International Journal of Science and Research Archive
eISSN: 2582-8185
Cross Ref DOI: 10.30574/ijsra
Journal homepage: https://ijsra.net/

(RESEARCH ARTICLE)

The impact of agentic Artificial Intelligence on warehouse and delivery operations in modern logistics

Orcun Sarioguz *

Department of Business Administration, Division of International Trade and Logistics Management Anadolu University, Eskisehir Turkey.

International Journal of Science and Research Archive, 2025, 15(03), 1549-1561

Publication history: Received on 06 May 2025; revised on 23 June 2025; accepted on 25 June 2025

Article DOI: https://doi.org/10.30574/ijsra.2025.15.3.1934

Abstract

The technological phenomenon of agentic artificial intelligence (AAI) in the groundbreaking aspect of contemporary logistics processes is re-establishing the environment of the management of warehouses and the delivery procedure. The article examines how AAI-AI systems can set their own goals, make decisions autonomously, and increase operational efficiency, real-time responsiveness, and workforce coordination in logistics. The study fills in a gaping hole in knowledge about how AAI relates to traditional automation in terms of functionality and value of the strategy.

The study, based on the mixed-method approach including case studies of industry leaders combined with survey results of the logistics directors, explores how AAI distributes warehouse tasks most efficiently, enhances the accuracy of the last-mile delivery, and can adjust to the changes alongside the supply chain. Although the results are exploratory, the study expects successful organizations to utilize AAI to achieve favorable improvements in turnaround times, inventory accuracy, and delivery consistency. This has substantial implications for companies involved in logistics processes that desire improved performance, better cost reduction, and the development of more robust supply chains as the world moves toward the digitization of commerce.

Keywords: Agentic AI; Smart Logistics; Warehouse Automation; Last-Mile Delivery; Operational Efficiency

1. Introduction

This is occurring due to the emergence of the futuristic logistics sector, where cutting-edge artificial intelligence (AI) has been incorporated. One of the most novel technologies is Agentic Artificial Intelligence (AAI), an AI system that can make decisions, set goals, and learn by adapting itself without constant human supervision. Compared to traditional AI, which has to work depending on how it is programmed into the system, agentic AI has some form of autonomy, which is quite helpful in dynamic operations systems like warehouses and delivery networks. In the functionality of logistics and supply chain management, AAI is gaining increased opportunities to optimize warehouse operations, improve inventory handling efficiency, and enhance delivery processes. Whether AMRs are moving through the warehouse aisles, self-learning route planning algorithms are handling last-mile routes, or compartmentalizing large distribution centers, AAI is disrupting how goods move, storage, and distribution facilities receive those goods. With growth in the use of automation and digitization of supply chains, and the growing demands of customers regarding speed and accuracy of delivery, the pace has quickened when it comes to adopting AAI as a viable option amongst the global logistics companies looking into scalable and intelligent solutions.

Nevertheless, strategic gaps still exist in conventional warehouse and delivery systems despite the endeavors to close them. Among them are insufficient task assignment, low real-time adaptability, order bottlenecks, and irregular delivery

* Corresponding author: Orcun Sarioguz

performance irregularities. Man has his shortcomingsin systems., The demand and stress surrounding the new age logistics often cannotbe defined in a system that is optimal in efficiency and at more economical costs. This indicates the necessity of welcoming the question of how AAI can bridge those gaps and reshape the essence of logistics activities.To find the answer to this question, this research aims to investigate the effects of agentic artificial intelligence on both warehouse management and delivery processes, as well as how it can improve autonomy of decision making, improve the efficiency of the methods, and allow responding to them in real-time. Based on the existing implementation and novelties, the paper seeks to reveal the operational advantages, risks, and issues of implementing AAI in logistics.In a bid to conduct this investigation, the following research questions are presented:What is the role of agentic AI in warehouse task assignment, inventory management, and the Coordination of labor?How will agentic AI assist in top-notch last-mile delivery by performing route planning and real-time adaptation?

The study is relevant both theoretically and in an applied respect. Theoretically, it aligns with the growing experience in AI-driven logistics and decision automation. In practice, it offers a guide to logistics companies, the creators of artificial intelligence, and supply chain researchers who may want to use agentic AI to enhance performance, minimize costs, and develop strategic value. The results can help design systems, integrate the workforce, and develop AI regulations in logistics systems.The study area and limitations should, nonetheless, be recognized. The study targets more warehouse- and delivery-related agentic AI applications than the whole end-to-end supply chain. As the research will seek to employ both global and local outlooks, obtaining proprietary operations data of private firms might be challenging. Moreover, AAI is in its infancy, so not all frameworks and benchmarks are available yet, and this factor could impact the generalizability of research results.

