



Impact of AI Adoption on Business Process

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Abstract – Artificial intelligence (AI) is changing the face of business processes, but the nature of this change is still a point of controversy. This paper aims to conduct an evaluation of the effect of AI adoption on business processes by considering the insights revealed by recent research. It was found out that adoption of AI brings about positive results in several dimensions of business processes. Quantitative information showed that tasks' completion rate with assistance of AI amounts to 78%, whereas in case of no assistance, this rate is 54%; moreover, up to 62.5% of efficiency increase is attainable via AI automation. AI fluency, which can be understood as integration of AI into thousands of tasks, is associated with 1.7× sales conversions increase, 1.5× customer satisfaction improvement, 35% productivity increase in software development, and 30% manufacturing throughput increase. However, the path to achieving all those benefits is a process that involves stages from personal productivity to company productivity and is accompanied by certain obstacles, such as high costs of implementation, etc.

Keywords – Artificial Intelligence, Business Process Management, Digital Transformation, Process Automation, Organizational Performance, AI Fluency.

I. INTRODUCTION

The incorporation of artificial intelligence in business processes is among the greatest changes in the area of enterprise management [1][3]. The use of AI-enabled applications has gone from being experiments to being common tools that provide functionalities that completely change the way businesses work and make decisions [1][3]. From automating mundane tasks to providing predictive analysis and personalized customer interactions, AI tools are transforming the world of BPM [1][3].

There are various reasons why organizations implement AI solutions, such as competition, necessity for digitalization, and the abundance of data and computing power [1][2][3]. AI presents numerous possibilities of process automation, data-based decision making, improving customer experience, and innovative delivery of products/services [1][2][3]. As it was stated in the recent systematic review of literature, the tools powered by AI have significantly improved business processes, allowing organizations to increase their efficiencies beyond what could be achieved with ordinary computer systems [1][3].

However, the effect of AI adoption in terms of business processes is neither consistent nor entirely beneficial [5][7]. There are many stages involved in going through the process of implementing AI solutions and achieving any value from them [5][7]. Recent studies have revealed a rather disconcerting discrepancy between interest in AI and its implementation, with some researchers pointing out that 95% of companies get no value at all from their investment into AI [5][7]. Such a discrepancy, commonly known as

"high interest but low adoption," implies the necessity to gain insights into the process of AI implementation [5][7]. The process of AI adoption becomes even more complicated with the advent of such concepts as generative AI (GenAI) and large language models (LLMs) [5][9]. In contrast to the usual AI solutions designed to automate routine tasks, GenAI offers unique opportunities for creating content, solving problems, and even interacting with humans [5][9].

The purpose of this paper is to conduct an exhaustive evaluation of the consequences of using AI in business process management [1][3]. Using a systematic analysis of the existing research in recent years, the research highlights the influence of AI on diverse aspects of business processes, reveals major problems and critical success factors for its implementation, and provides evidence on its results [3][5]. The research adds to the existing literature on AI in business, integrating fragmented studies into a coherent whole [1][5].

II. LITERATURE SURVEY

The current body of research has explored the influence of adopting AI on the process of running businesses, highlighting the complex nature of opportunities and threats in the process, among other contingent effects [3][5]. The research literature can be categorized into a number of topics, including business process transformation, efficiency, improved decision-making, organizational issues, and generative AI adoption [1][5].

Transformation of Business Processes: According to Niroula and Sharma's (2026) systematic review of 120

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articles across 16 business areas, four key areas of transformation of businesses through the use of artificial intelligence include: Operational Automation; Data-Based Decision Making; Customer Experience and Personalization; and Innovation in Product/Service Delivery [1]. The authors state that AI-based systems have considerably improved business processes in contrast to conventional computer systems which automated operations but did not solve inherent business problems [1]. Likewise, the research conducted in Latin America shows that in different industries, agriculture, finance, education, and public sector the application of AI is done for the sake of improving predictive abilities, automation, and decision making based on data [2].

Measuring the Value of AI in Business: The groundbreaking research carried out by Zebec & Stemmerger (2024) examined the mechanism through which the value of AI can be created through the mediating effect of Business Process Management abilities [3]. Through the use of structural equation modeling on the sample of 448 businesses based in the European Union, a serial multiple mediation model was developed and found that the adoption of AI technology leads to an increase in organizational performance via decision-making and business process performance [3].

