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Revolutionizing business operations – implementing AI for efficiency and growth

Rewolucjonizowanie procesów biznesowych – zwiększenie efektywności i rozwój poprzez wykorzystanie sztucznej inteligencji (AI)

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Abstract

Artificial intelligence (AI) is increasingly embedded in the core operations of organizations, reshaping how work is organised, decisions are made and value is created. Yet, despite the proliferation of AI initiatives, many firms struggle to move beyond pilots and to translate technical capabilities into measurable performance gains. This article examines how AI implementation affects business operations and business process management (BPM), with particular attention to efficiency, growth and the emerging role of generative AI (GenAI). Conceptually, we synthesise recent research on AI-enabled BPM, human–AI collaboration and GenAI in operations and supply chains. Empirically, we conduct a secondary analysis of successive waves of large-scale surveys (w and related industry reports), focusing on the diffusion of AI and GenAI across functions, the breadth of deployment within organisations, and self-reported effects on cost, productivity and earnings before interest and tax (EBIT). The findings show that while AI adoption has become nearly universal and increasingly multi-functional, substantial financial impact remains concentrated in a small subset of "AI high performers" with advanced BPM-related capabilities. AI generates its strongest and most consistent operational gains in process- and information-intensive functions, and GenAI delivers sizable task-level productivity improvements that only translate into firm-level impact when organisations redesign workflows, invest in data foundations and manage human–AI collaboration. The article concludes with implications for theory and practice and outlines directions for future research on AI-enabled process transformation.

Keywords

artificial intelligence (AI), Business Process Management (BPM), automation, decision-making, innovation, customer experience

1. Introduction

Over the past decade, artificial intelligence (AI) has moved from the periphery of business technology to the centre of strategic and operational debates. Once associated mainly with science fiction and experimental prototypes, AI systems now underpin everyday activities such as demand forecasting, credit scoring, customer service, maintenance planning and software development. In many organisations, AI has become a core mechanism for reconfiguring business processes, reshaping roles and responsibilities, and opening up new avenues for growth and innovation. At the same time, the trajectory of AI adoption has been uneven: while some organisations report substantial performance gains and strategic renewal, others struggle to move beyond isolated proofs of concept. Throughout the paper, we use the term organisations to reflect the terminology of the McKinsey surveys; in practice, the discussion primarily concerns business enterprises, although the survey respondent base may also include other types of institutions.

From a scholarly perspective, AI has become one of the most prominent and rapidly evolving topics in contemporary management and information systems research, spanning strategy, operations, marketing, human resources and business process management (BPM) (e.g. Dwivedi et al., 2021; Guler et al., 2024; Haenlein et al., 2022; Ratten, 2024). Recent work emphasises that AI should not be treated merely as an additional technology layer, but as a catalyst of deeper organisational transformation. In strategic management and entrepreneurship, AI is discussed as a driver of new business models and forms of competitive advantage (Ratten, 2024). In operations and supply chain research, AI is analysed as a tool for resilience, optimisation and sustainability across end-to-end processes (Li et al., 2024; Teixeira et al., 2025). In the BPM literature, AI is increasingly seen as integral to the design, execution and continuous improvement of processes, rather than as an exogenous add-on (Fettke & Di Francescomarino, 2025; Gomes et al., 2022; Weinzierl et al., 2024).

At the same time, managerial evidence paints a nuanced picture of AI's impact. Surveys and case-based studies suggest that value creation from AI tends to come from targeted, well-integrated applications that are tightly coupled to specific workflows, rather than from grand "moonshot" projects (Davenport & Ronanki, 2018; Tarafdar et al., 2019). Many organisations report that the main barriers to impact are organisational rather than technical: fragmented data, missing capabilities, lack of cross-functional collaboration and weak governance routinely undermine AI initiatives (Fountaine et al., 2019; IBM Institute for Business Value, 2024a; 2024b). Large-scale surveys such as McKinsey's State of AI series confirm that while AI adoption is now widespread across sectors and functions, substantial earnings contributions remain concentrated in a relatively small group of "AI high performers" with strong capabilities in process redesign, data management and change leadership (McKinsey & Company, 2024; McKinsey & Company, 2025).

The emergence of generative AI (GenAI) adds a new layer of complexity and opportunity. Large language models and related technologies dramatically expand the scope of tasks that can be augmented or partially automated, particularly in knowledge-intensive and customer-facing activities. Experiments in customer service and software development demonstrate double-digit productivity gains and the potential to narrow performance gaps between less and more experienced workers. At the same time, early survey evidence suggests that only a small subset of organisations currently realise material EBIT impact from GenAI: many firms experiment with chatbots and copilots, but few have yet reconfigured processes, governance and skills at scale.

