enhances innovation projects by simplifying processes, improving decision-making, and supporting creativity, particularly strengthening models through better collaboration and resource utilisation (Soni et al., 2020). Combined with human expertise, AI can accelerate innovation cycles and enable more efficient, strategically guided project outcomes (Füller et al., 2022).

3. Research methodology

This study adopts a mixed-method research design that integrates quantitative and qualitative approaches to investigate AI's role in innovation project management. The research proceeds through three interconnected phases. First, a bibliometric analysis maps the broader research landscape, identifying key trends and contributors across 207 publications spanning nearly three decades. Second, a focused literature review examines eight recent empirical studies that provide detailed evidence of AI applications in innovation contexts. Third, a comparative analysis systematically contrasts traditional management approaches with AI-supported methods across multiple dimensions. By combining these methods, the study achieves both breadth in understanding the field's evolution and depth in analysing contemporary practices, ultimately strengthening the empirical foundation for addressing both research questions.

3.1. Bibliometric analysis

To assess the current state of research, a bibliometric analysis was conducted using scientific publications indexed in the Web of Science database. The analysis focuses on two key domains: the management of innovation projects and AI. Bibliometric methods provide a structured overview of existing literature by revealing research trends, knowledge distribution, institutional influence, and collaboration patterns (Passas, 2024; Ng et al., 2024).

Following the four-stage approach proposed by Öztürk et al. (2024), the first step involved defining the research objective. The goal was to examine prior studies in order to identify key themes, trends, major contributors, and collaborative efforts. This helped establish a foundation for the subsequent comparative analysis. The second step involved collecting relevant literature. The Web of Science database was selected for its reliability (Falagas et al., 2008; Clarivate, 2021), comprehensiveness (Mongeon & Paul-Hus, 2016; Clarivate, 2021), and authority (Sharma & KS, 2018; Ng et al., 2024). The search query used was: "management of innovation projects" (Topic) AND "artificial intelligence" (Topic). This query specifically searches for scientific papers where both innovation project management and AI are significant topics of discussion. The Topic field was chosen because it covers the title, abstract, author keywords, and keyword plus, ensuring that both concepts are integral to the selected papers. This search resulted in 207 relevant records. The third and fourth steps involved analysis, visualisation, and interpretation. These were carried out using R-Studio with the Bibliometrix package (Aria & Cuccurullo, 2017), which provides tools for conducting bibliometric research in the R environment.

Table 3 presents the main metadata of the bibliometric dataset used in the analysis, including the timespan, number of sources, documents, and co-authorship indicators. As illustrated in Table 3, from 1997 to 2024, the number of relevant publications has grown at an average annual rate of 14.31%, involving 1,063 authors and 914 unique keywords.

Table 3. Descriptive metadata of the bibliometric dataset

Metadata indicator	Value
Timespan	1997-2024
Number of Sources	178
Number of Documents	207
Annual growth rate	14.31%
Number of Authors	1,063
Single-authored documents	25
International co-authorship	30.92%
Average co-authors per document	5.23

