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Original Article

Use of Artificial Intelligence in Logistics: Potentials and Limitations in Shopping Basket Analysis and Shipping Optimisation

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ABSTRACT

The increasing integration of artificial intelligence (AI) into logistics processes is changing conventional decision-making structures. In e-commerce logistics in particular, the question arises as to whether algorithmic systems lead to efficiency gains without undermining transparency and responsibility. The study combines a theoretical-conceptual analysis with a case study of the company Zalando. Existing literature is systematically evaluated in order to examine technical, organisational and ethical aspects of AI use in shopping basket analysis and shipping optimisation. AI systems can make shipping logistics more precise, faster and more individualised. At the same time, new risks arise such as algorithmic intransparency, biased decisions and data-based dependencies. Without stable data infrastructures and human control, many advantages remain hypothetical. For AI to be used responsibly in logistics, comprehensible rules, ethical guidelines and robust data structures are required. The study shows that progress depends not only on technological performance, but also on a conscious approach to responsibility.

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INTRODUCTION

Logistics has been undergoing an accelerated transformation for several years (BVL, 2023). What we used to call planning is now a flow of data that constantly moves through digital infrastructures. Decisions are no longer based solely on intuition or experience, but on calculation, probability and pattern recognition (Min, 2010; Hofmann & Rüsch, 2017). Logistics, once an expression of human organisation, is becoming a resonance chamber for automated systems whose interventions are often invisible but effective.

Artificial intelligence is not just a tool. It is both a mirror and driver of an economic logic that strives for speed, efficiency and predictability (Zuboff, 2019). What is happening is more than just technical optimisation. It is a new form of judgement, outsourced to machines, fed by the past but directed towards the future. The question of who makes decisions is no longer as clear as it used to be. In many areas, responsibility is now handed over to systems that calculate rather than explain. What used to be negotiated in discussions is now often made in the background by algorithms that search for patterns, compare probabilities and set priorities (Danaher, 2016).

This is particularly noticeable where large amounts of data are generated. This applies, for example, to the evaluation of shopping baskets or the management of shipping logistics. Companies hope that this will not only lead to savings, but also more accurate forecasts and more targeted offers (Wang et al., 2016). At the same time, there are growing hopes of using resources more sparingly and better balancing processes from an ecological perspective (Klumpp, 2018).

However, the more complex the systems become, the more difficult it is to control them. It is not enough for something to work - you also have to be able to understand why it works the way it does. Incorrect assignments, inexplicable results or biased structures often remain undetected until they become noticeable. This not only changes the pace of logistics. Its vulnerability is also changing. With speed comes a new form of uncertainty. What is intended as progress requires new rules that are not only oriented towards technology, but also towards the question of how responsibility should be distributed (Perrow, 1984).

Objectives and Research Question

This study begins with a simple yet far-reaching inquiry: What happens when the responsibility for thinking about logistics processes shifts from humans to data-driven systems? The focus lies on two areas where this transition becomes particularly tangible: shopping basket analysis and shipping control. Both are closely tied to everyday logistics operations and are therefore sensitive to subtle algorithmic changes, particularly when systems begin recognising patterns before conscious demand even arises. The goal is not to list technological advancements. Instead, the study critically investigates both the potential and the limitations of these processes. Automated decisions may generate efficiency, but they also introduce new forms of uncertainty. What happens when a system evaluates situations differently from a human? Who still understands the criteria behind prioritisation when algorithms operate independently?

To increase clarity, the guiding research question and objectives are outlined as follows:

Research Question:

- What potential does the use of artificial intelligence offer in analysing shopping baskets and controlling shipping logistics processes?

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Research Objectives:

- To explore the technical capabilities and operational limitations of algorithmic systems in logistics
- To analyse the ethical and legal implications of data-driven decision-making in logistical operations
- To examine Zalando as a case study for AI-supported logistics and adaptive shipping control
- To derive practical recommendations for responsible and transparent integration of AI into logistics processes

Structure of the Work

This introduction is followed in the second chapter by an overview of the logistics basics, relevant technologies and the terms that will be used in the further course. Chapter 3 presents specific fields of application for AI in logistics, focusing on shopping baskets and shipping processes. Chapter 4 then looks at the opportunities and risks, before Chapter 5 critically categorizes the analysis to date and highlights methodological limitations. It concludes with a summarizing conclusion and a cautious outlook on future developments and open questions.

METHODOLOGY

This study follows a conceptual-analytical methodology supported by a case study approach. The research design integrates theoretical frameworks, literature synthesis, and applied analysis to understand the use of artificial intelligence (AI) in logistics. Rather than conducting empirical fieldwork, the study relies on interdisciplinary sources from logistics research, data science, legal theory, and organisational studies.

Key methodological steps include:

- A structured literature review of relevant academic and industry sources on AI in logistics, focusing on shopping basket analysis and shipping optimisation
- A conceptual analysis of algorithmic decision-making and its implications for transparency, responsibility, and operational control
- A qualitative case study of Zalando, illustrating the application of AI systems in real-world e-commerce logistics
- Reflexive evaluation of normative aspects, including ethical risks, data dependencies, and system opacity

The methodological aim is to combine abstract reflection with contextual interpretation, allowing for a deeper understanding of how AI transforms logistical decision-making structures without reducing the analysis to technological determinism.

