Exploring Artificial Intelligence for third-party logistics service providers: a dynamic capabilities perspective

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Abstract

Purpose – Artificial Intelligence (AI) is increasingly considered a transformative force within the logistics industry, improving efficiency and enhancing effectiveness for many organisations including third-party logistics service providers (3PLs). However, the academic literature reveals a limited understanding of how 3PLs can approach the opportunities offered by AI. To fill this gap, we leverage the dynamic capabilities theory to explore AI adoption within the 3PL industry.

Design/methodology/approach – We developed a single case study focusing on a leading British 3PL that introduced AI to improve warehousing operations and planning activities. We collected data through two rounds of qualitative interviews with managerial-level stakeholders from different departments and two on-site visits. Through abductive reasoning, we iteratively compared empirics with the available theoretical knowledge to illuminate how 3PLs can approach AI

opportunities through their sensing, seizing, and reconfiguring dynamic capabilities.

Findings – Findings illustrate several micro-foundations underpinning higher-order dynamic capabilities. Sensing AI opportunities critically depends on building internal AI awareness as well as involving customers to embed their perspectives, leading to prioritising AI use cases. Seizing starts with aligning use cases with the business strategy, then procuring AI solutions and assessing their security and ethical implications before embedding different AI tools. These initiatives foster resource reconfiguration by embracing a cultural shift involving 3PLs and their customers and developing a robust data infrastructure to support AI efforts. Building on these findings, we suggest evolutionary patterns for dynamic capabilities through AI adoption.

Originality/value – Existing research has yet to fully explore how 3PLs can approach AI adoption. The study contextualises the dynamic capabilities theory for AI-driven opportunities, elaborating on earlier studies to identify micro-foundations for 3PLs' higher-order dynamic capabilities. It proposes a set of research propositions and offers a research agenda to foster future exploration about embedding AI into logistics operations. By focusing on 3PLs in the context of rising digitalisation, the study highlights how firms can navigate the complexities of AI adoption, offering original insights to leverage the synergies among human workforce, technological tools, and physical assets.

Keywords: 3PL, Artificial Intelligence, AI, Dynamic Capabilities

Data availability statement

Due to the sensitive nature of the research, supporting data is not publicly available. However, data that support the findings of this study are available from the corresponding author upon reasonable request.

Introduction

Artificial Intelligence (AI) is a branch of computer science that attempts to mimic human intelligence (Mikalef and Gupta, 2021; Jackson et al., 2024). Due to its ability to improve forecasts, generate original content, and automate repetitive tasks (Durach and Gutierrez, 2024; Pournader et al., 2021), in the last few years AI has emerged as a top technological priority for many organisations, with relevant use cases across several supply chain processes (Handfield et al., 2019; Guida et al., 2023; FourKites, 2025). In the logistics industry, AI is largely acknowledged as a transformative force (Richey et al., 2023; Toorajipour et al., 2021), envisioning potential cost reductions up to 20% (McKinsey, 2025). Many companies have been outsourcing their logistics operations to third-party logistics service providers (3PLs), leveraging 3PLs' ability to handle transport management, warehousing, and distribution on their behalf (Razzaque and Sheng, 1998; Marchet et al., 2017). Nevertheless, 3PLs operate in a highly competitive environment, where technology is increasingly critical to enhance operational efficiency and responsiveness (Cichosz et al., 2020; Rainer et al., 2025). With the emergence of digitalisation as a market differentiator but also given the importance of the technological expertise that 3PLs can bring to their customers (Wang and Sarkis, 2021; Cannas et al., 2024), AI tools can offer 3PLs the means to strengthen tailor-made service offerings, improve decision-making, and optimise their operations (Richey et al., 2023; Pournader et al., 2021).
However, 3PLs often struggle to understand the opportunities that AI may offer, also given the heterogeneity in the services they provide to multiple customers with highly different requirements, which hinders AI adoption (Jackson et al., 2024; McKinsey, 2025). The following research question was thus identified:

How can 3PLs approach AI-driven opportunities and navigate AI adoption?

To address this research question, we built on the dynamic capabilities theory (Teece et al., 1997), which emphasises the importance of organisations' ability to adapt to changing environments by integrating and reconfiguring resources (Teece, 2007). Since AI is rapidly evolving and requires strategic adaptation (Herold et al., 2024), recent studies position dynamic capabilities as a primary

lens to examine how firms approach digital transformation and change (Warner and Wager, 2019; Mele et al., 2024), including AI adoption within supply chain management (Guida et al., 2023; Li et al., 2024; Spreitzenbarth et al., 2024).

Given the scarcity of empirical studies delving into AI real-world implementation (Moretto et al., 2024), we designed a qualitative research approach based on a single case study conducted in collaboration with a leading British 3PL provider. The case company has introduced AI to improve warehousing operations and planning activities, launching projects concerning labour forecasting, labour scheduling, last-mile delivery vehicle selection, and network optimisation. We collected empirical insights through two rounds of qualitative interviews with managerial-level stakeholders from different departments and two on-site visits. Through abductive reasoning, we iteratively compared empirics with the extant theoretical knowledge to elaborate on how 3PLs can approach AI adoption by leveraging their dynamic capabilities to sense and seize AI opportunities, as well as to reconfigure their resources to capture such opportunities. Sensing depends on building internal AI awareness but also involving customers to embed their perspectives, thus identifying and prioritising AI use cases. Seizing starts with aligning use cases with the business strategy, then procuring AI solutions and assessing their security and ethical implications before experimenting with different AI tools. These initiatives foster resource reconfiguration by embracing a cultural shift that should also involve 3PLs' customers and developing a robust data infrastructure.

