Human TECHNOLOGY

ISSN: 1795-6889

https://ht.csr-pub.eu

Volume 22(1), May 2026, 49–67

FROM SUBSTITUTION TO AUGMENTATION: REIMAGINING THE HUMAN ROLE IN AI-ENABLED INNOVATION MANAGEMENT SYSTEMS

John Bessant
University of Exeter Business School, Exeter, United Kingdom
ORCID 0000-0002-5040-4949

Aknur Zhidebekkyzy
Al-Farabi Kazakh National University, Almaty, Kazakhstan
ORCID 0000-0003-3543-547X

Abstract: *Artificial intelligence (AI) is rapidly reshaping innovation management, moving from a peripheral technology to a potentially transformative force within organisational innovation systems. This paper examines AI's role within an Innovation Management System (IMS) using the ISO 56002 framework. Adopting a conceptual and integrative literature review approach, the study brings together insights from innovation management research, emerging evidence on AI applications, and prior studies of technological diffusion and socio-technical change. The analysis identifies two broad and complementary AI capabilities, analytical AI and generative AI, whose application across the innovation process highlights substantial opportunities in search, selection, implementation, and value capture. Findings indicate that current AI adoption is largely limited to substitution, improving existing tasks, while its transformative potential lies in augmentation and human-AI collaboration. The paper argues for deeper socio-technical integration of AI as a complementary partner within innovation management systems.*

Keywords: *artificial intelligence, human-AI collaboration, innovation management, innovation management systems, ISO 56002, absorptive capacity.*

DOI: https://doi.org/10.14254/1795-6889.2026.22-1.3

INTRODUCTION

In 1956, a group of scientists, including John McCarthy, Marvin Minsky, Nathaniel Rochester, and Claude Shannon, presented a paper at a conference in Dartmouth where they coined the term "artificial intelligence", using it to refer to "any aspect of learning or any other feature of intelligence can be so precisely described that a machine can be made to simulate it" (Cordeschi, 2007). Developments in the years that followed were slow and spread across a long frontier; for much of its 70-year life, AI was of little interest beyond the realm of computer science.

This changed dramatically in 2022, when OpenAI launched its ChatGPT transformer model, sparking a massive acceleration in both interest and application. For an increasing number of commentators, AI has become another example of “revolutionary" technology, offering a solution in search of a problem. Andrew Hargadon captures this kind of emergence as being characterised by a "long fuse, big bang" pattern (Hargadon, 2003).

AI appears, on the one hand, to offer enormous potential for applications and process improvements across a wide spectrum of the economy, leading many to worry that it will result in job losses, deskilling, and perhaps new and dystopian versions of future society (Brandao, 2025; Schinello, 2025). This kind of conversation is not new; similar versions can be found when we re-examine earlier technological revolutions – such as the "microelectronics revolution" of the 1980s or the first wave of hype around the internet in 2000 (Miles et al., 1988). Experience with those major shifts suggests we need to be more cautious and nuanced in our response. There will undoubtedly be significant changes, but these follow emergent pathways; new jobs may be created as well as destroyed, new activities and configurations of work may emerge, and old ones may fall away (Miles et al., 2014).

Experience since 2022 suggests that AI has made significant advances in capability, but along a frontier that Ethan Mollick and colleagues describe as a "jagged edge" (Mollick, 2024). Progress in some application areas is spectacular, while in others, AI lags well behind even basic human intelligence in its ability to carry out tasks. This "jagged edge" is matched on the demand side by a differing picture of adoption and impactful implementation; there are a handful of impressive cases where AI has been used to powerful effect to support and improve productivity. However, in many other areas, although the potential appears to be there, the actual impact so far has been limited (NANDA, 2025; Škare et al., 2025).

Therefore, there is a need to explore in greater depth several key research questions:

1. What is the specific nature of AI’s potential within the innovation management domain and across different stages of the innovation process?
2. What practical experience currently exists regarding the adoption of AI in these activities?
3. What are the factors influencing the adoption and successful deployment of AI technology?
4. How can organisations design and implement strategies to address the emerging challenges associated with AI adoption in innovation processes?

The goal of this paper is to take such an approach, focusing on a key application domain: innovation management. It is structured as follows: following a brief introduction that frames the range of AI technologies available, the field of innovation management is defined as an application domain. We then draw on a literature review to explore potential and actual applications of AI in this field before moving to a discussion of factors affecting its adoption and exploitation. The paper concludes with suggested directions for future research and practical experiments.

METHODS

This study adopts a conceptual and integrative literature review approach to examine the evolving role of artificial intelligence (AI) within innovation management systems. The aim is to develop an analytical understanding of how AI technologies may reshape the human role in innovation processes and organisational decision-making. The analysis integrates insights from three complementary strands of literature.

First, the study draws on the innovation management literature to establish the analytical framework for examining innovation processes. In particular, the paper uses the ISO 56000 family of standards for innovation management systems, with specific emphasis on ISO 56002. This framework synthesises decades of research on innovation processes, organisational capabilities, and strategic management of innovation. It provides a structured model of the innovation lifecycle and associated organisational support mechanisms, allowing the potential contributions of AI to be systematically mapped across the different stages of innovation activity.

Second, the study reviews current evidence on the application of AI in innovation-related activities, including both peer-reviewed academic studies and relevant industry reports. The inclusion of grey literature is appropriate given the rapid pace of AI development and the fact that many practical implementations emerge in industry settings before they are systematically examined in academic research. These sources provide examples of how AI is currently used in activities such as opportunity identification, ideation, decision support, product development, and innovation portfolio management.

Third, the analysis draws on research concerning the diffusion and organisational adoption of earlier technological transformations, including information technologies, advanced manufacturing systems, and digital platforms. This body of literature provides important insights into recurring patterns associated with technological change, such as the development of absorptive capacity, socio-technical adaptation, and the co-evolution of technology and organisational practices.

This integrative approach enables the paper to develop a narrative synthesis highlighting emerging opportunities, organisational challenges, and the evolving nature of human-AI collaboration in innovation management. The analysis also provides the basis for identifying key research questions and policy implications regarding the transition from AI as a tool for substitution to AI as a partner enabling augmentation within innovation systems.