BASIC PRINCIPLES

Logistics Processes and Digital Shopping Basket Analysis

Logistics is, quite fundamentally, the attempt to give direction to the disorganised. It is about organising movement without being able to control it completely. What we mean by logistics today is the interplay of many small decisions that ultimately ensure that something arrives at the right time, where it is needed and in the quantity that is just right (Christopher, 2016).

In the reality of a company, this rarely remains clear. Purchasing, production, storage, distribution, and returns interlock, shift and influence each other. The system is not a rigid structure, but an open one that is constantly reorganising itself. Digitalisation is changing this order once again. Logistics is no longer just planned; it is observed. The focus is no longer on the structure, but on the flow of data. This data not only documents, but it also anticipates. They look for patterns, interpret movements, and try to predict what might happen. Decisions are no

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longer made by instruction, but through recognisable repetition by what seems likely, not by what someone has decided (Winkelmann et al., 2020). A key tool in this development is digital shopping basket analysis. What was once considered statistics is now a glimpse into the future. Past purchases are used to develop hypotheses about future preferences. In e-commerce in particular, this logic means that offer design, warehouse logic and dispatch priority are no longer based on categories, but on relationships. Purchasing behaviour is reconstructed, fragmented, grouped and supported by methods such as clustering or association rules, fed by machine learning (Ngai et al., 2009; Ren).

A simple example is often used: products such as nappies, wet wipes and baby food appear together, not randomly, but with semantic depth. The system recognises this and uses it to form decision patterns, for example, for allocating storage space or bundling shipments. However, all of this depends on the quality of the data. Only if it is complete, up-to-date and sensibly structured can it be used to make viable decisions. If it is missing or distorted, the logic of the system will also begin to falter (Zarandi et al., 2011).

Artificial Intelligence Methods in Logistics

Artificial intelligence is fundamentally changing the perspective on logistics processes. It not only replaces traditional tools but also transforms the way questions are asked. While conventional systems were programmed to solve known problems, AI systems independently search for structures without knowing in advance which patterns they will discover. Two methodological approaches are particularly influential: supervised and unsupervised learning.

In supervised learning, the system works with existing data. It receives structured information, for example, on delivery times, return rates or demand trends, and uses this to forecast future developments. Typical areas of application are demand planning or the optimisation of ordering processes (Min, 2010). In contrast, unsupervised learning does not follow a predetermined goal. The system independently recognises groupings, separates data points or uncovers anomalies. Such methods are used when new customer segments are to be formed, order patterns recognised or hidden correlations identified in large amounts of data (Wang et al., 2016). But beyond the methodological structure, a more fundamental question arises: How do machines generate meaning? In logistics, this means not only making processes more efficient, but also understanding them as structures that change themselves. Decisions generate data, and this data becomes the basis for new decisions. The system begins to evolve in reverse, not linearly, but as a learning loop.

Neural networks are playing an increasingly important role in modern logistics, for example, in route optimisation, warehouse control or predictive maintenance of technical systems. Their ability to model non-linear dependencies in complex data spaces makes them particularly powerful. In addition, decision trees, random forests and support vector machines are considered stable methods when it comes to classifying orders or prioritising deliveries in real time (Uddin et al., 2024). Another field is reinforcement learning. Here, a system learns from feedback which actions are linked to positive results, for example by optimising delivery times or adaptively managing warehouse capacities. Such methods are considered particularly promising, but are also data-intensive, computationally complex and difficult to understand in their decision-making processes. These factors have so far limited their widespread use in real economic contexts (Bengio et al., 2021).

All AI methods in logistics have one thing in common: they are dependent on high-quality, continuously updated data. Without this basis, a

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system remains susceptible to distortions, a lack of generalisation and economic inefficiency.

Explanation of Terms

Before discussing the technical and organisational issues, it is worth taking a brief look at some of the terms that will play a recurring role later on. This is not a formal definition, but a common understanding that helps to organise thoughts more clearly. In this paper, artificial intelligence refers to programmes that use large amounts of data to independently recognise patterns, assess developments and derive suggestions. These systems are not firmly limited by rules. Rather, they react flexibly to what they find and adapt their behaviour over time (Russell & Norvig, 2020).

One term that is frequently used in retail logistics is shopping basket analysis. This involves analysing purchase data to understand which products are frequently bought together. Such information can help to stock shelves differently, plan inventory better or shorten shipping routes (Linoff & Berry, 2011).

This is followed by shipping optimisation. This involves the question of how deliveries can be organised in such a way that time is saved and routes are better utilised. This can mean recalculating routes, bundling deliveries or prioritising certain regions (Crainic and Laporte, 1998). The word logistics also deserves to be categorised. In this text, it is understood as a comprehensive term for all processes that ensure that goods and information are moved and distributed sensibly from the first step to the final delivery (Christopher, 2016). These terms form the framework for the following chapters. They should help to better understand the technical processes and operational requirements.

FIELDS OF APPLICATION AND TECHNICAL FUNCTIONALITY

AI in the Shopping Basket Analysis

Analysing shopping baskets is one of the most established applications of data-based systems in retail and logistics. The focus here is on the question of which products are frequently ordered together and what conclusions can be drawn about warehousing, shipping logistics or product range design. While conventional systems are based on fixed sets of rules, modern methods work with flexible structures that recognise patterns without having to explicitly define them beforehand (Kaur & Kang, 2016).