Challenges and Implementation Issues: However, there are a number of challenges that hinder the implementation of the AI solutions despite their benefits [5][6]. These include high cost of implementing AI-powered technologies in business operations and SCM, privacy of information, and lack of knowledge of how to use this technology on the part of staff members [5][6]. As a result of a thorough study of the problems associated with implementation of LLMs within organizations using the method of interviewing 27 experienced practitioners in detail, ten main contradictions have been discovered for each of the five stages of implementation [5].

The Adoption Gap: An important conclusion drawn from the literature on this topic is that there is a pronounced gap between interest and adoption [5][7]. It appears that while 75% of companies tried LLMs in 2023, only 9% have fully adopted the technology [5]. The high interest-low adoption pattern is explained by the complexity of AI adoption within the organizations, where many parties are involved and each of them pursues different objectives, and AI is being integrated into complicated socio-technical systems [5]. Unreliable data quality, privacy and security considerations, lack of guidance, and issues with community trust are among factors contributing to the gap [5].

AI Fluency and Organizational Capability: The contemporary discourse moves towards the notion of AI fluency as the penetration of AI in thousands of activities as opposed to one-off projects [7][8]. This means that the transformational nature of AI depends on the extent of its integration into processes [7]. It was found out that in terms

of enterprise AI adoption within Global 1000 firms, AI fluency is a driver of sustainable competitive advantage in the long run [7].

Transformation of the Workforce: One of the most recent trends in the implementation of AI technologies is the addition of AI application to the set of indicators used for evaluating employees' performance [8][10]. For example, Deloitte, Lenovo, Mphasis, and Accenture have already included their employees' skills in using AI systems into the list of KRAs, which means that the use of AI is becoming a fundamental skill rather than an option for them [8][10].

III. PROPOSED METHODOLOGY

Research Framework

For this study, the research method that is used to examine the effect of artificial intelligence adoption on business processes involves systematic literature review process. The process involves following the systematic literature review procedures while incorporating the quantitative performance metric analysis of industry data.

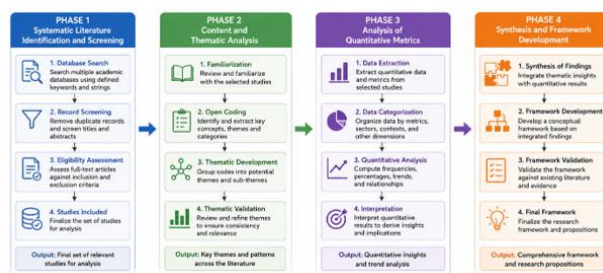


Figure 1: Framework of the Research Methodology

In this diagram, there are four phases of the research methodology process. Phase one consists of systematic literature identification and screening process. Phase two covers the process of content and thematic analysis. Phase three deals with the analysis of quantitative metrics. Phase four comprises of synthesis and framework development process.

Systematic Literature Review

The study will be undertaken using the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) methodology.

- **Inclusion Criteria:** Peer reviewed articles and conferences presented in the period from 2021 to 2026 that discuss AI implementations in business process settings, published in English language, and presenting empirical evidence or systematic reviews.
- **Exclusion Criteria:** Papers that address only the technical side of the problem without any business process considerations, papers with opinions not supported by empirical data, and papers that have no clear connection to the topic under discussion.
- **Search Strategy:** Extensive searches of academic databases Scopus, ScienceDirect, IEEE Xplore, and Web of Science through the combination of key words



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"AI adoption," "business process," "organizational performance," and "AI implementation."

- **Screening Procedure:** A multistage screening procedure was adopted, involving preliminary screening of records by their titles and abstracts, eligibility assessment according to inclusion criteria, and quality assessment applying systematic review criteria.

