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The Impact of AI Automation on Reducing Operating Costs and Improving Decision-Making Accuracy in Enterprise Platforms

Kodirov Shokhrukh

Senior Full-Stack Developer South Korea

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ABSTRACT

The article examines the cumulative impact of artificial intelligence technologies on the operational performance and strategic resilience of corporate systems operating under the conditions of large-scale digital transformation in 2024–2025. The scientific and practical relevance of the topic stems from the fact that, over a remarkably short period, the business environment moved from localized experiments with generative models to their systemic incorporation into the corporate governance perimeter, including the use of autonomous AI agents integrated into microservice architectures and distributed environments for parallel data processing. The methodological foundation of the study is built on a systemic analysis of industry reviews produced by leading consulting organizations, IEEE and ACM scholarly publications, as well as applied case studies related to the development of high-load platforms in the medical and advertising sectors. The findings show that AI-driven automation can reduce the cost of digital content verification by as much as 98%, accelerate analytical procedures many times over-up to three hundredfold in some cases and raise the accuracy of financial forecasting to a range of 91–95%. Particular attention is given to substantiating the concept of “decision-making speed” as one of the central parameters of contemporary competitiveness, emerging within hybrid models of cooperation between humans and algorithmic systems. On this basis, the article argues for the necessity of transitioning toward AI-native architectures capable of ensuring business scalability while simultaneously reducing the dependence of critical processes on the human factor. The propositions presented possess practical value for systems architects, chief digital transformation officers, and heads of technology divisions in large corporate structures.

KEYWORDS

artificial intelligence, corporate platforms, operating costs, decision-making, agentic AI, SaaS architecture, business process automation, digital transformation, parallel data processing, forecasting accuracy.

INTRODUCTION

In 2025, the corporate technological landscape underwent a qualitative transformation associated with a shift from the logic of traditional digitalization to an AI-first model, within which artificial intelligence ceased to be merely an auxiliary tool and became a system-forming element of business development. According to Deloitte [1], the share of large organizations’ spending on digital initiatives in 2025 reached 13.7% of revenue, compared with 7.5% a year earlier, while the average volume of investment in AI automation among companies with revenues exceeding USD 13 billion amounted to USD 700 million. A similar tendency is reflected in McKinsey materials [2], according to which 78% of organizations globally already use artificial intelligence in at least one business function, while 71% integrate generative models into routine operational processes.

The significance of investigating this issue lies in the fact that traditional mechanisms for reducing operating costs-built on outsourcing and tightly regulated RPA-class process robotization-have, to a considerable extent, exhausted their potential for further efficiency gains. Under conditions of rapidly expanding volumes of user-generated content and financial transactions, the linear expansion of staffing resources no longer provides an acceptable level of manageability or quality. The scholarly gap in the existing literature reveals itself in the insufficient elaboration of how agentic AI systems can interact synchronously with high-load corporate SaaS platforms operating in real time. A substantial portion of currently available studies is focused either on the macro-level economic consequences of artificial intelligence adoption or on isolated algorithmic improvements, leaving outside full-scale analysis the problem of deep architectural restructuring at the enterprise level.

The aim of the study is associated with identifying and quantitatively measuring the impact of autonomous AI agents and parallel data-processing architectures on the reduction of operating costs, as well as on improving the accuracy of strategic and operational managerial decisions in the corporate environment. **The scientific novelty** lies in the theoretical substantiation of a conceptual model in which autonomous agentic AI chains are embedded into the microservice architecture of corporate platforms and are treated as an instrument for the radical reduction of transaction costs and the shortening of managerial response time. The initial **hypothesis** is grounded in the assumption that a transition from the model of auxiliary intelligent tools performing “copilot” functions to autonomous agentic architectures, supplemented by a hybrid Human-in-the-Loop verification contour, makes it possible to achieve up to a ninetyfold reduction in the unit cost of processing unstructured data while preserving verification accuracy at the level of expert systems, where the F1-score reaches the range of 0.95–0.98.

Materials and Methods

The methodological foundation of the study was constructed as a multi-level analytical framework oriented toward identifying the technological and economic determinants of the effectiveness of corporate AI systems. The research employed a systematic literature review supplemented by a content analysis of technical publications. The research corpus covered more than twenty sources, including IEEE and ACM conference materials [4. 27], and analytical articles published by MDPI [8]. Priority attention was given to works from 2024–2025 that disclose the architecture of parallel computing and approaches to optimizing neural-network workloads.