A classic example is market basket analysis. If a system recognises that nappies are often bought together with wet wipes, for example, immediate measures can be derived from this. Items are stored together, shipping processes are adapted, or recommendations are personalised. The results of such analyses have a direct impact on operational logistics: picking areas are restructured and delivery times are managed in a more targeted manner (Tan et al., 2018). Modern systems also integrate context-related information. This includes, for example, the time of purchase, the end device used or external variables such as weather data. Behaviour within the online shop, such as the click sequence or the time spent on certain product pages, is also incorporated into the modelling. The result is differentiated profiles that lead to more dynamic control of logistical decisions.

However, this complexity brings with it new challenges. Distorted databases or statistically random correlations can lead to wrong decisions, for example, in the form of incorrect pricing strategies or inefficient stock prioritisation (Verma et al., 2020). Another difficulty concerns traceability. With deep neural networks in particular, it is becoming increasingly impossible to understand exactly how a decision was made. This makes both

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internal control and external evaluation more difficult. Against this backdrop, the discussion about explainable artificial intelligence (Explainable AI) is also becoming increasingly important for logistics applications (Arrieta et al., 2020).

The analysis of shopping baskets represents a mature and widely implemented application of data-driven systems in logistics and retail. The main goal is to identify frequently co-purchased items and derive actionable insights for warehouse layout, delivery logistics, or product assortment strategies. Whereas traditional approaches relied on rigid rules, modern algorithms use adaptable models that uncover associations without predefined assumptions (Kaur & Kang, 2016).

Market basket analysis serves as a classic example. When a system detects that nappies are frequently bought with wet wipes, operational measures are taken such as co-locating items in storage, adapting shipment priorities, or customising product recommendations. These outcomes have a direct operational impact, influencing processes like warehouse zoning and order picking times (Tan et al., 2018). Contemporary models also incorporate contextual factors, including purchase timing, device types, or environmental variables like weather conditions and user navigation behaviour. This integration supports more granular profiling and dynamic logistics responses.

However, these systems are highly dependent on data quality. Inaccurate or biased input can result in flawed decisions such as inefficient pricing, inventory misallocations, or suboptimal delivery routes (Verma et al., 2020). Another important challenge is the lack of interpretability. Although deep learning models can identify complex patterns, their internal decision logic is often not accessible to users or analysts. This makes it difficult to verify outcomes or to trace how specific results are produced. Arrieta et al. (2020) emphasise that transparency in algorithmic decision-making is essential. Without comprehensible models, organisations risk losing control over operational processes, especially in dynamic logistics environments where errors can multiply quickly.

AI in Shipping Logistics

The shipping process is one of those areas of logistics where complexity is concentrated. This is where planning, technology, speed, and expectations come together in real time. What used to be described as process organisation is now a network of data points, sensor values and timed decisions. With each new generation of technologies, whether adaptive systems, generative models or autonomous units, the boundary between what is planned and what is executed immediately becomes blurred. Decisions are made where the data is processed. Not at the desk, but in the flow of information itself (IPH Hannover, n.d.).

This development is not without consequences. It is also changing the questions that are being asked of logistics systems. It is no longer enough for them to be fast and efficient. They need to remain comprehensible, act fairly and be socially acceptable. Many companies are beginning to think about what criteria are inscribed in their systems, what interests play a role there and how openly decisions are made or concealed. The call for systems that not only work, but can also be explained is becoming clearer (Arrieta et al., 2020). At the same time, the foundations are shifting. More and more decisions are based on real-time data from a wide variety of sources. Sensors, mobile devices, platforms, and external providers - they all provide information, the coordination of which is becoming a challenge. AI is not only helpful here. It is becoming a prerequisite for orientation to remain possible at all. However, as this capability grows, so does dependency. Without stable networks, open standards and smart interfaces, every system

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remains vulnerable. And every decision is potentially confusing (Ivanov et al., 2019).

There are also signs of change at a social level. In future, logistics will not only have to justify itself economically, but also ecologically and socially. AI can help to reduce emissions, avoid empty journeys and make processes smoother. But it can also create new conflicts if algorithms make decisions based solely on efficiency and ignore social aspects. Progress alone is not enough. It needs rules. We need to think about how technology is embedded in the world for which it is intended (Crawford & Paglen, 2021). Perhaps the future of logistics can be described as follows: It will be data-based. Connected. Adaptable. But it will also remain dependent on people who are responsible for, scrutinise and correct these systems. Artificial intelligence is not a promise of salvation. Nor is it a threat. It is a tool. And like any tool, its impact depends on how it is used, how openly it is built and how comprehensible its decisions are. The shipping logistics of the future will not be finished. It will constantly change in a balance between automation and responsibility, between efficiency and insight (Fraunhofer SCS, 2023).

Shipping processes concentrate many of the challenges of modern logistics: real-time constraints, data flows, customer expectations, and technical execution converge in tightly coupled systems. The classic distinction between planning and execution is becoming blurred as decisions increasingly emerge within the data flow itself (IPH Hannover, n.d.).

AI enables real-time responses to traffic data, order volumes, and weather disruptions. Systems process information where it is generated, dynamically adjusting routes, capacities, and delivery windows. This responsiveness enhances efficiency but also changes the nature of decision-making. Many logistical actions are now guided by models whose internal operations are difficult for human users to interpret (Crawford & Paglen, 2021).

