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Generative Artificial Intelligence in Logistics-Intensive Organizations: Use Cases, Organizational Impact, and the Challenge of Measuring Operational Value

Gerald Schneikart[1*], Elka Xharo[2], Clemens Löffler[3], Maria Ludmilla Schallar[4], Walter Mayrhofer[5]

[1] FHWien der WKW/Institute for Digital Transformation and Strategy, Währinger Gürtel 97, 1180 Vienna, Austria
[2] FHWien der WKW/ Department of Digital Economy
[3] FHWien der WKW/ Competence Center for Business Controlling & Accounting
[4] FHWien der WKW/Institute for Digital Transformation and Strategy

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ABSTRACT

Recent generative artificial intelligence (GenAI) solutions attract high expectations, while their operational contribution in real-world logistics settings remains unclear. This study investigates how GenAI supports work in companies with logistics-intensive operations and how these organizations assess the added value of GenAI use cases. Between January and March 2026, we conducted 11 semi-structured expert interviews with decision-makers and artificial intelligence experts from Austrian organizations with established logistics operations. The transcripts were manually coded using ATLAS.ti 25. Interviewees frequently describe GenAI as a cognitive support tool for drafting, summarizing, translating, or information retrieval. Interviewees reported time savings in these activities, whereas end-to-end process automation remained limited. The findings indicate that GenAI adoption in logistics is still at an early stage. Formal assessments of operational or financial benefits using key performance indicators (KPIs) were largely absent in the organizations interviewed. Although many firms show strong interest in exploring new use cases, there is a lack of mature, out-of-the-box solutions tailored to logistics-specific processes. Some respondents from large organizations reported the development of customized in-house AI solutions, while general-purpose GenAI tools dominated the reported applications overall. It can be concluded that, in current practice, GenAI's near-term contribution in logistics lies in augmenting human work in manual processes rather than completely automating processes and replacing workers.

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[1*] Corresponding author, Gerald Schneikart, PhD, e-mail address:Gerald.Schneikart@fh-wien.ac.at (G. Schneikart).
[2] Elka Xharo, BSc., e-mail address: Elka.Xharo@fh-wien.ac.at (E. Xharo).
[3] Clemens Löffler, PhD, e-mail address: clemens.loeffler@fh-wien.ac.at (C. Löffler).
[4] Maria Ludmilla Schallar, Mag., BSc., e-mail address: Maria.Schallar@fh-wien.ac.at (M.L. Schallar).
[5] Walter Mayrhofer, PhD, Professor, e-mail address: Walter.Mayrhofer@fh-wien.ac.at (W. Mayrhofer). Published online first 25 of October 2026.
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1. Introduction

1.1 Artificial intelligence in logistics

In this study, logistics-intensive organizations refer to organizations whose operations or services involve significant logistics-related activities, such as transportation, warehousing, distribution, or the coordination of associated processes, regardless of whether logistics constitutes their primary business activity. Logistics operations are particularly suited to employ artificial intelligence (AI), since operational performance depends on the continuous alignment of demand, capacity, routing, scheduling, resources, and information flows under changing conditions. AI and machine learning have been widely discussed as instruments for forecasting, decision support, and the optimization of logistics processes. Recent research on AI-based logistics optimization shows these approaches as increasingly connected to sustainability-related objectives, while their operational implementation remains dependent on data availability, system integration, and organizational readiness (Chen et al., 2024).

In this study, AI is used as an umbrella term encompassing both established predictive and optimization-oriented applications and generative systems. Generative AI (GenAI) refers more specifically to AI systems capable of generating or transforming content, such as text, summaries, or other information outputs, often using large language models (LLMs). Unlike specialized AI applications for forecasting, routing, or tracking, LLM-based GenAI tools enable natural-language interaction and may therefore lower the entry barriers to AI-supported work (Schneikart & Mayrhofer, 2026a). This is relevant for logistics organizations because many tasks require communication, interpretation, coordination, and decision preparation under changing operational conditions, which corresponds to recent SCM literature, positioning GenAI as a decision-support layer for planning and enablement processes (Bahroun et al., 2026).

Previous work by Schneikart and Mayrhofer (2026a) reviewed GenAI applications for reverse logistics and closed-loop supply chains, particularly in the context of returnable transport items and circular logistics systems. It suggested that GenAI may support planning and data analysis, while predictive AI and customized systems can contribute to return forecasting, routing, inventory management, and resource planning. At the same time, the proposed use of GenAI as a natural-language interface to broader AI-of-Things environments, which combine AI capabilities with data from connected devices and sensors, was considered dependent on clearly defined use cases and pilot experiments. The presented study builds upon this view by complementing literature-based use case identification with field evidence from logistics practitioners.

Austria was selected as the empirical setting because the authors' established research and professional networks provided access to experts from organizations across several logistics-intensive sectors. As a member state of the European Union, Austria also provides a regulatory context in which AI adoption is subject to European requirements, including the General Data Protection Regulation (GDPR) when personal data are processed and measures supporting AI literacy under Article 4 of the EU Artificial Intelligence Act (European Parliament & Council of the European Union, 2016, 2024).

1.2. The added value of artificial intelligence applications

Despite the broad expectations associated with GenAI (Helmy et al., 2025), its operational added value remains difficult to determine. Productivity gains are often assumed, but whether they translate into measurable organizational benefits depends on the specific task, the user's preferences and capabilities, the work environment, and the extent to which AI outputs can be trusted and integrated into existing processes (Sánchez, 2025; Shrivastava, 2025). Recent research on GenAI for supply chain transformation frames GenAI as an emerging decision layer that can support scenario generation, synthetic data creation, and actionable textual insights, while also showing that most evidence remains at the prototype level and rarely reports system-wide key performance indicators (KPIs) (Bahroun et al., 2026).

In addition, research on GenAI value creation in organizations indicates that productivity effects are increasingly discussed, whereas financial assessments of GenAI applications are less developed (Sánchez, 2025).