This article focuses on the intersection of these developments from the perspective of business operations and BPM. It asks how AI, and more recently GenAI, is being embedded into operational workflows, which functions and process types benefit most, and under what conditions AI adoption translates into measurable improvements in efficiency and growth. Conceptually, the article builds on three strands of literature: (1) AI-enabled BPM and intelligent process management systems (Fettke & Di Francescomarino, 2025; Khabbaz, 2023; Paschek et al., 2017), (2) human–AI collaboration and augmented decision-making in organisational processes (Jarrahi, 2018; Leszczyński et al., 2025; Osuszek & Stanek, 2021; Wen et al., 2025), and (3) emerging research on GenAI in operations, supply chains and marketing (Chan & Choi, 2025; Li et al., 2024; Shalpegin et al., 2025; Zhou & Sheu, 2025).

Empirically, the article draws on a secondary analysis of large-scale survey results and industry reports to illustrate diffusion and reported impact patterns. Using the McKinsey Global Survey on AI (2017–2025) as the central empirical backbone, the study reconstructs the trajectory of AI and GenAI adoption across business functions, the breadth of AI deployment within organisations, and self-reported effects on cost, productivity and earnings before interest and tax (EBIT). These survey data are triangulated with evidence from the Stanford AI Index, IBM and BCG studies and controlled field experiments on GenAI and productivity. The analysis is descriptive rather than causal, but it allows for a systematic assessment of where AI is actually generating value in practice and how this aligns with theoretical expectations derived from the BPM and socio-technical systems literature on complementary capabilities, process redesign and human–AI collaboration.

The contribution of the article is threefold. First, it offers an integrated synthesis of the rapidly expanding literature on AI in BPM and operations, highlighting the mechanisms through which AI can “rewire” processes rather than simply automate individual tasks. Second, it provides up-to-date empirical evidence on AI and GenAI diffusion, functional deployment and reported economic impact, clarifying the gap between enthusiasm and realised value. Third, it draws out implications for managers and policymakers on how to design AI-enabled processes and organisational arrangements that balance efficiency, innovation, ethics and human agency. The remainder of the paper is structured as follows. Section 2 reviews the theoretical and empirical literature on AI in BPM, human–AI collaboration and GenAI in operations. Section 3 outlines the empirical design and data, including the operationalisation of adoption and impact measures. Section 4 presents the empirical findings concerning diffusion patterns, functional value creation and GenAI’s role. Section 5 concludes with a discussion of theoretical contributions, managerial implications, limitations and directions for future research.

2. Literature

The literature on artificial intelligence (AI) in business and business process management (BPM) has expanded rapidly, moving from speculative discussions about disruptive potential to increasingly fine-grained analyses of how AI is embedded in organizational processes, decision structures and governance systems. Recent contributions emphasise that AI is no longer a peripheral technology but a core driver of strategic renewal and process redesign. Ratten (2024), for example, frames AI as a central theme in strategic management research, highlighting its role in customer experience, personalization and the reconfiguration of business models (Ratten, 2024). Using machine-learning techniques to analyse a large corpus of publications, Guler, Kirshner and Vidgen (2024) demonstrate that research on AI in business and management is highly fragmented: distinct subfields have emerged around automation, predictive analytics, human resources, customer interaction and ethics, often with limited cross-fertilisation (Guler et al., 2024). A systematic review by Teixeira et al. (2025) focused on supply chains shows that in process-intensive domains such as logistics and manufacturing, AI has begun to shift from experimental initiatives to components of the operational architecture, supporting resilience, optimization and sustainability across end-to-end processes (Teixeira et al., 2025).

Foundational managerial work has consistently argued that value creation from AI typically arises from targeted, well-integrated applications rather than spectacular "moonshots". Davenport and Ronanki (2018) synthesise a large set of case studies and identify three dominant categories of successful AI use: robotic and cognitive automation of processes, AI-enabled enhancement of decision-making, and advanced analytics embedded into routine workflows (Davenport & Ronanki, 2018). Fountaine, McCarthy and Saleh (2019) similarly report that the main obstacles to AI impact are organisational rather than technical, stressing the need for a coherent AI strategy, cross-functional teams and a culture that supports experimentation and learning (Fountaine et al., 2019). Tarafdar, Beath and Ross (2019) conceptualise AI primarily as an instrument of augmentation rather than full replacement: in their framework, AI enhances human roles in operations by providing predictive insights, anomaly detection and decision recommendations, which become powerful only when tightly coupled with process metrics and monitoring structures (Tarafdar et al., 2019).

