From Human Experts to AI Agents: Agentic AI for Knowledge-Intense Problem-Solving in Logistics?

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Abstract: Logistics planning is a complex and complicated problem solving process requiring a wide range of knowledge and competence. A planning person or team represents a particular set of knowledge, skills, experience and personal attitudes. His, her or their level of competence decides about success or failure of the planning and about the quality of its results. With this, logistics planning is knowledge-based and knowledge-creating. Because of this, Knowledge Management can provide tremendous support to the planning person. Even though, there is a wide variety of (software) tools applicable to solve specific sub-problems throughout the planning process, human expertise is the key to develop creative planning solutions so far. Latest developments with regard to Artificial Intelligence (AI) might change this picture. AI is one of the most promising technological advancements, but also one of the most ambivalently discussed topics these days. It has surpassed humans at a number of tasks already and continues in doing so at new tasks in an increasing rate. Because of this, AI is capable to assist humans in many different ways. The latest boost of development moved AI application from those sophisticated communicators or task-oriented AI to intelligent agents or agentic AI allowing for autonomous, goal-driven decision-making. Hybrid approaches combine those advanced AI capabilities with human oversight, offering context-aware adaptability without full autonomy. In this way, artificial intelligence and human intelligence join forces in teams, for example, to solve complex problems creatively. Against this background, the paper analyses agentic AI with regard to its potential to support creative problem solving in a knowledge-intense field like logistics planning. Will AI agents become co-workers in logistics planning teams or can agentic AI design logistics solutions autonomously? With this, the paper focusses on chances and challenges coming with the highly dynamic evolution of AI within a complex, knowledge-intense application area where human experience, problem-solving capability and creativity is decisive. It contributes to discussions about necessary adjustments in how organizations manage their knowledge considering artificial and human intelligence.

Keywords: AI agents, Agentic AI, Problem-solving, Logistics planning, Knowledge management, Knowledge sharing

1. Introduction

Knowledge Management has been on the agenda of logistic companies since the mid-1990s, but has not realized its full potential in organizational practice yet. Even worse, it lost a lot of its credibility in logistics practice because of the wrong focus. However, knowledge is a strategic resource in logistics, too (Tomé and Neumann, 2014):

- *Whether or not a supply chain operates successfully* does not only depend on the intensity and quality of material and information flows in a supplier-customer relation. As generally recognized, the kind and quality of the collaboration between human resources involved on both sides of the partnership heavily affects the success of a supply chain as well. Knowledge, understanding, and trust form the basis of this collaboration.
- *The number and variety of methods and software tools* available to support logistics planning is permanently increasing. Unfortunately, those tools quite often dominate the planning person and prevent him/her from creative problem solving instead of purposefully giving personalized support.
- *Team building to master complex problems* in logistics planning and operation can be successful only if the team consists of the right mix of knowledge, experience and competence stakeholders, that is adequate to the problem to be solved. Within those well-balanced teams, combined individual strengths overcome a range of individual weaknesses in order to perform jointly better at a higher level.

Consequently, knowledge management can tremendously contribute to improving logistics planning and performance, i.e. problem solving in the logistics context (Neumann, 2003). Throughout the entire problem-solving process as well as in each problem-solving step in the planning, there are bidirectional links between activities for problem solving and knowledge management (see Figure 1). On one hand knowledge available with persons, inside organizations and in the form of technology is (re-)used to solve a particular problem. On the other hand, knowledge about the problem's final solution and the chosen mode of action for its generation characterizes the increased scientific basis and additional experience of the planning person, team or organization. Usually, these links mainly depend on the persons involved in the planning process. It is quite common to make use of own experience, but to benefit from knowledge, experience and lessons learned of other parts of the organization that is not the usual procedure. To overcome this and to make knowledge of a successful or even unsuccessful planning process available to future planning tasks that is the challenge for knowledge management and its integration into personalized problem solving.