RESULTS

Artificial Intelligence as a catalyst for innovation

AI can be defined as a suite of computational technologies that enable machines to perform tasks that typically require human intelligence, such as learning from data, reasoning about knowledge, perceiving environments, and solving complex problems. In particular, we can identify three complementary capabilities that are of relevance:

1. Analytical/predictive AI. Machine Learning (ML) algorithms learn patterns from historical data to make predictions or decisions about data without being explicitly programmed for the task. This capability enables multiple analytical tasks, including market forecasting, customer segmentation, and risk assessment, which are important in making informed innovation decisions.
2. Natural Language Processing (NLP). NLP enables machines to understand, interpret, and generate human language. This allows for the automated analysis of unstructured text data, such as customer reviews, scientific papers, patent filings, and social media conversations, unlocking insights that would be impossible to gather manually.
3. Generative AI (GenAI). Generative AI models, such as Large Language Models (LLMs) and Generative Adversarial Networks (GANs), are trained on massive datasets and can create entirely new, original content, including text, images, code, and complex designs. This technology has significant potential application at the 'front-end of innovation', particularly in the creative and development phases.

Importantly, we can characterise two distinct trajectories along which these AI capabilities might be deployed to support the innovation process. Analytical AI, particularly machine learning, excels at tasks that require structure, pattern recognition, and prediction from existing data. This makes it a good fit for tasks that require narrowing down options and converging on an optimal path (such as analysing project options or predicting return on investment (RoI) for projects based on historical experience with similar decisions). By contrast, generative AI's strength lies in its ability to create novel outputs and explore the solution space, tasks which require divergent thinking. Its function is to expand possibilities rather than narrow them. This capability could contribute significantly to the unstructured, creative stages of the innovation process, such as generating multiple initial product concepts or visualising novel design aesthetics. An effective AI-augmented innovation management process could leverage both aspects by deploying analytical AI to strengthen its analytical backbone and generative AI to expand its creative frontiers.

Innovation management systems

It is widely accepted that managing innovation involves multiple activities connected in a process that takes ideas through to something that creates value (Tidd & Bessant, 2024; Goffin & Mitchell, 2016; Mishchuk et al., 2025). And it is influenced by key factors such as the presence or absence of a strategic context and plan, the engagement of a wider external ecosystem (open innovation), and the mobilisation of human beings and their creativity and knowledge within the organization. These perspectives have been researched and written about for over a century and were recently codified in the ISO 56000 series of standards for an innovation management system (ISO, 2019).

At the heart of this series is ISO 56002, a guidance standard that offers a flexible, high-level blueprint for establishing, implementing, maintaining, and continually improving an innovation management system (IMS). It is built on a foundation of over a century of research and empirical experience in trying to organise and manage the process (ISO, 2019). The model, built around 7 'clauses', covers both the strategic context and the actual operations involved in the innovation process as well as its continual monitoring and improvement. It offers a framework for assessing organizations' innovation management maturity and development pathways, rather than a strict set of compliance rules. It aims to provide a structured framework for navigating uncertainty, fostering a supportive culture, and aligning innovation activities with strategic objectives.

One size does not fit all, but an increasing number of organizations are making use of the approach as a way of reviewing their approach to innovation management (Hyland et al., 2022). It offers us a helpful framework against which to review the potential contribution that AI could make and to map early case examples and experience.

Potential applications of AI

For some commentators, AI represents a general-purpose "method of invention" that can fundamentally reshape the entire R&D and innovation process (Bianchini et al., 2022). It has potential applications across a wide range of activities in the innovation process, deploying capabilities in learning, reasoning, and generating insights.

AI in the core innovation process

At the heart of the ISO model (covered in clause 5) are the key operations involved in translating an idea into something that creates value. In this section, we use a simplified version of such an IMS to map specific AI applications and tools onto four key stages of the innovation process - see Figure 1.

Figure 1. Simplified model of the innovation process (Tidd & Bessant, 2024).

Stage 1: Search – Enhancing Opportunity Discovery

The 'search' stage potentially benefits from AI's ability to process and analyse both structured and unstructured data to identify opportunity signals that might be missed by human analysis alone. Applications include:

- AI for Trend Analysis & Market Intelligence. AI algorithms excel at scanning diverse data sources–news articles, social media conversations, patent databases, academic publications, market reports–to detect emerging technological trends, shifts in consumer behaviour, competitor strategies, and potential market disruptions. Tools specifically designed for this include AI-powered market intelligence platforms, specialized trend analysis tools, market research tools and technology scouting platforms (Cooper, 2024a; Truong & Papagiannidis, 2022; Cooper & Brem, 2024).
- AI for Idea Generation. Generative AI models can act as powerful brainstorming partners. They can generate novel concepts based on specific prompts, combine information from disparate datasets to suggest new possibilities, explore variations on existing ideas, and help overcome creative blocks. A study exploring this option suggested that ideas created with the help of AI received significantly higher ratings for novelty and benefit to customers based on the results of a "blind" examination (Joosten et al., 2024). Piller and colleagues also demonstrated this capability for generating ideas for a (fictitious) outdoor equipment company (Bouschery et al., 2023).
- AI for User Need Identification. Natural Language Processing (NLP) and sentiment analysis techniques allow AI to analyse large volumes of customer feedback from sources like online reviews, customer support interactions, surveys, and social media. This analysis can uncover unmet needs, identify common pain points, gauge sentiment towards existing products or features, and reveal desired improvements, providing direct input for innovation efforts.
- AI Research Assistants. AI-powered research tools can help researchers find relevant papers, summarise key findings, visualise citation networks, and understand the state of the art in specific fields, thereby informing the search for technologically driven innovation opportunities.

AI is increasingly being used in these areas. For example, Amazon leverages ML extensively to predict consumer demand and inform its product strategy. Using NLP and sentiment analysis tools, AI systems can mine unstructured data sources such as customer reviews, support tickets, and social media conversations to uncover recurring pain points, desired features, and latent needs that customers may not be able to articulate clearly.

The sportswear company adidas uses AI similarly to gather real-time consumer feedback from social media, online reviews, and forums. This data informs their product design process, allowing them to create new sportswear that aligns with current trends. This approach has led to faster product development cycles and a better alignment between new products and consumer preferences (Machucho & Ortiz, 2025).

