A RESEARCH FRAMEWORK FOR THE EVALUATION OF OPERATIONAL IMPACTS OF AI SOLUTIONS IN LOGISTICS USE CASES

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Abstract:

The adoption of artificial intelligence (AI) in organizations is often fuelled by promises of improved efficiency and innovation, while its practical value and operational impact remain unclear. This paper presents a research framework for analysing the added value of generative AI (GenAI) in logistics organizations, with a focus on "difficult to automate" tasks and processes. It combines literature-based model development, semi-structured expert interviews, field studies, and user-cantered experiments to examine how GenAI affects task performance, user behaviour, and organizational structures. It integrates qualitative insights with experimental and modelling approaches to support a systematic assessment of value creation, efficiency gains, usability, user acceptance, and organizational impact. Preliminary results from expert interviews indicate that GenAI is primarily used for cognitive support enabling time savings in manual tasks, and less for process automatization. Eventually, the presented framework will provide a structured basis for the development of evidence-based roadmaps for user-centred AI adoption in logistics.

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1 Introduction

1.1 From generative AI hype to business value

The discussion about artificial intelligence (AI) and its impact on society as well as the economy was revitalized by the release of the generative AI (GenAI) tool ChatGPT. After two "AI winters" (a term coined by computer scientist Richard Gabriel [1], [2], which describes a phase of declining public interest in AI [3]), we are presently experiencing a phase of media omnipresence of the AI subject matter. The technological advances and envisaged opportunities for applications of currently "hyped" GenAI solutions are often deemed disruptive [4]. AI systems now can process and produce information in natural language, and at the same time the quality of AI-generated content (texts, images, videos, program codes, data) is comparable to that of human experts or even surpasses the quality of human-generated work product. In combination with the ability to learn from enormous amounts of data and to adapt to its users, the accessibility to AI technology constantly increases. The expectation of inherent economic potential leads to a constantly growing number of GenAI applications. Although there is often a lack in clarity with respect to AI's business models, it is expected that its application will require specialized AI competencies [5]. The continuous hype about AI has fueled interest in organizations from various industries to integrate suitable solutions into their operational processes [6]. However, often the fundamental problem with AI implementation is the lack of use cases with added value that can withstand a return on investment analysis, which has been dubbed "Return on AI" (RoAI) [7].

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1.2 AI as a component in socio-technical information systems

Decision-makers of digital initiatives are often encouraged to invest in AI initiatives due to exaggerated expectations, since the powerful capabilities of the latest AI solutions promise increased efficiency and effectivity over a wide area of work [8]. However, a key-question is how and which AI software solutions should actually be used in operations and how to measure the added value of AI usage [9], [10]. To answer such questions, one can follow a top-down strategy by starting from an aggregated organizational level [11], or a bottom-up approach by first addressing the user environment where the AI tool is in use [12], [13]. The latter is based on the hypothesis that an initiative to leverage AI potential will only develop successfully if those who are expected to work with the AI software actually use it. This human-centered principle is best illustrated by the model for "information technology-based information systems" by Piccoli and Pigni [14] (Figure 1).

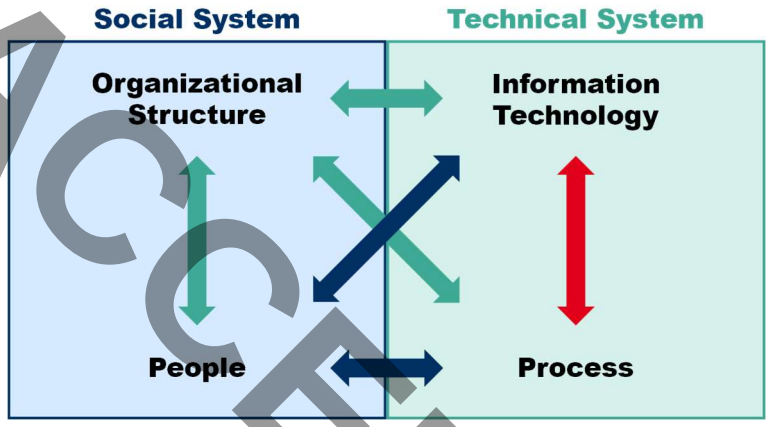


Figure 1. Model for IT-based socio-technical information systems adapted from Piccoli and Pigni [14]