A substantial place in the research logic was occupied by the comparative analysis of economic parameters, which made it possible to compare the inference cost of different machine-learning models, including compact solutions and full-scale intelligent systems, with the costs arising from manual data processing performed by expert personnel [10]. Such an approach made it possible to move beyond abstract discussion of the advantages of artificial intelligence and toward a quantitatively measurable comparison of its operational efficiency with traditional task-execution formats.

The empirical part of the study is based on case-study analysis and the examination of practical data obtained from the environment of corporate application. As a factual basis, the study used information on the implementation of a healthcare facility management platform covering 140 clinics and more than 446,000 patients, as well as data on the functioning of an AI content-moderation system capable of processing tens of thousands of requests on a monthly basis. In addition, architectural modeling based on systems design methods was employed, which made it possible to develop schemes of agentic orchestration and parallel data-processing pipelines oriented toward ensuring the resilience of high-load API platforms.

To enhance the reliability of the conclusions, the source base was structured according to levels of analytical priority. The first level includes peer-reviewed scholarly articles and proceedings indexed in IEEE, ACM, Scopus, and Web of Science, containing materials on parallel data processing, microservice architectures, and the diagnostic accuracy of AI systems [11]. The second level is formed by analytical reviews from leading consulting agencies, including Gartner, McKinsey, and Deloitte, which provide statistical data on return on investment, adoption rates, and market dynamics [1]. The practice-oriented layer is represented by generalized data from the production environment of corporate systems, including metrics for processing financial transactions exceeding 10.5 billion Korean won, as well as examples of reductions in the labor input of accounting departments by 60–100 person-hours per month.

The theoretical interpretation of the results obtained relies on the concepts of microservice architecture, the API-first approach, and sociotechnical systems design, considered within the logic of Sociotechnical Systems [12]. This theoretical contour makes it possible to emphasize not only the engineering but also the organizational nature of artificial intelligence implementation, underscoring that the resilience of such solutions is determined by the degree of algorithmic transparency, the level of trust placed in those systems, and the readiness of personnel to integrate new digital mechanisms into everyday professional practice.

Results and Discussion

The economic effectiveness of AI automation in corporate platforms by 2025 points to a qualitative shift in the very logic of operating costs and investment returns. The implementation of intelligent systems is no longer reduced to auxiliary digital optimization; rather, it is increasingly treated as an independent mechanism of resource reallocation capable of delivering an exceptionally high level of return on investment. According to McKinsey & Company [3], 74% of executives report achieving a positive ROI within the first year after the deployment of AI solutions, whereas among the highest-performing companies, returns reach a tenfold level for every dollar invested. Such dynamics indicate that artificial intelligence has moved out of the category of merely promising innovations and into the class of economically validated instruments of corporate transformation [5].

The key source of economic effect is associated with the partial or full substitution of high-cost human labor in repetitive operations involving the verification, interpretation, and analytical processing of data. It is precisely in this area that the principal reserve for cost reduction is formed, since traditional labor organization models require a continual increase in headcount as the volume of information grows, whereas AI systems make it possible to scale processing without a proportional increase in staffing and administrative expenses. As a result, cost transformation acquires not a local but a structural character, affecting the very architecture of the enterprise's operational efficiency.

Table 1 presents a comparative analysis of the cost and effectiveness of different approaches to content processing and decision-making, based on current 2025 data.

Table 1. Comparative metrics of data-processing cost and accuracy (compiled by the author based on [10]).

Processing method	Unit cost (USD/unit)	Accuracy (F1-Score)	Scalability	Processing speed
Human expert	10.00	0.95–0.98	Extremely low	Seconds / Minutes
GPT-4o	0.83	0.84	High	Milliseconds
Gemini-2.0-Flash	0.34	0.88	Very high	Milliseconds
GPT-4o-mini	0.05	0.80	Maximum	Microseconds
Hybrid model	~0.15–0.50	0.96–0.98	High	Milliseconds