LEGO uses machine learning technologies to conduct market analysis based on clicks and likes on popular online video materials in order to identify and predict new trends for the development of its product (Cooper & Sommer, 2023).

Unilever used AI to help develop a new line of skin care cosmetics based on the use of algorithms to analyse consumer preferences in social networks. Nestlé has created a “concept engine” with artificial intelligence, which transforms the data obtained by scanning social networks into conceptual proposals, which are then evaluated internally and then by potential consumers (Cooper, 2024b).

Beyond its extensive capacity for data analytics, AI in its generative mode offers significant scope for promoting divergent thinking. LLMs can be prompted to generate hundreds of novel product ideas or feature concepts in minutes, dramatically expanding the initial pool of possibilities. For instance, the design agency Loft used GPT-4 to rapidly generate 50 distinct concepts for a new guitar toy, a task that would have taken a human team much longer.

Generative AI is being used by Magnum (the recently spun-out ice cream confectionery division of Unilever) to guide R&D into new flavours, materials, and recipes. IBM Research has used AI to analyse chemical data and recipes to generate new flavours and scents. This provides a scientific approach to a traditionally creative process, resulting in innovative food and fragrance products. In the physical product space, generative design algorithms can create and optimise complex engineering components based on performance parameters like weight and strength, often resulting in novel forms that a human engineer might not have conceived. Airbus famously used this technique to design a lighter, more efficient aircraft partition (Heaven, 2025), while Toyota employs generative models in its car design process (Clifford, 2023).

These tools drastically accelerate the creative front-end of innovation and help overcome human cognitive biases. The primary risk is over-reliance on these tools, which can produce generic, context-lacking outputs or "hallucinations," and may inadvertently stifle the deep, critical thinking that leads to true breakthroughs.

Stage 2: Select – Improving Decision-Making

Applications here include:

- AI for Idea Screening & Evaluation. AI algorithms can be trained to assess ideas against predefined criteria such as technical feasibility, market potential, strategic alignment, novelty, and estimated cost/benefit. By analysing historical project data, market information, and idea characteristics, AI can provide scores or rankings to help managers filter and prioritise large volumes of ideas more efficiently and objectively. Increasingly collaborative innovation platforms incorporate such evaluation capabilities.
- AI for Predictive Analytics & Forecasting. Leveraging historical data and current market indicators, AI models can generate forecasts of a new product's potential market acceptance, estimate potential return on investment (ROI), predict resource requirements, and assess the overall probability of success for different innovation projects. These predictive insights enhance the quality of information available for making critical go/no-go decisions at stage gates (Cooper & Brem, 2024). AI can contribute by providing data-driven insights and predictions and streamlining decision-making (Pietronudo et al., 2022; Bilgram & Laarmann, 2023).
- AI for Feasibility Assessment. AI can assist in evaluating the technical and operational feasibility of an idea by analysing requirements, identifying potential risks or bottlenecks, and assessing the availability of necessary resources or technologies.
- AI for Portfolio Management. AI's analytical capabilities hold potential for assisting in the strategic management of the innovation portfolio, for example, by assessing alignment

with strategic goals across the portfolio and modelling the potential impact of different project combinations on overall business objectives (Cooper & Brem, 2024).

Stage 3: Implement – Accelerating Development & Launch

Applications include:

- AI for Rapid Prototyping & Design. Generative AI tools offer significant advances in rapid prototyping (Bilgram & Laarmann, 2023).
- AI for software development. AI-powered coding assistants can generate code suggestions, auto-complete functions, help identify bugs, automate parts of the testing process, and improve code quality. AI platforms and agents increasingly enable fewer technical users to build prototypes or simple applications.
- AI in process innovation and optimisation. AI tools have demonstrable capabilities in systematically optimising production processes, in enabling predictive maintenance to reduce downtime, and providing intelligent robots for complex assembly tasks.
- AI for project management. AI tools can automate various project management tasks, including scheduling, resource allocation optimization, progress tracking, risk identification, and even facilitating team communication.
- AI for testing & quality assurance. AI can automate crucial aspects of testing, including generating test cases, executing tests across different environments, performing visual validation to ensure user interface consistency, conducting performance testing, detecting bugs, and ensuring code compliance with standards and security protocols.

In practice, AI is increasingly being applied as an accelerator for the development stages of innovation. In software engineering, AI-assisted coding tools like GitHub Copilot can generate, test, and debug code, significantly boosting developer productivity.

For physical products, the concept of "digital twins" – highly detailed virtual models of a product or process – allows for extensive simulation and optimization before any physical prototypes are built. Siemens, for example, has integrated a generative AI interface into its complex Simcenter simulation software, making these powerful tools more accessible to a wider range of engineers. The collective benefit is a dramatic reduction in development time – by as much as 50-60% in some cases – along with lower costs and higher quality outputs (Cooper, 2024b).

GE reduced turbine design time by half, using AI to evaluate a million design options in just 15 minutes, compared with the 2 days needed with conventional methods for complex hydrodynamic analysis of turbine blades (Bogaisky, 2019). In airframe design, Siemens used AI to simplify the transition from the design stage to analysis, allowing developers to devote more time to iterative refinement. Unlike traditional aircraft design, where usually only 2-3 iterations are performed, the AI tool provides the possibility of weekly iterations, which leads to more improvements and allows achieving an almost "ideal design" that meets 99-100% of the specified requirements (Cooper, 2024a). Renault has applied artificial intelligence to optimise the development of an automatic manual transmission (AMT), again reducing development time by over 50%.

Stage 4: Capturing value

Applications include:

- AI for Market Feedback Analysis. After launch, AI tools can analyse customer reviews, social media sentiment, app store ratings, usage data (telemetry), and support interactions to gauge market reception, identify usability issues or bugs, understand how the innovation is being used, and gather insights for future improvements or iterations.
- AI for Performance Monitoring & Value Assessment. AI dashboards and analytics tools can track key performance indicators (KPIs) related to the innovation's success, assess its return on investment (ROI), analyse its contribution to overall business goals, and measure its commercial impact more accurately and dynamically.
- AI for Predictive Maintenance & Support. For innovations that are physical products or ongoing services, AI can predict potential failures, optimise maintenance schedules based on usage data, or power intelligent chatbots and virtual assistants to provide efficient customer support.
- AI for Knowledge Management & Learning. A critical but often overlooked aspect of 'Capture' is organisational learning. AI systems can help capture, organise, synthesise, and retrieve lessons learned from completed innovation projects. AI can summarise project reports, identify recurring challenges or success factors across projects, and make this knowledge more accessible to inform future activities.
- AI for IP Management. AI can assist with intellectual property management by automating prior art searches during development or by monitoring the competitive IP landscape after launch to identify infringement or new opportunities.