This study is based on a research framework by Schneikart and Mayrhofer (2026b), which proposes a user-centred approach for evaluating the operational impact of AI solutions in logistics use cases. The framework treats AI as part of socio-technical information systems. Accordingly, added value at the organizational level can only be assessed meaningfully, if the interaction between users, tasks, processes, and organizational structures is taken into account. In this view, successful human-AI interaction is a prerequisite for realizing added value, since AI initiatives are unlikely to generate benefits if employees do not use the tools, lack the required competencies, or if AI outputs fail to meet operational requirements.

The expert interviews presented in this article constitute the first empirical step in this framework and are used to identify relevant AI use cases in logistics-intensive organizations and to explore how these applications affect users, organizational routines, and the assessment of added value. The study contributes to theory by providing empirical evidence on how task-level GenAI use relates to user- and organizational-level effects within a socio-technical perspective. For managers and policymakers, it identifies capability, governance, and measurement challenges that shape the adoption and evaluation of GenAI in logistics-intensive organizations.

The study is guided by four research questions:

RQ1: How can GenAI be used to support processes and tasks in logistics?

RQ2: What impact does the use of GenAI have on the user?

RQ3: What impact does the use of GenAI have on the organization?

RQ4: How do logistics-intensive organizations assess the added value of GenAI applications?

1.3. Organization of the rest of the article

The remainder of the article is structured as follows. Section 2 provides an overview of the current state of knowledge in the field of GenAI impact evaluation. Section 3 describes the qualitative research design, including the semi-structured expert interviews, the interview sample, and the coding approach used for the analysis. Section 4 presents the findings, while section 5 discusses the results with respect to the use of GenAI tools and applications, their impact on users and organizations, and current practices for assessing added value. The article concludes by summarizing the main findings, outlining practical implications for logistics organizations, and identifying directions for future research on measurable AI impact in logistics.

2. Literature review

2.1. Human-AI Interaction and Organizational Adoption

The present study follows a socio-technical view of AI adoption, according to which the effects of GenAI depend on the interplay between the technology, its users, operational processes, and organizational structures (Schneikart & Mayrhofer, 2026b). This perspective is consistent with broader research on AI-related business value, which indicates that organizational benefits depend on more than the technical system itself and require complementary resources, skills, and organizational conditions (Enholm et al., 2022).

Employee-level research further indicates that willingness to use workplace AI is related to how employees evaluate the technology. In two samples of working adults, perceptions of AI as useful and trustworthy were associated with more favorable attitudes toward its use, which in turn were associated with stronger intentions to use AI at work; the corresponding findings for ease of use were less consistent (Nguyen et al., 2026). Human-AI collaboration should therefore not be assumed to generate uniform benefits. A meta-analysis covering 106 experimental studies found substantial variation across tasks and showed that combining human and AI performance does not generally outperform the better of the two acting separately (Vaccaro et al., 2024).

2.2. From Task-Level Productivity to Organizational Value

Empirical evidence for measurable GenAI benefits is particularly well established at the level of individual work tasks. A field study involving 5,172 customer-support agents found that introducing GenAI assistance increased the number of successfully resolved issues per hour, while the size of the effect differed consid-

erably between employees and was greater among less experienced workers (Brynjolfsson et al., 2025). Such heterogeneity reinforces the need to consider the characteristics of users and tasks when evaluating AI-supported work (Brynjolfsson et al., 2025; Vaccaro et al., 2024).

Demonstrating improvements at the task or process level, however, is not equivalent to demonstrating value for the organization as a whole.

The literature on AI business value distinguishes effects occurring within business processes from outcomes observed at the firm level and emphasizes that the latter need to be understood through the organizational processes from which they arise (Enholm et al., 2022). Evaluating these broader effects is complicated by the diversity of existing AI impact-assessment approaches. A systematic review identified substantial differences in their scope, organizational embedding, timing, and procedures, indicating that no single assessment approach currently covers all AI applications and contexts (Stahl et al., 2023).

2.3. GenAI in Logistics and Research Gap

Research on AI in logistics has examined a broad range of optimization and decision-support applications, including routing, demand-related planning, resource allocation, and other operational logistics problems (Chen et al., 2024; Tsolaki et al., 2023). GenAI extends this application spectrum by supporting the generation and synthesis of information as well as planning and decision processes. A recent systematic review of 98 studies on GenAI in supply chains found that research is concentrated particularly on planning and enabling activities. The same study also identified a predominance of prototypes and narrow evaluations, with organization-wide performance measures reported only rarely (Bahroun et al., 2026). Recent multi-case research expands this application-oriented perspective by showing that GenAI adoption can also affect the roles and competencies of supply-chain planners (Shurrab & Jonsson, 2026).

Taken together, existing research provides evidence for task-level productivity effects and an expanding range of GenAI applications, but comparatively less field evidence connects actual GenAI use with user effects, organizational consequences, and systematic value measurement in logistics-intensive organizations (Bahroun et al., 2026; Enholm et al., 2022; Schneikart & Mayrhofer, 2026b). The present study addresses this gap through the four research questions introduced in Section 1. Given the exploratory qualitative design of the study, no formal hypotheses are formulated; instead, the literature review provides the theoretical basis for the four research questions.

3. Methodology

3.1. Semi-structured interviews

A qualitative research approach using semi-structured interviews was applied to address the research questions (Filimonau & Gherbin, 2017; Silverman, 2010). All 11 interviews were conducted online via Microsoft Teams between January and March 2026, in German, and lasted approximately 30 minutes on average. The same interview guide was used throughout, comprising seven main questions addressing GenAI applications, tool selection, organizational adoption, changes in the working environment, expected benefits, and approaches to assessing organizational impact. Follow-up questions were asked flexibly according to the course of each interview. The interviews were recorded and automatically transcribed. An English translation of the original German interview guide is provided as Supplementary Material S1.

3.2. Interview partners

The interview sample comprised 11 decision-makers and experts from Austrian organizations with established logistics operations, including delivery or warehouse processes. Interviewees were recruited through the authors' professional and research networks, including contacts from previous research collaborations and referrals through existing contacts. Potential participants were approached by email. The selection focused on individuals with relevant insights into AI adoption and logistics-related operations. The participating organizations represented different business activities and industries, with seven classified as large, three as medium-sized, and one as small based on publicly available employee counts (Table 1).