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According to this model, the impact of AI as an information technology goes beyond the processes into which the technology is integrated. In the case of GenAI, the effects of AI technology on the individuals who will be working with it must be considered first. Additional value in operational processes, resulting from increased efficiency and effectiveness, only arises if employees accept and ultimately use the newly acquired AI tools. For example, if the AI output does not meet requirements or if the necessary competencies to operate the system are lacking, the investment in the AI initiative will be in vain. In other words, successful human-AI interaction is a prerequisite for releasing AI's added value for the organization [12], [15]. This raises fundamental questions about acceptance criteria that AI features must meet.

The research framework presented in this paper systematically addresses this question. As it was developed based on previous research in the context of a research project in AI applications for the logistics industries (SIBORC project; Simulation-based Optimization of Reusable Container Cycles) [16], the research framework can also be considered as an approach for evaluating the added value of generative (gen.) AI in logistics organizations. The underlying rationale should first define factors of user acceptance and user behavior followed by an evaluation of AI's effects on organizational processes. Accordingly, a series of four research questions (RQ1-4) were formulated in order to address the question about AI's added value based on user acceptance criteria:

- RQ1: How can GenAI be used to support processes and tasks in logistics that are difficult to automate?
- 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 does GenAI usage in logistics organizations result in added value?

1.3 State of research and related work

Recent research underpins a high interest in determining AI's impact on processes and organizational structure. For example, a recent study measured productivity gains of employees in a call centre by providing

GenAI assistance. The study found that workers in customer support, who were given access to GenAI assistance, improved work productivity by 15 % in terms of resolved customer issues per hour. It also suggested that less skilled workers could benefit the most from AI assistance, while workers with higher skill levels seemed to show less change in performance. The study partly explains these observations with AI expediting new hires to move along the experience curve because they would adhere more closely to AI recommendations, which seems decisive in profiting from AI assistance. In comparison, higher skilled workers were less likely to change their work routines, and tended to avoid utilizing AI, which might explain the lower efficiency gains [17]. In another study on measuring productivity, similar findings revealed "that high levels of AI tool usage and integration within organizational workflows significantly enhance productivity, particularly among younger employees" [18]. Together, these observations suggest significant improvement in productivity when GenAI assistance is accepted as a learning tool.

This, again, raises the fundamental question: Which factors drive user acceptance? There are several recent studies addressing this issue. Hernández-Tamurejo et al. found that trust in the AI solution, which is determined by "data management perceptions, transparency, and privacy risk", is a predictor of GenAI adoption in the organization [19]. Trust in AI might be enhanced by its design and by its perceived capabilities. For example, the ability for natural language processing and generation allows to adapt to the innate behaviour of their human users, which can elevate the "perceived humanness" and correlated variables, such as the "performance expectancy" [20], or is inversely correlated with the "perception of technology uncertainty and variation" [21]. Since these variables are integral in determining AI's perceived usefulness, consulting the previously published Technology Acceptance Model (TAM) might provide the context needed for estimations of AI impact or adoption [22]. Song et al. investigated the AI impact based on the previously published TAM [22], [23]. They determined top management support as a "significant" AI acceptance factor, while perceived usefulness would be the "core factor driving technology adoption", since AI increases decision-making efficiency and improves "overall performance […] by optimized resource allocation" [23]. In order to comprehensively evaluate AI impact, metrics are needed. The framework by Fragiadakis et al. could be applied on existing AI contexts or concepts to determine those factors most relevant, together with appropriate metrics for their evaluations [24].