The study contributes to the literature by contextualising the dynamic capabilities theory with respect to AI-driven opportunities for 3PLs. It formalises micro-foundations for higher-order capabilities, defining boundary conditions for theory elaboration and offering a set of research propositions. The study also suggests evolutionary patterns for dynamic capabilities through AI adoption, proposing a research agenda to navigate the challenges related to embedding AI into 3PLs' operations. In the next sections, we summarise the related academic literature and present our methodological approach. We then describe the study's findings and discuss them, before synthetising the research implications along with avenues for future theoretical advancements.

Related literature

3PLs: from transport and warehousing to Artificial Intelligence

Logistics services are essential to guarantee the smooth flow of materials, information, and money along supply chains (Lieb et al., 1993; Marchet et al., 2017). However, conducting logistics operations efficiently and effectively can be expensive (van Laarhoven et al., 2000). Therefore, companies often outsource logistics operations to 3PLs, i.e., companies executing logistics operations and adding more value to a shipper's business than the shipper can achieve alone (Marchet et al., 2017). Logistics outsourcing started with services like transport and warehousing (Razzaque and Sheng, 1998; Wilding and Juriado, 2004), then evolving into providing tailored solutions to meet specific requirements (Selviaridis and Norrman, 2015). Today, 3PLs offer both standard and advanced services, from transport and warehousing to value-added services like labelling, packaging, and return management (Marchet et al., 2017; Prataviera et al., 2021). 3PLs are thus essential players in streamlining supply chain operations, as their customers deeply rely on them to achieve operational efficiency and flexibility while improving customer satisfaction (Karagiannis et al., 2024).

However, 3PLs operate in a highly competitive environment, where technology is critical to enhance efficiency and responsiveness (Cichosz et al., 2020; Rainer et al., 2025) and the rising digitalisation is significantly affecting 3PLs' business (Jazairy et al., 2024; Manners-Bell and Lyon, 2022). Digitalisation refers to the process by which companies collect, store, analyse, and use customer and market data to capture value through digital technologies (Zhou et al., 2023). On one hand, digitalisation discloses a high potential to add further value to client services as it strengthens 3PLs' efficiency and responsiveness (Hofmann and Osterwalder, 2017; Mathauer and Hofmann, 2019). 3PLs have been moving towards more complicated tailor-made service offerings through increasing digitalisation (Baglio et al., 2025), whereas sharing benefits between 3PLs and shippers (i.e., 3PLs' customers) can increase customer loyalty and satisfaction (Barker et al., 2021). On the other hand, digitalisation is still in its infancy in the 3PL industry (Wallenburg and Knemeyer, 2022). As 3PLs venture deeper into the digital age, they also need to figure out how the leverage advanced technologies

to deliver customer value (Zhou et al., 2023), going beyond arm's length relationships and the further challenges introduced by the rise of digital platforms or robotic hardware providers who risk disintermediating 3PLs themselves (Manners-Bell and Lyon, 2022).

These technologies include Artificial Intelligence (AI), which has recently become a top priority for many organisations (FourKites, 2025; Jazairy et al., 2025; McKinsey, 2025). AI refers to the ability of a machine to reason, solve problems, and adapt to the environment, like how a human being could do (Chen and Chen, 2022), whereas the emergence of large language models like ChatGPT suggests we are on the brink of a significant technological upheaval for logistics and supply chain management (Kmiecik, 2023; Richey et al., 2023). In the supply chain context, AI tools can process vast amounts of data to help managers make better decisions regarding procurement (Guida et al., 2023; Guida et al., 2025), manufacturing (Helo and Hao, 2022; Merhi and Harfouche, 2023), and distribution (Toorajipour et al., 2021; Hendriksen, 2023). For 3PLs, AI provides opportunities to better manage the logistics processes, improving forecasting and raising productivity, safety, and performance but also decreasing operating costs (Pournader et al., 2021; Baglio et al., 2025). This emphasises not only the emergence of digitalisation as a market differentiator but also the importance of the technological expertise that 3PLs can bring to their customers (Wang and Sarkis, 2021; Cannas et al., 2024). Nevertheless, the tumultuous technological development and the wide range of available solutions urge 3PLs to deepen how different AI tools can contribute to remain competitive and meet the evolving expectations of their customers (Cannas et al., 2024; McKinsey, 2025).

AI tools for 3PLs: Predictive Analytics, Generative AI, and AI-driven Automation

AI tools can be classified into distinct types based on their cognitive ability, i.e., their capacity to learn, understand, and make decisions based on data and experiences (Siegel, 2024). This classification reveals three overarching types of AI tools: Predictive Analytics, Generative AI, and AI-driven Automation (Table I).

Types of AI tools	Main purpose	Specific tasks and impact areas	Related references
Predictive Analytics	Forecasting future events and outcomes	• Demand forecasting • Dynamic pricing • Dynamic vehicle routing • Inventory forecasting • Labour forecasting, planning, and scheduling • Predictive maintenance	Guida et al. (2023) Guida et al. (2025) Jackson et al. (2024) McCartney et al. (2024) Mediavilla et al. (2022) Richey et al. (2023)
Generative AI	Creating new content and data	• Chatbot dialog creation • Code writing • Content creation (job specifics, emails) • Report creation • Sentiment analysis • Training data creation (e.g., palletisation)	Cannas et al. (2024) Durach and Gutierrez (2024) Gezdur and Bhattacharjya (2025) Jackson et al. (2024) Hendriksen (2023) Pfaff (2023)
AI-driven Automation	Mimicking human tasks faster	• Digital twins support • Robotic process automation (payment processing, status updates) • Optimisation tools and software • Smart warehouses (machine vision, asset tracking, inventory counting) • Safety and security vision	Cannas et al. (2024) Guida et al. (2025) Grover and Ashraf (2023) Hendriksen (2023) Rainer et al. (2025) Richey et al. (2023)

Table I. Overview of distinct types of AI tools with related tasks and impact areas. Source: authors' own elaboration.