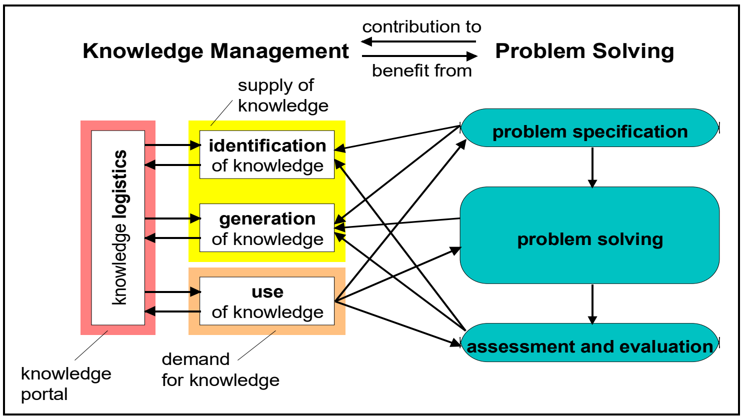

Figure 1: Knowledge management and problem solving in logistics planning

Traditionally, employers gave their planning juniors about three to five years for learning and growing before they became responsible for a planning project. Nowadays and because of increased economic pressure and competition at the market, companies are neither able nor willing to invest this amount of time anymore (Neumann and Masurat, 2016). Instead, they seek for directly recruiting employees with sufficient expertise in project-based professions who are able to take responsibility in complex engineering, design and planning projects more or less immediately. However, this becomes more and more difficult as the number of well-experienced planning experts available at the labour market shrinks. In the end, companies might lose many of their experiences and with this eventually even a part of their competitive advantage due to an ongoing exodus of long-time employees (e.g. because they retire) who cannot hand down their knowledge, networks and skills to any successor. Here, user-friendly designed tools can help to manage, distribute and provide access to knowledge on one hand and to solve problems on the other hand. They take over routine jobs and deal with those problems the planning person had converted into algorithmic tasks beforehand. In addition to this, intelligent systems can work with sub-problems if they had respective knowledge and suitably distributed processes based on a sophisticated human-computer dialogue. The advent of Artificial Intelligence (AI) with generative Artificial Intelligence (genAI) being the preliminary peak leads to even higher expectations towards computer-based planning support using intelligent agents. Following a hybrid approach artificial and human intelligence might join forces in teams to solve complex planning problems creatively.

Against this background, the paper analyses AI agents and agentic AI with regard to their potential to support creative problem solving in a knowledge-intense field like logistics planning. Will AI agents become co-workers in logistics planning teams or can agentic AI design logistics solutions autonomously? When answering this question, the future role of knowledge and experience management in such environment is in focus. The following sections will introduce into agentic AI and its potential in general (Section 2) and analyse problem solving in logistics planning with regard to challenges concerning experience-based knowledge management (Section 3). Findings from both sections are brought together in order to discuss the potential role of AI agents in logistics planning identifying current state-of-development and needs for further action (Section 4). Section 5 summarizes discussions and draws conclusions on both, the use of agentic AI for knowledge-intense problem solving in logistics and the future role of human experts in logistics planning.

2. Agentic Artificial Intelligence

Artificial Intelligence (AI) is one of the most promising technological advancements, but also one of the most ambivalently discussed topics these days. The latter starts with its definition already, as there are two different perspective, a psychological and a computational one. Gignac and Szodorai (2024) elaborated operational definitions of both artificial intelligence and human intelligence (HI). They differentiate artificial from human intelligence just by referencing to an artificial system and computational algorithm instead of a person and his/her perceptual-cognitive processes for completing a novel standardized task. The latter is a task (or test) with limited chances for preparation, as it neither was introduced before nor awareness was risen that this type of questions should be solved. Those kind of standardized tasks are used to evaluate intelligent capabilities, such as vision and language, of systems and humans. This is particularly effective for discrete tasks, e.g. image classification or answering multiple-choice questions. To benchmark AI its performance is put in competition to HI performance when dealing with the same tasks. The AI index report 2025 (Maslej et al., 2025) uses different benchmarks to monitor technical progress of AI systems over time. Results show that AI systems continuously improve exceeding human performance at many previously challenging tasks already (see Figure 2). However, authors also point on limitations of those benchmarks in areas of AI with, for example, human-AI interaction as variability in human behaviours and the sheer diversity of correct answers provide additional challenges in performance measurement. This need for benchmarks beyond the traditional ones, which were designed to measure human performance, to ensure reliable AI evaluation is another indicator of the rapid progress of AI systems.