While these empirical findings support certain hypotheses about factors driving adoption on the user level (i.e., increased perceived humanness elevates trust, which, in turn, results in higher adoption rates), there seems to be less research with regard to the question how to estimate the impact of AI on the organizational level, not to mention applying appropriate metrics to estimate financial impacts. As Stahl et al. put it, forecasting AI impact, be it on organizations or society, is difficult, since "many of the AI systems […] are still under development or found in a research setting. In such cases, even the intended outcomes may not be clear, which makes it difficult to determine which impacts to look for" [25].

Taken together, the latest research on the evaluation of AI impact suggests that, on one hand, factors determining the human-AI-collaboration must be taken into account in order to estimate effects on the operational level in terms of process efficiency and efficacy. On the other hand, an extension to the organizational level, which is needed for precise financial forecasts of AI initiatives, seems to be (to the best of our knowledge) a methodological gap. Jiang et al. suggested "to develop multi-disciplinary theories and integrate multi-level research methods to support the sustained development of the field" [26]. In agreement with this view, we present a user-based multi-method approach that is adaptable to different industries, in order to delineate models for estimations of AI impacts on the organizational level.

2 Development of the research framework

The development of the user-based research framework to evaluate the expected impact of AI initiatives on the organizational level followed an adaptive approach. While GenAI capabilities stimulate expectations about their economic potential, answers to the questions regarding the anticipated added value of specific AI applications to organizations are missing as are broadly applicable metrics. This gave the impetus to developing this research framework. It should be mentioned that the research framework builds on previous research in logistics [27]. While the goal of the research was to delineate an applicable AI impact model for logistics companies, the underlying concept for model development is adaptable to other types of industries.

Preceding to the development of the research framework interviews were conducted with small and medium-sized logistics companies that indicated that GenAI is primarily used for semi-automation of difficult-to-automate operational tasks and processes. For example, a grocery retailer cited the dynamic organization of

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delivery routes according to unexpected changes in the resource pool, such as changing driver availabilities, which usually requires a series of manual tasks to adapt to the new conditions (e.g., informing customers of changing delivery time, loading goods into different vehicles, changing routing according to the delivery addresses, etc.). In this context, some GenAI tools (e.g., ChatGPT and Claude) were referred to as "enablers" that expedited process adaptions without the necessity to consult external resources (unpublished). Specifically, GenAI serves as a user-friendly tool for coding and content creation (text or graphics) without the need of additional training. Benefits that were cited are lower entry barriers to process automation and shorter times for task completion [17] as well as employees performing broader spectrums of tasks [27].

Those initial insights resulted in several hypotheses about success factors of AI initiatives. Theoretically, the abovementioned efficiency gains have positive impacts on operational costs if the saved time can be used productively elsewhere. However, employees must be mentally ready to accept the increased dynamics of their workplace. While higher efficiencies due to reduced cognitive workloads might be motivating, there could be a reverse effect if the "reward" is an elevated workload. Such risks might require an organizational restructuring depending on the specific AI use case. This is defined by multiple factors, which basically cover the following areas of investigation:

- the task to be enhanced by AI,
- the features of the applied AI,
- the individual person working on the task, and
- the work environment.

Accordingly, the evaluation of the added value of GenAI is highly dependent on the context of its application, which requires a model that simplifies the dependencies of those factors. Hence, it was concluded that our research framework must define those factors and develop an AI-impact model using a stepwise approach for the different areas of investigation. The next section describes the details of the research framework.

3 Methodological components of the research framework

3.1 Semi-structured interviews

The first step is to identify promising GenAI use cases (RQ1) because it determines whether there is enough potential for added value to make an evaluation worthwhile. For example, if AI features suggest added value due to its assistance of cognitive tasks, it would be interesting to determine the added value to the organization. However, if the AI assistance is dependent on information currently unavailable in a digital format (e.g., due to potential violation of general data protection regulations), its potential for added value might be negligible.