Predictive Analytics tools contribute to the prediction of future activities (Mediavilla et al., 2022), examining data or content to answer the question, "What will happen?" or, more precisely, "What is likely to happen?" (McCartney, 2024). AI Predictive Analytics models enable more accurate demand forecasting, optimising inventory and reducing stock out alongside providing predictive maintenance of equipment helping reduce downtime (Guida et al., 2025). They often rely on machine learning algorithms to analyse historical data and trends to predict future demand, helping companies better prepare for demand and supply fluctuations (Richey et al., 2023). Such algorithms can help optimise transport

routes and schedules, reduce fuel consumption, and improve delivery times (Jackson et al., 2024). Accordingly, AI can provide benefits that 3PLs can offer to their clients (Wang and Sarkis, 2021); for example, real-time data can increase operational efficiency in terms of optimised picking routes in warehouses but also enable optimal repositioning of truck capacity in transport (Wallenburg and Knemeyer 2022).

Conversely, Generative AI tools enable new content generation (usually with limited predictive capabilities) while analysing or acting on existing data (Hendriksen, 2023). Generative AI opportunities relate to conversational interfaces and knowledge discovery, which can support organisational and administrative tasks (Durth et al., 2023; Gezdur and Bhattacharjya, 2025). Natural language processing models can oversee customer inquiries and resolve issues autonomously through the implementation of chatbots (Durach and Gutierrez, 2024). Generative AI can thus enhance operational efficiency by aiding in decision-making processes related to demand forecasting, supplier integration, inventory management, and resource scheduling (Pfaff, 2023). For example, palletisation is a challenge faced by most 3PLs, extending beyond basic load balancing or route sequencing. Its pain points include stability (stacking items to prevent toppling or damage to items at the bottom) or layering (loading items considering the different customers to serve and their order in the delivery route). By evaluating millions of combinations, AI algorithms can suggest the best arrangement for each pallet, aligning pallet-building processes with shipping while minimising travel times and efforts (Cannas et al., 2024).

Lastly, AI-driven Automation involves using AI to support the automation of various logistics processes (Richey et al., 2023). Logistics automation usually entails adopting physical robots like Automated Guided Vehicles (AGVs) and Autonomous Mobile Robots (AMRs) (Benzidia et al., 2019). AGVs and AMRs are self-guided vehicles equipped with sensors and cameras, providing efficient material transport within logistics facilities (Moretti et al., 2019). Both AGVs and AMRs can retrieve products from their locations and deliver them to picking stations, helping improve picking efficiency (Rainer et al., 2025). AI can reinforce logistics automation and specifically warehousing operations overseen by 3PLs,

reducing errors and increasing throughput by optimising navigation and enhancing precision and adaptability (Grover and Ashraf, 2023). AI-driven Automation enables robots to communicate with other systems in real-time, and this interconnected ecosystem contributes to optimising logistics operations (Hendriksen, 2023). Given the rising shortage of qualified supply chain personnel (Flöthmann and Hoberg, 2017), including transport and warehousing operations (Klumpp, 2017; Phares and Baltrop, 2022), AI could also help solve labour shortages (Rainer et al., 2025). However, the broader impact of AI on labour demand is under discussion as it might lead to job displacement (Chen et al., 2020). To fully benefit from the adoption of the new technologies, 3PLs should cultivate an open-minded culture and embrace innovation processes to adapt to the changed scenarios (Cichosz et al., 2020; Baglio et al., 2025). Implementing AI not only concerns using the right technology but equally considering the people working alongside it (Richey et al., 2023; Guida et al., 2025). The continuous advancement in computing power and data availability eases AI adoption, allowing for efficient and robust human-AI collaboration through the flexible integration of AI into workflows (Jackson et al., 2024; Hendriksen, 2023). Organisations should equip their workforce with the necessary skills to leverage AI tools effectively, though such an undertaking is not a one-time training but the premise for a cultural shift towards continuous learning and upskilling (Jaiswal et al., 2022; Shrestha et al., 2019). Overall, companies need to understand the implications of AI integration in operational settings along with the importance of data management and organisational culture to drive AI maturity (Dhamija and Bag, 2020). This perspective aligns with the dynamic capabilities' theory, which is increasingly adopted by management scholars to describe and explain how firms respond to rapid technological and market changes (Helfat et al., 2007; Warner and Wager, 2019).

A Dynamic Capabilities perspective: digital transformation and AI development in logistics

Dynamic capabilities theory was introduced by Teece and Pisano (1994) to describe and explain firms' abilities to better adapt to dynamic environments.