Once again, the number of reported applications of AI in these domains is growing (Table 1). Market development, customer support, and ongoing technical service are all key areas where AI is making inroads. The primary problems in this stage are often ethical, such as the potential for manipulative pricing or biased ad targeting, as well as the technical challenge of integrating these AI systems with complex legacy enterprise systems.

Table 1. AI capabilities across stages of the innovation process.

Stage of the innovation process	**Key activities**	**AI capabilities**	**Examples of applications**
Search (opportunity discovery)	Trend scanning, market analysis, idea generation	NLP, generative AI, machine learning	Trend analysis, idea generation, sentiment analysis, technology scouting
Select (decision making)	Idea evaluation, project prioritisation, portfolio management	Predictive analytics, machine learning	Idea screening, ROI prediction, feasibility assessment
Implement (development)	Design, prototyping, testing, project management	Generative design, AI coding tools, simulation models	Rapid prototyping, automated testing, digital twins
Capture value (post-launch learning)	Market feedback analysis, performance monitoring, and learning	NLP, predictive analytics	Customer feedback analysis, predictive maintenance, and innovation performance monitoring

In the strategic context, innovation requires careful direction and support to deliver value, as reflected in the IMS model layers associated with leadership, direction, and governance. This view is consistent with Bencsik's (2021) argument that the synergy between artificial intelligence and knowledge management can strengthen managerial foresight, support strategic decision-making, and improve the conditions for the success of innovation. AI could enhance these functions by providing deeper insights and more robust analytical capabilities. For example, machine learning and NLP algorithms can be deployed to continuously scan, ingest, and analyse large, heterogeneous datasets, including news articles, patent databases, academic publications, social media trends, and competitor press releases, to identify emerging technological threats, nascent market opportunities, and shifts in customer sentiment. In this way, it can provide a capability for "strategic intelligence management" as recommended in the ISO standard. Also, AI-powered business intelligence dashboards, predictive analytics models, and scenario simulation tools can provide senior leaders with real-time insights into market dynamics, resource allocation effectiveness, and the potential outcomes of different strategic choices. AI can optimise the strategic planning process, particularly in the context of innovation portfolio management (Bolton, 2025; Dell Aqua et. al., 2025). Predictive models can be used to analyse historical and market data to forecast potential risks, resource requirements, and return on investment (ROI) for various innovation projects.

Regarding AI in the Support Structure, a third aspect of the model (Clause 7) details the resources and support mechanisms necessary for a functioning IMS. AI can enhance several of these critical support functions.

• Clause 7.2 (Competence) & 7.3 (Awareness): as AI tools become more intuitive, they can democratize access to complex tasks, such as data analysis or design, lowering skill barriers and empowering a broader range of employees to participate in innovation activities.

• Clause 7.7 (Strategic Intelligence Management): AI systems can serve as the engine for strategic intelligence, automating the collection, filtering, analysis, and dissemination of relevant information to decision-makers throughout the organisation, ensuring that strategy is continuously informed by the external environment.

• Clause 7.8 (Intellectual Property Management): Intellectual property (IP) is a critical asset in innovation. AI tools can perform large-scale analysis of patent landscapes, identifying "white space" opportunities for new innovation where there is little existing IP, or flagging potential infringement risks associated with a new product concept.

This picture is, by necessity, a snapshot and is likely to change significantly as AI continues to develop at high speed. While many point solutions exist for specific tasks, there is a noticeable trend towards integrated AI platforms that aim to support multiple stages of the innovation process. This suggests a move towards more holistic AI integration, potentially addressing the challenge of fragmented tooling and improving the flow of data and insights across the traditionally siloed stages of innovation.

DISCUSSION

The systematic application of AI across the IMS promises a range of benefits that could significantly enhance innovation capability. And the previous section indicates a growing number of use cases confirming this potential. But surveys also suggest that there is still a significant gap between general awareness of AI's potential and its specific implementation (Brown, 2025; Kowalkiewicz, 2024).

Recent reports suggest growing dissatisfaction with the results of a flurry of expensive investments and concern that AI has perhaps reached a turning point in the ‘hype cycle’, where expectations are being scaled down along with investment (McKinsey Consultants, 2025; NANDA, 2025). A report by NTT DATA suggests that 70-85% of AI initiatives fail to meet their ROI targets. The report cites several reasons for this high failure rate, including poor data quality, lack of proper infrastructure, and an inability to define clear business objectives.

To some extent, this is a familiar pattern with high-potential technologies – seen, for example, in the microelectronics revolution of the 1980s, the automated factory of the 1990s, and the internet bubble around 2000 (Rush & Bessant, 1992). The disappointment comes not from a complete failure of the technology but rather from an inability to apply it in ways that produce significant benefits. In such cases, the process of widespread deployment first follows a ‘substitution’ trajectory, being used to do what we already do in better ways. Only gradually do possibilities for using the technology in novel ways – an ‘augmentation trajectory’ begin to emerge. The parallel with many studies, such as Paul David's analysis of how electric motors were deployed at the turn of the 20th century, is a useful reference framework here (David, 1990).

Take, for example, CIM: the substantial gains came not from improved automation of existing control loops but from integration into intelligent and automated manufacturing systems and networks (Bessant et al., 1992). Local-level improvements in services in the early days of the internet involved upgrading what was already there; it was the shift to integrated and platform-based models that had the greatest impact on productivity and changed industrial structures (Cusumano et al., 2019; Llewellin et al., 2014).

Arguably, at present, AI is being deployed in ‘substitution’ mode, replacing what we already do with an AI version of that. While end-to-end AI integration across the entire innovation lifecycle is a potential future state, current tangible successes frequently stem from more focused, pragmatic applications – doing what we do but better, delivering incremental gains.