In order to discover potential GenAI use cases, interviews with logistics experts on current trends in AI applications are intended as an initial work step according to the research framework. Those experts are expected to provide a highly practical perspective, which is needed to identify genuine AI use cases. The expert interviews are semi-structured following a sequence of fundamental questions:

- Which specific tasks do employees use GenAI for?
- Which specific GenAI tools do employees use?
- Which specific features of the GenAI tools in use do employees value?
- Is the use of GenAI within the organization or for specific use cases a strategic decision?
- How did the application of GenAI in different uses cases change the work environment?
- What is the expected added value of AI usage?
- How is the impact of GenAI use in processes and within the organization evaluated overall?

Using this list of questions provides a coherent structure for all interviews. The expected outcomes are manyfold, depending on the varied AI knowledge levels of the interviewees. In any case, a broad overview of current trends and challenges in AI applications, as well as practical implementation experiences, will create a pool of defined, valid AI use cases. This initial information about factors impacting potential added value

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would be worthwhile for deeper investigation. Once GenAI use cases are defined, AI's impact on work environments as well as on processes and organizational structures can be investigated.

3.2 User-centred field studies and experimental research

The starting point for research on AI's impact on work environments is RQ2 (What impact does the use of GenAI have on the user?), which directly addresses user acceptance and behaviour. This part of the research framework aims at defining key factors at the user level, which make users integrate AI into their work or, possibly, ignore or refuse to use it. Field studies are thought to provide most genuine insights on user behaviour since users work in real operational environments where they can carry out their daily routines without biases created by experimental set-ups. While the acquired data from field studies is valuable for the experimental study design, which are also intended to address RQ2, conducting on-site field studies can be hindered by company confidentiality and worker privacy. Furthermore, the widely known Hawthorne experiments show that the presence of observers might directly impact employee behaviour, which can result in biased user observations [28].

Moreover, for the purpose of a comprehensive investigation into user acceptance of AI systems, experimental studies are included in the research framework. For instance, usability experiments, such as tests based on the "wizard-of-oz principle", where volunteers are made to believe they are working with the fully functioning software or technology (in this case a mock-up AI solution) [29], [30], would provide insights on factors that influence user adoption in specific use cases. In addition, efficiency gains can be investigated with experimental set-ups based on the keystroke-level principle, which is designed to detect time differences when working with a technological (AI) solution [31]. Such experiments require a controlled study design, where different cohorts of volunteers are asked to accomplish specific tasks with or without AI, depending on the experimental purpose. In the "wizard-of-oz" set-up, participants would be either given information about the solution (e.g. a real AI or a mock-up) to be used or this information would be withheld. The expected results of such controlled studies provide insights on user-centric factors directly affecting organizational efficiencies and efficacies of AI adoption.

3.3 Case-based game theory modelling and process optimizations

The data generated by addressing RQ2 directly supports the research area of RQ3, i.e., the AI impact on the organization, and vice versa. Thus, the research framework considers parallel investigations with respect to RQ3, once sufficient insights are acquired from the semi-structured interviews (RQ1). The research framework considers different methodologies for RQ3. Game theory modelling allows for estimations on the interactions of factors identified by addressing RQ2 in different scenarios. For instance, it is applicable for the comparison of different AI investment strategies in terms of their financial impact on logistics organizations.

Since logistics is a process-based industry, the research framework also integrates student projects in process optimization. For example, the process management class of the Digital Business Bachelor's study course at the University of Applied Sciences for Management & Communication in Vienna enables students to develop concepts for digitally enhanced processes in partnership with industry companies. Since the partnering organizations need to directly collaborate with students, such a teaching setup supports the estimation of AI impacts with direct input from industry. Both methodologies, game theory modelling and student projects, are case-based approaches, thus comprehensive case studies also need to be part of the research framework.