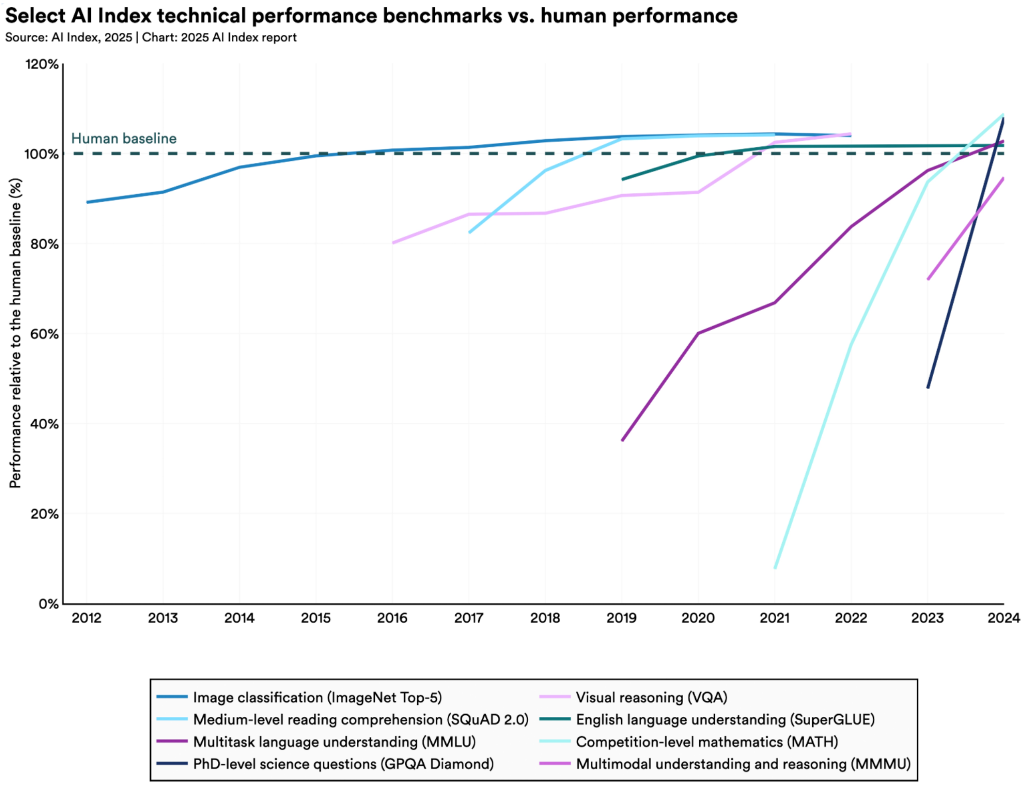

Figure 2: State of AI performance (Maslej et al., 2025, p. 94)

In recent years, *generative AI (genAI)* and open access AI tools like ChatGPT, Gemini, DeepSeek, or CoPilot provided a more common user interface moving the use of AI from an expert's competence to an almost everyday tool. Schneider (2025) characterizes genAI as an AI system based on a foundation model that generates and transforms content based on specific user interactions. In other words, genAI can generate new data similar to the training data it has seen. Generative models learn the underlying probability distribution of the (enormous amount of) training data and can then generate new samples from this learned distribution (Baum, 2024). *Large Language Models (LLMs)* are specific applications of genAI designed to understand human language and to generate intelligent, creative responses similar to human-produced content when queried. Because of the ability of processing natural language, AI is capable already to assist humans in many different ways:

- AI-powered *translation systems* use artificial neural networks to translate texts in various languages at high quality of language.
- GenAI tools create *new content* as text, image or video usually in response to human prompts.
- AI chatbots simulate *human-like conversation* through text or speech interfaces to help in customer service, manage appointments, or support travellers in booking trips.