Three themes are emerging that may have an impact on the rate and extent to which this shift to augmentation and major impact will happen: (1) absorptive capacity (AC) issues; (2) synthesising AI trajectories; (3) mutual adaptation.

Absorptive capacity

Successful application of new technologies like AI depends on organisations having ‘‘the ability …. to recognise the value of new, external information, assimilate it, and apply it to commercial ends” (Cohen & Levinthal, 1990). Zahra & George (2002) reconceptualised AC as a dynamic capability comprising four distinct but related dimensions, grouped into two components.

The first component, potential absorptive capacity (PACAP), refers to the firm's ability to acquire and assimilate external knowledge. Acquisition involves identifying and obtaining relevant knowledge generated outside the organisation, while assimilation refers to the organisational routines and processes that enable the firm to analyse, interpret, and understand this knowledge.

The second component, realised absorptive capacity (RACAP), reflects the firm's ability to apply the knowledge that has been absorbed. This includes transformation, which involves adapting and integrating new knowledge into existing organisational structures and processes, and exploitation, which refers to leveraging this knowledge to refine existing competencies or create new ones in order to generate value.

Arguably, firms have made progress towards the first of these, demonstrating increasing awareness of AI and its importance, and coupling this with its acquisition and experimentation. But deployment is taking place along the substitution trajectory, particularly exploiting AI’s considerable analytical potential. More imaginative uses of generative AI remain unclear and confined to ‘quarantined’ experiments outside the mainstream.

This pattern is exacerbated by the huge investments in AI development, which means there is a strong ‘technology push’ element in the innovation landscape. With the arrival of DeepSeek and similar open-source, low-cost variants, the cost of entry is coming down. Surveys confirm that the problem is not that organisations aren’t aware of AI and its huge potential; it’s just that they don’t (yet) know what to do with it. This challenge is also context-dependent, since the innovation effects of AI appear to vary with institutional quality, human development, and R&D capacity (Temerbulatova et al., 2025).

The challenges associated with integrating AI into organisational processes are extensive. These include compatibility with existing IT infrastructures and organisational policies, as well as the availability of appropriate skills, particularly those required for effective collaboration between AI developers and domain experts. Another important constraint is the availability of relevant and context-specific training data, which is essential for developing reliable AI systems (Agrawal et al., 2018; Máté et al., 2024). At the same time, concerns remain regarding the reliability and contextual limitations of generative AI models, which are known to produce so-called “hallucinations,” generating outputs that may appear convincing but are factually incorrect or poorly grounded in a specific organisational context. Additional issues relate to transparency and accountability, since many advanced AI systems operate as “black boxes,” making their decision-making processes difficult to interpret and raising questions about responsibility when AI-supported outcomes lead to harm. Organisations must also address privacy and cybersecurity risks, as AI-enabled activities often involve extensive interaction with sensitive customer and employee data. Finally, algorithmic bias remains a concern, since AI models trained on historical data may reproduce or amplify existing societal biases related to factors such as gender, ethnicity, or other characteristics.

A number of writers draw attention to these challenges and highlight the need for a strategic response (Brown, 2019; Kowalkiewicz, 2024; Bilan et al., 2025). Recent survey evidence likewise suggests that attitudes toward AI are often cautious rather than purely resistant, with support for its use increasing when appropriate regulation is in place (Yarovenko et al., 2024). They highlight the emerging paradox in AI implementation; on the one hand, there is considerable pressure to adapt to realise the potential of enhanced speed and agility.

On the other hand responsible implementation of AI demands slow, careful, and deliberate action. Establishing robust ethical guidelines, ensuring data quality, auditing models for bias, and creating transparent accountability structures are all inherently methodical and time-consuming processes. This is consistent with broader responsible AI research, which shows that, across disciplines, the field remains strongly oriented toward social principles and descriptive analyses, with persistent concerns about accountability, transparency, fairness, and privacy (Memarian & Doleck, 2024).

Synthesizing AI trajectories

We saw earlier that AI is a term covering a wide range of technologies whose characteristics offer support for capability enhancement along two distinct trajectories. The first (primarily deploying AI's analytical and pattern-recognition capabilities) enables focus and convergence; the second (primarily using generative AI) is about divergence and exploration.

AI's potential contribution and role are not uniform across the innovation lifecycle. In the search phase, AI primarily supports divergent activities – expanding the range of possibilities by uncovering trends, generating diverse ideas, and identifying needs from vast datasets. As the process moves to selection, AI's role shifts toward convergence – helping analyse, evaluate, predict, and prioritise, thereby narrowing down options based on data-driven insights.

During implementation, AI acts as an accelerator and efficiency booster, automating tasks, speeding up development and testing, and improving quality control. Finally, in the value capture stage, AI provides analytical and reflective support, enabling a deeper understanding of market reception, performance assessment, and crucial organisational learning.

The implication of this is that AI offers much more than a 'plug and play replacement of human activities; instead, its different capabilities need careful matching to the nature of the tasks involved. This might form a key part of the transition to augmentation suggested above, but it will require a more nuanced approach to application, built on deploying on a 'horses for courses' basis while also seeking synergistic complementarities.

Mutual adaptation (the potential for partnership)

At the heart of much concern around AI (and the accompanying reluctance to adopt the technology) is an understandable anxiety about the extent to which it will change both the quantity and quality of employment (Gmyrek et al., 2025). This is relevant to many situations, including that of innovation management; studies suggest that, unlike other automation technologies, AI may have a particular impact on what are currently considered 'creative' jobs. However, analysis of earlier experience during 'technological revolutions' suggests that the reality is more nuanced; there will be both loss and gain in employment linked to the changing nature of evolving tasks (Miles et al., 2014). In addition, the patterns of work organisation around such new technologies play a key role; rather than a simple replacement for human skills, the evidence suggests that integrating those skills with the new technology capabilities can often be a more promising and productive option.

Trist and Bamforth's detailed case study of the introduction of new mining technology offers a well-known blueprint for such a process (Trist & Bamforth, 1951). The emergence of socio-technical systems design represented a way of working with technology to build on the strengths offered by both parties; it took the form of an implementation methodology based on mutual adaptation and the evolution of a hybrid mode of working.