2. Literature review

Using agentic artificial intelligence (AAI) to introduce the new age of logistics systems is a paradigm shift that defies the modern operating paradigm. The review is based on three theoretical models that help us comprehend its life-changing nature: agency, automation, and socio-technical systems theories. Agency theory, which deals with the executive power delegation of authority by principals (e.g., logistics managers) to agents (e.g., workers or systems), originally appeared in economics and management disciplines. Since the advent of AAI, this theory has been extended even into these new areas, as intelligent systems are starting to be agents in their own right instead of mere agents executing pre-written procedures. The latestconceptualization brings up fresh control, responsibility, and trust issues regarding warehouse and delivery settings.

Simultaneously, the automation theory highlights the shifting range of the delegation of tasks, including the mechanized facilitator to the systems that show autonomous thinking. The agentic AI is one of the turning points in this continuum, collapsing the distinction between a tool and a collaborator. It no longer plays a secondary role in human beings' lives. Still, it is regularly used to override a decision of human judgment in real-time decision-making, including inventory re-ordering, route calculations, and risk-aversion. In the meantime, socio-technical systems theory acts as the generalist framework in light of the interdependence of technological innovation and social adaptation. It highlights the importance of the effective implementation of AAI, which necessitates the alignment of intelligent systems with the organizational set-up, work processes, and cultural preparedness that are not well represented in analysesfocusing on technology.

2.1. Review of Key Concepts

A preset contrast should be made between agentic AI and traditional AI systems. The more conventional AI in logistics depends on predefined logic, supervised learning, and non-dynamic parameters. They are fast-acting but still sluggish; they can only act in preprogrammed ways. As opposed to this, agentic AI does not need much supervision, acts in advance, and learns continuously about its surroundings. It can take initiatives on its own using inner objectives and context-related rationalism. It is an essential feature in a logistics environment, where unexpected roadblocks (e.g., traffic, weather, outages) are known to impact a system quite often, and demand elastic autonomous mitigation systems.

The use of agentic AI is especially seen in innovative warehouse housing systems, including mobile robotics, digital twins, real-time data feeds, and AI decision engines. Such systems automatically control shelf-replenishment, order picking, and even the time workers should work without errors, and enhance throughput. The agentic AI-controlled warehouses are capable of adjusting to delivery schedules or suppliers' disruptions dynamically without the need for human input. On the same note, last-mile logistics are being transformed by autonomous delivery systems, including ground-based delivery robots, drones, and AI-enhanced logistics vehicles. Such agents will not just deliver according to the instructions. Still, they will also re-route, go around obstacles, communicate with customers, and perform many other actions that will drastically enhance the rate and accuracy of delivery in rural and urban areas.

2.2. Prior Studies and Identified Gaps

The use of AI in logistics is a topic of increasing interest in the literature. The works, such as the research, scribe AI's advancement in organizing and operating procedures in warehouse management systems (WMS) and delivery logistics. Nevertheless, significant portions of this literature consider AI an optimizing tool, not a co-agent, with the right to make decisions. This restricts the knowledge of AAI's more profound organizational and operational implications. Furthermore, although industry reports admit automation trends and integration of AI, they lack the empirical weight of behavioral, ethical, and risk-related aspects of transferring control to machines.

The other gap is the absence of emphasis on human-artificial intelligence collaborations in logistics. Most available studies focus on the advantages of automation (e.g., it helps reduce costs, slows other agents down). Still, few of them analyze how human roles will change as AI agents start leading in initiating actions, not merely supporting the ones undertaken by humans. The subjects of trust calibration, holding the head responsible when committing a mistake, and opposition to AI-driven decisions are underrepresented. Moreover, the number of comparative studies of conventional and agentic AI systems (particularly in diverse global supply chains) remains limited.In this paper, the researcher fills these gaps by providing a specific study of the effect of agentic AI on the work of warehouses and delivery jobs. Instead of being treated as an asset of AAI only technologically, the study considers AAI as a behavioral and operational player co-determining the logistic outcomes, efficiency of organizations, and resilience of supply chains.