This opacity increases the demand for explainable systems. Companies need to understand the underlying logic of their AI tools to evaluate implications for fairness, employee workload, and customer outcomes (Arrieta et al., 2020). However, such understanding is only possible if systems are built upon reliable and interoperable data streams from sensors, mobile devices, and external platforms. This growing dependence introduces a new layer of fragility: performance is directly tied to the availability and quality of data (Ivanov et al., 2019).

In addition, shipping logistics must respond to rising expectations in social and environmental responsibility. AI technologies can support sustainability goals by optimising routes, preventing empty runs, and monitoring emissions. But if system priorities are based exclusively on operational costs, broader objectives such as social equity or ecological balance may be overlooked. The future success of AI in logistics thus hinges on the integration of ethical principles and regulatory safeguards into system design and operation.

Ultimately, intelligent logistics systems should not only react efficiently but also remain transparent, correctable, and adaptable to shifting priorities beyond cost alone.

Case Study: Zalando

Zalando is one of the big names in European online retail and one of the companies that focused on data-based logistics early on. The processes in the background, from inventory management to dispatch control, are now supported by algorithmic systems. This does not mean that people have become superfluous. But many decisions that used to be made manually are now made automatically,

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prepared by models that recognise patterns and calculate probabilities (Zalando SE, 2022).

One example of this is the "Algorithmic Fashion Companion" system. It processes how users move around, which products they look at and how long they linger. These interactions result in recommendations that are not only intended for sales but also for logistics. Products that are expected to be in high demand end up in warehouses that are as close as possible to potential customers. This makes the journey shorter, shipping faster, and warehousing more efficient (Karl, 2021). This infrastructure is supplemented by dynamic fulfilment. This is a system that constantly recalculates where each item should be located. The decisions are based on returns, seasonal movements and regional preferences. The aim is to remain flexible and react to fluctuations in demand without losing time. This sounds simple, but it requires the data to be up-to-date and of high quality. Without this basis, the system would be blind (Göpfert and Braun, 2021).

Even within the warehouses, the extent of automation is now evident. Sorting machines, robotic arms and adaptive control processes interlock. As a result, Zalando can maintain a consistent quality of service even when order volumes fluctuate greatly. But this stability comes at a price. Much of what used to be visible now runs behind the scenes. Decisions on when a parcel is delivered are no longer made by people, but by systems, and it is not always clear exactly why. This raises questions. Questions about responsibility, transparency and the possibility of recognising errors before they have consequences (Arrieta et al., 2020).

Zalando shows how logistics changes when data sets the pace. Processes are accelerating. Decisions move closer to the customer. Many actions run automatically and efficiently, but also unnoticed. But what happens if the system is wrong? If the data is incorrect, the model is misinterpreted, or the reality is different than expected. The question of how robust such systems are does not only arise in the event of a crisis. It is part of day-to-day operations. And it remains open.

Zalando, a leading European online retailer, has implemented AI across its logistics chain. From inventory management to dispatch optimisation, many formerly manual decisions are now handled by models trained on user behaviour, return rates, and location data (Zalando SE, 2022).

One notable system is the "Algorithmic Fashion Companion," which analyses browsing patterns and dwell time to generate both product recommendations and logistical actions. High-demand items are prepositioned in local warehouses, reducing shipping times and increasing customer satisfaction (Karl, 2021). A second layer is dynamic fulfilment: item locations are constantly recalculated based on seasonality, region, and return trends. This allows for rapid adaptation to demand fluctuations—but only if data quality is continuously ensured (Göpfert & Braun, 2021).

Warehouse automation at Zalando includes sorting machines and robotic systems, which help stabilise operations during high-volume periods. However, this comes at a cost: decision processes increasingly occur in the background, often without human interpretability. Questions arise regarding responsibility, error detection, and systemic resilience (Arrieta et al., 2020).

Zalando illustrates the shift from reactive logistics to predictive, data-driven systems. While this transformation improves efficiency and scalability, it also introduces new dependencies, requiring ongoing evaluation of system robustness, transparency, and organisational oversight.

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OPPORTUNITIES AND CHALLENGES

Focus on Efficiency and Costs

When we talk about efficiency, we usually mean the relationship between effort and result. In logistics, this means less time per delivery, lower costs per kilometre and less idle time in the warehouse. Systems that can analyse large amounts of data help here. They take over tasks that used to be done manually. This includes, for example, deciding where certain products should be placed in the warehouse or which route a transport vehicle should take to minimise detours. Programmes make these decisions faster than humans, especially when many factors have to be considered simultaneously (Wang et al., 2016).

This is particularly evident in the shipping sector. Current information on traffic, weather or consignment volumes can be analysed in real time. This allows routes to be adjusted, delays to be avoided and capacity utilisation to be better managed. Some studies suggest that such processes can reduce ongoing logistics costs by around a fifth compared to conventional planning models (Min, 2010). However, whether such values can be achieved in every company remains an open question. The decisive factor is how well the data is maintained and how reliably the system works on a day-to-day basis. There is also potential in personnel planning: AI systems forecast requirements, shift distributions and bottlenecks. On this basis, personnel resources can be deployed more flexibly and in a more targeted manner, especially during seasonal peak periods. The resulting efficiency therefore not only affects material resources, but also human labour (Klumpp, 2018).