Table 1
Interview Partners

Expert #	Job Role	Type of Business	Industry	Organization size
1	Founder, CEO	Caterer	Food industry	Small
2	ESG officer	Parcel services provider	Parcel logistics	Large
3	Energy and mobility officer	Logistics company	Pharma and healthcare	Large
4	Innovation manager	Parcel service provider	Parcel logistics	Large
5	Head of IT	Logistics company	Pharma and healthcare	Large
6	CEO	International transport and logistics company	Transport industry	Large
7	General manager	Logistics and river shipping company	Transport industry	Large
8	Head of logistics	Logistics hub and terminal operator	Logistics, transport, traffic, and infrastructure industry	Medium
9	Business developer	Federal, public service-oriented consultancy and agency	Transportation & mobility	Medium
10	Founder, CEO	Caterer	Food industry	Medium
11	Head of logistics	Pharmaceutical wholesaler	Pharma and healthcare	Large

Note. Authors' own elaboration. Organization size refers to the entire corporate group and is classified according to the number of employees: small (10–49), medium (50–249), and large (250 or more). Classifications are based on publicly available workforce information.

3.3. Data analysis

Following automatic transcription, the interview transcripts were anonymized, checked for accuracy, and edited for readability. The qualitative data were manually coded using ATLAS.ti 25. The initial codebook was drafted by the first author and subsequently discussed and revised in a workshop involving the co-authors. Following an initial analysis of the interview transcripts, the codebook was further refined collaboratively.

The final coding system comprised 41 codes, including 7 parent codes and 34 subordinate codes, organized into seven thematic groups (corresponding to the parent codes) and linked to the four research questions. An English translation of the final codebook is provided as Supplementary Material S2. Coding was distributed among the authors, with ambiguous coding decisions discussed and resolved jointly by consensus. Code co-occurrences were examined using the built-in analysis functions of ATLAS.ti 25 to identify thematic overlaps, particularly between governance, measurement practices, and perceived organizational added value. Code frequencies and co-occurrences were interpreted descriptively rather than as statistical associations. Interview quotations were translated from German into English by the author team.

An earlier publication introduced the underlying research framework and reported preliminary observations from related expert interviews (Schneikart & Mayrhofer, 2026b). The present study builds on this work by providing a systematic qualitative analysis of the interview material, including detailed findings on GenAI use cases, user and organizational impacts, and approaches to assessing operational added value.

4. Results

4.1. Use of GenAI tools and applications in logistics organizations

The interviews provide a detailed picture of how GenAI tools are currently used in logistics organizations. Across all cases, AI adoption remains in an exploratory stage, with a strong focus on general-purpose tools rather than highly specialized logistics solutions. The findings show consistent patterns regarding types of tools used, supported tasks, features valued by users, and the extent to which their use is strategically embedded within organizations. The interview quotations

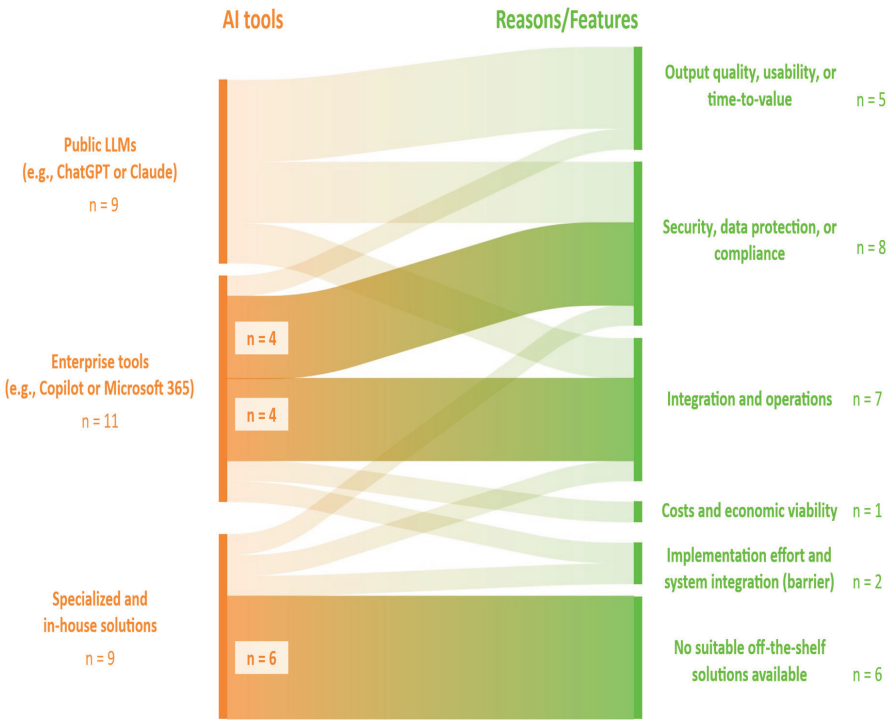
presented in the following sections serve as illustrative examples of the identified themes and do not represent an exhaustive account of each interviewee's contribution to the analysis.

A first key finding concerns the types of tools employed. The most frequently mentioned tools are widely available, general-purpose GenAI systems such as ChatGPT, Microsoft Copilot, and Google Gemini. Publicly available no-cost solutions or subscription models are commonly preferred by users due to low entry barriers and associated short time-to-value (Figure 1). Several participating organizations reported relying on Copilot due to its integration into existing Microsoft environments and perceived advantages regarding data security and compliance (Figure 1). For example, Expert #11 explained that Copilot was selected because it operates within an "internal environment where company data does not leave the system". Another respondent noted that Copilot fits naturally into the company's existing software stack and is therefore easier to adopt in everyday work (Expert #4).

Simultaneously, the interviews highlighted a lack of mature, out-of-the-box AI solutions on the market. Many of the available tools are still in an experimental and early-stage phase. Expert #4, for example, explicitly stated that currently no solutions adequately match the organization's level of complexity, necessitating in-house development. However, such internally developed systems appeared to be the exception and were primarily mentioned by respondents representing large organizations. Given the composition of the interview sample, this observation should not be interpreted as evidence of systematic differences between organizations of different sizes.