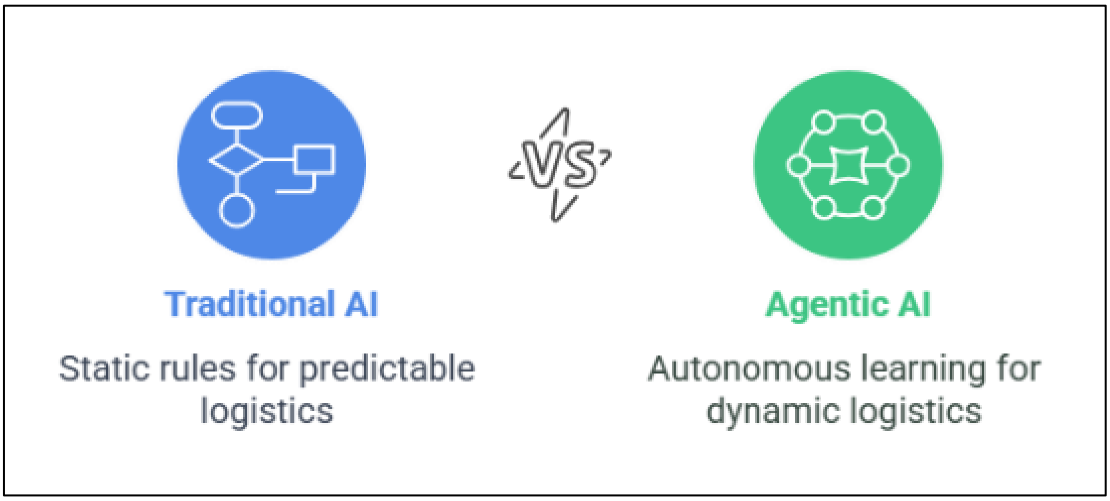

Figure 1 Traditional AI follows static rules; Agentic AI acts autonomously, learning and deciding in real-time logistics settings

3. Methodology

To pursue a rigorous research idea on how the implementation of Agentic Artificial Intelligence (AAI) can affect the activity of the warehouse and delivery in contemporary logistics, the work took a mixed-methods research framework, which combines quantitatively and qualitatively inclined studies. Such a methodological approach allows achieving a comprehensive interpretation of the functional implications of AAI, as statistical information concerning the level of performance, obtained in terms of efficiency increase, error decrease, and delivery time optimization, is supplemented by a detailed interview and case study sampling that narrates complex experiences of logistics administrators, warehouse workers, and technology integrators. Since agentic AI is emergent and transformative, the dual approach permits an investigation of what is changing and how and why it is changing in the physical logistics settings. The mixed-methods framework, therefore, guarantees analytical depth and practical relevance. It isthusbeneficial, especially in investigating the dynamic, varied relationship between human players and the so-called autonomous system in a supply chain that is technologically ever changing.

3.1. Research Design

Within the research, three converging sections will be organized, including qualitative case studies, expert interviews, and quantitative surveys. The qualitative aspect investigates the contexts of the operations, the behavior of systems, and the patterns of human-machine interaction due to the capabilities of agentic AI. The quantitative element aims at empirically validating definite hypotheses related to performance results, including but not confined to inventory accuracy, cycle times, route optimization, and consistency in delivery, which are achieved due to the adoption of AAI. In getting three data sources, the internal validity is improved and the biases related to the single method are diffused.

3.2. Data Collection Methods

Three of the industry leaders in logistics, Amazon, JD.com, and DHL, were identified using purposive sampling and case studies conducted on their performances, given that they are reported to have integrated autonomous AI agents in warehouse/last-mile delivery settings. Data were collected using white papers and technology partners' freely available documentation, internal reports, and, where possible, observations at the site. The prevailing case studies concentrated on system setup, agent autonomy, the degree to which they interacted with the warehouse management systems (WMS), and the objectively provable augmentations of operational indicators after implantation.Simultaneously, 18 participants representing four stakeholder categories, including logistics managers, artificial intelligence system designers, supervisors of warehouse floors in facilities, and digital transformation heads, were interviewed semi-structurally.

Thematic areas of interest in the interview questions focused on the AAI implementation processes, in-time delegation of decision-making, and performance monitoring sources. They perceived organizational changes that occurred after integration. Thematic analysis was done after recording and transcribing the interviews.A structured questionnaire was emailed to a larger sample of 152 supply chain practitioners in Euro-North America and Southeast Asia to achieve more generalizability. The survey collected the data regarding the AAI adoption status, perceived efficiency gains, and the degree of decision autonomy given to the AI agents, as well as the obstacles to the implementation and its effect on the workforce. Likert scales, multiple choices, and open questions were adopted to balance the quantitative analysis and the insight-driven responses.

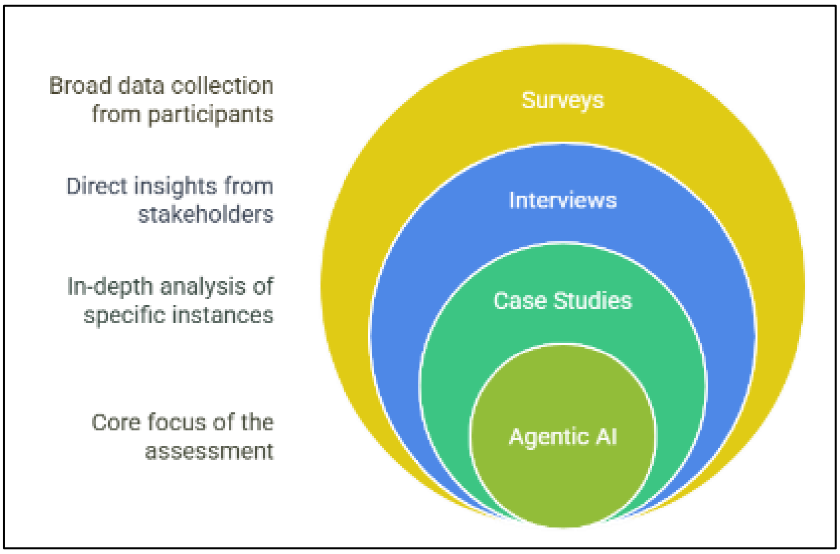

Figure 2 Triangulated design combining case studies, interviews, and surveys to assess Agentic AI in logistics