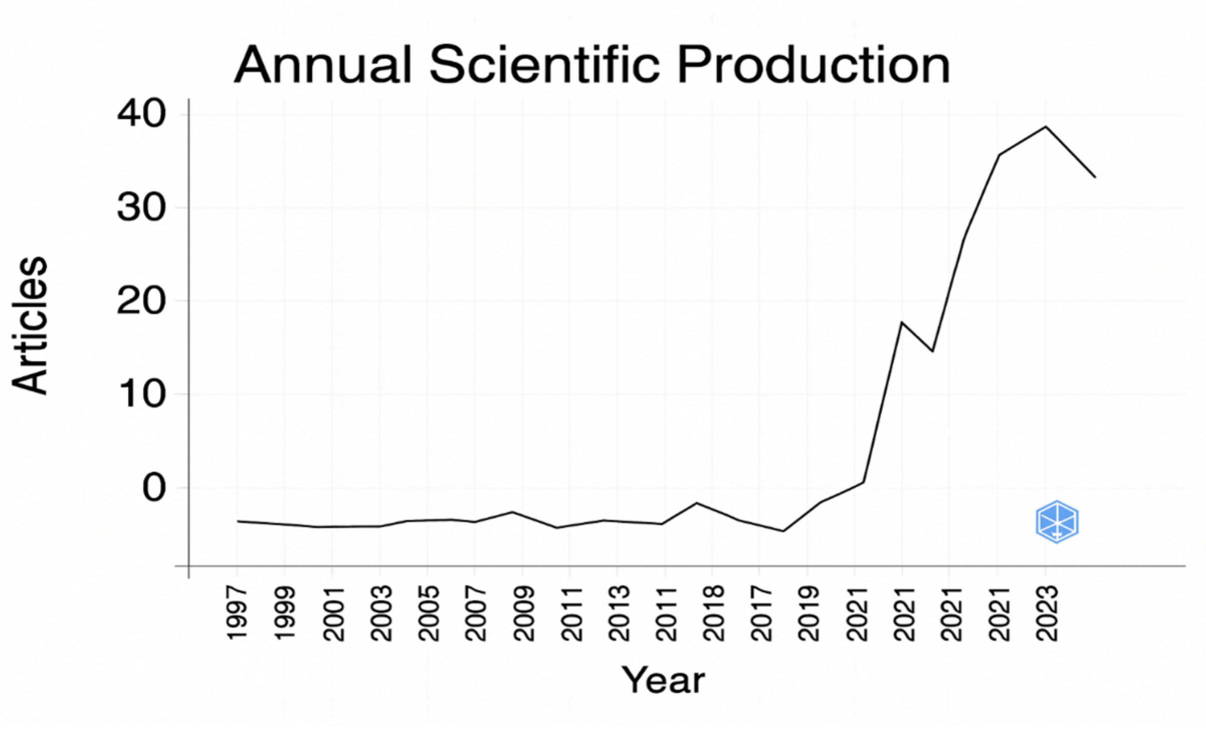
Table 3 continued

Author keywords (DE)	914
Total references	10,506
Average document age	3.07 years
Average citations per document	13.95

Source: Edited by the author

The temporal distribution of publications reveals telling patterns about when scholarly attention to AI in management of innovation projects intensified. Figure 2 shows that research output remained modest through 2017, then began rising in 2018 before accelerating sharply from 2020 onward. This trajectory likely reflects several converging developments: AI tools becoming more accessible and mature for practical deployment, digital transformation initiatives gaining urgency, particularly during the pandemic years, and researchers accumulating enough implementation experience to generate meaningful empirical studies. The steep recent growth in publications speaks to both the field's dynamism and the timeliness of synthesising what has been learned thus far about integrating AI into management of innovation projects.

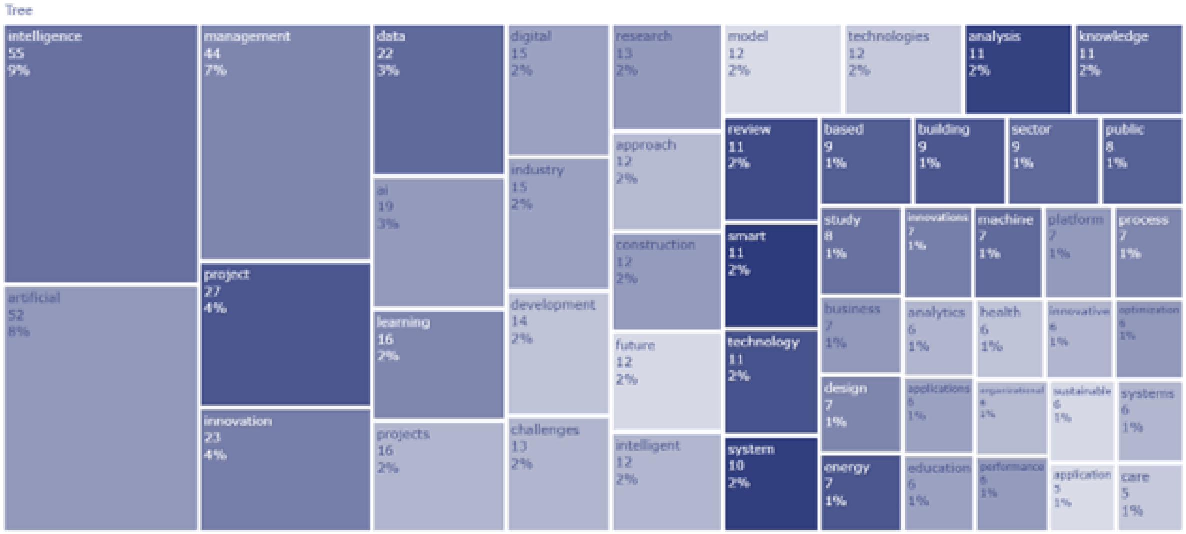
Figure 2. Annual scientific production of the articles included in the bibliometric metadata analysis