Figure 1

Common Categories of AI Tools Mentioned to be Preferably in Use in Logistics and the Reasons for Usage



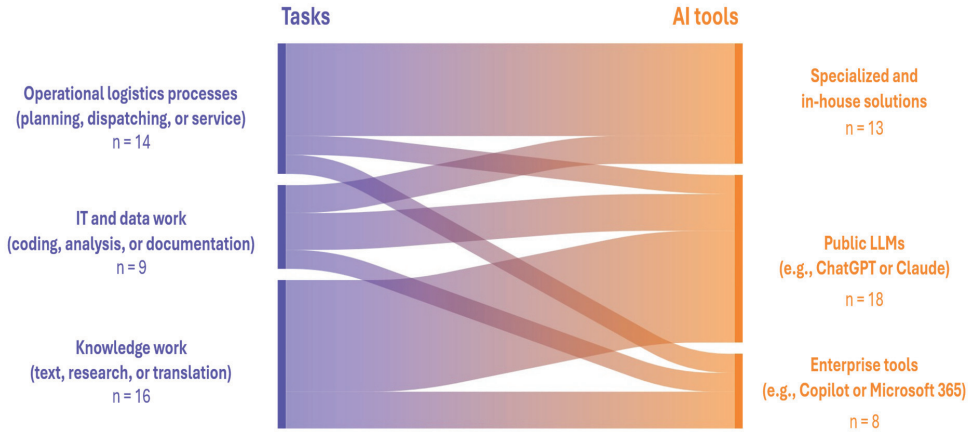
Note. Authors' own elaboration based on interview data. Frequencies represent coded references rather than numbers of interviewees; individual interviews may contribute multiple references.

A second major theme relates to the specific tasks that GenAI applications are used for. Across the interviews, general-purpose AI tools were frequently described as supporting cognitive and knowledge-intensive tasks, while specialized AI applications were also reported for operational processes (Figure 2). The most common use cases mentioned include text generation, summarization, translation, research, and the structuring of information. Interviewees reported that employees frequently used AI to draft emails, reports, presentations, or project documentation. One interviewee explained that AI is mainly used as an "enhanced search engine" that helps users quickly gather and structure information (Expert #11).

Beyond these generic tasks, some organizations also use AI in more specialized contexts. In logistics-specific settings, reported AI applications included forecasting, tracking, and process optimization, which were distinct from the general-purpose GenAI tools described above. Examples included real-time shipment tracking, demand forecasting, and route planning support (Expert #2); however, these applications were described as tailor-made software programs rather than off-the-shelf GenAI tools (Figure 2).

Figure 2

Group of Tasks (left) Mentioned to be Considerably Enhanced by Using Different Categories of AI Tools



Note. Authors' own elaboration based on interview data. Frequencies represent coded references rather than numbers of interviewees; individual interviews may contribute multiple references.

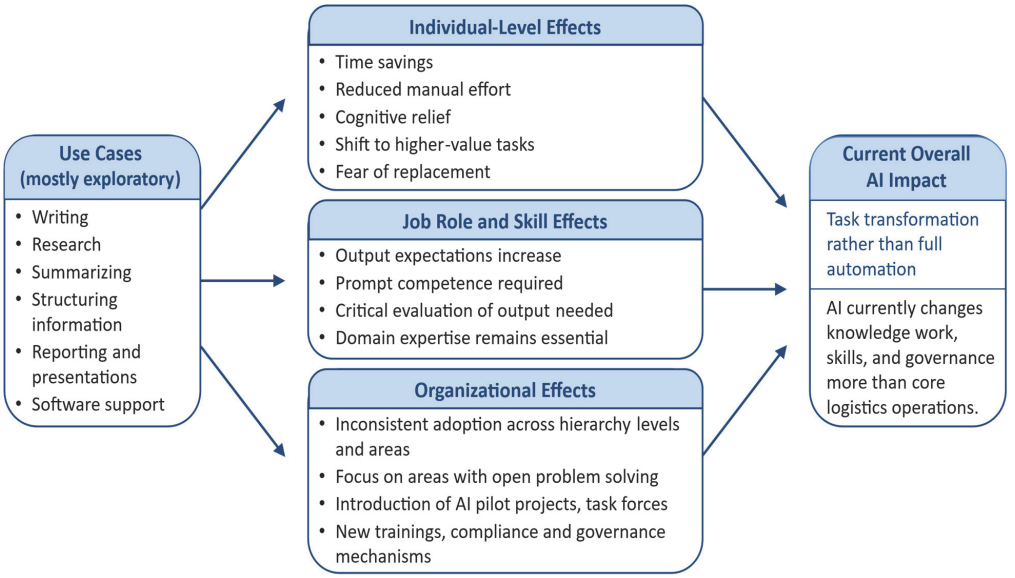
In many cases, GenAI is not directly embedded in operational processes but instead supports the design, planning, or improvement of such processes. For instance, one company used AI to redesign packaging workflows and eliminate manual steps, even though the final system itself does not contain AI components (Expert #1). In this regard, several respondents also described AI as a "sparring partner" that helps with generating ideas, structuring problems, and identifying potential solutions.

Overall, the findings imply that the current use of GenAI in logistics is characterized by broad but shallow adoption. While many organizations actively experiment with AI tools and recognize their potential, usage is still largely concentrated on general-purpose applications and individual productivity gains. Fully integrated, process-level applications appeared limited in the interviewed organizations and, where reported, often involved customized systems rather than widely available GenAI tools. As a result, GenAI currently serves mainly as a flexible support tool that enhances existing workflows rather than fundamentally transforming logistics operations.

4.2. AI's impact on users and organizations

The interviews suggest that the impact of GenAI on users and organizations is currently less a matter of radical organizational disruption but rather a matter of individual exploratory experiments in order to achieve incremental productivity gains, introducing selective role changes, and new governance requirements. Figure 3 summarizes the insights acquired by the interviews with respect to the impacts on the level of individual work practices, the effects with respect to job roles and skills, and the consequences on the level of the whole organization.

Figure 3
Current AI Impact on Individuals, Job Roles and Organizations



Note. Authors' own elaboration based on interview data.