Many subsequent studies across generations of technology support this approach; for example, Jaikumar's studies of flexible manufacturing systems (Jaikumar, 1986) and studies of computer-integrated manufacturing (Leonard-Barton, 1988; Bessant, 1991). All confirm the potential of exploring the 'design space' opened up by the emergence of powerful new technologies by exploring, via mutual adaptation, a hybrid model. Viewed through this lens, AI and its integration into the innovation process can be seen as a socio-technical challenge, with recent work on generative AI likewise emphasising collaborative human-AI arrangements rather than simple replacement (Kaczorowska-Spychalska et al., 2024). Just as with earlier 'revolutionary' technology, the real benefits are likely to emerge through a process of mutual adaptation.

It appears to have considerable validity 70 years on; a recent study on using AI within Procter and Gamble to support the innovation process suggests a similar model (Dell Aqua et al., 2025). Using a controlled experiment, four variants of working were explored: teams working without AI, a fully automated AI-only process, a team using AI as an assistant support tool, and finally a team that learned to incorporate AI as a full team member. The results measured on a variety of performance criteria came out strongly in favour of this last category, AI as a full partner in the process. This offers a pathway for the future, which certainly merits further exploration.

A prospective German study suggests a similar path in which the complementary strengths of human and AI players offer the most promising contribution to product innovation (Bouschery et al., 2023). And Mollick, in his book, discusses the possibilities of co-intelligence, working with AI, and discovering ways to partner to build on complementary strengths (Mollick, 2024).

The discussion above suggests that AI adoption in innovation management follows an evolutionary trajectory (Figure 2).

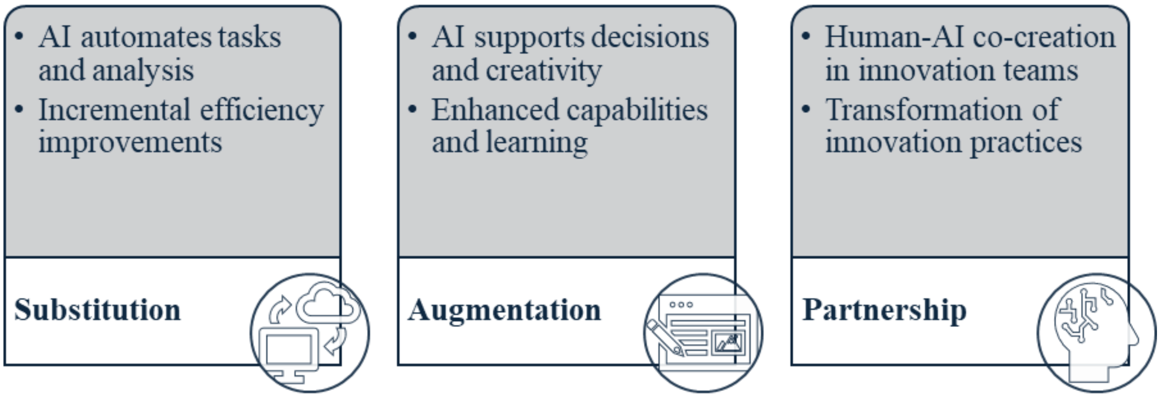

Figure 2. Evolution of AI roles in innovation management systems.

The transition from substitution to augmentation, and eventually toward human-AI partnership, represents a key trajectory in the evolution of AI-enabled innovation management systems. While early implementations primarily focus on replacing existing analytical tasks, more advanced implementations increasingly integrate AI into collaborative innovation processes, where human and machine capabilities complement each other.

CONCLUSION

This paper has sought to provide a comprehensive overview of how AI might augment and transform the innovation process in organisations. The future of innovation management will not be defined by a choice between human intuition and machine intelligence. Instead, it will be shaped by the thoughtful, strategic, and ethical integration of both. The challenge for leaders is not simply to adopt AI, but to architect an organisation where humans and machines can collaborate effectively – where AI handles the scale of data and computation, and humans provide the strategic direction, creative judgment, and ethical compass.

In a rapidly evolving field where patterns of AI adoption are still emerging, there are numerous opportunities for further research that could provide valuable insights for scholars, policymakers, and practitioners. Several questions appear particularly relevant.

First, further research is needed to understand how the integration of AI into innovation processes reshapes required competencies and professional roles. Traditional innovation management has emphasised skills such as project management, team leadership, and domain expertise. However, AI-augmented systems may require additional capabilities, including data literacy, prompt engineering, awareness of AI ethics, and the ability to critically evaluate AI-generated outputs. Empirical studies could examine how innovation roles evolve in practice and what new organisational structures emerge to support these changes.

Second, governance mechanisms for managing the ethical and organisational risks of AI represent an important research area. While the need for responsible AI governance is widely recognised, there remains limited empirical evidence regarding which approaches are most effective. Future work could explore alternative governance models, including centralised AI ethics committees or decentralised “ethics champions,” as well as mechanisms for bias auditing, accountability allocation, and responsible AI deployment within innovation management systems.

Third, the growing use of generative AI in ideation and concept development raises questions regarding the nature of innovation outcomes. While generative models can produce many novel ideas, their reliance on existing data may favour the recombination of known concepts. Future research could therefore examine whether AI-supported ideation tends to produce primarily incremental innovations or whether it can also enable more radical forms of innovation. Longitudinal studies comparing innovation portfolios across organisations with varying levels of AI integration could provide valuable insights.

Finally, further work is needed to understand the long-term implications of human-AI collaboration for innovation culture and organisational learning. While AI may augment human creativity and support exploratory thinking, there is also a risk that excessive reliance on automated outputs could reinforce automation bias or reduce critical reflection. Qualitative and ethnographic studies could therefore explore how human-AI collaboration reshapes innovation practices, decision-making processes, and organisational culture over time.

IMPLICATIONS FOR RESEARCH AND PRACTICE

This study opens several directions for future research and practice in AI-enabled innovation management. For research, it highlights the need to examine how organisations operationalise human-AI collaboration and how different configurations of analytical and generative AI shape innovation performance. Greater attention is also required to micro-level processes, including changes in roles, decision-making, and learning dynamics within innovation teams.