Source: Edited by the author

The next step of the analysis focused on thematic patterns derived from keyword frequency. TreeMap visualises hierarchical data using nested rectangles sized by variable frequency (Jadeja & Shah, 2015; Long et al., 2017). In Figure 3, term frequency in article titles shows "intelligence" (55), "artificial" (52), "management" (44), "project" (27), and "innovation" (23) as most prominent, underscoring the focus on AI, innovation, and project management. Frequent terms like "data" (22), "learning" (16), and "digital" (15) highlight the role of data-driven methods, while "energy" (7), "health" (6), and "sustainable" (6) indicate AI's relevance across sectors.

Figure 3. TreeMap visualisation of the bibliometric metadata analysis



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3.2. Focused literature review

The focused literature review adopts a systematic approach to identifying, analysing, and synthesising recent research on the application of artificial intelligence in the management of innovation projects. The reviewed publications were identified through a bibliometric analysis and the screening of relevant abstracts.

The inclusion criteria for this review were as follows:

- Studies in which innovation projects are clearly defined
- Studies that explicitly describe the application of AI within innovation processes
- Publications dated between 2019 and 2024, ensuring coverage of recent technological and methodological developments

The inclusion criteria balance conceptual precision with practical relevance. Requiring studies to clearly define innovation projects addresses a persistent problem in the literature: the term is sometimes applied loosely or inconsistently, making comparisons difficult (Yordanova, 2018). Similarly, studies must explicitly describe AI applications rather than merely mention AI in passing, ensuring sufficient detail for meaningful analysis. The 2019-2024 timeframe captures a period when AI moved from experimental curiosity to operational reality for many organisations, yielding empirical evidence grounded in contemporary technological capabilities and organisational contexts. This focused scope ensures findings reflect current AI affordances rather than earlier, more speculative discussions of what AI might someday accomplish.

Table 4 synthesizes eight empirical studies that met the inclusion criteria and provide complementary insights across different dimensions of AI integration in innovation management. For each publication, the table presents the citation, publication year, core findings, managerial and practical implications, and theoretical contributions. This structure enables a comparative view of how different authors conceptualise and apply AI within the context of the management of innovation projects.

Table 4. Studies included in the focused literature review

Citation	Main findings	Theoretical contribution	Managerial / Policy implication	Primary research focus
Haefner et al. (2021)	Identifies three levels of AI involvement in innovation: exploiting, expanding, and exploring, showing AI complements rather than replaces human decision-making.	Connects Behavioural Theory of the Firm with a framework of AI information-processing capabilities.	Apply AI for data-intensive analysis while retaining human oversight in creative or ambiguous contexts.	Decision support and organisational cognition.
Roberts and Candi (2024)	Finds that AI use is strongest in the development phase of innovation and is positively linked with outcomes, with traditional AI currently demonstrating higher effectiveness than generative AI.	Provides recent empirical evidence mapping AI effects across innovation stages.	Focus on mature AI applications for near-term process improvements and scale generative AI gradually.	Process optimisation across innovation stages.
Bakke (2023)	Identifies how statistical, deep-learning, and language models support distinct phases of the innovation process in project contexts.	Proposes a five-phase conceptual framework mapping AI functionalities to key innovation activities: idea generation, conversion, development, market insight, and post-launch evaluation.	Suggests that project managers tailor AI tool selection to the innovation phase, using predictive models for evaluation and llms for communication and market intelligence.	AI integration across project innovation phases.
Busch and Duwe (2023)	Demonstrates that AI improves ideation, decision-making, and collaboration but poses integration and capability challenges.	Practice-based analysis connecting AI adoption to organisational process adaptation.	Strengthen cross-departmental skills and integration practices when embedding AI.	Organisational adoption and collaboration.
Prem (2019)	Shows that AI drives efficiency in Austrian smes but is limited by data quality, expertise, and cost barriers.	Offers one of the first empirical accounts of AI adoption barriers in national SME contexts.	Promote data readiness and targeted policy programs to support SME digital innovation.	SME adoption and policy perspective.