In addition, capacity utilisation is improved: storage space is allocated algorithmically, and stocks rotate systematically. This has a direct impact on capital commitment costs. Companies such as Zalando and Amazon report significant efficiency gains through adaptive management of their logistics centres, especially with high product diversity and rapidly changing demand (Boysen et al., 2021). Moch (2024b) makes it clear that it is not individual systems that generate long-term efficiency. The decisive factor is interaction with adaptive technologies that are linked to data streams and recognise changes in operations in good time. It is not just a matter of running processes automatically. Rather, these systems can self-adjust that makes the difference. Maintenance is planned with foresight, faults are recognised at an early stage, and resources are channelled to where they are needed. This creates room for manoeuvre - and changes the way we think about production and logistics.

Nevertheless, the potential is not limitless. Efficiency gains require high data availability, robust system architectures and continuous maintenance. If a system fails or accesses incorrect information, this can lead to delayed deliveries or incorrect scheduling. The efficiency achieved is therefore not only a result of technical innovation but also of the organisational ability to integrate it securely and sensibly.

Data Protection and Algorithmic Bias

When systems are used that process large amounts of data, the question of how this data is handled almost always arises. This is particularly true where information is not only collected, but is also directly incorporated into decisions about shipping processes. In logistics, this can be seen in the link between shopping basket analysis and delivery: who buys what, in what combination, how often, from which device and to which location - all this information flows into the system in order to improve processes.

However, this is precisely where an area of tension arises. Because with every additional piece of information, knowledge about individual users also grows. The boundary between technical efficiency

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and personal traceability is not always clear. When data is combined, conclusions are often drawn that are almost impossible to control in everyday life. This applies not only to specific orders, but also to recurring patterns that emerge over time, such as preferred delivery times, regional characteristics or certain preferences in product selection. The systems themselves do not differentiate between anonymous structures and personal contexts. They work with probabilities, not with individual cases. This raises the question of how transparent these processes are and how well those affected understand the basis on which decisions are made.

Although companies argue with anonymised data streams, re-identifiability remains a given in many cases, for example by linking several data sources or through fine-grained analysis of behavioural patterns (Wachter et al., 2017). Furthermore, AI systems are suspected of reproducing or even reinforcing existing biases. If historical data is used that already contains discriminatory patterns, these are systematically reflected in algorithmic decisions. In logistics, for example, this can lead to certain customer groups being disadvantaged through longer delivery times, poorer conditions or incorrect prioritisation (Moch, 2024a).

The situation is particularly critical where logistics systems make independent decisions. If, for example, an adaptive algorithm predicts the probability of returns and, on this basis, makes certain items only available to a limited extent, this immediately raises questions of fairness. The criteria according to which such assessments are made often remain opaque. External monitoring is rarely provided for, and affected users have little insight or opportunity to object (Binns et al., 2018). The European General Data Protection Regulation (GDPR) sets clear limits here. However, many systems operate on the threshold between authorised statistical analysis and personal profiling. The separation is often technically almost impossible to maintain, especially when analysing transaction data in real time in combination with location and device information (Voigt & Von dem Bussche, 2017). The challenge, therefore, lies not only in the legally compliant processing of data but also in the ethically justifiable design of algorithmic logic. Where logistics processes are automated by AI, not only do new forms of operational efficiency arise, but also new questions of responsibility. The protection of personal data must not be an afterthought - it must become part of the system itself.

The question of legal responsibility for such processes also arises. As Moch (2024a) points out, learning systems create a new form of decision delegation in which it remains unclear who is liable if an automated recommendation leads to damage. In his article on AI liability, Moch argues in favour of a redefinition of the logic of responsibility that takes greater account of both the system architecture and the providers' transparency obligations. For the logistics sector, this means Legal frameworks must not only safeguard technical systems but also create the possibility of making automated decisions legally traceable (Moch, 2024a).

Dependencies on Data Infrastructure

Whether a digital system in logistics works effectively depends not only on its technical architecture, but often on an invisible foundation: the data on which it is based. If this data is incomplete, outdated or incorrectly linked, delays, incorrect control or unnecessary routes are the result. Particularly in areas with high reaction speeds, such as dispatch or warehouse distribution, even small gaps can be enough to bring entire processes to a standstill (Ivanov et al., 2019).

In addition, many companies are reliant on external platforms and data sources. Traffic information, customer behaviour and market data often come from third-party providers. These dependencies often remain in the background but are gradually

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changing the way decisions are made. What initially seems practicable has long-term consequences for the sovereignty of operational management (ZEW, 2024). Another obstacle lies in the structure of internal data landscapes. In many companies, purchasing, warehousing, shipping and customer contact are organised in separate IT systems. These work in parallel, but are rarely integrated. If a system only receives fragmented information, its decisions are also based on a fragmented picture. This becomes a problem if such decisions are later to be considered objective and automated (Winkelmann et al., 2020). This raises not only technical but also normative questions. Who defines what is considered relevant information? Who determines how heavily certain data is weighted or which forecast horizons are considered appropriate? Such decisions are increasingly being made within automated systems invisibly but with far-reaching effects (Crawford & Paglen, 2021).