Those chatbots are *AI agents*, i.e. autonomous single-entity systems enhancing LLMs by perceiving their environment, making decisions, and taking actions to achieve specific goals. They can be seen as *virtual assistants* that can interact with users, systems, or the real world in a task-oriented way (with regard to specific tasks) or in a general-purpose way (capable to deal with a wide range of tasks). The integration of LLMs with retrieval mechanisms enhances their response generation to answer precise questions from large databases or address customer queries using information from different company documents. This *Retrieval Augmented Generation (RAG)* is another increasingly common capability of AI combining the strengths of information retrieval and genAI (Maslej et al., 2025): The model first retrieves relevant information from databases, files or documents and then combines them to generate a response tailored to the user's query based on retrieved content. Because of using those (relevant) external sources instead of training data purely, responses are more accurate and up-to-date. The latest boost of development moved AI application from those sophisticated communicators or task-oriented AI to agentic AI allowing for autonomous, goal-driven decision-making. With this, AI evolved from prompt-driven content generation (genAI) via tool-based task execution (AI agents) towards orchestration of full-fledged workflows (agentic AI). *Agentic AI* represents a significant advancement over traditional AI agents by incorporating features such as self-learning, real-time adaptability, and multi-agent collaboration (Hosseini and Seilani, 2025). This constitutes a paradigm shift in AI enabling to act independently, pursue broad objectives rather than isolated decisions, and carry out complex tasks that require reasoning elements such as planning and reflection (Sapkota et al., 2025; Schneider, 2025).

An AI system's capability of planning is of particular interest within the context of this paper. Maslej et al. (2025) describe planning as an intelligent task that involves reasoning, i.e. the ability to draw logically valid conclusions from different forms of information, about actions that alter the world. It requires considering hypothetical future states, including potential external actions and other transformative events. Here, human experts still outperform frontier AI models (LLMs) in solving planning problems when given enough time (Maslej et al., 2025): The best AI systems achieve scores four times higher than human experts do in short time horizon settings, e.g. with a two-hour budget. If given an eight-hour budget, human performance slightly exceeds AI already. It achieves a factor of two with a 32-hour budget. To generalize, in certain situations AI agents already demonstrate planning expertise comparable to humans, but they can deliver results significantly faster and at a lower cost. On the other hand, human expertise is still of value from an economic perspective, too, if problems show a certain level of complexity requiring creative approaches to find high-quality solutions.

As in various other disciplines, the potential from applying latest AI advancements is subject to scientific research and practical case studies in logistics and supply chain management, too. Potential application areas are manifold including market research or trend analysis, automating tasks in human resource or customer relationship management, and accelerating basic coding by use of genAI (IBM, 2023). Global sharing of AI-generated intelligence across ecosystems and industries might be of particular relevance for value creation from genAI application. At the same time, increased risks associated with data privacy, data provenance, and data integration must remain in focus; policies and controls must protect the individual and the integrity of the operation.

3. Problem-Solving Processes in Logistics Planning

Logistics planning aims at the planning of logistics processes and systems in general and at both levels the strategic one and the operational one. For this, different procedures are underlying and different methods are used. Planning of logistics processes and systems is a complex and complicated, usually ill-structured problem, since it is subject to a large number of many and diverse influences (Neumann, 2003). This is true not only to the problems to be solved but also to the planning processes for solving those problems. To act purposefully and expediently in this dynamic scenario, specific planning competencies are required. To date, the planning person was and is key problem solver, knowledge holder and knowledge user in the planning process. Hence, his or her level of competence decides about planning success or failure and about the quality of its result. Well-developed planning competencies do not only include the need for detailed declarative knowledge about logistics planning and procedural knowledge about how to do planning in logistics, but also distinctive problem solving competencies and social skills for team working and communication. The planning (i.e. problem-solving) person needs to be able to learn, to be curious and interested in gaining new experience and acquiring additional knowledge. Competence levels reached in this process might range from novice to expert, from amateurs to professionals. The main difference between them is their knowledge and skills base leading to more or less effective and efficient problem-solving strategies (Neumann et al., 2016). Developing a person's problem-solving competence is a longer-lasting process requiring the use of appropriate methods and means, like purposefully using appropriate planning tools, building well-balanced planning teams, or initiating and supporting learning processes in learning-about-planning or learning-by-planning scenarios.