Dynamic capabilities, which are underpinned by organisational routines and managerial skills, can be defined the firm's ability to integrate, build, and reconfigure internal competences to address changes in the business environment (Teece et al., 1997). For analytical purposes, dynamic capabilities can be disaggregated into the capacity to sense and shape opportunities and threats, to seize opportunities, and to reconfigure the business enterprise's intangible and tangible assets to maintain competitiveness (Teece, 2007). Sensing capabilities usually concern scanning, learning, and interpreting new opportunities – including focusing on understanding customer needs and latent demands by continuously exploring available technologies (Schilke et al., 2018). Seizing capabilities relate to the ability to capture the sensed opportunities or neutralise the emerging threats, thus focusing on the implementation of those opportunities by mobilising internal and external resources (Kähkönen et al. 2023). Reconfiguring capabilities then encompass the alignment and realignment of the firms' assets (including technological and human capital) so that firms can renew and ensure their resources are in line with the detected changes and sensed opportunities (Helfat et al., 2007; Schilke et al., 2018).

While Teece et al. (1997) initially identified three dynamic capabilities, Teece (2007) later elaborated on the microfoundations of these "higher-order" capabilities. The microfoundations of dynamic capabilities are defined as "the distinct skills, processes, procedures, organisational structures, decision rules, and disciplines – which undergird enterprise-level sensing, seizing, and reconfiguring capacities" (Teece, 2007, p. 1319). In a nutshell, microfoundations can be interpreted as the actions that underpin and shape higher-order dynamic capabilities and firm performance (Eisenhardt et al., 2010; Schilke et al., 2018). Recently, scholars have investigated microfoundations related to building dynamic capabilities for digital transformation (Wagner and Wager, 2019; Herold et al., 2024), identifying nine microfoundations for digital procurement (Wagner and Kurpjuweit, 2024). Sensing capability can build on microfoundations like "digital scouting" (based on scanning for technological trends or sensing customer-centric trends) and "digital mindset crafting", while seizing capability leverages piloting or "rapid prototyping" and "balancing digital portfolios", i.e.,

assessing internal and external solutions to set an appropriate speed of execution (Wagner and Wager, 2019). Reconfiguring capability relates to transformation and thus builds on “redesigning internal structures” and “improving digital maturity”, including workforce development and strengthening digital knowledge within the firm (Herold et al., 2024).

In the logistics industry, the dynamic capabilities’ theory is increasingly adopted to explain and predict how firms confront technological advancements and evolving customer demands (Dovbischuk, 2021; Sandberg, 2021; Li et al., 2024). However, the microfoundations of dynamic capabilities are still a nascent concept (Wagner and Kurpjuweit, 2024). Few studies investigated the microfoundations of dynamic capabilities in logistics (e.g., Eriksson et al., 2022), suggesting the importance of building loyalty and commitment through managerial knowledge and presence (Sandberg and Abrahamsson, 2011), the criticality of external partnerships to access knowledge (Sandberg, 2021), and the need of a learning orientation across organisations (Defee and Fugate, 2010). For 3PLs, AI offers significant potential to enhance their business operations through improving forecasting, route optimisation, and processes automation (Richey et al., 2023; Toorajipour et al., 2021). However, successful AI adoption requires specific capabilities and competences (Jackson et al., 2024), including human and digital resources to create a firm culture which embraces AI and is coupled with a customer-centric perspective that consistently scrutinises the value delivered to prospective clients (Cichosz et al., 2020). Given the limited available literature, phenomena like AI adoption into logistics operations by 3PLs require a deeper understanding of the needed higher-order capabilities as well as the underlying microfoundations, as recently acknowledged by Wagner and Kurpjuweit (2024) who explicitly encouraged supply chain scholars to articulate, explore, and/or develop the microfoundations of dynamic capabilities.

Methodology

Research Design

This study aims to explore how 3PLs can approach AI-driven opportunities and successfully navigate AI adoption. Given the scarcity of empirical studies

illustrating the real-world implementation of AI by supply chain managers and enterprises (Moretto et al., 2024) – including 3PLs – we designed a single case study to investigate this contemporary phenomenon and its challenges (Ketokivi and Choi, 2014) and capture in-depth insights about our unit of analysis, i.e., "AI-related projects developed by 3PLs". Although a single case design could reduce transferability, our case can be interpreted as revelatory (Tight, 2022) as it offered the opportunity to collect rich insights and investigate this underexplored phenomenon in practice (Stake, 2008). Despite the hype around AI adoption in logistics (Richey et al., 2023; Jackson et al., 2024), very few companies have experimented with AI, including 3PLs (Baglio et al., 2025). Our exploratory single case allowed us to uncover new understandings about this nascent phenomenon and its topical real-life challenge (Flyvbjerg, 2006). We could focus on a unique setting to gather rich and detailed data, leading to deep insights concerning both practical implications and possible theoretical developments (Dyer and Wilkins, 1991; Voss et al., 2002). To this end, we leveraged the dynamic capabilities theory as it expounds the foundation of enterprise-level competitive advantage in regimes of rapid (technological) change (Teece, 2007). Recent studies adopted this theory to examine recent AI advancements within the procurement field (e.g., Guida et al., 2023; Spreitzenbarth et al., 2024), with several scholars highlighting its appropriateness for investigating digital transformation (Herold et al., 2024; Li et al., 2024). As 3PLs experience the tumultuous development of AI types around them, their ability to sense, seize, and reconfigure their processes and resources becomes crucial to effectively harness AI.

The case company is a British 3PL provider representing a rare example of an organisation concretely involved in developing and implementing AI solutions, as shown by the creation of a structured open innovation programme including an Innovation Centre to trial AI solutions. It has introduced AI to improve processes and activities related to warehousing and logistics planning, launching various projects focusing on labour forecasting, labour scheduling, last-mile delivery vehicle selection, and network optimisation. The case offered unique potential to explore AI adoption by 3PLs since it allowed to examine in detail the current business landscape and understand how to enhance value for customers. The

implementation of the aforementioned projects allowed to investigate in practice the ongoing transformations, even if the company is at the beginning of its long-term AI journey. However, this potential drawback disclosed other opportunities not only to examine the current state of AI adoption but also to discuss the potential for future development.