This development brings with it a new form of vulnerability. Systems that continuously rely on external and internal data streams react sensitively to disruptions. A network failure, a defective interface or a data leak can be enough to destabilise processes or trigger incorrect decisions. In practice, it is clear that the performance of digital systems stands and falls with the quality of their database. Only if this database is resilient, accessible and well-linked can the system based on it function reliably.

From an efficiency perspective, the advantages initially outweigh the disadvantages. AI-supported scheduling systems reduce storage costs, improve the utilisation of logistics capacities and accelerate planning processes through predictive control. They enable a faster response to changes in demand or interruptions in the supply chain. Platform models such as Zalando's illustrate how algorithmic control can also lead to more flexible, personalised delivery, for example through local warehousing or dynamic route planning (Göpfert & Braun, 2021). However, transparency remains an ambivalent concept in the application of artificial intelligence. Although many processes in digital systems can be precisely recorded, what happens on the inside often remains incomprehensible. The decision-making mechanisms according to which complex models act are usually obscure to users. They see the result - a suggestion, a delivery, a prioritisation - but not how it came about. Even if the recommendations are correct, even if the delivery arrives quickly, a feeling of uncertainty remains as soon as the decisions cannot be explained. Trust can be lost, especially if the selection seems arbitrary or penalising (Arrieta et al., 2020).

Many things work well in the short term. Systems provide early notification, delivery times are adjusted, and options appear personalised. This ensures satisfaction as long as everything runs smoothly. But these positive effects are not guaranteed. They depend on the stability of the technical infrastructure, the reliability of the data and the accuracy of the logic in the background. As soon as the prioritisation does not fit, a recommendation is missed or the system reacts incorrectly for no apparent reason, frustration, delays, and confusion arise. The technology is then no longer supportive, but alien. Responsibilities become blurred. Who is responsible when no one decides anymore, but only observes? (Verma et al., 2020)

What follows from this is not a technological promise, but a structural one: Artificial intelligence can improve processes in logistics - yes, it can make many things faster, more accurate and more efficient. But this capability only unfolds where it is embedded. Embedded in a framework that not only looks at technology but also at traceability. On the relationship with people. On the question of whether the decision is not only correct but also understandable. Progress is made when efficiency and responsibility are considered together. When

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systems do not function on their own, but are part of a model that remains open, sustainable and fair.

DISCUSSION

Evaluation of the Effects on Efficiency, Transparency, and Customer Satisfaction

The use of data-based systems is changing logistics processes in many ways. These changes are particularly evident in three areas: the efficiency of operational processes, the transparency of algorithmic decisions and customer perception.

Automated processes offer measurable benefits in terms of efficiency. Stock levels can be managed more precisely, supply chains can be more closely coordinated, and potential bottlenecks can be identified at an early stage. With the help of predictive analyses, personnel deployment can be better planned, vehicle utilization increased, and the error rate reduced. These advances do not have a one-off effect but are a permanent structural gain. The effects are particularly visible in shipping: routes are dynamically adjusted, delivery times optimized and resources can be managed according to demand (Wang et al., 2016). At the same time, the understanding of transparency is changing. At a technical level, this is initially being strengthened: data is collected in real time, decisions are documented, and processes are visualized. However, this form of openness often remains on the surface. The internal processes of algorithmic decision-making models are difficult for outsiders to understand. What is visible is the result, not the path to it. For many users, this creates the impression of a functioning but non-transparent system. Nevertheless, the result can be positive for customers. Deliveries are faster, shipping options are better tailored to individual needs, and information on the delivery process is always available. However, these improvements are based on stable, well-calibrated systems. As soon as the system malfunctions, whether due to inappropriate suggestions, incorrect addressing or inexplicable route selection, the positive effect is reversed. Uncertainty, frustration, and a loss of trust arise (Verma et al., 2020).

Overall, the picture is ambivalent. Technical performance is increasing, but so is the complexity of requirements. Efficiency can be achieved when systems work consistently and reliably. Transparency is not only created by open data but also by explainable decisions. And satisfaction is achieved when technology not only accelerates but also remains comprehensible and reliable.

Relationship between Man and Machine

The introduction of digital systems is not only changing how logistical processes are carried out, but the interaction between people and technology is also shifting. Decisions that used to be made based on experience or in conversation are now often made in the background of a programme. Models evaluate data, calculate probabilities, and provide suggestions before anyone has asked for them.

This development is changing the roles in the company. What used to be in the hands of experienced employees is now prepared, sorted, and weighted by a system whose functioning is only partially comprehensible. The responsibility remains with people, but the basis for decision-making is shifting. This also raises the question of how this new form of collaboration can be organized: as a supplement that supports or as a structure that replaces it. The introduction of digital control systems initially reduces the workload. Repetitive tasks such as route planning, warehouse allocation or demand forecasting are carried out faster, more precisely and more consistently. However, this relief is not automatically accompanied by simplification. Anyone working with such systems must not only understand the inputs but also be able to scrutinize the results. The task shifts: from active decision-making to

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monitoring, checking, and intervening if the system does not react as expected (Klumpp, 2018). Not all employees feel up to this new role. While technical systems are increasingly functioning smoothly, the need for guidance is growing on the human side. Those who can no longer understand why the system sets a certain prioritization lose confidence in their work. What used to be based on experience is now being replaced by modelling logic, often without this being transparent. This can lead to a feeling of alienation: The system decides and the person observes (Crawford & Paglen, 2021).