One major effect concerns the users' everyday work experience. Several interviewees described AI as a practical aid that reduces time spent on routine, repetitive, or cognitively draining tasks. Expert #1 explained that AI helps remove low-value manual work and frees up capacity for more meaningful tasks. In the expert's words, the goal is to move "from pure operational work that gives nothing to organizational development toward work that can actually move the company forward." The expert also emphasized that the main benefit is time savings in "extremely lengthy and relatively dull" tasks. This shows that, from the user's perspective, AI is not primarily experienced as an abstract strategic technology, but as a distinct productivity tool that reduces friction in everyday work.

A similar pattern appears in larger organizations. Expert #3 who regularly uses Copilot for reports, presentations, and internal documents stated that many standard tasks can now largely be delegated to the tool. In this regard, the interviewee explained that when he asks the system to summarize material, extract key bullet points, and draft presentation content, "80% of the task is finished from my point of view". The expected benefit in using GenAI for content creation was explicitly described not only as a gain in time, but also as a reduction in mental burden. AI should create "time-related advantages" and also "nervous relief," meaning that repetitive tasks that "only cost time and nerves" become less burdensome.

The interviews also showed that productivity gains do not automatically translate into less work. Instead, freed-up time is often reabsorbed by new tasks. Expert #3 noted that productivity gains mean that "the time gets filled up again with something else." Expert #1 made a similar point, explaining that AI had not led to dismissals, but had made work "the same, only a bit faster."

A second major impact concerns roles and skills. The interviews indicated that effective AI use requires prompt competence, digital literacy, domain knowledge, and critical evaluation of outputs. Respondents emphasized that AI does not remove the need for expertise. Expert #10 noted that developers can process more workload with AI but also need to be better qualified because prompt writing itself requires specialists who "know what they are doing."

At the organizational level, AI adoption seems to be still uneven. Access to tools was often mentioned as selective and concentrated among management or staff working on open-ended tasks. Expert #3 reported that Copilot licenses were mainly available to "middle management and above," while Expert #8 described access for managing directors, department heads, and selected support roles.

Some organizations had begun to establish new structures and governance mechanisms around AI. Interviewees mentioned dedicated AI responsibilities, internal task forces, workshops, training programs, and compliance rules. Expert #3 described workshops with business unit leaders to identify pain points and use cases, while Expert #9 referred to an internal AI task force. Expert #8 reported mandatory e-learning on permitted and prohibited AI use, including rules for personal and company data.

Finally, the interviews pointed to a persistent tension between support and fears of replacement. Some employees expressed concern that AI or robotics could eventually threaten jobs. Expert #4 described such fears as "definitely a topic," even if often raised jokingly. At the same time, the current evidence from the interviews does not indicate immediate job displacement. Instead, AI is mainly framed as a support tool that helps employees cope with workload, increase output, and improve scalability.

4.3. Assessing the added value of AI initiatives

Another important indication by the interviews was a gap between experimentation and systematic evaluation of AI implementation (Figure 4). Many of the interviewed organizations were using AI or planning to deploy it, but formal KPIs for assessing its effectiveness were largely absent. One respondent said plainly: "We do not measure anything. That would be an operational overkill for us" (Expert #1). A similar response came from Expert #11 stating that no specific metrics were yet in place, apart from reminders encouraging employees to keep using Copilot.

Expert #3 mentioned that the executive board once presented plans to track expected impacts "on the organizational, technical and performance side," but the respondent was unaware if plans had been followed up systematically. Expert #4 suggested a more advanced decision logic, noting that no technical initiative would be started without a business case demonstrating financial benefit. Despite this general absence of formal KPIs, some responses suggested implicit means to measure AI impact. For example, Expert #7, who also answered that KPIs were missing in their organization, referred to the potential of measuring saved time.

According to these statements, the considered organizations tend to operate AI (in particular, GenAI) in an exploratory mode. They perceive benefits of using GenAI casually, but formal performance measurement is still limited or absent. Instead, currently the added value and financial benefits of AI initiatives seem speculative and based on crude estimations.

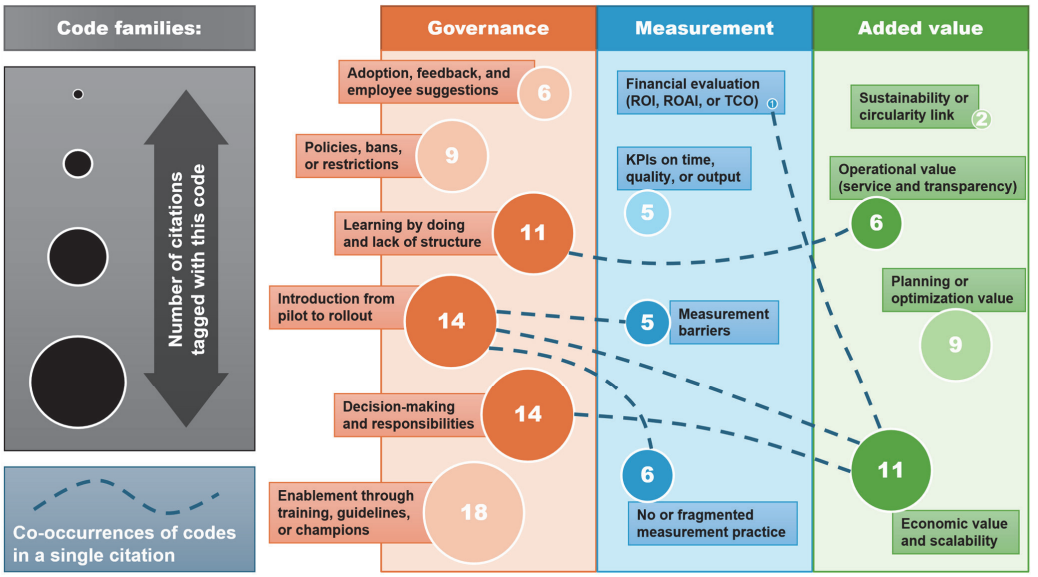
Expert #5, who also noted that internally a "concept" for using KPIs is missing, outlined the outcome of an AI implementation project in the human resource department as a failure, despite high expectations and reasonable project costs in the beginning: "Last year, we tried setting up our own infrastructure to build our own chatbot - an HR chatbot, to be specific. And the costs just skyrocketed. […] It was just a massive undertaking, and for a small use case, it simply isn't worth it. The management was disillusioned by how poor the value for the investment was, but it was defined rather as a proof-of-concept. In that sense, it's manageable because it was labeled as such in first place […].".