With regard to planning support, there is a permanently increasing number and variety of *methods and tools*. They range from simple deterministic methods for calculation to complex and complicated tools like CAD, simulation or virtual realities providing the planning person with an enormous functionality to take over routine jobs and – in a certain amount – also to participate in the creative phases of problem solving. Apart from the challenge to choose the appropriate tool for a particular task, the planner often faces the problem to cope with the tools' increasing complexity. This often leads to a kind of "trust in God" when being confronted with the solution produced by the tool: Since knowledge and methods embedded in these tools are often hidden the critical distance to what the tool is doing and what is resulting from this is getting lost. Because of this, experience from using tools are mainly moved into more perfect operational skills, but only seldom contribute to a lasting improvement of generalized planning knowledge. In the end, those tools cannot really be creative; they are of most benefit when being purposefully used by a knowledgeable planning person.

Well-balanced planning teams combine a range of individual strengths to overcome a range of individual weaknesses for better performing at a higher level. As pointed out by Rump (2000) teamwork might be advantageous especially in those situations requiring the effective collection and use of knowledge out of many minds. As many experience show, teams need to form the right mix of capabilities according to the individual planning competencies from the subject matter, social and methodical points of view. They need to unite different personalities, such as doers (the dynamic type who just gets on with things),

- realisers (who aim at putting things into effects),
- presenters (who market and sell ideas, concepts, solutions),
- finishers (who go over work and complete it) or
- combiners (who link persons, opinions, knowledge, ideas etc. from different sources),

representing the appropriate set of knowledge, skills, information, and authority to solve difficult problems quickly and easily. Here, the individual level of knowledge and experience in planning represents just one aspect; another one can be defined as ability to recognise, structure and solve problems as well as assess, evaluate and even implement a problem's solution (see Figure 3). Every new situation requires new team building, because the same team that worked very well in the previous context does not necessarily need to work well again in a future context. The challenge is to identify personalities and individual strengths and weaknesses for an appropriate team building.

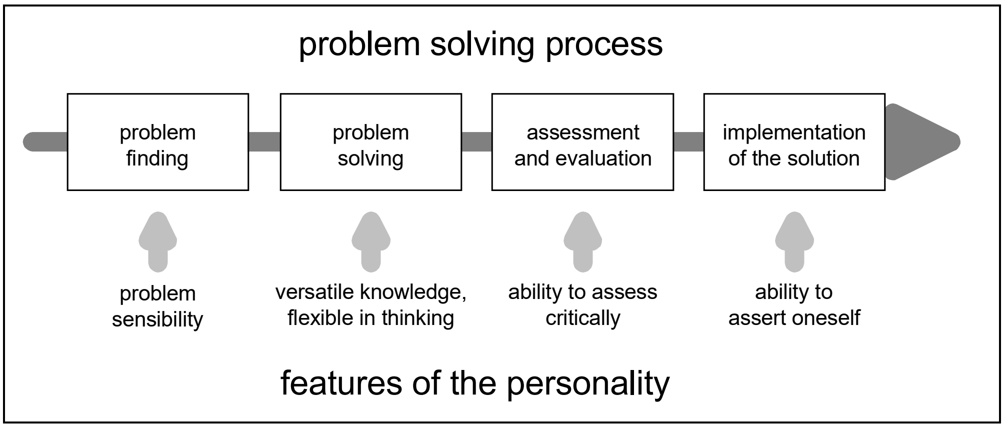

Figure 3: Problem-solving steps and problem-solving personality

4. Agentic AI in Logistics Planning

To integrate AI support into logistics planning it must build upon knowledge-management-based approaches. Against this background, a framework to support logistics planning in a customized, sophisticated way must enable the effective, efficient and purposeful use of the right method in the right problem-solving step. Furthermore, it should provide the respective knowledge specifically required in a particular step within a social environment encouraging creativity. To offer this kind of functionality the framework must contain planning methodical, knowledge-based and software technological components (see Figure 4).