Within this broader landscape, a clearly defined research stream has emerged at the intersection of AI and BPM. Fettke and Di Francescomarino (2025) provide a comprehensive survey of studies on BPM and AI, classifying contributions along both the BPM lifecycle (process identification, modelling, analysis, redesign, implementation, monitoring) and AI techniques (machine learning, natural language processing, computer vision, robotics). They conclude that integration is most advanced in process analysis and monitoring (e.g. process mining, predictive monitoring), whereas AI-driven support for process redesign, goal-driven orchestration and autonomous control of workflows remains comparatively under-researched (Fettke & Di Francescomarino, 2025). Gomes et al. (2022) complement this view with a systematic review of AI-based methods for business processes, identifying the predominance of classical classification and regression models, clustering techniques and metaheuristic optimisation in applications such as prediction of case durations, segmentation of process instances and anomaly detection (Gomes et al., 2022). Weinzierl et al. (2024) offer an extensive mapping of machine-learning applications along the BPM lifecycle, documenting use cases in SLA violation prediction, next-activity recommendation, conformance checking and automated process discovery, but also noting that most studies focus on well-structured, single-process settings rather than complex, cross-functional value chains (Weinzierl et al., 2024).

A related body of work examines the evolution of BPM systems towards more "intelligent" platforms. Paschek, Luminosu and Draghici (2017) introduce the notion of "automated business process management" in the context of digital transformation, arguing that machine-learning models can be used to infer or adapt process control rules based on operational data rather than relying solely on manually defined workflows (Paschek et al., 2017). Khabbaz (2023) traces the integration of AI components into BPM suites, showing how classification, routing and exception-handling can be increasingly delegated to AI modules and suggesting that large language models (LLMs) further accelerate the transition from static workflows to more adaptive, conversational interfaces and "process agents" (Khabbaz, 2023). Empirical evidence from specific national contexts underscores the importance of organisational capabilities. Sliż and Jackowska (2024), in a study of Polish service firms, find that AI implementation in BPM is strongly associated with organisational ambidexterity: organisations capable of simultaneously exploiting existing processes and exploring novel opportunities display higher AI maturity and are more likely to integrate AI into end-to-end process designs (Sliż & Jackowska, 2024).

A second major stream, closely linked to BPM, focuses on human–AI collaboration in decision-making processes. Jarrahi's (2018) seminal paper proposes the metaphor of "human–AI symbiosis", arguing that AI systems excel at pattern recognition, large-scale data analysis and probabilistic reasoning, while humans contribute contextual knowledge, sense-making and ethical judgment. Effective organisational decision-making, in this view, relies on carefully designing joint human–AI systems rather than substituting one for the other (Jarrahi, 2018). Osuszek and Stanek (2021) transpose this argument directly into the BPM domain, analysing how AI can augment managerial judgment in exception handling, resource allocation and decision-making under uncertainty. Their results suggest that AI works best as a "second opinion" embedded in the process rather than as an autonomous decision-maker, which has implications for role design, authorisation structures and escalation mechanisms in process models (Osuszek & Stanek, 2021).

Recent empirical studies dig deeper into the psychological and social dynamics of human–AI collaboration. Wen et al. (2025) investigate how trust in AI and perceived "free will" of AI agents influence the weight that human decision-makers assign to algorithmic recommendations in organisational settings; they find that lack of transparency can lead either to over-reliance on AI or systematic neglect of its input, both of which can degrade process outcomes (Wen et al., 2025). Leszczyński, Gaczek and Munzel (2025) propose a taxonomy of managerial adoption mindsets, "AI trailblazers", "AI strategists", "pragmatic adopters" and "AI sceptics", and show that these mindsets shape whether AI is strategically embedded into marketing and customer-facing processes or remains confined to isolated tools (Leszczyński et al., 2025).

Complementing this work, Gaczek (2025) analyses how perceptions of locus of causality in human–AI decision-making affect responsibility and accountability, suggesting that ambiguous attributions of agency can lead to defensive delegation of decisions to AI or, conversely, to reluctance to rely on AI even when it outperforms humans (Gaczek, 2025). Together, these contributions support the broader BPM insight that process performance depends not only on technological capabilities but also on socio-cognitive configurations of roles, trust and accountability.

The fastest-growing strand of the literature concerns generative AI (GenAI) and its implications for operations and BPM. Shalpegin et al. (2025) explore how GenAI transforms empirical research methods in operations management, demonstrating that LLMs can support idea generation, literature classification, data analysis and report writing, effectively reconfiguring the "knowledge processes" through which research projects are executed (Shalpegin et al., 2025). In operations research, Zhou and Sheu (2025) review emerging applications of GenAI, including scenario generation, synthetic data creation, automatic formulation of optimisation models and assistance in solving complex decision problems; they argue that GenAI may evolve into a meta-tool for designing decision processes themselves rather than just an additional analytic module (Zhou & Sheu, 2025). Li et al. (2024) examine GenAI in sustainable supply chain management, highlighting its potential for "what-if" simulations, demand forecasting under sparse data and optimisation of logistics networks under uncertainty (Li et al., 2024). In the marketing domain, Chan and Choi (2025) show how GenAI enables automated campaign design, deep content personalisation and continuous optimisation of customer communications, with direct consequences for the design and execution of front-office processes (Chan & Choi, 2025).