This example illustrates the distinction between implementing an AI proof of concept and establishing whether its benefits justify the required investment. Together with the limited use of formal KPIs reported by other interviewees, it highlights a gap between AI experimentation and systematic value assessment.

Figure 4 illustrates co-occurrences between codes related to governance, measurement, and added value. In particular, references to introducing AI initiatives from pilot to rollout co-occurred with discussions of measurement barriers, fragmented measurement practices, and economic value and scalability. The figure also links learning by doing and a lack of structure with operational value. These relationships indicate thematic overlaps within coded interview passages rather than causal effects. Sustainability or circularity appeared in only two coded references, providing no evidence of measurable environmental benefits.

Figure 4

Code Frequencies and Co-Occurrences Across Governance, Measurement, and Added Value



Note. Authors' own elaboration based on interview data. Code frequencies represent coded references rather than numbers of interviewees; connections indicate code co-occurrences within coded passages.

5. Discussion

Building on these findings, the observed adoption pattern suggests that the current organizational role of GenAI is shaped less by the availability of advanced technical capabilities than by implementation barriers, accessibility, and the ability to realize benefits quickly. The following discussion relates these patterns to prior research on GenAI productivity, adoption barriers, human-AI collaboration, and value measurement.

The prevalence of readily accessible, general-purpose GenAI tools suggests that early adoption is driven primarily by low entry barriers and rapid time-to-value, which is consistent with evidence that GenAI assistance can yield measurable productivity gains soon after deployment (Brynjolfsson et al., 2025). The parallel preference for enterprise-integrated tools such as Copilot indicates that adoption decisions are also shaped by compatibility with existing software environments and by data-security and compliance requirements. This security and compliance emphasis aligns with previous research on large language model (LLM) usage in supply chain management which identified risk and security management as a prominent theme shaping LLM adoption choices (Srivastava et al., 2024).

The limited availability of mature logistics-specific solutions suggests that tailored AI applications may require substantial technical and organizational capabilities. In the present sample, references to in-house development came mainly from interviewees representing large organizations. However, the uneven distribution of organization sizes in the sample limits systematic comparisons across size categories. Previous literature similarly identifies knowledge gaps, cost constraints, and insufficient infrastructure as important barriers to AI implementation in SMEs (Oldemeyer et al., 2025). This reinforces the perception that the market for GenAI applications in logistics is still evolving, consistent with bibliometric evidence describing GenAI research in logistics and supply chains as an emerging domain and highlighting the need for more robust and scalable real-world deployment (Sharma et al., 2026).

The task profile observed in the interviews suggests that the perceived benefits of GenAI currently arise primarily in cognitive and knowledge-intensive work rather than through direct automation of core logistics processes. Its concentration in writing, summarization, translation, research, and information structuring suggests that organizations initially deploy GenAI where experimentation is relatively easy and individual productivity gains can be realized quickly. This usage pattern is consistent with evidence that GenAI delivers immediate benefits in knowledge-work and text production.

Noy and Zhang (2023) examined ChatGPT in midlevel professional text production and documented sizable reductions in time and improvements in output quality. In addition, the interviewees' framing of GenAI as an "enhanced search engine" is consistent with recent information-retrieval research describing a shift from conventional keyword-based retrieval toward more interactive LLM-supported retrieval and synthesis (Breuer et al., 2025). Finally, supply-chain-specific LLM literature identifies knowledge management as a core application theme, suggesting that early LLM use in logistics-related contexts is likely to concentrate on information synthesis and decision preparation before deeper operational embedding becomes widespread (Srivastava et al., 2024).

Unlike general-purpose GenAI tools, the specialized forecasting, tracking, and optimization applications identified in the interviews require deeper integration into logistics processes, a distinction consistent with previous research on machine-learning applications in freight transportation and logistics Tsolaki et al. (2023).

The findings further suggest that GenAI can contribute indirectly to logistics performance by supporting problem framing, process design, and solution development rather than executing the final operational process itself. This positions GenAI as a cognitive partner in early-stage and semi-structured work, where value arises from assisting users in generating, structuring, and evaluating alternatives.

This view is supported by previous literature on applying LLMs for iterative decision-making by reducing cognitive effort in generating, evaluating, and refining options, rather than replacing operational execution end-to-end (Ghiani et al., 2024). This is particularly relevant in early-stage tasks such as research, planning, or concept development. The emphasis placed on domain expertise and critical evaluation of AI outputs in section 4.2 points to the continued importance of human oversight. This interpretation is consistent with documented hallucination risks in LLMs (Anh-Hoang et al., 2025). Accordingly, a human-in-the-loop approach remains important for reviewing and validating AI-generated outputs.

At the individual level, the most immediate effects of GenAI appear to be reduced effort and time spent on routine cognitive tasks, with freed-up capacity potentially redirected toward higher-value activities. Users therefore experience GenAI primarily as a productivity-enhancing work aid rather than as a technology that fundamentally changes the nature of their roles. These findings align with literature suggesting that human-AI collaboration yields the most consistent performance gains in tasks that involve creating content (as opposed to some decision-making tasks) (Vaccaro et al., 2024).

A workplace-focused study associated greater confidence in GenAI with lower self-reported critical-thinking effort (Lee et al., 2025), highlighting a potential risk that was not directly assessed in the present interviews. Beyond time savings, the findings indicate a perceived reduction in cognitive burden when repetitive information-processing tasks are delegated to GenAI, which is in line with findings in previous studies

showing that ChatGPT can lower intrinsic and extraneous cognitive load via detailed responses and efficient information search (Patac & Patac, 2025).

The productivity effects observed do not imply a corresponding reduction in workload or employment. Instead, efficiency gains appear to be absorbed by additional or higher-value tasks. Thus, AI changes the composition and pace of work rather than eliminating work itself, which aligns with evidence that automation technologies may create new job demands even when they improve efficiency (Valtonen et al., 2026) and that AI affects tasks more strongly than employment levels (Bonney et al., 2024).