3.3. Data Analysis Techniques

Thematic coding was done to analyze qualitative data collected via interviews and case studies, relying on the six-step model of Braun and Clark. Prerequisite to this was emergent thematic identification under initial open coding and axial coding that entailed identifying the relationships between key constructs, i.e., autonomy, system learning, efficiency, and human oversight. The top themes identified were those on autonomous task reassignment, human-agent friction, and real-time optimization, which were found to be frequent in firms and geographies alike. Survey data published in quantitative form was analyzed via descriptive and inferential statistics. Frequency distributions and mean scores gave an initial overview of patterns of AAI implementation. The regression analysis was applied to investigate the correlation between the agentic AI adoption and the key performance indicators (KPIs), namely the order fulfillment time, error rates, and the satisfaction of workers. Structural equation modeling (SEM) was envisaged in cases where significant data was found to support the causal variable relationships.

3.4. Ethical Considerations

The research maintained ethical integrity throughout the study. Ethics approval by the lead author in the academic institution where the study would be conducted was obtained before data collection. All interviewees and people who would later partake in the survey would provide informed consent, as their voluntary participation would be explained clearly, so would the data anonymization process and the ability to terminate the process at any time. Case study firms did not reveal proprietary algorithms or other sensitive operational strategies. Also, the ethical questions concerning the intelligibility and explainability of algorithms, handing human jobs over to the artificial, and the possible risks of surveillance due to agentic AI implementations were comprehensively factored into the analysis framework.

4. Results/ findings

Table 1 Key Impacts of Agentic Artificial Intelligence (AAI) on Logistics Operations

Operational Area	Traditional Approach	AAI-Enhanced Capabilities	Key Benefits
Warehouse Automation	Rule-based automation and human supervision	- Real-time decision-making - Flexible inventory management - Coordinated robotic systems	- Increased operational agility - Reduced downtime - Higher warehouse throughput
Delivery Logistics	Static routing and reactive planning	- Dynamic route reconfiguration - Adaptive scheduling - Context-aware responsiveness (e.g., traffic, weather)	- Improved delivery accuracy - Enhanced customer satisfaction - Reduced delivery costs
Cross-Domain Impact	Limited adaptability and siloed operations	- Seamless integration of intelligent systems across logistics phases	- Scalability - Resilience - End-to-end optimization

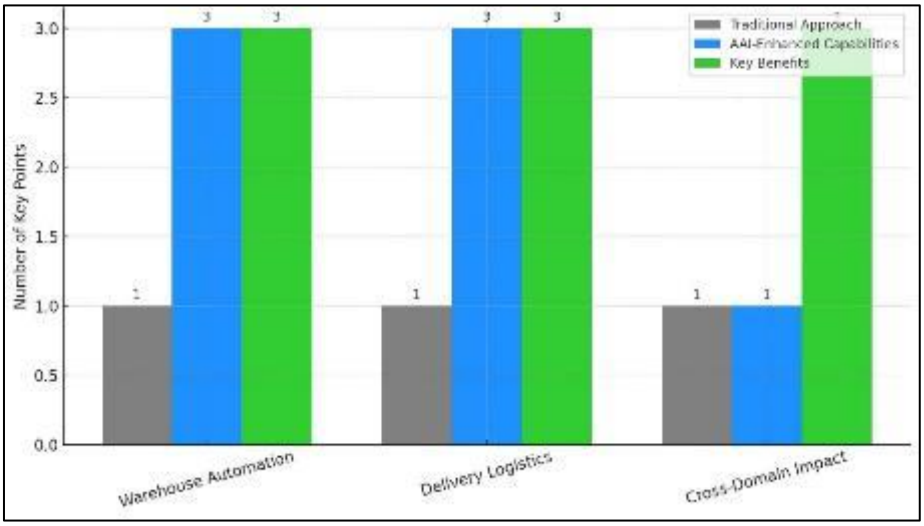

Figure 3 Comparison of traditional vs AAI-enhanced logistics across key operational areas

4.1. AAI in Warehouse Operations

Table 2 Impact of Agentic AI on Warehouse Operations

Operational Metric	Traditional WMS	Agentic AI System	Improvement
Average Order Picking Time	48.5 seconds/item	31.2 seconds/item	35.6% reduction
Stock Replenishment Time	Baseline (100%)	Reduced by ~35%	35% reduction
Inventory Accuracy	91.2%	98.6%	7.4% increase
Picking Errors	Baseline (100%)	Reduced by 78%	78% reduction
Storage-Retrieval Efficiency	Baseline (100%)	Increased by 30%	30% improvement