We bridged empirical findings with extant knowledge and leveraged abductive reasoning to match empirics with theory through “systematic combining” (Dubois and Gadde, 2002). Abductive reasoning focuses on looking for suitable theories for empirical observation, resting on the cultivation of surprising empirical findings against the extant theory (Kovács and Spens, 2005; Timmermans and Tavory, 2012). First, we reviewed the available academic knowledge to develop a broader view of AI strategic opportunities and adoption within and beyond the 3PL industry. Supply chain magazines and other secondary sources were also analysed to contextualise the academic insights within the practitioners’ perspective, strengthening the study’s practical relevance (Stentoft and Rajkumar, 2018). Next, in-depth empirical insights were collected, analysed, and systematically combined with the existing literature, including the dynamic capabilities theory. As observed in Figure 1, through systematic combining we followed “a non-linear, path-dependent process of combining efforts with the ultimate objective of matching theory and reality” (Dubois and Gadde, 2014; p. 1279), matching empirical findings with prior theoretical constructs (e.g., micro-foundations) and developing them “through a mixture of established theoretical models and new concepts derived from the confrontation with reality” (Dubois and Gadde, 2002; p. 559). Dashed lines in Figure 1 illustrate how abductive reasoning involved bouncing back-and-forth between academic knowledge and empirics (Timmermans and Tavory, 2012). Further details are provided when illustrating data analysis processes.

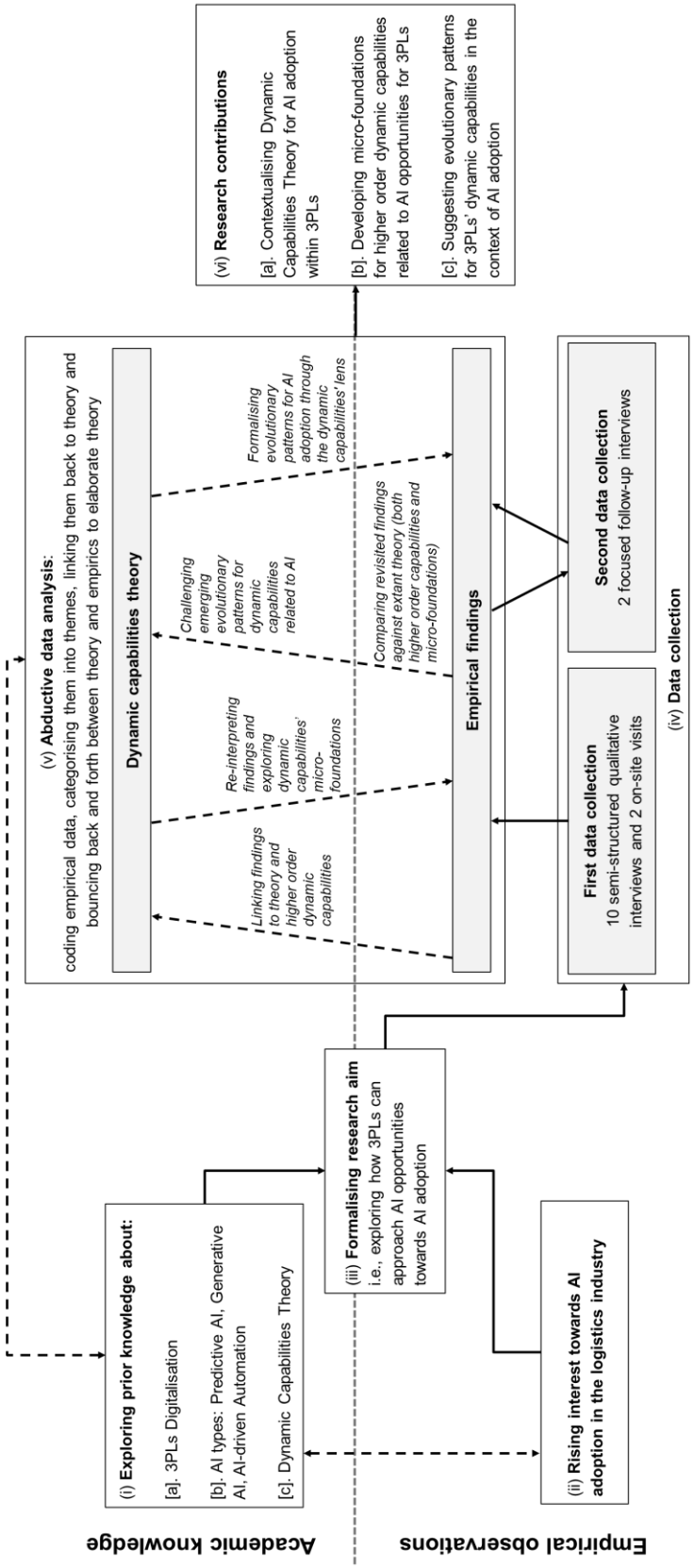

Figure 1. Abductive research framework. Source: authors' own elaboration, adapted from Kovács and Spens (2005).