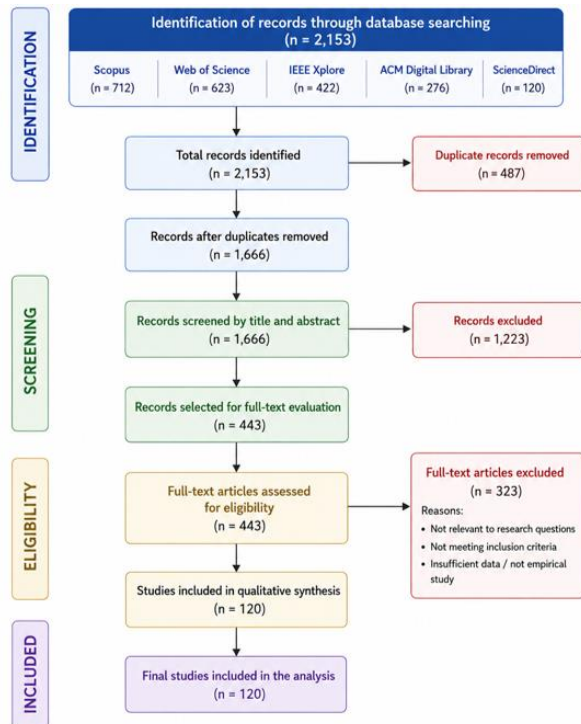


Figure 2: Flow Diagram for Literature Selection Based on PRISMA Approach

In this flow diagram, the process of systematic selection of literature is presented. The process starts with record identification from academic databases. Duplicate records are excluded. Record screening takes place according to titles and abstracts. Full texts are evaluated in terms of their eligibility. Selected studies form the final sample for the analysis.

Thematic Analysis

Content and Thematic Analysis was used for the final sample to extract primary research themes. The process was conducted using the following steps:

- **Coding Process:** Using open coding, the first phase entailed identification of concepts and themes associated with motivations and drivers of AI adoption, processes, impact and challenges associated with AI. The subsequent phases involved axial coding, which entailed finding associations between concepts and developing overarching themes.
- **Themes:** Four primary themes associated with AI adoption were identified using previous literature and research: Operational Automation, Decision-making through Data Analytics, Customer Experience and

Personalization, and Innovative Approach to Product and Services Delivery.

- **Quantitative Analysis:** If the research involved quantitative performance metrics, such metrics were extracted and analyzed to find out performance patterns. Such metrics entailed task completion rate, efficiency lift rate, adoption rate and organizational performance.

Analytical Framework

Analytical framework for assessing the effect of AI implementation from various angles:

- **Process Performance Angle:** Effectiveness, accuracy, task accomplishment, and process duration
- **Decision-Making Angle:** Quality of decision-making, its speed, and data involvement
- **Organizational Capability Angle:** Development of skills and abilities, and learning AI
- **Business Value Angle:** Financial performance, customer satisfaction, and competitiveness

Data Sources for Quantitative Analysis

Quantitative analysis is based on several sources of data, including:

- Oracle telemetry data on AI usage and effectiveness in Fusion Cloud applications
- Surveys and studies in the industry on AI usage and its effects
- Research case study results from current scientific literature
- Organizational performance data from systematic reviews

IV. ANALYSIS AND DISCUSSION

Quantitative Impact on Task Effectiveness and Efficiency

Telemetry analysis allows for an impressive amount of empirical data to show the effect that AI has on the efficiency of business processes. The analysis of AI usage by Oracle shows significant improvement in terms of task effectiveness and efficiency.

Table 1: Quantitative Analysis of AI Impact on Business Process Performance

Metric	Unassisted Performance	AI-Assisted Performance	Improvement
Goal Creation Completion Rate	54%	78%	+24 percentage points



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Metric	Unassisted Performance	AI-Assisted Performance	Improvement
Job Profile Creation Time	120 seconds	45 seconds	62.5% efficiency gain
Sales Conversion	Baseline	1.7×	70% increase
Customer Satisfaction	Baseline	1.5×	50% increase
Software Development Productivity	Baseline	35% improvement	35% increase
Manufacturing Throughput	Baseline	30% improvement	30% increase
Document Analysis Time	Baseline	80% reduction	5× faster

When analyzing the HCM employee goal creation tasks, the average AI-assisted task completion rates are 78% in comparison with 54% in unassisted cases. Hence, we can assume that AI eliminates barriers and minimizes the cognitive load, thus improving the chances of successful task completion. The provided statistics, which are based on thousands of daily goal creation tasks from the production environment, provide statistically significant evidence of the positive effect of AI on task completion.

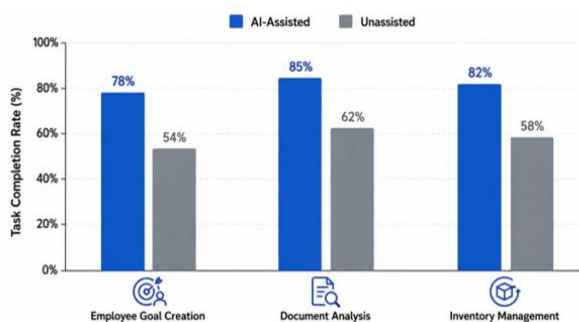


Figure 3: AI-Assisted vs. Unassisted Task Completion Rates

In the provided bar chart, task completion rates are compared between AI-assisted and unassisted processes. When it comes to employee goal creation, the AI-assisted task completion rate equals 78%, while unassisted is 54%. Document analysis has an AI-assisted rate of 85% in comparison with 62% in unassisted situations. Inventory management provides an AI-assisted rate of 82% and unassisted 58%.