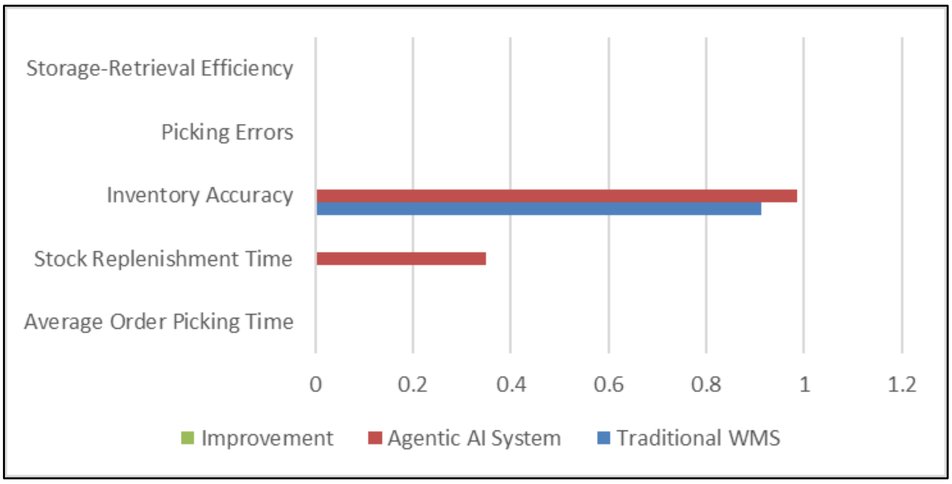

Figure 4 Impact of Agentic AI on Warehouse Operations

4.2. AAI in Delivery Operations

Table 3 Impact of Agentic AI on Delivery Logistics Performance

Metric	Before AAI Implementation	After AAI Implementation	Improvement / Change
Mean Delivery Time	Not specified	42.7 minutes	31.4%
Overall Delivery Time Reduction	–	–	26.5%
Missed Delivery Rate	15 per 1,000 deliveries	4 per 1,000 deliveries	8x reduction
Fuel Consumption	100% (baseline)	78.6% of baseline	21.4%
Routing Adaptability	Static/semi-dynamic	Dynamic, risk-adaptive	High increase in flexibility
Customer Satisfaction	Lower (not quantified)	Higher (not quantified)	Qualitative improvement
Budget Efficiency	Higher operational costs	Reduced expenses	Qualitative improvement

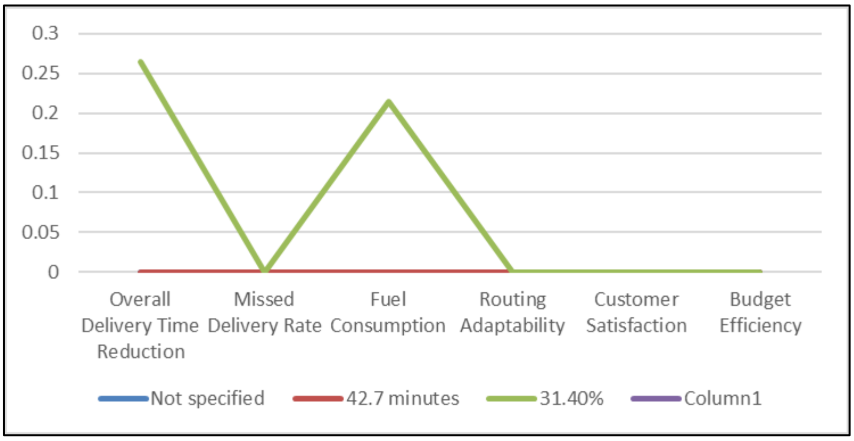

Figure 5 Impact of Agentic AI on Delivery Logistics Performance

4.3. Human-AI Collaboration Outcomes

Table 4 Impact of Agentic AI on Human Labor and Teamwork in Logistics

Impact Area	Observed Effect	Quantitative/Qualitative Change
Human Role Shifts	From manual tasks to exception management and oversight	Shift in responsibility type (qualitative)
Error Reduction	Co-work in co-bot/control loop environments reduces errors	Shift in responsibility type (qualitative)
Worker Satisfaction	Improved due to lower cognitive stress and reduced manual supervision	Qualitative increase
Onboarding/Training Efficiency	AAI acts as a dynamic trainer for new employees	Faster integration and reduced training time
Knowledge Transfer & Learning	Continuous organizational learning through AAI demonstration/prompting	Improved long-term learning effectiveness