3.4 Iterative integration of qualitative and quantitative research into an AI impact model

Together, the versatility of qualitative and quantitative data generated by the semi-structured interviews (RQ1), field-studies and user-centred experiments (RQ2) as well as case-based modelling and students' concept development (RQ3) will eventually be integrated into a model for impact estimation of AI initiatives in logistics organizations. In order to enhance the data, comprehensive literature research on GenAI use cases and pre-existing models are ideally validated in field tests. Since the insights acquired by the literature research and the model development are expected to be valuable for preceding steps of the research framework (RQ2 and 3), feedback loops permit the backflow of information, thus enabling an iterative-recursive approach and model development.

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The final AI impact model ideally allows for the estimation of financial return-on-AI-investments for specific logistics use cases (Figure 2). In addition, the model could be a basis for industry consulting, i.e. road-mapping of AI initiatives.

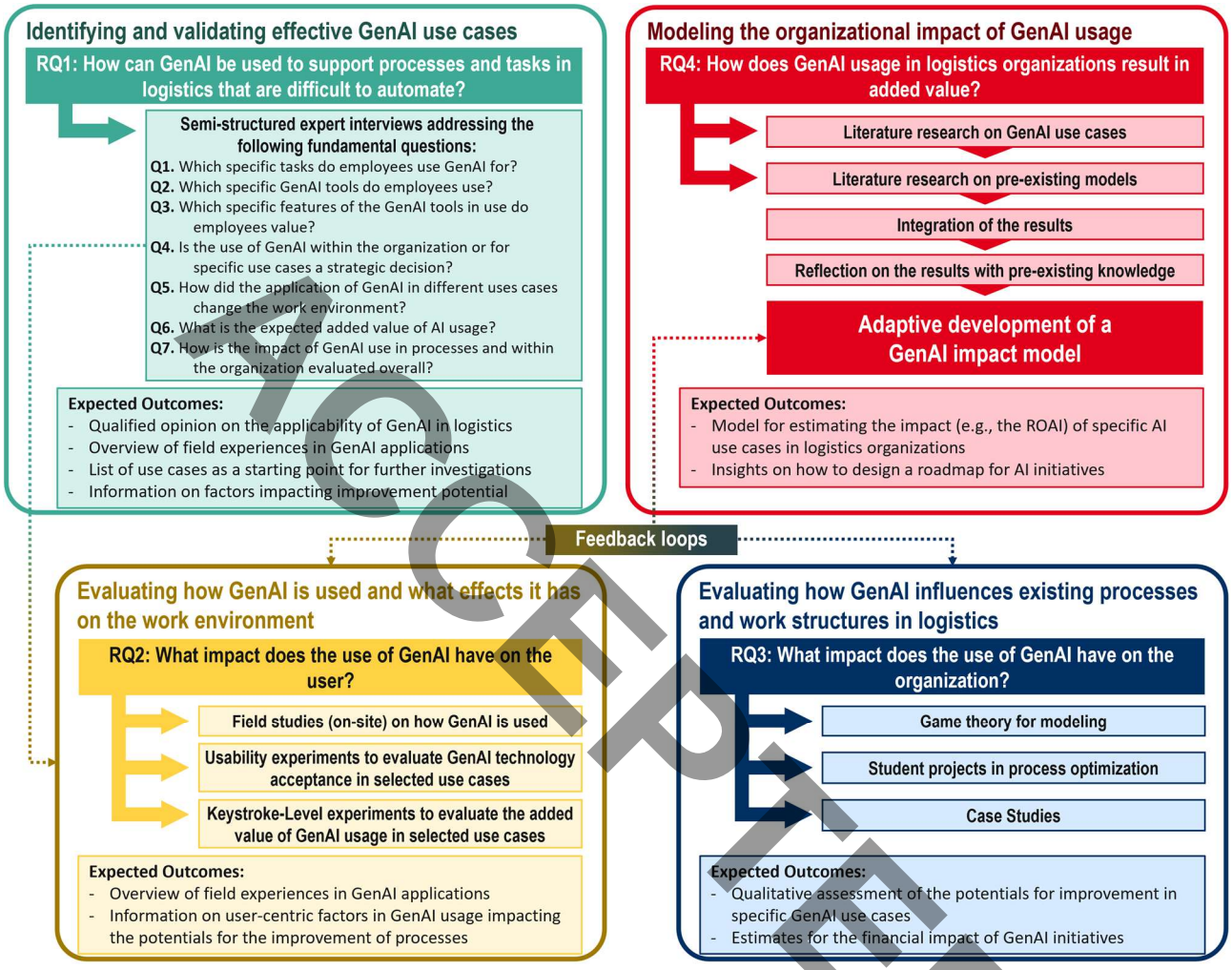


Figure 2. Research framework

4 Preliminary results and discussion

At the time of writing this paper, work to address RQ1 is in progress. We conducted 10 interviews with experts employed in the logistics industry with different roles and responsibilities from middle to top management. The current analyses of the interviews indicate diverging purposes for AI usage. While GenAI tools (mostly ChatGPT, Co-pilot, Claude) primarily serve as “sparring partners” to expedite ideation in all interviewed organizations, responses concerning other AI implementation levels vary. As expected, GenAI users valued that cognitive tasks could be accelerated by consulting AI assistance. The tasks that are performed using AI assistance ranged from decision making to more repetitive work, for example, text generation to give written instructions to workers. Interestingly, a correlation between company size and AI implementation level appears to be lacking. Some larger companies (more than 100 workers) mentioned a high level of automation and digitalization with AI in general, suggesting a broader understanding of AI’s definition and its potential with respect to automation. Others implied to be at the starting point by mentioning initiatives or novel roles to evaluate or teach specifically GenAI usage. Some respondents even suggested that they recognized the trend of GenAI but did not seem to be ready for large-scale rollout initiatives. Interestingly, some smaller companies appeared to be more tech-savvy, as GenAI assistance in ideation and process optimization were mentioned. In consequence, time-savings allow for the reassignment of workers to other tasks. Since working on other tasks

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might require additional training, GenAI was cited to be of value in that respect and the role of GenAI for training assistance was also reported by another larger company interviewed.