Additional efficiency lift measures add further support to the effectiveness of AI technology. When considering the creation of a job and position profile as a task that requires assistance, analysis shows that about 12,000 unassisted activities were completed on average within 2 minutes. At the same time, ~300 activities that were performed with the help of AI took, on average, 45 seconds to be completed – a 62.5% efficiency lift.

Enterprise-Level Performance Results

The analysis of the adoption of AI solutions by enterprises among the Global 1000 companies shows considerable performance improvements on several aspects. Sales conversions grew 1.7x times, customer satisfaction increased 1.5x times, software development productivity rose by 35%, manufacturing productivity increased by 30%, and document analysis time dropped by 80%.

Table 2: Enterprise-Level Performance Outcomes from AI Adoption

Performance Metric	Reported Improvement	Context
Sales Conversion	1.7× increase	Global 1000 enterprises
Customer Satisfaction	1.5× increase	Global 1000 enterprises
Software Development Productivity	35% improvement	Enterprise software teams
Manufacturing Throughput	30% improvement	Production environments
Document Analysis Time	80% reduction	Enterprise document processing
Financial Forecasting Accuracy	Significant improvement	SME financial operations
Operational Cost	Reduction	Various business contexts



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A case study conducted on AI integration within small and medium sized firms proved that AI boosts agility, precision of finance, and personalized marketing. Firms that had more developed AI had greater agility and flexibility; AI technologies made financial processes simpler, more cost-effective, and more accurate in financial forecast and risk management.

The Adoption Process: Staged Development

The analysis of AI adoption process has shown that development process to business value is a staged one. Typically, there are three stages within the process: personal productivity, team productivity, and company productivity.

Phase 1 - Personal Productivity: AI acts as an enabling tool for individual tasks like composing emails or extracting summaries. While Phase 1 provides conveniences, the financial gains do not accrue but are redistributed instead. Savings made individually in the form of time do not result in financial gains for organizations.

Phase 2 - Team Productivity: Agentic use cases at the departmental level have measurable objectives. The key elements of Phase 2 include AI that is capable of contextualizing situations, memorization, planning multiple steps, coordinating between different tools and information, and acting with measured autonomy. These include finance agents that handle reconciliations and exception routing, software agents that create tickets, write tests, and commit code, and clinical trial protocol agents that prepare evidence packs.

Phase 3 - Company Productivity: Multi-agent-based processes at the company level provide financial gains through savings in touchpoints, improved cycle times, conversions, and cost to serve. Phase 3 includes the complete integration of AI in the process of doing business, with full AI fluency across thousands of tasks.

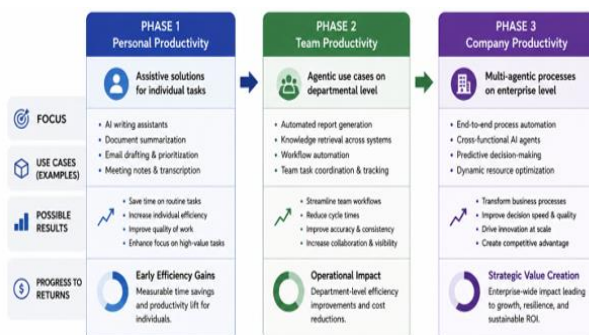


Figure 4: The Three Phases of AI Maturity

This figure shows the sequential progression of AI maturity in organizations. In phase one (Personal Productivity), emphasis is on assistive solutions for individual tasks. In phase two (Team Productivity), there are agentic use cases on departmental level. Phase three (Company Productivity) represents multi-agentic processes on enterprise level. Each of these phases presents use cases, possible results, and progress to returns on investment. It is shown how returns grow as AI gets embedded into organizational processes.

Challenges and Implementation Barriers

Although there is a lot of proof of the benefits from using AI in business, there are still many challenges that make its implementation difficult. Systematic study revealed ten major contradictions at five stages of implementation: agenda-setting, matching, redefining and restructuring, clarification, and routinization.