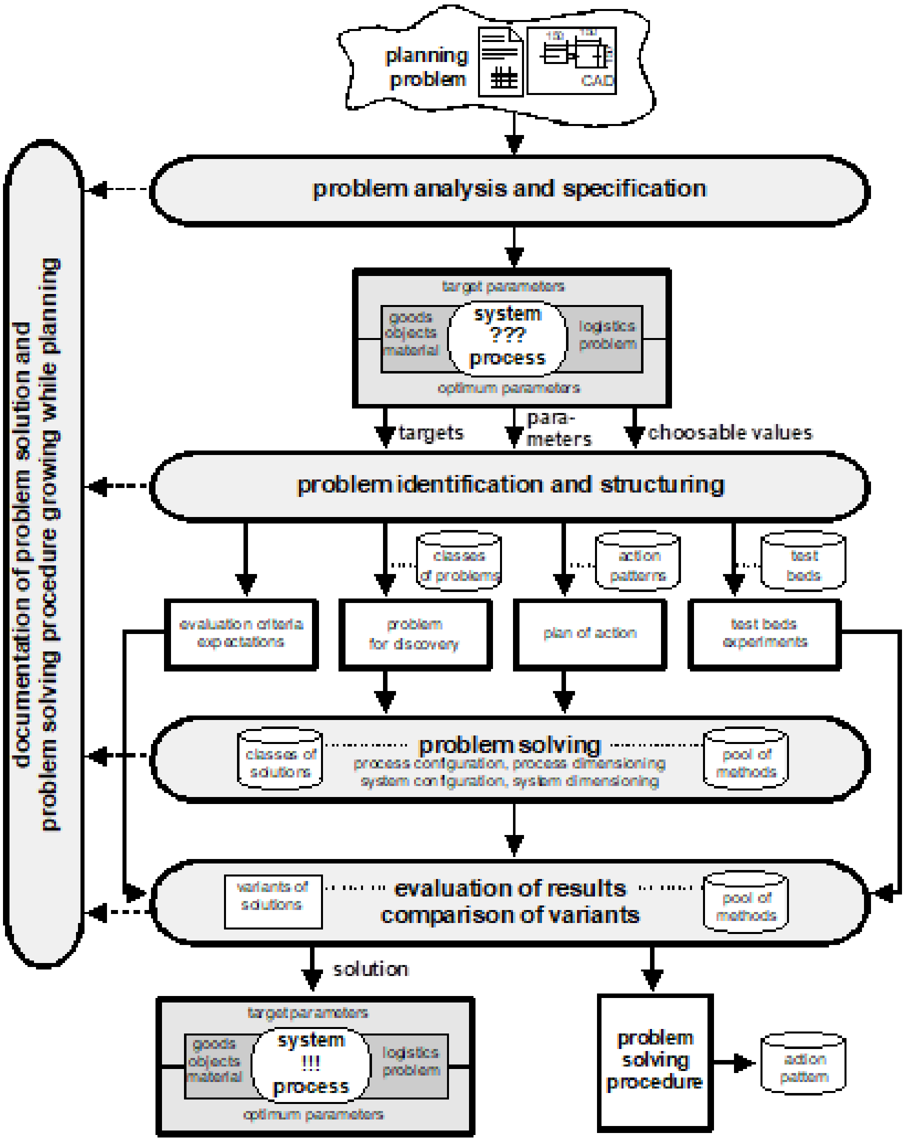

Figure 4: Framework to provide knowledge-based support in logistics planning

Among them, knowledge elements representing logistics as well as planning knowledge are of special importance:

- A *catalogue of principal planning problems and system performance* requirements supports the analysis, specification and classification of the planning problem.
- A *pool of planning solutions* providing classes of alternative variants of logistics systems and processes of varying level of detail and complexity enables the framework to suggest possible, suitable, appropriate solutions taking parameters and conditions into consideration as defined by the planner.
- By use of a *pool of problem solving procedures* of varying level of detail and complexity the framework can recommend tried and tested problem solving strategies of high effectiveness or suitable, applicable planning methods and tools for solving a particular problem situation.
- *Target and optimum parameters and a pool of testbeds* for model-based functional tests enable to evaluate selected, newly developed or modified solutions according to suitability, appropriateness and performance measures.