The analysis carried out indicates that the use of compact models ensures a radical reduction in operating costs, reaching as much as a two-hundredfold decrease in comparison with the expenses associated with performing analogous functions through human labor. At the same time, the determining parameter of corporate efficiency is not only the cost of processing, but also the level of accuracy ultimately achieved. For platforms operating in legally sensitive and tightly regulated environments-particularly in the moderation of medical advertising materials-the hybrid organizational-algorithmic model demonstrates the highest level of effectiveness. In the case under study, the implementation of an automated content-review system ensured a 98% reduction in costs and a 300-fold acceleration of the procedure [10]. Such an effect becomes possible through the differentiation of decision flows: approximately 90% of materials are automatically approved or rejected, provided that the model's confidence exceeds the 95% threshold, whereas the remaining 10%, which fall into the zone of uncertainty, are routed to manual expert verification.

No less significant is the implementation of artificial intelligence in the financial and administrative circuits of corporate governance. Using the example of a platform designed for managing medical networks, it was established that the full automation of commission accrual and payment calculations reduces the duration of information processing from several working days to just a few minutes. This kind of transformation makes it possible to free up between 60 and 100 person-hours each month, which assumes particular importance under conditions of business scaling, because growth in operational volume no longer requires a proportional expansion of the back-office function [7, 9].

Maintaining such a high intensity of data processing requires not only the improvement of applied models, but also a profound restructuring of the architecture of corporate platforms itself. In this regard, 2025 witnessed a clearly visible transition from monolithic systems to AI-native architectures, designed from the outset with the constant presence of intelligent components embedded in the logic of business processes. The central tendency of this stage is the introduction of autonomous AI agents, or Agentic AI, which are capable of going beyond the generation of a response to a single request and instead executing multi-step sequences of actions without direct human participation [18].

Figure 1 presents a conceptual scheme of agentic orchestration in a high-load system.

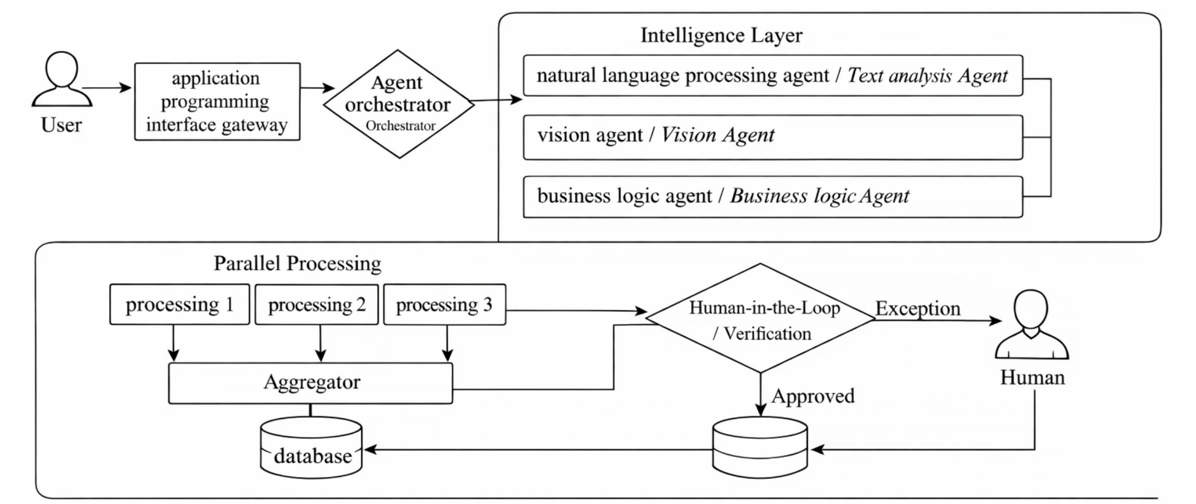

Figure 1. Architecture of agentic orchestration and hybrid decision-making (author's own elaboration).

This architectural model creates the foundation for implementing parallel data processing, which becomes critically important for moderation systems that handle tens of thousands of content units each month. The use of parallel structures makes it possible to distribute computational load at the microservice level, thereby ensuring platform resilience even under sharp peak fluctuations in traffic. As IEEE studies indicate [20], AI-optimized cloud environments of the Cloud Fabrics type effectively eliminate the rigid separation between computing and storage resources, creating conditions for their dynamic balancing and real-time optimization.