These studies collectively suggest that GenAI may push BPM beyond the paradigm of static, pre-specified workflows towards more conversational, adaptive, agent-mediated processes. Khabbaz (2023) explicitly discusses the potential of LLMs to support automatic documentation of procedures, generation of business rules and orchestration of "process agents" that adapt process paths in real time to case-specific context (Khabbaz, 2023). At the same time, most contributions remain conceptual or based on small-scale case studies, and there is a clear lack of large-sample quantitative evidence on how GenAI adoption affects process performance indicators such as cycle time, cost, quality and customer satisfaction across different business functions.

Finally, a cross-cutting theme in the literature concerns implementation challenges, organisational maturity and risk. Managerial writings by Davenport and Ronanki (2018), Fountaine et al. (2019) and Tarafdar et al. (2019) converge on the view that technology is only one component of a broader socio-technical system; complementary investments in data architecture, skills, culture and governance are essential for AI to generate measurable improvements in business processes. Empirical findings by Sliż and Jackowska (2024), Wen et al. (2025) and Leszczyński et al. (2025) underline that even organisations with access to advanced AI tools may fail to achieve significant process benefits when trust in AI is low, responsibility for AI-supported decisions is unclear or managerial mindsets remain firmly rooted in traditional practices. At the same time, broad reviews by Guler et al. (2024), Teixeira et al. (2025) and

Ratten (2024) emphasise the growing importance of ethical and regulatory considerations, algorithmic bias, explainability and compliance with emerging frameworks such as the EU AI Act, which directly affect how AI can be embedded in processes in domains such as lending, human resources or healthcare.

Building on these strands of research, the empirical section of this article derives and examines a set of hypotheses about the relationship between AI adoption in core business processes, the configuration of BPM-related capabilities and observed performance outcomes. In particular, we hypothesise that (H1) AI adoption has moved from isolated pilots to broad diffusion across business functions, but measurable efficiency and performance gains remain concentrated among a subset of organisations that invest in complementary BPM capabilities; (H2) organisations that embed AI specifically into process-intensive functions, such as operations, supply chain and customer service, report higher improvements in operational metrics than those that focus on peripheral or purely analytical use cases; and (H3) early adoption of generative AI in process execution and knowledge-intensive tasks is associated with additional productivity gains beyond those attributable to earlier waves of AI. To assess these propositions, the next chapter conducts a secondary analysis of large-scale surveys and industry reports (e.g. McKinsey *The State of AI* surveys, Stanford *Artificial Intelligence Index Report* [Maslej et al., 2024], IBM and Boston Consulting Group studies) that report on AI use across functions, AI-related capabilities and self-reported impacts on efficiency, productivity and profitability. By triangulating these data with the conceptual expectations outlined above, the empirical analysis aims to provide quantitative support, or counter-evidence, for the mechanisms proposed in the literature on AI-enabled BPM and human–AI collaboration.

3. Empirical design and data

3.1 Overall research design

The empirical component of this article uses large-scale secondary data to substantiate the conceptual claims developed in the literature review. Specifically, it triangulates evidence from successive waves of the McKinsey Global Survey on AI (2017–2025), which consistently track organizational AI adoption, breadth of use across business functions, and perceived economic impact in terms of cost savings and earnings before interest and tax (EBIT).

The empirical strategy is descriptive rather than causal. It reconstructs a coherent time series for:

1) the diffusion of AI and, more recently, generative AI (gen AI);
2) the breadth of AI deployment across business functions;
3) self-reported economic impact and the emergence of "AI high performers."

These indicators are then interpreted against the theoretical expectations that:

- as adoption spreads and AI is embedded in more functions, the distribution of value creation shifts from isolated pilots to enterprise-level EBIT contributions;
- gen AI amplifies this trend particularly in knowledge-intensive functions (marketing, product development, IT, supply chain);

- governance and workflow redesign act as key enabling conditions for translating adoption into measurable financial outcomes.

The following section details the data, measures, and analytical approach and presents a set of harmonised tables that will be used in the subsequent hypothesis-oriented discussion.

3.2 Data sources and scope

The empirical basis consists of four closely related survey series conducted by McKinsey & Company:

4. The state of AI in 2022 – and a half decade in review (fieldwork 2022; covering adoption since 2017 and impact up to 2021).
5. The state of AI in 2023: Generative AI's breakout year (fieldwork April 2023; covering adoption and impact up to 2022).
6. The state of AI in early 2024: Gen AI adoption spikes and starts to generate value (fieldwork Feb–Mar 2024; including an extended module on generative AI by business function).
7. The state of AI in 2025: Agents, innovation, and transformation (fieldwork June–July 2025; focusing on AI agents, enterprise-level value, and high performers).