Data Collection

Data was collected through two rounds of semi-structured interviews and two on-site visits at one of the company's primary distribution centres, where the Innovation Centre is also located. Semi-structured interviews allowed for inquiring broad, open-ended questions to stimulate conversation and then continued with more specific questions to explore specific issues that emerged during the interview (Yin, 2014). By adopting a semi-structured approach, we could ask additional questions triggered by the answers of the respondents (Miles and Huberman, 1994). We then integrated semi-structured interviews with on-site visits because field-based observations offer a deeper understanding of logistics research problems, enhancing theory elaboration and the advancement of managerial practice (DeHoratius and Rabinovich, 2011; Stank et al., 2024).

The first round of semi-structured interviews took place between April 2024 and June 2024, involving ten senior management stakeholders carefully selected based on their potential to provide details about the investigated unit of analysis. In more detail, interviewees stood for all senior stakeholders that would be decision makers or influencers in AI adoption, being Executive Board Members, part of the Senior Leadership Group, or Head of Departments. On-site visits took place in May and July 2024, adding contextual understanding and first-hand insights into the company's technological landscape and operational processes. Lastly, the second round of semi-structured interviews took place in February 2025 to follow up on the study's preliminary findings and elaborate our contextualised emerging knowledge. To this end, we interviewed again the two company's stakeholders who are mostly involved with innovation and AI developments but also had higher familiarity with the academic environment and could enhance theoretical elaboration. Table II illustrates the details about the interviewed stakeholders, including their job role, years of relevant experience, and their relevance to the research.

Job role	Years of Work Ex	Relevance to Research
Chief Innovation Officer**	33	Provided in-depth insights on customer-led requirements, such as AI, employee skill set requirements, and organisational structure and business strategy changes.
Product Director–Technology*	18	Shared insights on the future of the company's technology strategy, with AI use cases and the need for innovation.
Head of Innovation**	26	Offered in-depth overview of the company's customers, the Innovation Labs initiative, current AI initiatives and future aspirations concerning AI.
Head of Data*	12	Provided insights on data management, preparing for an AI future, and skill training requirements.
Head of Robotics Solutions*	16	Provided insights on current automation efforts, future aspirations, and potential use cases within warehouses.
Product Development and Innovation Manager*	4	Led the two on-site visits and provided insights on potential use cases of AI.
Head of Technology Solutions*	22	Discussed potential AI use cases related to technology solutions, procurement and operations while understanding current capabilities and capacity.
Procurement Manager – IT*	12	
Operational Excellence Director*	25	
Strategy Manager*	35	Discussed the company's strategy concerning innovation, competitor analysis and attitude towards AI.

Table II. Interviewed stakeholders overview (*Note: * for stakeholders involved in the first round of data collection; ** for stakeholders involved in both rounds*). Source: authors' own elaboration.

Semi-structured interviews occurred either in person or online through Microsoft Teams. The interview questionnaire (available in Appendix A) was divided into three sub-sections. The first section included a set of general questions for all the interviewees, exploring how AI is transforming the 3PL industry, the high-level AI challenges and opportunities, and the impact of AI on workforce skills. The second section held department-specific questions tailored for each interviewee, focusing on individual roles and responsibilities in technology initiatives, the

opportunities AI presents for business strategy and within single departments, employee skills and training, and challenges related to AI implementation. The last section focused on the current AI initiatives, invariant among all the interviewees. In the second interview round, we first discussed the empirical findings concerning AI adoption and implementation, then built on them to introduce more theoretical constructs and ask for further details about the emerging micro-foundations for higher-order dynamic capabilities.

Each interview lasted 45 to 60 minutes. Interviewees were provided with consent forms before the interview and were ensured that their information would be confidential and anonymous (Voss et al., 2002). To strengthen internal and construct validity, all the interviews were recorded and transcribed verbatim to ensure accuracy, and transcripts were condensed and returned to our interviewees for fact-checking and accuracy verification. By writing up memos after each interview, it was also possible to "look for recurring phrases or common threads in informants' accounts" (Miles and Huberman, 1994; p.70). All the interviewees were available to answer questions or provide further contextual elements needed for our analysis. Primary data collected through semi-structured interviews were triangulated with academic literature and grey literature in the form of reports from Gartner and other global firms, which provided additional insights into the current state of AI applications in logistics and supply chain management. Furthermore, observations from two visits of the Innovation Centre and the primary distribution centre offered on-field insights about the technologies currently adopted, providing a source of original disciplinary knowledge (Stank et al., 2024). We observed the impact of AI adoption on warehousing operations (e.g., goods receiving, picking, packing, labelling) as well as back-end activities, with observations contributing to strengthening understanding (Goldsby and Zinn, 2018). Notes from the visit were also taken down manually to capture details of the various stimuli.

Data Analysis

Coding procedures followed the approach suggested by Gioia et al. (2013) to move from 1st order concepts (centred on the informants' perspectives) to 2nd

order themes and then aggregate dimensions, more abstract and closer to theoretical arguments. To familiarise and clean the data collected from the semi-structured interviews and site visits, each transcript was read thoroughly, followed by familiarisation of the data to take notes and jot down early impressions from each interview (Voss et al., 2002). As illustrated in Figure 2, data analysis was characterised by a structured progression from empirically driven codes (1st order concepts) to more conceptual categories (2nd order themes). 2nd order themes were then further abstracted to overarching themes (aggregate dimensions) explicitly linked to the extant theory and its higher-order dynamic capabilities (sensing, seizing, reconfiguring), enabling an iterative process where empirics and theory inform each other (Kovács and Spens, 2005; Prataviera and Norrman, 2024).