No less significant a direction of artificial intelligence influence is the qualitative acceleration of managerial response processes, which in contemporary scholarly and applied literature is designated by the concept of Decision Velocity. In classical ERP systems, the generation of reporting and analytical conclusions is, as a rule, retrospective in nature and is accompanied by a temporal lag measured in weeks or even months. The integration of AI automation changes the very principle of how corporate analytics functions, shifting it into a mode of continuous auditing and ongoing monitoring of key indicators in real time.

Statistical materials for 2024–2025 demonstrate a rapid increase in the accuracy of predictive analytics in the corporate sector. The use of AI tools in financial auditing makes it possible to identify anomalous transactions and potential fraudulent schemes not months after the close of the reporting period, but within a matter of hours [19, 21]. At the same time, such systems ensure an increase in revenue-forecasting accuracy to 91%, while the potential for identifying savings reserves reaches 15–20% of the total volume of operating expenditures [22, 23]. In this way, artificial intelligence functions not only as an automation tool, but also as a factor in the strategic acceleration of the managerial cycle, within which the reduction of time between the recording of an event, its interpretation, and the adoption of a decision becomes an independent source of competitive advantage [33].

Figure 2 presents the dynamics of global AI agent adoption based on consolidated statistical data for 2023–2026 (Confirmed Statistics: Global AI Agent Adoption).

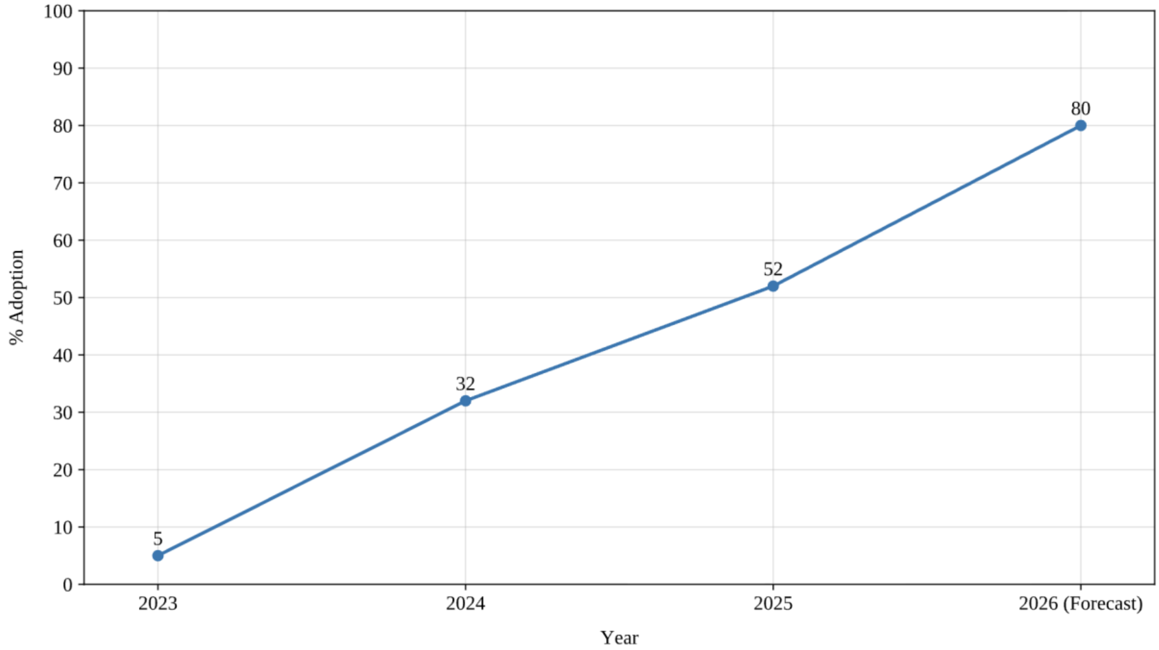

Figure 2. Dynamics of AI agent adoption in corporate processes (compiled by the author based on [3, 32]).