For practice, the findings suggest that organisations should prioritise capability development and organisational redesign rather than focusing solely on AI tools. Effective implementation requires aligning AI with innovation strategy, embedding cross-functional collaboration, and establishing governance mechanisms to manage ethical and operational risks. Adopting a socio-technical perspective becomes critical for translating AI potential into sustained innovation outcomes.

REFERENCES

Agrawal, A., Gans, J., & Goldfarb, A. (2018). *Prediction Machines: The Simple Economics of Artificial Intelligence.* Harvard Business School Press.

Bencsik, A. (2021). The sixth generation of knowledge management – the headway of artificial intelligence. *Journal of International Studies*, 14(2), 84–101. https://doi.org/10.14254/2071-8330.2021/14-2/6

Bessant, J. (1991). *Managing advanced manufacturing technology: The challenge of the fifth wave*. NCC-Blackwell.

Bessant, J., Smith, S., Tranfield, D., & Levy, P. (1992). Organisation Design Implications of Computer Integrated Technology. *International Journal of Computer Integrated Manufacturing*. Special Issue on Human Factors.

Bianchini, S., Müller, M., & Pelletier, P. (2022). Artificial intelligence in science: An emerging general method of invention. *Research Policy*, 51(10), Article 104604. https://doi.org/10.1016/j.respol.2022.104604

Bilan, Y., Mishchuk, H., & Oliinyk, O. (2025). Migration of highly skilled workers as a driver of digital economy development. *Knowledge and Performance Management*, 9(2), 113-123. doi:10.21511/kpm.09(2).2025.09

Bilgram, V., & Laarmann, F. (2023). Accelerating Innovation with Generative AI: AI-augmented Digital Prototyping and Innovation Methods. *IEEE Engineering Management Review*, 51(2), 1–5. https://doi.org/10.1109/EMR.2023.3272799

Bogaisky, J. (2019, June 3). GE says it's leveraging Artificial Intelligence to cut product design times in half. *Forbes Magazine*. Retrieved from https://www.forbes.com/sites/jeremybogaisky/2019/03/06/general-electric-ge-artificial-intelligence/

Bolton, R. (2025, March). I Thought I Knew Strategy Development – Then ChatGPT Blew My Mind. *Mile Zero.* Retrieved from https://www.milezero.io/2025/03/26/i-thought-i-knew-strategy-development-then-chatgpt-blew-my-mind/

Bouschery, S. G., Blazevic, V., & Piller, F. T. (2023). Augmenting human innovation teams with artificial intelligence: Exploring transformer-based language models. *The Journal of Product Innovation Management*, 40(2), 139–153. https://doi.org/10.1111/jpim.12656

Brandao, P. R. (2025). The Impact of Artificial Intelligence on Modern Society. *AI (Basel)*, 6(8), Article 190. https://doi.org/10.3390/ai6080190

Brown, A. (2019). *Delivering digital transformation: A manager's guide to the digital revolution*. De Gruyter Oldenbourg.

Brown, A. (2025). *Digital Economy Dispatches*. Retrieved from https://dispatches.alanbrown.net/

Clifford, J. (2023, September 27). How Toyota is using AI to help car designers. *Toyota UK Magazine*. Retrieved from https://mag.toyota.co.uk/car-designers-using-ai/

Cohen, W. M., & Levinthal, D. A. (1990). Absorptive Capacity: A New Perspective on Learning and Innovation. *Administrative Science Quarterly*, 35(1), 128–152. https://doi.org/10.2307/2393553

Cooper, R. G. (2024a). The AI transformation of product innovation. *Industrial Marketing Management*, 119, 62–74. https://doi.org/10.1016/j.indmarman.2024.03.008

Cooper, R. G. (2024b). The Artificial Intelligence Revolution in New-Product Development. *IEEE Engineering Management Review*, 52(1), 195–211. https://doi.org/10.1109/EMR.2023.3336834

Cooper, R. G., & Brem, A. M. (2024). The Adoption of AI in New Product Development: Results of a Multi-Firm Study in the US and Europe. *Research Technology Management*, 67(3), 44–53. https://doi.org/10.1080/08956308.2024.2324241

Cooper, R. G., & Sommer, A. F. (2023). Dynamic Portfolio Management for New Product Development Companies can use a Value Based Scorecard, developed using proven, research-based criteria, to select and prioritize NPD projects effectively. *Research Technology Management*, 66(3), 19–31. https://doi.org/10.1080/08956308.2023.2183004

Cordeschi, R. (2007). AI turns fifty: revisiting its origins. *Applied Artificial Intelligence*, 21(4–5), 259–279. https://doi.org/10.1080/08839510701252304

Cusumano, M., Gawer, A., & Yoffie, D. (2019). *The business of platforms*. MIT Press.

David, P. A. (1990). The Dynamo and the Computer: An Historical Perspective on the Modern Productivity Paradox. *The American Economic Review*, 80(2), 355–361. http://www.jstor.org/stable/2006600

Dell'Acqua, F., Ayoubi, C., Lifshitz, H., Sadun, R., Mollick, E., Mollick, L., Han, Y., Goldman, J., Nair, H., Taub, S., & Lakhani, K. (2025). The Cybernetic Teammate: A Field Experiment on Generative AI Reshaping Teamwork and Expertise. In *National Bureau of Economic Research*. https://doi.org/10.3386/w33641

Goffin, K., & Mitchell, R. (2016). *Innovation management* (3rd ed.). Macmillan.

Gmyrek, P., Berg, J., Kamiński, K., Konopczyński, F., Ładna, A., Nafradi, B., Rosłaniec, K., Troszyński, M. (2025). Generative AI and Jobs: A Refined Global Index of Occupational Exposure, ILO Working Paper

140 (Geneva, ILO). https://doi.org/10.54394/HETP0387 Hargadon, A. (2003). *How breakthroughs happen: The Surprising Truth About How Companies Innovate*. Harvard Business School Press.

Heaven, D. (2025, November 29). The designer changing the way aircraft are made [BBC London]. *Machine Minds.* Retrieved from https://www.bbc.co.uk/future/article/20181129-the-ai-transforming-the-way-aircraft-are-built

Hyland, J, Karlsson, M, Kihlander, I, Bessant, J, Magnusson, M, & Kristiansen, J. (2022). *Changing the dynamics and impact of innovation management*. World Scientific.