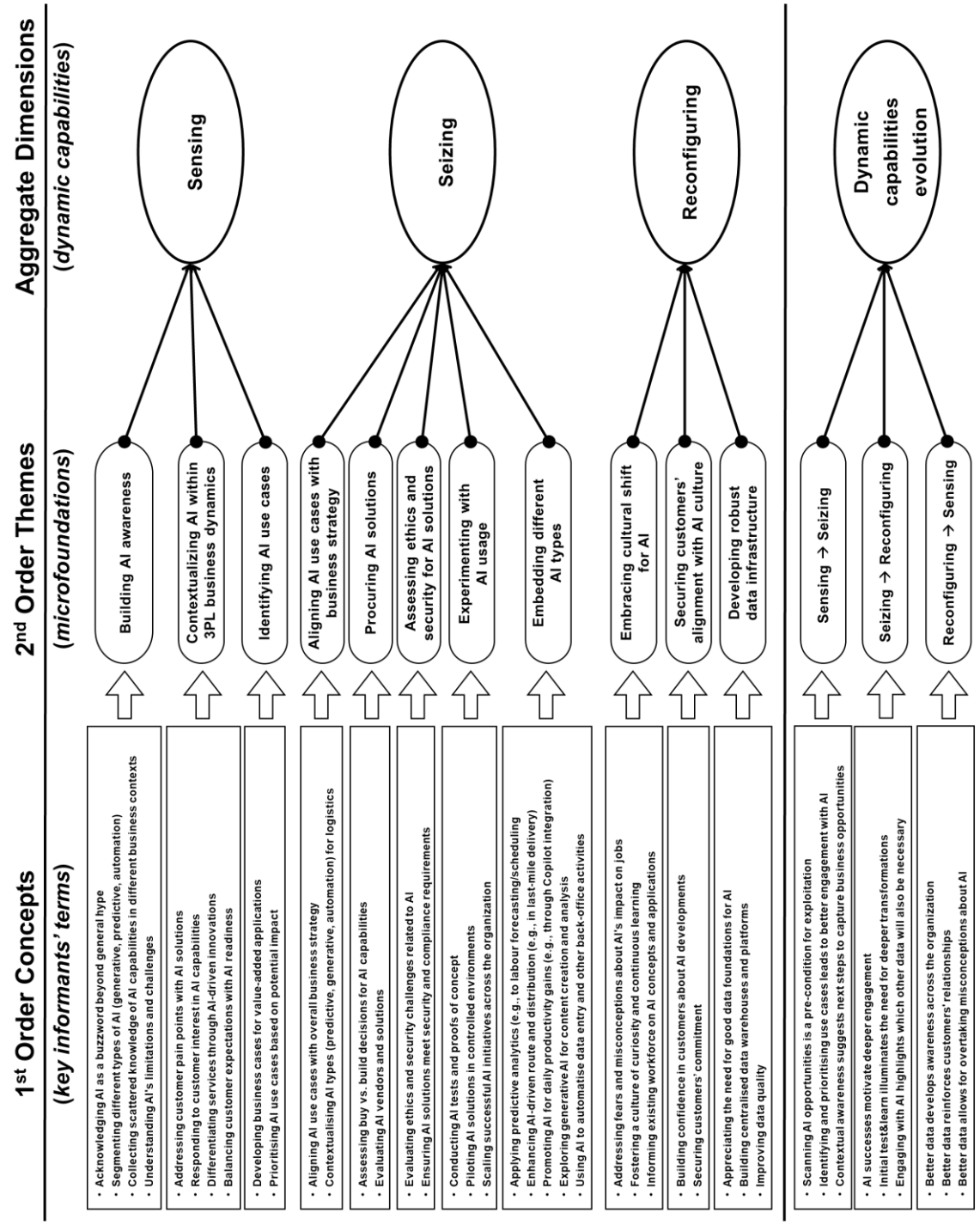

Figure 2. Data structure. Source: authors' own elaboration, based on Gioia et al. (2013).

Abductive reasoning suggests that researchers should enter the field with the deepest and broadest theoretical base and develop their theoretical repertoires throughout the research process (Timmermans and Tavory, 2012). Accordingly,

data analysis began by manually examining transcripts to identify key phrases, codes, and ideas related to AI-related projects developed by 3PLs. 1st order codes were inductively determined from interviewees' perceptions and insights, and were later compared for pattern matching and grouped into broader 2nd order themes (as illustrated in Appendix C). For example, a 2nd order theme named "AI Awareness" emerged by abstracting 1st order concepts such as "Acknowledging AI as a buzzword beyond general hype" and "Understanding AI's limitations and challenges". As another example, observations about AI testing at the Innovation Centre were grouped into the 2nd order theme of "Experimenting with AI usage", while 1st order concepts concerning specific AI tools led to formalising "Embedding different AI types" as a 2nd order theme. The level of detail within the transcripts helped organise data into more conceptual categories, and 2nd order themes were further consolidated into aggregate dimensions to capture the essence of higher-order dynamic capabilities. For example, "3PL business dynamics" emerged as an important 2nd order theme, reflecting the 3PLs' specific business environment and the importance of liaising effectively with customers. We considered which aggregate dimension could best fit this 2nd order theme, and "Sensing" was chosen because it most accurately reflects how customers influence AI decisions as customer dynamics have a sizeable influence on identifying new business opportunities for 3PLs. Overall, three aggregate dimensions were formalised, following the established literature on dynamic capabilities (e.g., Teece et al., 1997) for theory matching (Dubois and Gadde, 2002).