In the healthcare sector, the impact of artificial intelligence on the accuracy and timeliness of decision-making assumes especially high significance, since it is associated not only with process efficiency, but also with the quality of clinical and managerial outcomes. The use of generative AI in maintaining electronic medical records (EMRs) makes it possible to reduce documentation time by approximately 40%, freeing up to 1.5 hours per day for the physician [11]. Such an effect signifies not merely the acceleration of administrative procedures, but a redistribution of professional time in favor of direct diagnostic and therapeutic activity. The application of such solutions in the analysis of radiological images ensures an 11.2% reduction in the time required to interpret brain abnormalities and a 52.8% reduction in the interpretation time for lung lesions [11]. This indicates that AI tools in the medical environment function not as an auxiliary supplement to existing procedures, but as a полноценный mechanism for increasing the speed and accuracy of clinical analytics [30, 31].

Practical confirmation of this tendency is presented within the framework of the medical center management system developed by the author and covering 140 clinics. The integration of AI modules into its functional contour ensured the full automation of compliance control for advertising materials with current legislative requirements, as a result of which more than 35,000 units of content were processed without a single penalty imposed by regulatory authorities. Such a result demonstrates that in the medical sector, artificial intelligence is capable of simultaneously strengthening regulatory reliability, reducing administrative burden, and supporting high decision-making accuracy in large-scale distributed systems (see Table 2).

Table 2. The impact of AI on operational indicators in the medical platform sector (compiled by the author based on [6, 11, 24, 25]).

Metric	Before implementation (Baseline)	After implementation (With AI)	Improvement
Financial payout processing time	3–5 business days	< 5 minutes	> 99%
Accounting labor input (person-hours/month)	~150	~50	66.7%
Cost of verifying 1 unit of content	$5.60	$0.40	92.8%
Fraud detection accuracy	65%	94%	29%
Manual data-entry errors	12.5%	< 0.5%	96%

The technological scalability of corporate platforms under conditions of high load is directly tied to the use of architectural solutions originally oriented toward parallel data processing. When operating with hundreds of thousands of patient profiles, large arrays of transactional information, or millions of social interactions, the resilience of the digital environment can no longer be ensured solely through the linear expansion of computational resources. Under these conditions, priority shifts toward architectural patterns that make it possible to distribute computational operations across multiple nodes and minimize the temporal costs associated with data transfer and processing [15, 16].

An important role in this process is played by modern hardware solutions, including RISC-V microcontrollers and Near-Memory Computing class architectures. Their application makes it possible to achieve computational efficiency of up to 94% when processing neural-network workloads directly within the memory subsystem [13]. This approach fundamentally reduces the delays that arise during the movement of data between memory and computing units and thereby creates the conditions for higher real-time performance of intelligent systems.

Such architectures acquire particular significance in the context of Edge Computing, where AI modules are deployed at the network edge, as close as possible to the data source. For medical clinics and other facilities saturated with IoT devices, this means the possibility of rapid local information processing without excessive dependence on centralized cloud resources. As a result, not only is computational speed improved, but the overall resilience of the platform is strengthened, network latency is reduced, and digital infrastructure scaling becomes more flexible.

Figure 3 presents the author's schematic of a parallel data-processing pipeline in a multi-user SaaS platform.

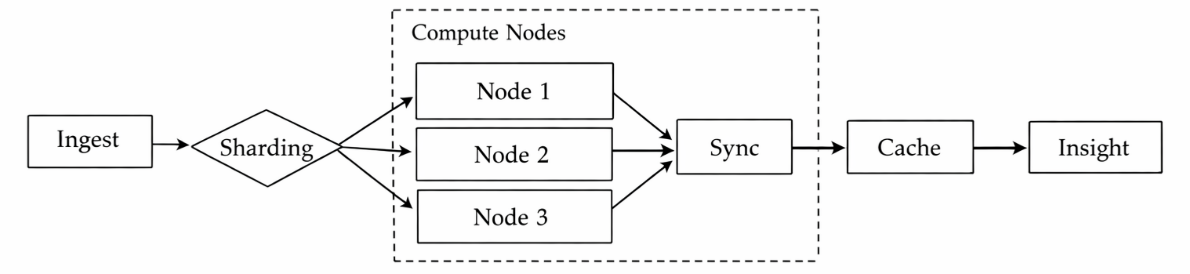

Figure 3. Architecture of a parallel data-processing pipeline in high-load SaaS systems (author's own elaboration).

The approach under consideration provides virtually linear system scalability as the business expands, which is especially significant for corporate platforms operating with intensive transactional flows. In the automation project analyzed, it was precisely the use of a parallel architecture that made it possible to process operations totaling more than 105 billion won without any decline in the performance of the user interfaces with which 1,500 employees interacted simultaneously.