The findings suggest that GenAI adoption shifts competence requirements toward prompt competence, digital literacy, domain expertise, and critical evaluation of AI outputs. This reflects research on emerging AI literacy and prompt engineering skills (Federiakin et al., 2024; Knoth et al., 2024), as well as findings that human-AI cooperation depends on users' ability to assess AI outputs appropriately (Vaccaro et al., 2024).

Selective access to GenAI reported by interviewees, particularly in managerial and information-intensive functions, suggests that adoption was not yet organization-wide in the participating organizations. This reinforces the need to develop AI literacy across managerial and non-IT groups rather than assuming uniform organizational readiness (Benlian & Pinski, 2025).

The emergence of AI-specific responsibilities, task forces, training activities, and usage rules indicates that adoption is beginning to produce organizational responses beyond individual experimentation. These examples show that GenAI creates not only productivity effects, but also new requirements for governance, training, and risk management, as emphasized in research on AI governance and organizational safeguards (Batool et al., 2025). The mandatory AI training reported by Expert #8 provides a practical example of such organizational measures and is relevant to the AI literacy requirements established under Article 4 of the EU Artificial Intelligence Act (European Parliament & Council of the European Union, 2024).

The contrast between concerns about job replacement and the absence of reported displacement suggests that GenAI is currently experienced primarily as work augmentation in the interviewed organizations. This distinction aligns with research on heterogeneous perceptions of AI-related employment risks (Barrera-Jimenez et al., 2025) and evidence that AI affects tasks more directly than employment levels (Bonney et al., 2024).

The findings on value measurement reveal a mismatch between the pace of GenAI experimentation and the maturity of evaluation practices. Although organizations are adopting or testing AI, formal KPIs and systematic post-implementation assessments remain underdeveloped. This observation reflects insights from a recent literature review on GenAI value creation in organizations, which points out that research has so far focused more on productivity outcomes than on quantifying financial returns (Sánchez, 2025). The variation between organizations relying on informal assessments and those requiring a business case before implementation further suggests that evaluation practices are not yet standardized and depend strongly on organizational maturity and governance. Recent studies also suggest that conventional evaluation methods often fall short for GenAI and recommend metric-driven frameworks to assess output quality and potential risks beyond simple usage tracking (Yu et al., 2025).

Although sustainability-related objectives are considered in research on AI-based logistics optimization (Chen et al., 2024), sustainability and circularity played only a minor role in the coded interview material (Figure 4). The present findings therefore do not support conclusions about realized environmental benefits from AI use.

A practical implication of these findings is that task-level efficiency measures may provide an accessible first step toward more systematic impact evaluation. Indeed, time savings could serve as a proxy KPI when more comprehensive impact measurement is absent. It can be operationalized by comparing the time (e.g., person-hours) required to perform the same task with and without AI support (Marquard et al., 2026; Virendrakumar et al., 2026).

6. Conclusions and implications

This study examined how GenAI is currently used in logistics-intensive organizations, how its use affects users and organizations, and how its operational added value is assessed. The findings indicate that GenAI adoption remains exploratory and selectively embedded.

Current applications primarily augment knowledge work and information-intensive tasks, whereas direct integration into core logistics processes remains limited. Reported near-term benefits therefore relate mainly to time savings, reduced manual effort, improved process preparation, and perceived improvements in scalability rather than end-to-end automation. However, whether these task-level benefits translate into measurable organizational or financial value generally remains unclear.

6.1. Theoretical contributions

The study contributes to the emerging literature on GenAI in logistics by empirically linking task-level use with effects on users, organizational structures, and value assessment. From a socio-technical perspective, the findings indicate that organizational value does not result from technology adoption alone, but depends on the interaction between task suitability, user competencies, human validation, organizational integration, and governance. The findings further distinguish between broad but relatively shallow adoption of general-purpose GenAI tools and deeper operational integration, which requires substantially greater organizational and technical capabilities. Finally, the study identifies a persistent gap between perceived benefits at the task level and their translation into systematic measures of organizational value.

6.2. Policy and managerial implications

For managers, the findings support a use-case-oriented approach to GenAI adoption. Organizations should initially prioritize clearly defined tasks for which expected benefits can be assessed and human review of AI-generated outputs remains feasible. Tool access should be accompanied by AI literacy, domain-specific competence, data-protection and compliance rules, and clear responsibilities for validating outputs. Organizations should also define basic performance indicators before wider implementation, for example task completion time, output quality, error or rework rates, and output volume.

Particularly for SMEs, resource-intensive in-house development should be preceded by a clear assessment of expected operational benefits. For policymakers and business-support institutions, the findings suggest prioritizing practical support for SMEs, including accessible AI literacy training, guidance on responsible AI use, and opportunities to evaluate applications before committing substantial resources. Chambers of commerce, industry associations, and applied research institutions could contribute by offering sector-specific training and simple evaluation frameworks that compare task completion time, output quality, and rework with and without GenAI support. Such measures could help organizations assess operational benefits without requiring complex measurement systems.

6.3. Limitations and suggestions for future research

The study is subject to several limitations. First, the empirical evidence is based on 11 expert interviews conducted in Austrian organizations and is therefore not intended to be statistically generalizable. Although common EU regulatory requirements provide a shared institutional context, the transferability of the findings to organizations in other European countries requires further empirical investigation.

Second, the sample includes seven large, three medium-sized, and one small organization across different industries and interviewee roles, providing breadth but limiting systematic comparisons between individual groups.

Third, the findings primarily reflect self-reported experiences and perceptions rather than independently measured process or performance data. Finally, the rapid development of GenAI technologies means that adoption patterns and available solutions may change quickly. Future research should therefore examine implemented use cases longitudinally, compare organizations across countries, sectors, company sizes, and levels of digital maturity, and complement interview evidence with direct task- and process-level measurements. Particular attention should be given to developing and validating indicators that connect time, quality, output, and process effects with sustained organizational and financial value.