At the same time, these developments also offer new room for manoeuvre. Where technology is not seen as a replacement, but as support, man and machine can find productive interaction. Experience from day-to-day operations can flow back into the systems if feedback is taken seriously and algorithms remain customizable. However, the prerequisite for this is that the systems remain explainable, correctable, and understandable in everyday life. This is the only way to create an environment in which technology empowers rather than disempowers.

Reflection: Methodological Limits and Transfer Problems

Many of the models used draw on the past. They analyse historical data and derive assumptions about future developments. As long as the environment changes slowly, this works well. However, as soon as there are sudden upheavals, economic crises, political tensions or changes in consumption habits, these systems begin to falter. They continue to calculate, but under conditions that no longer fit their foundations. As a result, forecasts become less reliable (Tichy, 2020).

Another problem lies in transferability. What works in a company with a strong digital infrastructure cannot automatically be transferred to smaller companies. They often lack the technical requirements, the necessary database or simply the personnel to operate complex systems. This creates a gap between the pioneers and traditional SMEs that cannot be explained by technology alone, but rather by structural differences that can also have an impact in the long term (Winkelmann et al., 2020).

Even within a company, it is clear how limited the use of some applications remains. Many models are tailored to very specific tasks. A system that can plan tours well is not automatically suitable for organising warehouse processes. It needs to be customised. Sometimes, even completely new approaches. This is time-consuming, expensive and requires specialised knowledge and resources that are not available everywhere (Ngai et al., 2009). There is also the question of how to actually check whether a system is doing what it is supposed to do. What counts as success? How do you measure quality when a programme not only calculates but also prepares decisions? The answers to this question are often very one-sided. Companies look at figures such as delivery times, costs and quantities. But many things are left out: the resilience of the processes, the trust of the employees and the ability to deal with errors. All of this is more difficult to measure, but is no less important (Arrieta et al., 2020).

In the end, it turns out that it's not just about the technology. The introduction of such systems requires a conscious decision. It touches on questions of responsibility, organisation and attitude. If you want to use AI in logistics, you not only have to understand the systems but also the conditions under which they work.

The integration of data-based systems into logistics has significantly reshaped operational processes. AI-driven optimisation leads to measurable gains in efficiency. Stock levels are managed more precisely, supply chains are more closely coordinated, and potential bottlenecks can be identified earlier. Predictive analytics improve personnel scheduling, vehicle utilisation, and

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reduce error rates. These gains are not isolated but structural, especially in dynamic areas such as shipping, where delivery routes can be adjusted in real time (Wang et al., 2016).

Despite these benefits, many organisations face difficulties in achieving transparency. While technical data collection and process documentation have improved, the internal functioning of algorithms often remains inaccessible. Stakeholders may observe the results of AI decisions but lack insight into how these outcomes were generated. This limits trust and complicates regulatory and ethical oversight. Users may benefit from improved services but also express concern when prioritisation patterns or delivery outcomes seem arbitrary or discriminatory (Arrieta et al., 2020).

From a customer perspective, automation has raised expectations. Shorter delivery times, flexible options, and personalised recommendations increase satisfaction. However, these effects are conditional. They depend on stable systems, valid data, and consistent performance. As soon as anomalies occur, such as inappropriate delivery routing or product misallocation, the perceived benefits are quickly reversed. This underlines the importance of designing AI systems not only for efficiency but also for reliability and explainability.

Human-Machine Interaction and Organisational Transformation

AI changes not only how logistics is executed but also how people engage with these systems. Many traditional roles in logistics were grounded in manual processes and experiential knowledge. As AI tools take over decision-making, human actors shift into supervisory and intervention roles. This shift requires new skills. Employees must understand data flows, monitor automated outputs, and assess when manual intervention is necessary (Klumpp, 2018).

However, the readiness for this change varies. Some employees feel empowered by AI-supported tools, while others experience disorientation or loss of control. This is especially pronounced when decision processes become less transparent. The delegation of operational logic to machines can reduce users to passive observers unless systems are intentionally designed to include opportunities for explanation, feedback, and correction.

Successful integration depends on organisational support. Training programmes, internal communication, and clear responsibility structures are essential to bridge the gap between human expertise and algorithmic automation. Otherwise, technology risks reinforcing asymmetries rather than improving processes.

Empirical Gaps and Normative Orientation

Although case examples such as Zalando demonstrate the potential of AI in logistics, many findings remain context-specific. High performance depends on mature data infrastructures, internal resources, and scalable processes. Smaller companies may lack these prerequisites. Therefore, more comparative studies are needed to identify which AI strategies are transferable across sectors and firm sizes (Göpfert & Braun, 2021).

Moreover, success in logistics cannot be reduced to technical indicators alone. Delivery speed, cost savings, and stock turnover are relevant, but so are robustness, employee trust, and error tolerance. These dimensions are often harder to measure but are critical for long-term system acceptance. Organisations should define broader performance criteria that also reflect social, ethical, and environmental objectives.

Normative orientation becomes crucial where automation creates new uncertainties. Who bears responsibility when algorithmic decisions cause harm? How can fairness be maintained in resource

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allocation? And what principles should guide the development of learning systems that continuously adapt their own logic? These questions suggest that technological innovation must be accompanied by ethical reflection and regulatory foresight.