These knowledge elements result from theoretical and research findings as well as from prior planning experience. They are completed by a set of rules for grouping and classifying planning problems, selecting favourite solutions (i.e. relating problems and solutions) and suggesting modes of action (i.e. relating problems and problem solving procedures). To define these rules major research and development work needs to be undertaken, since they can hardly be derived from experience and generalization due to missing standards for describing problems and solutions as well as a lack of general problem solving procedures and test beds.

Obviously, identifying existent knowledge, explicating and integrating it into a knowledge base that allows easy access to the right (portion of) knowledge in the right way matching requirements of the current problem or sub-problem to be solved or task to be accomplished, that is the challenge in implementing a knowledge-based approach. Brandt et al. (2001) present of a case-based approach to gain experience-based knowledge on project management in the field of software engineering and make it available for re-use in future projects. For this, all kinds of experiences, e.g. templates of documents, guidelines, observations, problems and their solutions, proposals for improvements and lessons learned, are gathered from interviews with project team members and stored in a central repository, the experience base. As this causes many extra efforts not always seen as beneficial within a planning project with hard time constraints, agentic AI might find a promising application area, here.

Disselkamp et al. (2024) investigated this with regard to factory planning. Similar to logistics planning existing factory planning methods often involve labour-intensive and time-consuming processes that require significant human expertise and manual input at every stage. Because of tis, challenges are comparable. GenAI-supported factory planning is expected to show potential in:

- *streamlining planning processes* by providing integrated and cohesive planning tools that enhance collaboration and ensure that all relevant factors are considered simultaneously;
- *providing dynamic and real-time scenario analysis* allowing planning persons to quickly adjust layouts and workflows to meet evolving needs;
- *being able to explore a vast number of design permutations* and identify optimal configurations that maximize space utilization, minimize material handling costs, and improve overall production efficiency;
- *providing advanced decision-support* by processing and analysing complex data sets, providing actionable insights, and recommending data-driven decisions.

From exploring ChatGPT in various use cases alongside the entire factory planning process, authors conclude on genAI being particularly beneficial for retrieving and providing initial information or suggesting, comparing and recommending workplace locations. In contrast to this, trials to generate ideal (technical) layouts were not successful. With regard to logistics and supply chain management, an IBM Think Circle (IBM 2025) identified a number of use cases despite implementation challenges:

- *Document retrieval and analysis*: Intelligent agents search unstructured data in documents such as product documents, sales documents, contracts and identify what is the best document to choose.
- *Complex data querying*: Code models are used to create SQL queries.
- *Proactive outlier detection*: Intelligent agents look at sets of data, scan them, run and find outliers overnight. They send back results as a morning briefing.

These examples and first use cases underline the potential proper AI integration might have. In logistics planning, AI might enrich the knowledge-based framework assisting the planning expert at different stages.

Bots are the simplest form of AI assistance. These automated systems are typically rule-based and designed to carry out predefined tasks without human intervention. Bots can manage repetitive tasks, answer basic questions, and execute straightforward functions. They follow scripts and rely on if-then-else logic, meaning their responses are limited to the scenarios they have been programmed to handle (Alosious, 2024). Repetitive tasks in logistics planning might be related to calculations, but also to completeness or plausibility checks concerning required input data and information. In terms of chatbots they might guide a planning person through the first stage of the problem solving process which is problem specification. The bot asks questions according to a checklist and formalizes natural language responses by the planning person. In the other way round, chatbots integrated into a planning software tool might provide an intelligent help system. Here, the user can ask the help system for support concerning a specific functionality of the software or a proposal for how to master a certain challenge.