Table 3: Key AI Implementation Challenges and Mitigation Strategies

Challenge Category	Specific Challenges	Mitigation Strategies
Technical	Data quality limitations, integration complexity	Decision-support platforms, agile modular architectures
Organizational	Workforce skill gaps, resistance to change	Tiered training programs, AI-linked KRAs
Governance	Transparency issues, algorithmic bias	Accountable governance frameworks, internal controls
Strategic	Misalignment with business goals, unclear ROI	Tiered rollout strategies, clear use case definition
External	Regulatory uncertainty, privacy concerns	Shared responsibility models, co-creation with partners

Studies of the adoption of AI in emerging economies point out differences in the context of problems faced by organizations in emerging economies and those in developed nations. While ethical and regulatory issues become more relevant in the former, in the latter there are problems relating to availability of talent and infrastructure. The problem of "high interest but low adoption" represents the complex socio-technical nature of the issue of organizational implementation of AI systems. Research on AI implementation at an organizational level rather than at an individual level will provide a good understanding of the adoption barriers.

Workforce Transformation and AI Fluency

One of the major developments regarding the adoption of AI is the inclusion of AI fluency as part of workforce

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performance criteria. The organizations using such criteria include Deloitte, Lenovo, Mphasis, and Accenture.

Deloitte.	Lenovo.	Mphasis	accenture
Strategy: AI-Based KPIs and Training of Leadership	Strategy: KRAs Linked to AI and Aligned with Bonus	Strategy: Train 70% of Workforce with AI Tools and Recalibrate KRAs	Strategy: AI Training to More Than 550,000 Employees with Personal AI Goals
Key Actions - Integrated AI adoption metrics into performance KPIs - Trained leaders to champion AI-first mindset - Embedded AI goals in leadership scorecards	Key Actions - Linked Key Result Areas (KRAs) to AI adoption and outcomes - Aligned performance bonuses with AI-driven achievements - Encouraged teams to deliver measurable AI impact	Key Actions - Trained 70% of the workforce on AI tools and applications - Recalibrated KRAs to include AI usage and impact - Built capability and confidence across all levels	Key Actions - Provided AI training to more than 550,000 employees - Set personal AI learning and application goals - Fostered a culture of continuous AI-enabled learning
Expected Impact Stronger leadership accountability and measurable AI adoption driving organizational transformation.	Expected Impact Strong performance linkage ensures AI adoption translates into business results and employee incentives.	Expected Impact Widespread AI capability building leading to higher productivity and innovation across the organization.	Expected Impact Large-scale AI literacy with individual accountability driving sustained adoption and business value.

Figure 5: Workforce AI Integration Strategies

The following figure is demonstrating integration strategy used by each of the four companies in workforce adoption for AI. In each organization mentioned, the specific strategy used has been provided – in the form of Deloitte using AI-based KPIs and training of leadership, Lenovo using KRAs linked to AI and aligning them with bonus, Mphasis training 70% of its workforce with AI tools with recalibrated KRAs, and Accenture's AI training to more than 550,000 employees with personal AI goals.

The Deloitte innovation program includes 'innovation' as a key performance indicator (KPI), where all partners and executive directors need to work with one or multiple use cases involving an AI tool. The KRAs of Lenovo have also been used for workforce adoption of AI through aligning of KRAs in all functions for sales teams and KPIs for product and technical teams.

More than 70% of the technology workforce at Mphasis has been trained in AI tools along with KRAs calibration for adoption and usage of AI. More than 550,000 employees have been trained by Accenture in GenAI fundamentals and plans to train its entire workforce in agentic AI.

The move towards AI-related performance measures can be viewed as an acknowledgement that the successful implementation of AI requires not just technological but also organizational capabilities to be developed. As indicated by researchers, "AI fluency is no longer an optional but a fundamental capability."

V. CONCLUSION

In this paper, a thorough analysis of the impact of AI adoption on business processes was provided based on a number of systematic literature reviews, empirical studies, and industrial data. It has been demonstrated that AI adoption leads to tangible improvements in business performance while posing a lot of challenges at the same time. First, use of AI leads to positive changes in business process performance. Quantitative analysis of telemetry data demonstrates that AI-supported task completion rate is 78% against 54% for non-AI supported tasks, which means 24 percentage point improvement. Process improvement up to 62.5% in task completion time shows that there is a great

potential of time saving through AI usage. There are other examples of enterprise-level improvement due to AI use: 1.7× sales conversion, 1.5× customer satisfaction, 35% software development productivity gains, 30% manufacturing throughput improvement, and 80% reduction in document analysis time.