Table 4 continued

Füller et al. (2022)	Defines four organisational AI-adoption profiles, frontrunners, practitioners, occasional innovators, and non-AI innovators, reflecting differing readiness levels.	Develops a typology of AI adoption in innovation management.	Align AI strategy and resource allocation with organisational maturity and readiness.	Organisational strategy and adoption pathways.
Mühlroth and Grottke (2020)	Proposes an AI-driven pipeline for automated trend detection supporting technology and innovation foresight.	Establishes a model of AI-enabled strategic foresight based on data mining and topic modelling.	Use AI to identify emerging technologies early and guide innovation portfolio planning.	Foresight and early-trend detection.
Cooper (2024)	Finds that AI integration across the stage-gate product-development process accelerates design cycles and enhances decision quality.	Links AI applications with established engineering-management and NPD frameworks.	Incorporate AI into gate reviews for forecasting, risk evaluation, and concept validation.	Product development and engineering management.

Source: Authors' synthesis based on data collected from the Web of Science database

3.3. Comparative analysis

Based on the reviewed literature and the authors' synthesis, Table 5 compares traditional and AI-supported approaches to the management of innovation projects across several core dimensions, including data processing, decision-making, risk management, speed, scalability, and implementation complexity. The comparison clarifies both where AI tools provide measurable advantages and where traditional, human-driven approaches remain essential.

The results indicate that AI-supported methods substantially enhance the analytical and operational aspects of the management of innovation projects. They excel in tasks that depend on large-scale data processing, rapid iteration, and continuous monitoring, particularly in trend detection, forecasting, scheduling, resource allocation, and risk assessment. These functions benefit from AI's capacity to process vast datasets, detect correlations that are not immediately visible to human analysts, and deliver near real-time feedback. Consequently, AI adoption in these domains enables faster innovation cycles, more precise project control, and an earlier identification of emerging opportunities or risks.

Conversely, traditional approaches retain superiority in cognitively demanding and socially complex contexts, where interpretation, negotiation, and creativity are central. Human-driven methods are better suited to managing organisational ambiguity, ethical dilemmas, and the political dimensions of innovation, which cannot be fully codified in data. In such cases, tacit knowledge, experience, and contextual understanding continue to play an irreplaceable role.

Overall, the comparative analysis demonstrates that the greatest potential lies in hybrid human–AI collaboration models, in which AI supports evidence-based analysis and prediction, while human managers provide strategic framing, ethical oversight, and creative synthesis. This combination balances efficiency with adaptability, and analytical precision with interpretive depth. Table 5 formalises these distinctions and highlights where hybrid configurations of human and AI contributions are most likely to deliver value.

Table 5. Comparative analysis of traditional and AI-supported approaches in the management of innovation projects, with managerial implications