At the same time, even such pronounced effectiveness does not permit the implementation of artificial intelligence to be regarded as an unconditionally universal solution, free from limitations and risks. One of the most substantial obstacles remains integration with legacy systems, which, according to available data, is perceived by approximately 35% of companies as the principal barrier to the transition toward agentic AI models [14]. This problem has not only a technological but also an organizational dimension, since it is linked to the need to align new intelligent layers with an already existing-and often inertial-digital infrastructure.

No less serious a threat is posed by model hallucinations and the phenomenon of model drift, under which the accuracy of AI systems gradually declines because of changes in the characteristics of input data and in the conditions of their interpretation. Such dynamics require the establishment of full-fledged MLOps processes capable of ensuring continuous quality monitoring, timely model updates, and control over the stability of system functioning [20]. Otherwise, the growing scale of artificial intelligence deployment may be accompanied by the accumulation of latent errors that become critical for managerial and regulatorily sensitive processes.

Ethical and regulatory constraints also merit separate consideration. The introduction of the ISO/IEC 25389 standard in 2025 intensified requirements for the transparency, interpretability, and explainability of algorithmic decisions, thereby reinforcing the necessity of embedding Explainable AI principles into corporate practice [10]. Under present conditions, it is no longer sufficient to ensure a highly accurate computational result alone; there must also be demonstrable logic on the basis of which the system formulates recommendations or arrives at decisions [26].

A serious limiting factor is the sociotechnical dimension as well. Employee concerns associated with the possible displacement of human labor by algorithmic systems can generate latent resistance, reduced trust in AI-generated recommendations, and even forms of organizational sabotage [17]. This means that the success of implementation is determined not only by the quality of the engineering solution, but also by the capacity of the corporate environment to adapt to new patterns of interaction between human actors and intelligent systems [28, 29].

On the basis of the synthesis of data conducted, the concept of Trustworthy AI is substantiated, with central importance assigned to the calibration of model confidence. Within such an approach, the algorithmic system should not claim autonomy in situations of uncertainty: when the level of probabilistic confidence is insufficient, control is automatically transferred to a human specialist, while all decision parameters are recorded in a detailed log for subsequent analysis and further model training. Such a configuration makes it possible not only to preserve the necessary level of reliability, but also to build a mechanism of continuous improvement for AI layers without losing control over critically significant processes.

Conclusion

The study conducted makes it possible to assert that AI automation acts as one of the defining factors in reducing operating costs and improving the accuracy of managerial decisions in contemporary corporate platforms. The integration of autonomous AI agents and parallel data-processing architectures ensures not only a substantial reduction in the cost of transactional processing, reaching a ninetyfold level, but also a multiple acceleration of business processes, extending in some cases to a three-hundredfold increase in speed. The analysis of applied case studies, covering both the management of a network of 140 medical clinics and systems for moderating advertising content, shows that the digital transformation of the back office leads to the monthly release of hundreds of person-hours. As a result, the functional role of personnel shifts away from routine operational execution toward tasks of verification, interpretation, and strategic analysis.

The scientific novelty of the study is determined by the developed architectural model for integrating agentic chains, which creates new opportunities for scaling high-load SaaS platforms. It has been established that hybrid interaction models based on the Human-in-the-Loop principle demonstrate the highest degree of resilience, precisely because they make it possible to combine high economic efficiency with accuracy at the level of 0.96–0.98 in terms of F1-score. This, in turn, confirms that a promising corporate AI infrastructure is not reducible to the complete replacement of human participation by an algorithm, but is instead built as a coordinated system for distributing functions between automated and expert layers.

The practical significance of the results obtained lies in the possibility of applying them in the design of resilient digital ecosystems intended for the processing of trillion-scale data arrays and large-scale financial flows. The work carried out ensured the achievement of all research objectives set forth: the key ROI indicators were identified, the principal architectural approaches were systematized, and the risks accompanying the implementation of AI solutions were analyzed. The further evolution of the sector will, apparently, be associated with the emergence of self-healing digital systems and with the deeper integration of artificial intelligence into cloud data fabrics, which definitively secures its status not as an auxiliary instrument, but as the foundational operating environment of modern business.