Each survey samples 1,300–2,000 managers and executives across regions, sectors and firm sizes, with responses weighted by national GDP contribution. The underlying respondent-level microdata are not publicly available, so the empirical section relies on the aggregated percentage estimates and sample sizes reported in McKinsey's tables and exhibits. This approach is appropriate for the paper's purpose, which is descriptive: reconstructing broad diffusion and impact patterns over successive survey waves rather than estimating causal effects at the firm level. Accordingly, the surveys are treated as a quasi-panel at the level of the "global corporate population," where the unit of analysis is the share of respondents (i.e., organisations) with a given characteristic in a given survey year (adoption in at least one function, use of gen AI, or reporting a certain level of EBIT impact).

In the McKinsey survey reporting, the unit is the respondent's organisation (typically the respondent's company). The published materials do not indicate that successive waves track the same organisations over time; accordingly, the series should be interpreted as repeated cross-sections rather than a longitudinal panel. Because respondent-level microdata and detailed composition tables are not available to the authors, we cannot directly test whether shifts in sectoral composition (e.g., a rising share of IT-related organisations) contribute to changes in function-level patterns; this remains a limitation of inference based on aggregated figures.

3.3 Harmonising adoption measures

Across surveys, McKinsey maintains a broadly comparable, though evolving, definition of AI adoption. In 2017 adoption meant using AI "in a core part of the organization's business or at scale"; in 2018–2019 it was "embedding at least one AI capability in business processes or products"; since 2020 it is defined as the organization having "adopted AI in at least one business function."

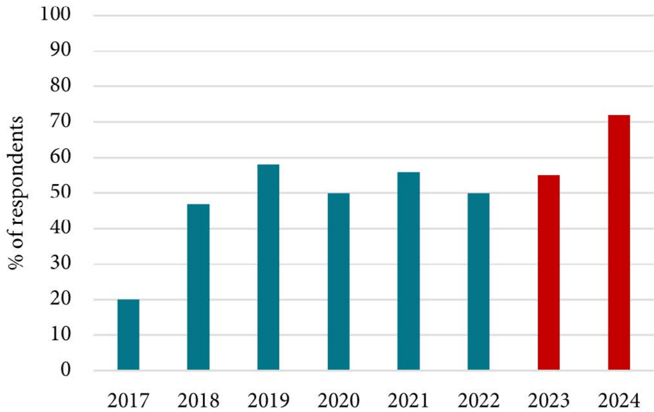

Figure 1. AI adoption in at least one business function (% of respondents)

S o u r c e: Authors' own elaboration based on McKinsey survey.

These data (Chart 1) show a two-phase diffusion pattern. From 2017 to 2022, adoption increases from 20 to about 50–56 percent and then plateaus around the 50 percent mark ("years of little meaningful change") (McKinsey & Company, 2022). Between 2022 and early 2024, adoption jumps from 50–55 percent to 72 percent, coinciding with rapid gen-AI diffusion: organizations regularly using gen AI in at least one function increase from roughly one-third (33 percent) in 2023 to nearly two-thirds (65 percent) ten months later (McKinsey & Company, 2023; 2024).

The 2025 survey reports that 88 percent of organizations use AI in at least one business function, up from 78 percent a year earlier, suggesting continued diffusion beyond the early-2024 baseline shown in Table 1 (McKinsey & Company, 2025). As a simple sensitivity check, the main diffusion conclusions were verified against both early-2024 adoption baselines reported in the series (72% in the early-2024 wave versus 78% as referenced in the 2025 report). Using either value does not change the qualitative interpretation: the 2023–2024 period still marks a clear acceleration relative to the 2017–2022 plateau, and by 2025 adoption remains close to universal in the sense that it clearly exceeds two-thirds and approaches nine-tenths of surveyed organisations. The difference affects the precise level assigned to 2024, but it does not alter the direction of change or the paper's subsequent emphasis on the widening gap between diffusion and concentrated EBIT impact among a small subset of high performers (McKinsey & Company, 2024; 2025).

Beyond "any adoption," the surveys capture how widely AI is deployed within organizations. The early-2024 report provides a longitudinal view of the share of respondents whose organizations use AI in at least 1, 2, 3, 4 or 5 business functions (McKinsey & Company, 2024). Table 2 summarises the evolution since 2021.

Table 1. Breadth of AI deployment across business functions, 2021–2024

Year (survey)	≥1 function	≥2 functions	≥3 functions	≥4 functions	≥5 functions
2021	56	27	15	8	(not reported)
2022	50	28	17	11	7
2023	55	31	18	12	7
2024	72	50	27	15	8

S o u r c e: Own elaboration based on McKinsey survey.

The table confirms that the 2023–2024 inflection is not only a matter of more organizations adopting AI, but also of organizations deploying it more broadly. Half of respondents in early 2024 report that their organizations use AI in at least two business functions (up from less than one-third in 2023), and more than a quarter report use in three or more functions (McKinsey & Company, 2024). This expansion of breadth is central to the hypotheses tested later, which link multi-function deployment to enterprise-level impact.