Management dimension	Traditional methods	AI-supported methods	Managerial implication
Data processing and analysis	Relies on manual collection, expert interpretation, and retrospective analysis; time-consuming and limited in scale.	Automates data mining, pattern recognition, and predictive analytics, enabling rapid processing of large and heterogeneous datasets.	Invest early in data infrastructure and analytics literacy; managers must interpret model outputs, not only consume them.
Decision-making	Driven by managerial intuition, experience, and negotiation; effective in ambiguous and politically sensitive situations.	Uses model-based insights, scenario forecasts, and risk signals to support decisions; constrained by data quality and model design.	Use AI as structured input to decision forums while retaining human accountability for strategic and ethical calls.
Speed and efficiency	Progress depends on scheduled reviews and manual approval cycles; iteration speed is limited.	Automates monitoring, reporting, and resource allocation, shortening review cycles and accelerating implementation.	Redirect human effort from reporting to exception handling and escalation instead of routine control.
Trend detection and foresight	Based on expert judgment and historical knowledge; risks late recognition of opportunities and threats.	Scans large volumes of technical, market, and customer data to identify emerging patterns.	Use AI-driven scanning to prioritise exploration areas, with experts evaluating relevance and feasibility.
Innovation life-cycle management	Managed through linear stage models and formal gate reviews with strong human oversight.	Supports continuous tracking across all phases (ideation, development, testing, commercialisation) and partial automation of phase transitions.	Integrate AI into established governance models (e.g., Stage-Gate) while maintaining human review accountability.
Risk management	Relies on experience and periodic assessment; often reactive rather than continuous.	Continuously monitors schedule, cost, quality, and market risk, enabling earlier intervention and more systematic mitigation.	Treat AI as an early-warning system; keep humans responsible for response prioritisation.
Cost efficiency	Requires intensive human effort for planning, reporting, and coordination; labour cost scales with complexity.	Reduces recurring coordination and analysis costs through automation, though initial investment in data, tools, and skills is high.	View AI as a cost-reallocation tool rather than a cost-reduction one; invest in capability building.
Personalisation and customisation	Limited tailoring of outputs to users or segments due to effort and time constraints.	Adapts recommendations and designs in near-real time based on behaviour and feedback.	Apply AI-driven tailoring in feedback-rich phases while monitoring for bias and exclusion.

Table 5 continued

Scalability	Scaling across projects or functions is constrained by available staff and managerial attention.	Analytical and monitoring tasks can be replicated across projects with minimal additional effort.	Centralise and standardise AI capabilities to avoid duplication across teams.
Learning and improvement	Organisational learning is slow and experience-based; knowledge transfer relies on documentation and informal sharing.	Systems adapt continuously using new data and feedback, supporting process optimisation.	Combine machine-driven feedback loops with structured human retrospectives to prevent black-box drift.
Implementation complexity	Low technical complexity but high human effort; suitable for smaller organisations.	Requires data readiness, technical expertise, and governance on transparency, accountability, and bias.	Begin with pilot projects; expand only when data quality, governance, and skills are established.

Source: Edited by the author

In summary, the findings underscore that AI does not replace traditional management practices in innovation projects but rather redistributes cognitive and operational responsibilities. It assumes repetitive, data-intensive tasks, allowing managers to focus on high-level strategic reasoning, stakeholder alignment, and creative exploration. This reinforces the view that AI functions most effectively as a decision- and execution-support system integrated into human governance, rather than as an autonomous decision-maker.

Furthermore, when contrasting AI-driven and human-driven approaches, the distinctly human, irrational dimension of innovation management becomes especially evident. This encompasses elements such as intuition, emotional intelligence, empathy, intrinsic motivation, creativity, and even spontaneous judgment under uncertainty, all of which shape how managers interpret information, inspire teams, and make decisions in ambiguous environments. These non-algorithmic aspects of human behaviour remain central to fostering trust, organisational cohesion, and visionary leadership within innovation projects. Recognising and preserving these qualities alongside data-driven decision support is therefore critical for achieving balanced and sustainable innovation outcomes.

4. Discussion and conclusion

This section systematically addresses the study's two research questions by discussing the main findings and their theoretical and managerial implications. Section 3.1 explores how AI tools influence the management of innovation projects compared to traditional approaches (RQ1), whereas Section 3.2 examines the key challenges and opportunities associated with AI adoption (RQ2). The discussion integrates these insights within the broader academic context and concludes with the study's implications, limitations, and directions for future research.

4.1. The role of AI versus traditional approaches in the management of innovation projects (RQ1)

The comparative analysis presented in Table 5 shows that AI-supported methods enhance those dimensions of the management of innovation projects that depend on scale, speed, and continuous monitoring. AI systems outperform traditional practices in high-volume data processing, forecasting, scheduling, resource allocation, trend detection, and early risk identification. These capabilities allow organisations to shorten iteration cycles, detect threats earlier, and maintain tighter control over complex development and commercialisation activities.