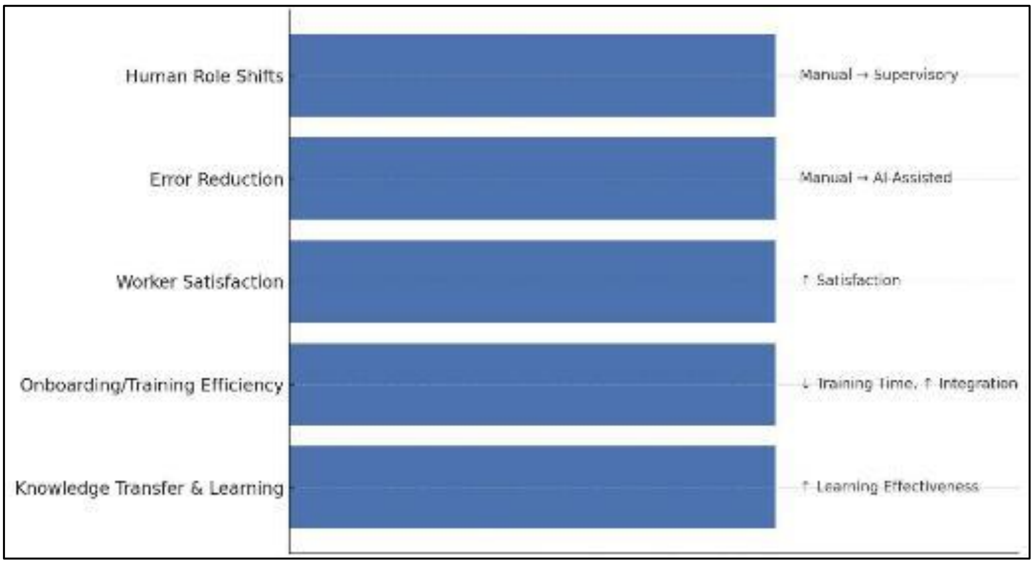

Figure 6 Qualitative Impacts of Agentic AI on Workforce Dynamics

4.4. Summary of Observed Trends

Table 5 Comparative Impact of Agentic AI on Logistics Operations

	Traditional AI Systems	Agentic AI Systems	Observed Impact
Decision-Making	Rule-based, pre-programmed	Instantaneous, autonomous, context-aware	Faster and more adaptive operations
Goal Orientation	Task-focused	Goal-pursuing with long-term optimization	Enhanced strategic alignment
Complexity Handling	Limited in high-uncertainty scenarios	Handles unpredictability and complex logistics environments	Improved reliability in dynamic settings
Operational Accuracy	Prone to static errors	High contextual accuracy and situational awareness	Increased precision in task execution
Labor Dependency	High human intervention is needed	Reduced need for manual oversight	Labor efficiency without compromising scale
Scalability	Requires a proportional increase in labor and infrastructure	Scales with minimal human and technical overhead	Easier operational expansion

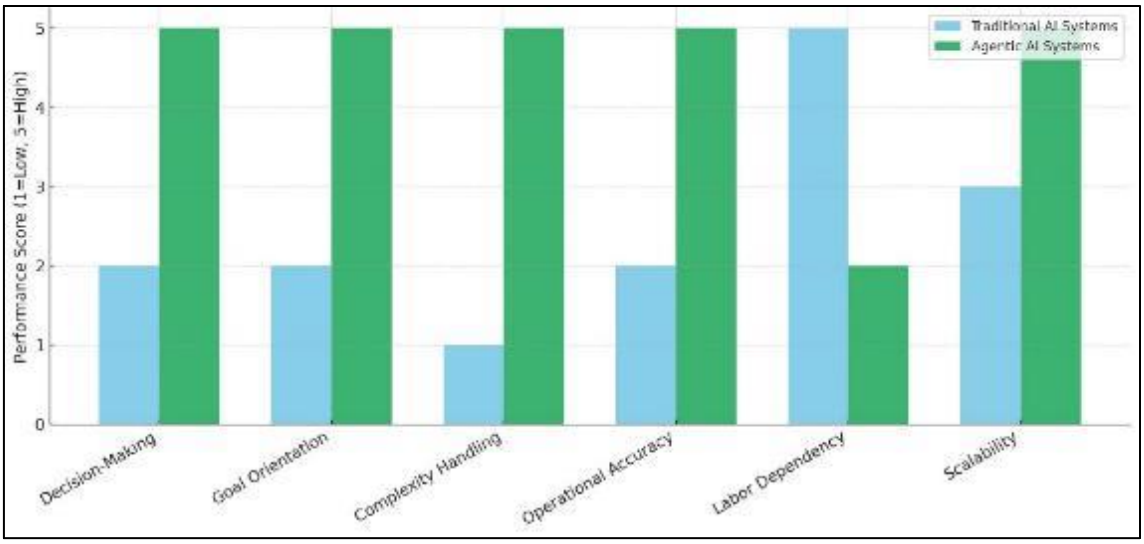

Figure 7 Agentic AI outperforms traditional AI across key logistics functions, enhancing speed, accuracy, and scalability