Broader Perspective: People, Systems, and Direction

The human impact of AI integration extends beyond operational tasks. It affects how organisations function, how decisions are legitimised, and how future capabilities are shaped. AI systems do not simply automate processes, they restructure how logistics is conceptualised and managed. Their introduction should not be seen as a technical upgrade, but as a systemic shift that requires deliberate design and collective negotiation.

Future directions must consider plural goals. Logistics should be efficient, but also resilient, inclusive, and transparent. The success of AI depends on whether it serves these goals. Human involvement remains essential not only to correct errors but also to ask the right questions, challenge assumptions, and ensure that systems evolve in directions that reflect shared values.

CONCLUSION AND OUTLOOK

Findings

The study has shown that data-based systems are capable of transforming logistics. They offer more precise control of processes, faster decision-making, and better coordination of workflows. These effects are particularly visible in areas where speed is a competitive factor, such as online retail (Wang et al., 2016). However, these advantages do not arise by default. Their realisation depends on reliable data, stable infrastructures, and skilled personnel. While large companies may meet these conditions, many smaller enterprises operate with limited resources, lower data availability, and narrower operational buffers (Göpfert & Braun, 2021).

The shift also changes the relationship between human actors and technical systems. Automation can relieve burdens and increase speed, but it can also lead to alienation. Tasks that used to be performed by individuals are increasingly shaped by system logic. Balancing efficiency gains with the preservation of human agency remains a central challenge.

Many AI systems base their outputs on historical data. This works well when environments remain stable. In periods of rapid change, however, predictions lose their reliability. External shocks, political crises, or shifting consumption patterns may quickly exceed a model’s adaptive range (Tichy, 2020). Another challenge is transferability. Models developed in large digital firms are not easily applied to smaller ones. Structural conditions differ, and the requirements for implementation may exceed the capacity of many small and medium-sized enterprises (Winkelmann et al., 2020).

In addition, many systems are limited in scope. Tools that work well for routing may not apply to warehouse control. Customisation is often necessary. This increases the need for expertise, time, and resources (Ngai et al., 2009). Success also depends on how it is measured. While delivery times and cost savings are commonly used metrics, less tangible elements such as process stability, employee trust, and error tolerance are equally important (Arrieta et al., 2020).

Ultimately, technology alone does not produce progress. The use of AI requires thoughtful decisions about purpose, responsibility, and context. Those who adopt such systems must not only understand how they work but also the conditions under which they remain effective.

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What Remains of the Findings

AI can enhance logistics operations. It can speed up decisions, support coordination, and improve precision. These effects are evident in warehousing, routing, and scheduling (Wang et al., 2016). However, these outcomes are conditional. Without supportive structures, accessible data, and human understanding, even powerful systems fail to deliver results (Göpfert & Braun, 2021).

At the same time, automation influences how work is done. It reassigns roles, introduces new responsibilities, and removes others. While it can increase efficiency, it may also lead to a loss of orientation or trust. Organisations must manage these transitions with awareness.

Relevance for the Sector

Logistics companies face growing pressure. Supply chains are sensitive to disruption, and customers expect fast, reliable service. AI technologies offer options to improve planning and responsiveness. But they also shift how decisions are made. Those using AI take on new responsibilities. Choices about data, logic, and prioritisation become encoded in automated routines (Min, 2010).

This shift requires transparency and clarity. Stakeholders must understand how systems work and which goals they pursue (Asdecker, 2013). Fairness and accountability must be considered alongside technical performance (Binns et al., 2018). Especially in small firms, the risk of being left behind increases without targeted support (Winkelmann et al., 2020).

AI is no longer a future issue. It is already reshaping the logistics sector. Its success depends not only on technological capability but on responsible and inclusive implementation.

Outlook: The Future of AI in Logistics

Artificial intelligence will continue to shape logistics. Technological developments proceed quickly. Systems that learn and adapt are becoming more common. This changes not only how tasks are performed but also where and when decisions are made (IPH Hannover, n.d.). Data streams are processed directly within operational flows. Organisational hierarchies are increasingly bypassed by real-time feedback loops.

In this dynamic context, ethics, regulation, and co-determination become more important. Companies must be able to explain their systems and justify their outcomes. Users and regulators alike will demand transparency. Systems must be verifiable, even as they learn and evolve (Arrieta et al., 2020).

Data infrastructures are also changing. Sensors, platforms, and mobile devices generate constant flows of information. These must be linked, cleaned, and secured. Without robust standards, the risk of fragmentation grows (Ivanov et al., 2019).

The goals of logistics are also evolving. Speed and cost remain important, but social and ecological sustainability are gaining ground. AI can help align logistics with these values. But it can also amplify tensions. Efficient outcomes are not always socially acceptable. Choices must be made within frameworks that reflect wider concerns (Crawford & Paglen, 2021).

Regulation will need to keep pace. As Moch (2024a) notes, legal responsibility must be clarified. Systems that decide must remain subject to control. Liability and accountability cannot be left behind. Only then can trust in automation grow. Without such measures, uncertainty and gaps in responsibility will persist.

The future of logistics will be shaped by data and algorithms. But outcomes will depend on the people

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and organisations who design, oversee, and use these tools.

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