The early-2024 survey contains the most granular published breakdown of gen-AI adoption by business function. Exhibit 3 in the report lists the share of respondents whose organizations regularly use gen AI in each function (McKinsey & Company, 2024).

Figure 2. Regular use of generative AI by business function (2024)

S o u r c e: Authors' own elaboration based on McKinsey survey.

Gen-AI adoption is thus highest in marketing and sales, product/service development, and IT, functions where prior research also expects the greatest value creation from language- and knowledge-intensive use cases (McKinsey & Company, 2023). Within these functions, the most common gen-AI use cases include content support for marketing strategy (16 percent of respondents), personalised marketing (15 percent), and sales lead identification in marketing and sales (8 percent); design development (10 percent) and scientific literature review (6 percent) in product development; and IT help-desk chatbots (7 percent), data-management support (7 percent) and AI assistants for help-desk staff (6 percent) in IT (McKinsey & Company, 2024). These distributions will later be used to test the expectation that gen-AI value materialises first in knowledge-heavy, customer-facing and R&D-intensive functions, rather than in traditional automation domains such as core manufacturing.

To operationalise value creation, the analysis draws on three families of indicators:

1. **Enterprise-level EBIT contributions from AI (all AI capabilities)**. The 2022 report notes that for the third consecutive year "about a quarter" of respondents say at least 5 percent of their organizations' EBIT is attributable to AI use in 2021; the share is described as similar for 2019 and 2020 (McKinsey & Company, 2022). The 2023 survey finds 23 percent of respondents report that AI accounted for at least 5 percent of EBIT in 2022 (McKinsey & Company, 2023). The 2025 survey changes the question slightly and reports that 39 percent of respondents attribute any EBIT impact to AI, but that most of these report less than 5 percent; only about 6 percent qualify as "AI high performers" with both ≥5 percent EBIT impact and self-reported "significant" value from AI (McKinsey & Company, 2025).
2. **EBIT contributions from gen AI specifically**. The early-2024 report introduces a separate concept of "gen-AI high performers." Among 876 organizations that have adopted gen AI, only 46 respondents, about 5 percent, report that more than 10 percent of their organizations' EBIT is attributable to gen-AI deployment (McKinsey & Company, 2024). These organizations also typically attribute substantial additional EBIT to non-generative ("analytical") AI.
3. **Function-level cost and revenue effects**. For gen AI, the early-2024 survey provides, by function, the share of respondents who report cost decreases and the share who report revenue increases greater than 5 percent. Although the detailed percentages vary by function, the report highlights that cost decreases are most frequently reported in human resources, while meaningful revenue increases are most often observed in supply chain and inventory management. For analytical AI, cost benefits are most common in service operations and revenue uplifts in marketing and sales (McKinsey & Company, 2022, 2024).

Table 2. Selected indicators of AI-related EBIT impact in McKinsey surveys

Survey / reference year	Indicator definition	Value reported
2019–2021 (reported 2022)	Share of organizations attributing ≥5% of EBIT to AI use	"About one-quarter" (≈25%) each year
2022 (reported 2023)	Share of organizations attributing ≥5% of EBIT to AI use	23%
2023 (reported early-2024)	Share of AI-adopting organizations where >10% of EBIT attributable specifically to gen-AI use	46 of 876 respondents (≈5.3%)
2024 (reported 2025)	Share of organizations attributing any EBIT impact to AI	39%
2024 (reported 2025)	"AI high performers" (≥5% EBIT impact and "significant" value)	≈6% of respondents

S o u r c e: Authors' own elaboration based on McKinsey survey.

The pattern in Table 2 is consistent with the narrative that AI's economic impact, while observable, is still concentrated in a minority of firms. Roughly one quarter of organizations report that AI contributes at least 5 percent of EBIT, a share that has been relatively stable over several years despite growing adoption (McKinsey & Company, 2022, 2023). Gen-AI high performers, those attributing more than 10 percent of EBIT specifically to gen-AI deployment, remain a very small subset (around 5 percent of organizations with gen-AI adoption), reinforcing the idea that value capture lags far behind diffusion (McKinsey & Company, 2024). Function-level patterns, although reported in more aggregated form, show that both analytical AI and gen AI are already associated with measurable cost and revenue effects in the functions where diffusion is highest. For example, between roughly one-third and one-half of respondents whose organizations use gen AI in a given function report cost decreases in that function, and similar or higher shares report revenue increases; the largest shares of revenue increases (>5 percent) are found in supply chain and inventory management, while cost decreases are particularly prominent in human resources.