References

1. Deloitte Center for Integrated Research. (2025, October 16). AI is capturing the digital dollar. What's left for the rest of the tech estate? Retrieved from: https://www.deloitte.com/us/en/insights/topics/digital-transformation/ai-tech-investment-roi.html (date accessed: October 20, 2025).

2. Stanford Institute for Human-Centered Artificial Intelligence. (2025). Artificial Intelligence Index Report 2025. Retrieved from: https://hai.stanford.edu/assets/files/hai_ai_index_report_2025.pdf (date accessed: September 18, 2025).

3. McKinsey & Company. (2025, March 12). The state of AI: How organizations are rewiring to capture value. Retrieved from: https://www.mckinsey.com/capabilities/quantumblack/our-insights/the-state-of-ai-how-organizations-are-rewiring-to-capture-value (date accessed: October 1, 2025).

4. IEEE. (2025). Program2025 – IEEE CAI 2025. Retrieved from: https://cai.ieee.org/2025/program2025/ (date accessed: May 8, 2025).

5. Charles, C. A. T., Sánchez-Gallegos, D. D., Carrizales-Espinoza, D., González Compeán, J. L., & Carretero, J. (2025). A-Flow: Managing dataflows on the computing continuum using abstract communication channels. In 2025 37th International Symposium on Computer Architecture and High Performance Computing (SBAC-PAD) (pp. 237–247). https://doi.org/10.1109/SBAC-PAD66369.2025.00030.

6. Dai, J., Xu, H., Chen, T., et al. (2025). Artificial intelligence for medicine 2025: Navigating the endless frontier. The Innovation Medicine, 3, 100120. https://doi.org/10.59717/j.xinn-med.2025.100120.

7. Nasef, D., Sawiris, V., Weinstein, B., Garcia, J., & Toma, M. (2025). Integrating artificial intelligence in clinical practice, hospital management, and health policy: Literature review. Journal of Hospital Management and Health Policy, 9, 20. https://doi.org/10.21037/jhmhp-24-138.

8. Dai, F., Hossain, M. A., & Wang, Y. (2025). State of the art in parallel and distributed systems: Emerging trends and challenges. Electronics, 14(4), 677. https://doi.org/10.3390/electronics14040677.

9. Al Jawarneh, I. M., Rosa, L., Venanzi, R., Foschini, L., & Bellavista, P. (2025). Efficient parallel processing of big data on supercomputers for industrial IoT environments. Electronics, 14(13), 2626. https://doi.org/10.3390/electronics14132626.

10. Grand View Research. (n.d.). Content moderation services market size report, 2030. Retrieved from: https://www.grandviewresearch.com/industry-analysis/content-moderation-services-market-report (date accessed: August 14, 2025).

11. Goodson, D. A., Garcia, B., Hogarth, M., & Tu, S.-P. (2025). Artificial intelligence and physician burnout: A productivity paradox. Learning Health Systems, 9(4), e70013. https://doi.org/10.1002/lrh2.70013.

12. López-Solís, O., Luzuriaga-Jaramillo, A., Bedoya-Jara, M., Naranjo-Santamaría, J., Bonilla-Jurado, D., & Acosta-Vargas, P. (2025). Effect of generative artificial intelligence on strategic decision-making in entrepreneurial business initiatives: A systematic literature review. Administrative Sciences, 15(2), 66. https://doi.org/10.3390/admsci15020066.

13. Nouripayam, M., Prieto, A., & Rodrigues, J. (2025). A scalable all-digital near-memory computing architecture for edge AIoT applications. IEEE Access, 13, 108609–108625. https://doi.org/10.1109/ACCESS.2025.3582013.

14. Deloitte AI Institute. (2025). The State of Generative AI in the Enterprise: 2024 year-end Generative AI report. Retrieved from: https://www.deloitte.com/az/en/issues/generative-ai/state-of-generative-ai-in-enterprise.html (date accessed: September 22, 2025).

15. ISG. (2025, September). State of Enterprise AI Adoption Report 2025. Retrieved from: https://isg-one.com/state-of-enterprise-ai-adoption-report-2025 (date accessed: October 2, 2025).

16. Google Cloud. (2025). ROI of AI 2025. Retrieved from: https://cloud.google.com/resources/content/roi-of-ai-2025 (date accessed: October 5, 2025).