CRediT authorship contribution statement:
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Biography:

Gerald Schneikart, MBA, MSc, PhD, is Project Leader and Senior Researcher at FHWien der WKW, where he works on applied research in digital transformation, artificial intelligence, circular economy, and logistics. He leads and contributes to externally funded R&D and innovation projects and teaches project and process management as well as digital assistance systems. He holds a PhD in Life Sciences from the University of Siena, an MBA in General Management from TU Wien, and an MSc in Molecular Biology from the University of Vienna. Before moving into applied business research, he gained research and industry experience at GSK Vaccines, Novartis Vaccines & Diagnostics, Sanofi-Aventis, and the Robert Koch Institute. His current research interests include generative AI and human-centered AI applications in logistics, digital transformation, circular supply chains, and technology-supported organizational processes. He is also a PMI-certified project management professional (PMP) and co-author of a textbook on hybrid project management.

DI Elka Xharo, BSc, is an Academic Expert and Lecturer in Information Technology at FHWien der WKW. Her professional background spans software development, business analysis, medical physics, and applied research, including positions at Agfa HealthCare, Accenture, and the Wiener Gesundheitsverbund. Since 2024, she has also served as an examiner in the "AI Manager" certification program of Austrian Standards. She holds a degree in Biomedical Engineering from TU Wien, specializing in Medical Physics and Imaging, as well as a BSc in Medical Informatics and postgraduate training in Medical Physics. Her expertise combines information technology, software development, biomedical engineering, and the practical application and assessment of digital and AI-based technologies. She is also certified as a Professional Scrum Master.

DI Dr. Clemens Löffler, is an Academic Expert and Lecturer at the Competence Center for Business Controlling and Accounting and a Senior Researcher at the Institute for Digital Transformation and Strategy at FHWien der WKW. Previously, he held academic positions at WU Vienna, the University of Vienna, and TU Wien and worked at the Austrian energy regulator E-Control. He completed his habilitation in Business Administration at the University of Vienna and holds a doctorate in Social and Economic Sciences and a degree in Industrial Engineering and Mechanical Engineering from TU Wien. His research focuses on decision structures in supply chains, organizational design and strategic procurement, decentralized corporate control, and performance measurement. His work has been published in journals including European Accounting Review, Management Accounting Research, and European Journal of Operational Research.

Mag. Maria Ludmilla Schallar, BSc is a Research Manager at FHWien der WKW, where she works at the intersection of research development, strategic positioning, and applied research. Her current work includes research on reusable load carriers and related logistics processes. Previously, she managed an international research project at BOKU University focusing on strengthening innovation in the bioeconomy through closer collaboration between SMEs and research and technology organisations. Before moving into research management, she gained several years of professional experience across industry and auditing, providing her with a strong understanding of corporate structures, business processes, and industry practice. She holds a Master's degree in Business Administration and a BSc in Landscape Planning and Landscape Architecture.

FH-Prof. DI Dr. Walter Mayrhofer, MBA, ME, is Head of Research and Head of the Institute for Digital Transformation and Strategy at FHWien der WKW, where he coordinates research activities, scientific cooperation, project acquisition, and teaching related to the digitalization of organizations. He has extensive experience in research and innovation management and previously held senior research and management positions at TU Wien, Fraunhofer Austria Research, Forschung Burgenland, and the research and innovation agency of the Province of Burgenland. He holds a doctorate in Technical Sciences and a degree in Electrical Engineering from TU Wien, an MBA from Danube University Krems, and a Master of Engineering from the University of Colorado Boulder. His professional and academic work combines digital transformation, organizational development, research and innovation management as well as the management of applied R&D and industry projects.

Генеративна вјештачка интелигенција у логистички интензивним организацијама: случајеви употребе, организациони утицај и изазов мјерења оперативне вриједности

Gerald Schneikart[1], Elka Xharo[2], Clemens Löffler[3], Maria Ludmilla Schallar[4], Walter Mayrhofer[5]

[1] FHWien der WKW / Институт за дигиталну трансформацију и стратегију, Währinger Gürtel 97, 1180 Беч, Аустрија
[2] FHWien der WKW / Департман за дигиталну економију
[3] FHWien der WKW / Центар компетенција за пословни контролинг и рачуноводство
[4] FHWien der WKW / Институт за дигиталну трансформацију и стратегију
[5] FHWien der WKW / Институт за дигиталну трансформацију и стратегију

Кључне ријечи:
усвајање вјештачке интелигенције;
утицај вјештачке интелигенције;
сарадња човјека и вјештачке интелигенције;
генеративна вјештачка интелигенција;
логистика

JEL класификација: M15; O33; M11

САЖЕТАК

Савремена рјешења генеративне вјештачке интелигенције (GenAI) побуђују велика очекивања, али њихов оперативни допринос у стварним логистичким окружењима остаје нејасан. Ово истраживање испитује на који начин GenAI подржава рад у предузећима са логистички интензивним пословањем. Такође испитује како ове организације процјењују додату вриједност случајева употребе GenAI. Од јануара до марта 2026. године спровели смо 11 полуструктурисаних интервјуа са доносиоцима одлука и стручњацима за вјештачку интелигенцију. Сви испитаници долазе из аустријских организација са развијеним логистичким пословањем. Транскрипти су ручно кодирани у софтверу ATLAS.ti 25.Испитаници GenAI често описују као алат когнитивне подршке при изради нацрта, сажимању, превођењу и претраживању информација. У тим активностима навели су уштеду времена, док је потпуна (end-to-end) аутоматизација процеса остала ограничена. Налази указују на то да је усвајање GenAI у логистици још увијек у раној фази. Организације обухваћене интервјуима углавном нису формално процјењивале оперативне или финансијске користи помоћу кључних показатеља учинка (KPI).Многа предузећа показују снажан интерес за истраживање нових случајева употребе. Ипак, недостају зрела, готова рјешења прилагођена процесима специфичним за логистику. Поједини испитаници из великих организација навели су да развијају прилагођена интерна AI рјешења. У укупно наведеним примјенама ипак су доминирали GenAI алати опште намјене. Може се закључити да се краткорочни допринос GenAI у логистици, у садашњој пракси, огледа у оснаживању људског рада у ручним процесима. Тај допринос није у потпуној аутоматизацији процеса нити у замјени радника.