4. Conclusion

The article combines a conceptual synthesis with a descriptive reading of large-scale survey evidence to clarify why diffusion of AI does not translate uniformly into firm-level financial impact. The empirical patterns reported in successive survey waves are consistent with the view that tangible value capture is concentrated among a small subset of organisations that pair AI adoption with process redesign, data foundations, governance and effective human–AI collaboration. Building on a rich and rapidly evolving body of literature and on large-scale survey evidence, the analysis paints a nuanced picture. AI is no longer an experimental curiosity at the fringes of the firm: it is widely deployed across functions and is increasingly embedded into core workflows. At the same time, the empirical results show that widespread adoption does not automatically entail widespread value creation.

From a theoretical perspective, the findings reinforce the view that AI should be conceptualised as part of a broader socio-technical system. The literature on AI-enabled BPM, human–AI collaboration and GenAI consistently emphasises that algorithms, data infrastructures, processes, roles and governance mechanisms are tightly interdependent. The survey evidence is consistent with this view: organisations that report substantial EBIT contributions from AI tend to be those that have invested in end-to-end process redesign, robust data platforms, cross-functional operating models and explicit governance of AI risks and responsibilities. In contrast, organisations with fragmented data, ad hoc pilots and limited process orientation report more modest and localised benefits.

The analysis also clarifies where and how AI currently generates the strongest operational gains. Both the literature and the survey data point to process- and information-intensive functions, such as service operations, supply chain management, manufacturing, IT and software engineering, as early and consistent beneficiaries of AI and GenAI deployment. In these domains, AI supports forecasting, allocation, anomaly detection, resource scheduling and content generation, often delivering clear improvements in throughput, quality and cost. Generative AI extends this logic into knowledge-intensive tasks, enabling new forms of assistance in customer interaction, product development and coding. Yet the step from task-level productivity to firm-level financial impact is neither automatic nor guaranteed.

For practitioners, the results imply that AI strategies need to be anchored in a clear process perspective. It is not enough to acquire models and tools; organisations must identify which processes are most amenable to AI-enabled transformation, redesign workflows around new capabilities, and invest in the skills and structures needed to support human–AI collaboration. This includes attention to trust, transparency, accountability and ethics, especially in domains where AI influences high-stakes decisions about customers, employees or citizens.

Finally, the study has limitations that affect the generalisability of the empirical conclusions. It relies on self-reported survey data aggregated at a high level, which cannot establish causality and may be affected by reporting biases such as social desirability, heterogeneous interpretations of "use" and "impact," and differences in internal measurement practices across organisations. The McKinsey surveys are also not based on a pure probability sample: participation is voluntary and respondent selection may tilt the sample toward larger, internationally exposed organisations and managers already engaged with AI-related agendas, while non-response may further amplify this skew. In several waves, McKinsey adjusts for cross-country differences in response rates by weighting responses by each country's contribution to global GDP; while this can reduce geographic over- or underrepresentation, it does not fully correct for imbalances by industry, firm size, or digital maturity, and it may systematically shift the implied "global" picture toward higher-income economies. The focus on global surveys and harmonised indicators also means that sector-specific idiosyncrasies and regional regulatory frameworks are only partially captured, so the results should be read primarily as broad patterns in managerial perceptions rather than definitive estimates for particular industries or countries. Future research should complement this macro-level perspective with fine-grained case studies, longitudinal analyses of specific AI-enabled processes, and more systematic evaluations of GenAI's impact on quality, fairness, and resilience, not just efficiency and cost. In summary, the main findings of the article can be distilled into four key points:

AI adoption has become widespread, but impact is concentrated. By the mid-2020s, a large majority of organisations report using AI in at least one business function, yet substantial EBIT contributions from AI remain limited to a relatively small group of "AI high performers" with advanced capabilities in BPM, data and governance.

Process- and information-intensive functions capture the earliest and strongest gains. Service operations, supply chain, manufacturing, IT and software engineering are the domains where AI and GenAI most consistently deliver measurable improvements in cost, productivity and quality, confirming the centrality of workflow "rewiring".

Generative AI delivers large task-level productivity effects but modest aggregate financial impact so far. Experiments demonstrate double-digit efficiency gains in customer service and software development, but only a small subset of organisations currently translate these effects into material EBIT contributions, highlighting the need for complementary organisational changes.

Organisational and process capabilities are decisive for AI-enabled transformation. The difference between pilots and scalable value lies less in the algorithms themselves and more in how organisations design processes, manage human–AI collaboration, build data and platform foundations and govern AI deployment in an ethical and responsible way.