Co-pilots represent a collaborative approach between AI and humans. Acting as assistants, they provide real-time, contextually aware support, allowing users to complete complex tasks more efficiently. Co-pilots excel in roles requiring decision support and act as an “extra set of hands” that brings data-driven insights and recommendations directly into workflows. This way, they enhance human judgment enabling more nuanced and strategic decision-making (Alosious, 2024). In logistics planning, there is a permanent need for making decisions on next steps and candidate solutions within a phased process of loops aiming to develop variants and versions concerning both the logistics process and the logistics system. There are analysing steps and creative, evaluating steps for synthesis by turns with partially changing cognitive problems and views. Here, logistics planning co-pilots might help in evaluating variants and versions comparatively enabling the planning person to consider more candidate solutions in the same amount of time. For this, the co-pilot can search in and combine scattered documents related to previous projects (i.e. experiences), current problem descriptions, or customer requirements concerning the solution.

Agentic AI enables autonomous decision-making, automates processes, and enhances efficiency though transition from assisted (co-pilot") to autonomous (autopilot) models (Hosseini and Seilani, 2025). Agentic AI systems composed of multiple, specialized agents that coordinate, communicate, and dynamically allocate sub-tasks within a broader workflow to achieve a common goal are comparable to human experts working in teams. Those Agents, i.e. more advanced AI applications with a degree of autonomy and cognitive capability beyond that of a bot, can interpret data, learn from interactions, and make independent decisions within set parameters. They are crucial for tasks that require context-awareness, data analysis, and ongoing adaptability (Alosious, 2024). In logistics planning, agents might coordinate bots fulfilling tasks proposed above, but also work autonomously to identify and structure problems, find suitable process or system configurations from purposefully matching operational steps or materials handling technology, or optimize candidate solutions based on results from model-based simulations to test their functionality and performance. The open question here is how much of the overall planning process can or should be subject to such kind of automation in order not to lose curiosity, care, collaboration, and critical thinking – the crucial elements humans still can (and should) bring in despite of AI implementation. Implementing a hybrid approach with human experts and intelligent agents collaborating in a team enriches the challenge of building well-balanced planning teams by an additional facet.

5. Conclusions

Supply chain technologies proceeded from automation and AI assistants to autonomous AI agents or agentic platforms (IBM 2025): Process automation implies that human intelligence programs a very well-defined logic of actions that happen consequently, one to another. In contrast to this, human intelligence provides an agent with capabilities, but the intelligent agent decides how to fulfil a request and take advantage of these capabilities. Unlike assistants that support human decision-making, intelligent agents can handle complex, multi-step processes autonomously. Logistics planning is such a complex and complicated process requiring a wide range of competencies with all players involved: the individual planning expert, the planning team, the planning organization, and even the organization the planning solution will be implemented in. As discussed in this paper, AI application will not be suitable, purposeful, and valuable everywhere. Because of this, next steps need to focus on identifying and evaluating promising use cases to deploy the transformative potential of these technologies from a human-centred approach, i.e. thoughtful implementation preserving human capabilities and judgement while using technology to address increasingly complex and volatile business environments. Hosseini and Seilani (2025) see agentic AI as basis for shaping a Smart Future. A *Smart Future* refers to an era where AI-driven automation, intelligence augmentation, and autonomous decision-making systems contribute to optimized operations in various industries. By leveraging agentic AI, businesses and governments can enhance efficiency, reduce operational costs, and improve service delivery. However, this transition also raises significant concerns regarding ethical AI deployment, data security, and workforce displacement. Understanding these challenges is crucial for ensuring responsible AI adoption in logistics planning, too. Even though human intelligence still is and continues to be the key problem solver, knowledge holder and knowledge user in logistics planning, particular training is required for planning experts to understand AI and its proper (and improper) use.

Ethics declaration: For this research, ethical clearance is not required.

AI declaration: This paper was created without any use of AI tools.

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