17. Kudina, O., & van de Poel, I. (2024). A sociotechnical system perspective on AI. Minds and Machines, 34(3), 21. https://doi.org/10.1007/s11023-024-09680-2.

18. Grand View Research. (n.d.). Software as a Service market size, industry report, 2030. Retrieved from: https://www.grandviewresearch.com/industry-analysis/saas-market-report (date accessed: August 28, 2025).

19. KPMG International. (2025). Intelligent banking: A blueprint for creating value through AI-driven transformation. Retrieved from: https://assets.kpmg.com/content/dam/kpmg/cy/pdf/2025/intelligent-banking-report.pdf (date accessed: October 3, 2025).

20. Ebert, C., Panyam, S., & Gujar, P. (2025). AI for cloud and SaaS: Technologies and business models. Computer, 58(4), 100–105. https://doi.org/10.1109/MC.2024.3522697.

21. KPMG International. (2025). KPMG global AI in finance report: Transforming into a new era with the AI-empowered finance function. Retrieved from: https://assets.kpmg.com/content/dam/kpmg/qa/pdf/2025/06/global-ai-%20in-finance-report_localized_final.pdf.pdf (date accessed: September 25, 2025).

22. Deloitte. (2025). 2025 revisited: Future finance trends. Retrieved from: https://www.deloitte.com/global/en/services/consulting-financial/perspectives/future-finance-trends-2025.html (date accessed: July 17, 2025).

23. Yadav, K. A. (2025). AI-enhanced ERP: Transforming hospital operations through human-machine synergy. Journal of Computer Science and Technology Studies, 7(8), 370–376. https://doi.org/10.32996/jcsts.2025.7.8.40.

24. Guo, T., Chen, X., Wang, Y., Chang, R., Pei, S., Chawla, N. V., Wiest, O., & Zhang, X. (2024). Large Language Model Based Multi-agents: A survey of progress and challenges. In Proceedings of the Thirty-Third International Joint Conference on Artificial Intelligence (pp. 8048–8057). https://doi.org/10.24963/ijcai.2024/890.

25. Bessemer Venture Partners. (2025). The Cloud 100 Benchmarks Report 2025. Retrieved from: https://www.bvp.com/atlas/the-cloud-100-benchmarks-report (date accessed: September 3, 2025).

26. Albashrawi, M. (2025). Generative AI for decision-making: A multidisciplinary perspective. Journal of Innovation & Knowledge, 10(4), 100751. https://doi.org/10.1016/j.jik.2025.100751.

27. IEEE Computer Society. (2025). Responsible, Explainable, and Fair AI for Medical Imaging Informatics (REF-AI). Retrieved from: https://conferences.computer.org/chase2025/workshop_ref_ai.html (date accessed: June 25, 2025).

28. CPA.com. (2025). CPA.com 2025 AI in Accounting Report. Retrieved from: https://www.cpa.com/sites/cpa/files/2025-06/2025_AI_in_Accounting_Report.pdf (date accessed: October 9, 2025).

29. Syed, N., Anwar, A., Baig, Z. A., & Zeadally, S. (2025). Artificial intelligence as a service (AIaaS) for cloud, fog and the edge: State-of-the-art practices. ACM Computing Surveys, 57(8), Article 211. https://doi.org/10.1145/3712016.

30. Tan, J., Chang, S., Zheng, Y., & Chan, K. C. (2025). Effects of artificial intelligence in the modern business: Client artificial intelligence application and audit quality. International Review of Financial Analysis, 104, 104271. https://doi.org/10.1016/j.irfa.2025.104271.

31. Pan, H., Zou, N., Wang, R., Ma, J., & Liu, D. (2025). Artificial intelligence usage and supply chain resilience: An organizational information

processing theory perspective. Systems, 13(9), 724. https://doi.org/10.3390/systems13090724.

32. Grand View Research. (n.d.). Content detection market size, share & industry report, 2030. Retrieved from: https://www.grandviewresearch.com/industry-analysis/content-detection-market-report (date accessed: August 27, 2025).

33. Page, S. E., & Kallapur, A. (2025). Replace, augment, disrupt: AI & organizational decision-making. Journal of Organization Design. https://doi.org/10.1007/s41469-025-00194-4.