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Abstrakt

Sztuczna inteligencja (AI) odgrywa coraz większą rolę w procesach organizacyjnych, zmieniając sposób organizacji pracy, podejmowania decyzji i tworzenia wartości. Pomimo rozpowszechnienia inicjatyw z zakresu AI, wiele firm jednak ma trudności z wyjściem poza etap pilotażowy i przełożeniem możliwości technicznych na wymierny wzrost wydajności. W artykule poddano analizie wpływ wdrożenia AI na działalność operacyjną i zarządzanie procesami biznesowymi (BPM), ze szczególnym uwzględnieniem efektywności, wzrostu i rosnącej roli generatywnej AI (GenAI). Przedstawiono najnowsze badania dotyczące BPM z wykorzystaniem AI, współpracy człowiek–AI oraz GenAI w operacjach i łańcuchach dostaw. Przeprowadzono analizę wyników kolejnych edycji badań ankietowych: McKinsey Global AI Survey 2017–2025 i powiązane z nimi raporty branżowe, koncentrując się na wykorzystaniu AI i GenAI w różnych funkcjach, zakresach wdrożenia w organizacjach oraz deklarowanym wpływie na koszty, produktywność i zysk przed opodatkowaniem (EBIT). Wyniki pokazują, że chociaż wdrożenie sztucznej inteligencji stało się niemal powszechne i coraz bardziej wielofunkcyjne, znaczący wpływ finansowy nadal koncentruje się w niewielkiej grupie „wysoko wydajnych użytkowników sztucznej inteligencji" dysponujących zaawansowanymi możliwościami w zakresie BPM. Sztuczna inteligencja generuje największe korzyści operacyjne w obszarach wymagających intensywnego przetwarzania procesów i informacji, a GenAI zapewnia znaczącą poprawę produktywności na poziomie zadań, co wywiera wpływ na przedsiębiorstwo czy organizację wtedy, gdy zostaną przeprojektowane procesy pracy i właściwe będzie zarządzanie współpracą między człowiekiem a sztuczną inteligencją.

Artykuł kończy się implikacjami dla teorii i praktyki oraz nakreśla kierunki przyszłych badań nad transformacją procesów wspomaganą przez sztuczną inteligencję.

Słowa kluczowe

sztuczna inteligencja (AI), zarządzanie procesami biznesowymi (BPM), automatyzacja, podejmowanie decyzji, innowacje, doświadczenie klienta

Appendix A

Methods: Harmonisation of McKinsey survey indicators

This appendix documents how published percentage estimates from successive McKinsey & Company "State of AI" survey waves (as cited in the main text) were harmonised into a single descriptive time series, and how the "AI high performer" and "gen AI high performer" shares were computed.

Because the survey series evolves over time (field periods, sampling frames, question wording and reported denominators), the harmonised dataset should be read as a set of wave-specific cross-sectional observations. All measures are interpreted as shares of responding organisations for a given wave, not as a longitudinal panel. For consistency across waves, we index observations by the wave year (year of fielding/publication), preserve the original denominators used in report tables (unconditional vs. conditional subsamples), and keep reported rounding. When a value is described only approximately in the report text, we code the closest percentage and treat it as approximate.

For the adoption series, we harmonise to the closest available "any AI adoption" indicator in each wave (typically phrased as using AI in at least one business function, or an equivalent "adopted AI" measure). When a report provides multiple adoption figures due to differing field periods or reporting modules (e.g., early-2024 versus 2025 comparisons), we do not average or smooth them. Instead, we treat these as separate wave-specific estimates and attribute differences to the underlying fieldwork/reporting context rather than forcing a single reconciled value.

Breadth-of-deployment measures are recorded following the McKinsey reporting convention, i.e., the share of respondents indicating use of AI in at least N functions. If a particular threshold is not reported in a given wave, we leave the corresponding entry as not reported rather than interpolating.

Impact measures are not forced into a single unified metric because thresholds and wording differ across waves (e.g., "any EBIT impact" versus "≥5% of EBIT attributable to AI," and AI overall versus gen-AI-specific attribution). We therefore retain the wave-specific indicator definition used by the report and report it transparently in the text; we do not convert "any impact" into "≥5% impact," as that would require distributional assumptions not supported by the published tables.

The "AI high performers" share is taken from the report's own definition in the 2025 wave: organisations reporting at least 5% of EBIT attributable to AI and also reporting "significant" value from AI. When the report provides the percentage directly, we record that percentage as the share of all respondents in that wave; if only counts are provided, we compute the share as . In the main text, this is reported as a wave-specific descriptive statistic (approximately 6%).

The "gen AI high performers" share is computed from the early-2024 wave table that reports, among organisations that have adopted gen AI, the subset attributing more than 10% of EBIT specifically to gen-AI deployment. Using the published numerator and denominator, the share is $46/876 \times 100 \approx 5.25\%$ (reported as 5.3% after rounding). This measure is explicitly conditional on gen-AI adoption. An unconditional share among all respondents would only be approximable if the same wave provides a compatible gen-AI adoption rate, but because adoption and performance measures may come from different modules or field periods, we retain and report the conditional statistic to avoid compounding inconsistencies.

Overall, the harmonised series is intended for descriptive inference only. Differences across waves may reflect real change as well as shifts in question wording, thresholds, field periods, weighting, and denominators; accordingly, the empirical section highlights these definitional differences and avoids causal interpretation.