The research framework presented in this paper aims at filling the methodological gap between the analysis of AI technology acceptance on the user level and AI technology assessment on the organizational level. The presented research framework considers technology acceptance as the essential starting point for drawing valid assumptions on AI's impact on the organization, measured most and foremost in financial terms. Hence, research questions specifically address problems concerning the user, processes and organizational structure in a sequential order, starting with the user and providing individual methodologies for each item. The goal of the framework is to acquire sufficient knowledge to identify the factors and their relationships that determine AI's impact on the organizational level in order to support financial forecasting of AI initiatives.

Since novel insights will be acquired along the way, the model uses an iterative-recursive strategy. Once pieces of information are put together to build a model, feedback loops are part of the framework, and as such readdressing preceding RQs and readjusting the model will be done until the final AI impact model is complete.

Obviously, different organizations and industries will likely draw different values from AI implementations. Depending on the AI impact, the research framework needs to focus on specific use cases. While logistics served as the "paradigm industry" in this paper, the presented research framework can be adapted to determine AI impact in any industry or individual organization.

As is the case with any model or concept, the presented research framework has its limitations. The framework is still at a conceptual developmental stage and still needs validation. As shown under Section **Error! Reference source not found.** of the preliminary results, we are currently in the stage of addressing RQ1 by analyzing the transcripts recorded during the expert interviews. Furthermore, the final model to be developed for GenAI usage in logistics settings will also need validation in order to demonstrate its applicability.

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5 Conclusion

This paper presents a user-centred, multi-method research framework for evaluating the operational impact of GenAI in logistics use cases that are difficult to automate. By linking user acceptance, task characteristics, process integration, and organizational effects, the framework supports more reliable estimates of GenAI's added value and return on AI initiatives. Preliminary interviews suggest that GenAI currently creates value mainly through cognitive support, time savings, and assistance in semi-automating manual tasks rather than through full process automation. Further empirical validation is required to refine the framework into a practical impact model and roadmap for user-centred GenAI adoption in logistics.

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