International Organization for Standardization (ISO). (2019). ISO 56002:2019 *Innovation Management System – Guidance*. International Standards Organization.

Jaikumar, R. (1986). *Post-industrial manufacturing*. Harvard Business Review.

Joosten, J., Bilgram, V., Hahn, A., & Totzek, D. (2024). Comparing the Ideation Quality of Humans With Generative Artificial Intelligence. *IEEE Engineering Management Review*, 52(2), 153–164. https://doi.org/10.1109/EMR.2024.3353338

Kaczorowska-Spychalska, D., Kotula, N., Mazurek, G., & Sułkowski, Łukasz. (2024). Generative AI as source of change of knowledge management paradigm. *Human Technology*, 20(1), 131–154. https://doi.org/10.14254/1795-6889.2024.20-1.7

Kowalkiewicz, M. (2024). *The economy of algorithms*. Bristol University Press.

Leonard-BartoN, D. (1988). Implementation as mutual adaptation of technology and organization. *Research Policy*, 17(5), 251–267. https://doi.org/10.1016/0048-7333(88)90006-6

Llewellin, D, Autio, E, & Gann, D. (2014). Architectural Leverage: Putting Platforms in Context. *Academy of Management Perspectives*, 28(2), 198–219. https://doi.org/10.5465/amp.2011.0105

Machucho, R., & Ortiz, D. (2025). The Impacts of Artificial Intelligence on Business Innovation: A Comprehensive Review of Applications, Organizational Challenges, and Ethical Considerations. *Systems (Basel),* 13(4), Article 264. https://doi.org/10.3390/systems13040264

Máté, D., Raza, H., Ahmad, I., & Kovács, S. (2024). Next step for bitcoin: Confluence of technical indicators and machine learning. *Journal of International Studies*, 17(3), 68-94. doi:10.14254/2071-8330.2023/17-3/4

McKinsey Consultants. (2025). *AI in the workplace: A report for 2025*. McKinsey and Co.

Memarian, B., & Doleck, T. (2024). A review of caveats and future considerations of research on responsible AI across disciplines. *Human Technology*, 20(3), 488–524. https://doi.org/10.14254/1795-6889.2024.20-3.4

Miles, I, Rush, H, & Bessant, J. (2014). Services Transformation Through New Information Technology: Information Horizons Revisited. In *Driving Service Productivity*. Springer.

Miles, I., Rush, H., Turner, K., & Bessant, J. (1988). *Information horizons*. Edward Elgar.

Mishchuk, H., Oliinyk, O., Bilan, Y., & Skare, M. (2025). The Role of Leadership in Attracting Intellectual Migrants and Boosting Innovative Development of Countries. *Contemporary Economics*, 19(3), 339-354. DOI:10.5709/ce.1897-9254.570

Mollick, E. (2024). *Co-intelligence: Living and Working with AI*. W.H. Allen.

NANDA. (2025). *The GenAI divide: State of AI in business, 2025.* MIT.

Pietronudo, M. C., Croidieu, G., & Schiavone, F. (2022). A solution looking for problems? A systematic literature review of the rationalizing influence of artificial intelligence on decision-making in innovation management. *Technological Forecasting & Social Change*, 182, Article 121828. https://doi.org/10.1016/j.techfore.2022.121828

Rush, H., & Bessant, J. (1992). Revolution in three-quarter time: Lessons from the diffusion of advanced manufacturing technologies. *Technology Analysis & Strategic Management*, 4(1), 3–19. https://doi.org/10.1080/09537329208524075

Schinello, S. (2025). Challenges and opportunities in the use of artificial intelligence in creative economy: Insights from expert interviews. *Economics and Sociology*, 18(1), 199-216. doi:10.14254/2071-789X.2025/18-1/10

Škare, M., Porada-Rochon, M., & Veselica Celić, R. (2025). Total factor productivity dynamics and the artificial intelligence paradox: Evidence from long-memory analysis. *Journal of International Studies,* 18(4), 218-242. doi:10.14254/2071- 8330.2025/18-4/11

Temerbulatova, Z., Zhidebekkyzy, A., Sagiyeva, R., & Ludwiczak, A. (2025). Artificial intelligence as a driver of innovation and patent activity: an empirical analysis of cross-country data. *Economics & Sociology*, 18(3), 184–201. https://doi.org/10.14254/2071-789X.2025/18-3/11

Tidd, J, & Bessant, J. (2024). *Managing innovation* (8th ed.). John Wiley & Sons.

Trist, E. L., & Bamforth, K. W. (1951). Some Social and Psychological Consequences of the Longwall Method of Coal-Getting: An Examination of the Psychological Situation and Defences of a Work Group in Relation to the Social Structure and Technological Content of the Work System. *Human Relations (New York)*, 4(1), 3–38. https://doi.org/10.1177/001872675100400101

Truong, Y., & Papagiannidis, S. (2022). Artificial intelligence as an enabler for innovation: A review and future research agenda. *Technological Forecasting & Social Change*, 183, Article 121852. https://doi.org/10.1016/j.techfore.2022.121852

Yarovenko, H., Kuzior, A., Norek, T., & Lopatka, A. (2024). The future of artificial intelligence: Fear, hope or indifference? *Human Technology*, 20(3), 611–639. https://doi.org/10.14254/1795-6889.2024.20-3.10

Zahra, S. A., & George, G. (2002). Absorptive Capacity: A Review, Reconceptualization, and Extension. *The Academy of Management Review*, 27(2), 185–203. https://doi.org/10.2307/4134351

Authors' Note

All correspondence should be addressed to
Aknur Zhidebekkyzy
Al-Farabi Kazakh National University
Higher School of Economics and Business
Al-Farabi avenue 71, Almaty, Kazakhstan
Email: Aknur.zhidebekkyzy@kaznu.edu.kz

Acknowledgement. The authors sincerely thank JSC "Centre for International Programs" and the "500 Scientists" research internship program of the Republic of Kazakhstan for their valuable support. A. Zhidebekkyzy's participation in the "500 Scientists" program offered relevant academic resources and opportunities that supported the progress of this research.

Funding. This research was funded by the Science Committee of the Ministry of Science and Higher Education of the Republic of Kazakhstan (Grant No. AP23487651).

Human Technology
ISSN 1795-6889
https://ht.csr-pub.eu