However, traditional, human-driven approaches remain more effective in domains requiring contextual judgment, ethical reflection, negotiation, and creativity. These are areas where tacit knowledge, intuition, and socio-political sensitivity cannot be fully represented in data. Human actors also play a central role in shaping legitimacy and trust, critical elements of successful innovation management. Therefore, rather than substituting human roles, AI enhances them by assuming routine analytical and monitoring tasks, while humans continue to provide strategic framing, creativity, and ethical oversight. This pattern varies systematically by innovation model type (Table 2), with structured frameworks such as Stage-Gate accommodating higher AI integration than human-centred approaches like Design Thinking, where preserving empathy and creativity remains essential (Goel, 2024).

4.2. Challenges and opportunities of AI adoption in managing innovation projects (RQ2)

The findings also highlight both the opportunities and constraints of applying AI in the management of innovation projects. On the opportunity side, AI enables a shift from reactive to proactive management. It provides continuous visibility, real-time monitoring, and data-driven decision support, which together increase efficiency, agility, and scalability. These capabilities manifest differently across project phases (Table 1), from NLP-enabled trend detection in early stages to customer analytics in commercialisation. Organisations using AI gain the ability to identify market trends earlier, optimise resources, and reduce operational risk, thus gaining a measurable competitive advantage.

Nevertheless, the implementation of AI introduces several critical challenges. Effective use of AI depends heavily on data quality, algorithmic transparency, and organisational readiness. Poor data quality or biased datasets can lead to flawed conclusions, while limited technical expertise may result in either overreliance on or underutilisation of AI systems. Furthermore, ethical issues, such as privacy, accountability, and explainability, remain central to responsible AI deployment. These findings imply that AI integration is not merely a technical process but a strategic and managerial challenge, requiring leaders to develop interpretive, ethical, and communicative competencies.

4.3. Theoretical and managerial implications

The results collectively indicate that the management of innovation projects is entering a hybrid phase, where human and artificial intelligence are integrated rather than opposed. Theoretically, this supports the growing view that AI functions as an augmentative capability expanding, rather than replacing, managerial cognition (Jarrahi et al., 2023; Taherdoost & Madanchian, 2023). Practically, it suggests that project managers must redefine their roles from direct control to sense-making and orchestration of human-AI collaboration. Julia and Khayat (2020) emphasised the irreplaceable value of human creativity and cognitive flexibility, while Santoro et al. (2024) underscored that AI should support, not substitute, creative processes. This aligns with the present study's findings, showing that the irrational, emotional, and intuitive aspects of human behaviour, such as moral judgment, empathy, and creative insight, remain the foundation of innovation success.

4. 4. Limitations and future research directions

The main limitations of this study arise from its methodological scope and data selection. The bibliometric analysis relied solely on the Web of Science database, which, despite its comprehensiveness, may have excluded relevant publications from other sources such as Scopus or IEEE Xplore. Moreover, the focused literature review applied specific inclusion criteria to maintain conceptual accuracy, which may have omitted studies using alternative terminology or interdisciplinary approaches. Finally, since this research is based exclusively on secondary data, its conclusions have yet to be empirically validated.

Despite these limitations, the present study offers practical guidance by clarifying which aspects of management of innovation projects can already be reliably augmented by AI and which still rely on human judgment. In doing so, it provides an actionable foundation for organisations seeking to introduce AI into innovation projects without undermining strategic intent, trust, or accountability.

Future research could extend this work by incorporating mixed-method approaches that combine bibliometric and qualitative analyses with case studies or experimental designs. Further exploration is also needed on hybrid human-AI models in innovation management, particularly in relation to ethical decision-making, creativity support, and organisational learning. The integration of explainable AI (XAI) could further enhance transparency and trust in AI-supported innovation processes. Moreover, research should continue to examine how AI tools can foster collaboration across geographically dispersed teams and global innovation networks.

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