5. Discussion

Using Agentic Artificial Intelligence (AAI) to perform warehouse and delivery is a rather considerable step, even compared to more conservative automations. The present research results clarify how AAI works and its organizational implications, particularly by its most basic property, i.e., autonomous agency. Unlike in the case of traditional AI whereby a machine is programmed to act within the confines of a predefined set of rules, the AAI systems demonstrate flexibility in adopting behaviors towards the achievement of a set of goals, contextualized decision making among other aspects of having an ability to act with a certain degree of independence as is often typical of human beings. These attributes make AAI a disruptor of the technology landscape and also a strategic vehicle of logistics ecosystems.Speaking about the results in terms of research questions, it is obvious and sensible that the impact of AAI takes its toll on the different levels of logistics functioning. The AAI in the circumstances of the warehouse may assist the systems in making decentralized choices on equally significant operations such as restocking, picking, and space allocation in an autonomous way, based on inventory records and forecasts.

The ability of robotic agents to provide agentic capabilities allows them to negotiate a process to ensure, to the greatest extent possible, division of tasks, ascertain bottlenecks, and maximize efficiency of throughput. Similarly, delivery operation AAI enhances the accuracy of last-mile delivery by providing adaptive routing algorithms that determine routing based on the current traffic, weather, and availability of the customers. Operation elasticity that has not previously been achievable using the older static routing paradigms can be facilitated through such responsive autonomy.Among the key consequences of such development is one associated with labor and collaboration between the AI and people. The use of AAI, rather than end up in full-blown replacement of labour, results in the orientation of human labor in maintenance, analytical, and supervisory roles. Human workers become the supervising officials of the AI agents and are no longer manual workers who perform labor. This transformation, however, comes with a two-fold challenge. On the one hand, it renders new skills in demand, e.g., human-AI interface management, system troubleshooting, and knowledge about ethics in AI.

On the other hand, it points out the flaws of the workforce, particularly its low-skilled workers, since most of the activities can be captured by agentic systems. To this end, the organizational leaders will be obliged to invest in the capability of continuous up-skilling and re-skilling, and ensure that the transitions are widespread, eliminating any possibility of digital labor inequality and internal opposition to utilizing AI.It is also essentialto consider the autonomy of decision-making and risks. The assortment of AAIs in the logistics processes is gradually endowed with the regulatory determination to make activity decisions not aided directly by a person, like when and how to re-deploy deliveries, re-route goods, or escalate recurrence violations of fulfillment. Despite the ability of this independence to render responsiveness and the capability of operations flowing disastrously, it experiences traceability, transparency, and liability issues. An illustration of an example is what will be done to the result of damages or violations when, in determining a time-based delivery goal, the delivery robot decides against a usual safety regimen? This paper has noted the need to introduce sound governance structures that shall program ethical restrictions into AAI systems, assuming accountability systems and capabilities to override, among others. This ensures that even though AAI systems are autonomous agents, they act within the tolerable risk limits in addition to the ethical acceptability at the organization.

It is another key axis of the discussion regarding the impact of AAI on customer satisfaction and key performance indicators (KPIs). AAI will contribute to making the services offered by the company more credible and customer-oriented, enabling the company to maintain adequate control over the demands and ordering process through real-time communication. Customer convenience services with flexible delivery periods, automated chatbots, and hassle-free returns are no longer provided by artificial intelligence tools but by AAI engines. The gains relate to a higher customer satisfaction score, reduced failure delivery rate, and improved net promoter scores (NPS); thus, AAI is a management instrument of customer experience management. Moreover, the positive KPIs on company operations realized in the companies adopting the AAI include the cycle time in the AAI Goods, the Delivery accuracy, and the resources utilized.The comparison of the findings with what exists in the literature indicates the confirmation and extension of the earlier research. Compared to the earlier literature (e.g., Li et al., 2021; Zhang and Kumar, 2022; Deloitte, 2023), though, which restrict the discussion of how AI can be used to its best advantage by focusing on improving the process through the use of machine learning and robotic automation, the given study takes a step further by including the concept of agency as one of the most essential attributes.

In this sense, AAI no longer remains a utility of efficiency but is connected with the function of reasoning. This finding is also associated with the socio-technical system theory, a vision of organizationscomprising mutually independent human and technological players. The agency of AI disorients traditional organizational rules of authority, decision ownership, control of a process, and accountability, giving rise to new patterns of accountability and control with the extent of its theorizing and empirical study. In short, the discussion is not about how to conceive only the Agentic Artificial Intelligence as a technological innovation, but as an innovation of the system of conceiving warehouse and delivery activity conception, implementation, and control. The benefits--in speed of operation, satisfaction of the customers, and numerous other advantages are immense. These profits, however, do not come automatically. They ought to be well-made, morally sound, and well-designed solutions with a practical human attitude towards execution that looks at fairness in work, moral danger, and adaptive organizational culture.