Second, there are several mechanisms of the influence of AI on business processes. Empirical studies identify process automation, organizational learning, and process innovation as important mediators of the influence of AI on business results. These mechanisms work complementing each other; thus, organizations should be interested in AI adoption in multiple aspects and not only in automation. One of such mechanisms is data-driven decision-making, which helps companies to become flexible and efficient at the same time.

Third, the path to business value creation via AI is a progressive one. Companies will progress from individual productivity increases to collective increases and eventually organizational transformation. Nevertheless, the shift from the prior phases to organizational level benefits entails the need for changes in organizational operations and people. It is the embeddedness of AI in thousands of activities, or what we call AI fluency, that drives compounding benefits.

Fourth, numerous barriers exist to prevent the uptake of AI within organizations and realizing its value. Barriers include issues such as data quality problems, skills gap, governance problems, and strategy alignment. The "high interest but low adoption" problem is rooted in the socio-technical complexities involved in the organizational implementation of AI technologies, with the process involving the interplay of technology, processes, strategy, and inter-organizational relations.

Finally, the inclusion of AI skills in performance metrics of employees is a huge organizational change. Organizations like Deloitte, Lenovo, Mphasis, and Accenture have incorporated the use of AI in the KRAs of their employees, implying that having an AI capability is now a core organizational capability. This transformation in the workforce is driven by the realization that successful AI adoption will depend on developing an organizational capability rather than technology adoption alone.

There are some limitations of the current study that need to be discussed. The findings obtained through quantitative analysis are drawn from specific enterprise environments only and cannot be generalized for all industries or organizations of different sizes. Since AI technology keeps changing constantly, results may need an update in the coming years. Further research can be conducted on how organizational capabilities influence AI adoption success, on the effect of generative AI on business operations, and on the development of AI fluency measures.

All in all, the incorporation of AI solutions is drastically changing the way business is conducted and providing



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tangible increases in productivity and performance. Nevertheless, in order for organizations to achieve such results, they have to deal with significant challenges of AI implementation, develop necessary competencies, and gradually acquire AI fluency. Organizations which can be considered the most efficient ones in their efforts to transform through AI are those which perceive AI as not a project but rather a capability which reshapes the way things are done with executive support, governance embedded into processes, and scale-up from pilots to production.

REFERENCES

1. N. Niroula and G. Sharma, "The Role of Artificial Intelligence (AI) in Business Transformation: A Systematic Literature Review," East West University Institutional Repository, Apr. 2026.
2. L. M. Vásquez-Vásquez, E. J. Alvarado-Cáceres, and V. H. Fernández-Bedoya, "Artificial Intelligence for Business Decision-Making in Latin America: A Systematic Review of Evidence, Contributing Countries, and Key Insights," *Administrative Sciences*, vol. 16, no. 3, p. 121, Feb. 2026.
3. A. Zebec and M. I. Štemberger, "Creating AI business value through BPM capabilities," *Business Process Management Journal*, vol. 30, no. 8, pp. 1-26, 2024.
4. "The transformative power of AI and its impact on business strategy, financial operations, and marketing decision-making: a case study method," *Journal of Business Research*, 2025.
5. "High interest but low adoption: Navigating organizations' journey towards generative artificial intelligence implementation," *International Journal of Information Management*, 2025.
6. A. Bradshaw and C. M. Tang, "Transforming Operations and Supply Chain Management with AI-Driven Digital Applications," in *Handbook of AI and Digital Transformation*, Taylor & Francis, 2026.
7. S. Srivastava, "Enterprise AI, Large-Enterprise Edition: What MIT Missed," *Forbes*, Oct. 2025.
8. D. Sagar, P. Tikare, R. Vasantraj, and L. Chandrasekharan, "India Inc pushes for AI fluency in staff performance metrics," *The Economic Times*, Nov. 2025.
9. C. T. Rodriguez Jacobs, "Quantifying AI Success: An Analysis of Generative AI Usage in Oracle Fusion Cloud Applications," *Oracle Blogs*, Jan. 2026.
10. "India Inc puts AI in KRAs as firms push workforce to upskill, adopt tech faster," *The Economic Times*, Nov. 2025.