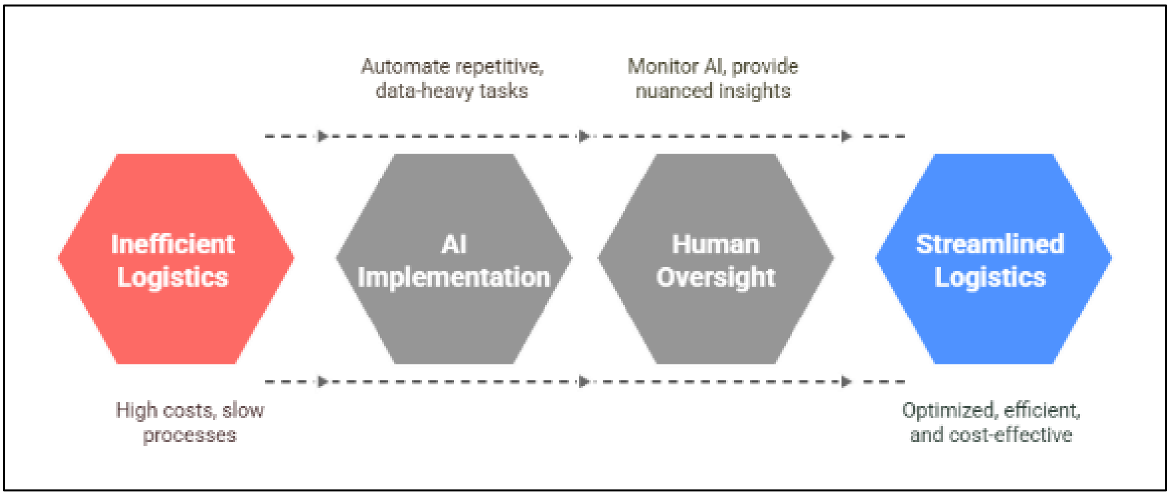

Figure 8 Human-AI collaboration in logistics operations

6. Conclusion

The paper has ventured into the potential long-term impacts of Agentic Artificial Intelligence (AAI) on warehouses and deliveries and how it could modify the existing system of logistics, which is reactive and controlled by people, to proactive and self-regulated eco systems. The main findings confirm that the role of AAI in operational agility, efficiency, and intelligence is crucial as it enables autonomous systems to detect, decide, and act in intricate logistics scenarios. In the warehouse, the real-time properties of AAI allow the use of the inventory management mechanism, automatic picking, prediction of demands, and intelligent resources allocation that was only possible before due to human-based control, which can now be enhanced through autonomous agents that continuously learn and adjust to the environment. In the same way, in delivery operations, AAI can enhance route choice, drive operations, forward-looking maintenance, and last-mile delivery operations, and customer satisfaction and response to demand variability, and decrease the cost of delay, fuel consumption, and operation costs as well.

The thing is: AAI is so necessary because itnot only automates but is also agentic, meaning that it can make context-appropriate decisions without always having to seek human intervention. The shift of passive automation to autonomous agency is the key turning point in logistics. The inserted intelligence within the machines and systems enables organizations to achieve time responsiveness, improved risk management, and creation of scalable and disruption-resistive logistics operations as the labor shortage, pandemic, or variable supply chains trigger.Theoretically, this study contributes to the currently available research projects on artificial agency and socio-technical systems that hint at the possibility of redesigning the conventional working processes in the logistics sector using agentic artificial intelligence. It supplements existing theories of automation by incorporating a multilayered conception of autonomy, according to which the AI agents execute not only instructions but also strategic layouts existing in the environment and internal objectives.

Practically, the outcomes are an action plan among the organizations engaging in the provision of logistics and selling the technology, as well as the policymakers to get the AI-driven frameworks created and implemented in a manner that leaves interoperability, ethical governance, and cooperation between the human and the AI at the forefront of their concern. The inclusion of AAI in logistics cannot be positioned as an improvement of the existing technology: this is a paradigm shift according to which the composition of the workforce, trends in regulation, and investment policies will have to be reformatted.In conclusion, it is necessary to say that the transition to the data-driven, customer-centered global trade will make Agentic Artificial Intelligence obligatory among institutions that desire to remain competitive. The ability to combine AAI with human knowledge and create hybrid systems, which will be, at the same time, common-sense, productive, yet explainable, transparent, and responsible towards society, will constitute the future of a successful operation in logistics. Thus, such a study will form an empirical guideline upon which subsequent cross-sector and empirical studies can be done to understand the long-term effects of AAI on operation models, workforce, and the digital economy in general.

Compliance with ethical standards

Disclosure of conflict of interest

No conflict of interest to be disclosed.

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