However, when formalising 2nd order themes and linking findings to higher-order dynamic capabilities, we started reinterpreting our findings while also considering microfoundations as offered by the extant literature (e.g., Herold et al., 2024). Systematic combining requires researchers to "constantly going back and forth […] between empirical observations and theory" (Dubois and Gadde, 2002, p. 555), and we compared our findings with the extant theory (both higher-order capabilities and microfoundations). Accordingly, we elaborated 2nd order themes as they progressively emerged as microfoundations for higher-order capabilities. For example, "AI awareness" became "Building AI Awareness" while "3PL business dynamics" evolved into "Contextualising AI within 3PL business

dynamics". We also compared emerging microfoundations against those already offered by previous studies (e.g., Wagner and Wager, 2019). Nevertheless, those studies focused on digital procurement, while our focus on 3PLs allowed for theoretical elaboration through formalising contextualised microfoundations. For example, we formalised "Contextualising AI within 3PL business dynamics" as a development of "digital scouting" (relating to scanning technological and customer-centric trends) (Herold et al., 2024) to acknowledge the need for 3PLs to match any AI initiative with specific customers' requirements.

Moreover, during data analysis, additional insights emerged concerning the potential evolution of dynamic capabilities through AI adoption. We identified 1st order concepts describing how scanning AI opportunities is a pre-condition for exploitation, or how initial tests prompted the need for deeper transformations. We then formalised additional 2nd order themes suggesting interdependencies among higher-order dynamic capabilities. As these interdependencies were not entirely novel (see e.g., Herold et al., 2024), we combined our empirical data and their analysis (which also detailed the implementation and evolution of the ongoing projects - as provided in the Findings subsection "Seizing") with recent academic literature about AI capabilities in logistics and supply chain management (Richey et al., 2023; Jackson et al., 2024). Since we are still at the dawn of AI in logistics (Rainer et al., 2025), we also borrowed knowledge from close research domains focusing on AI maturity (e.g., Sonntag et al., 2024), which represents the level of development and sophistication in an organisation's utilisation of AI tools and capabilities (Chen et al., 2021). This approach stimulated a fruitful cross-fertilisation, where new combinations were developed through a mixture of established theoretical models and new concepts derived from the confrontation with reality (Dubois and Gadde, 2002). For example, Richey et al. (2023; p. 533) suggested three critical dimensions to describe AI business applications: contextual knowledge, degree of human intervention, and data availability. We merged these dimensions with the insights resulting from our empirical analysis, formalising potential evolutionary patterns of dynamic capabilities driven by AI adoption (Figure 4) and formulating a set of research questions prompting a future research agenda (Table III).

Findings

Sensing

The case company views AI as a transformative technology in logistics, yet AI adoption is a long-term process rather than an easy "quick win". As the Head of Innovation explained, *"AI is not something we wanted to jump in and invest much money in, but equally, it is something we feel the need to test the water off."* The importance of AI innovation is driven by the commitment at the Executive Board level, as noted by the Product Director–Technology*: "AI is a buzzword, our board's talking about it, our executive board is talking about it. Our leaders are aware they need to take risks, otherwise who will be innovating at the bottom of the chain?"* With this commitment, the company set out to assess AI awareness and explore AI's potential by focusing on defining what AI capabilities meant to the 3PL business. As noted by the Head of Innovation: *"we segmented AI for our purpose into generative, which is obvious; predictive (decisions for the future); and automation (e.g., robotics mimicking human behaviour)."*

If building AI awareness is critical to fostering innovation, our case showed that involving customers is extremely important for 3PLs and raised the criticality of the business dynamics between 3PLs and their customers. As illustrated by the Head of Innovation, *"3PLs' commercial structure is unique in logistics. Unlike in-house logistics, we are a fragmented business of contracts for various customers. Without contracts, we have no business*." The company owns only about 40% of its entire truck fleet and an even smaller percentage of its distribution warehouses, heavily relying on its customers' commitment**.** Interviews revealed that customers are deeply involved in the company's business, directly influencing AI adoption, as multiple stakeholders highlighted that customer interest is a critical driver to motivate AI exploration. The Chief Innovation Officer highlighted that *"we're excited about AI because our customers are excited. And everything we need to do has to be of value to customers. So even if it's something in our back office, it will only be done if it adds value to customers."* However, there is a gap between customer expectations and their understanding of AI applications. The Chief Innovation Officer also reported that "*customers are asking for solutions to their problems, including those that might be underpinned*

by AI innovations. However, even when our customers want us to use AI, they don't know what they want us to do with it." As explained by the Strategy Manager, "*we should ask the correct question: not how could we use AI, but rather what problems do we think AI can help us with*." This also involves customers having a say in the Innovation Centre selection criteria to test specific technologies, while senior executives talk with major customers to inquire about the AI tools they may be implementing. The Chief Innovation Officer highlighted that they "*encouraged our Product Director–Technology to directly connect with his counterparts. We need our customers to share examples of what they are doing with AI, and us to openly share with them what we're doing with AI."* As the Product Director — Technology mentioned, "*innovation is hard without knowing what we are trying to solve; that starts with defining use cases so that we avoid the hype."* Upon scanning AI opportunities, identifying and prioritising use cases leads to better engagement with AI. As explained by the Chief Innovation Officer, "*AI will be a significant piece of business analytics for 3PLs. Initial use cases can focus first on efficiency improvements for low-hanging fruit like back office administrative functions and warehouse operations. We're doing a lot, but the question becomes: are we doing enough?"* Based on the use cases identified, business cases are prioritised as initiatives require a strong return on investment (ROI), usually within 3–5 years, by providing demonstrable productivity gains. As the Strategy Manager mentioned, *"we look at business case options, and then if there's something that has massive productivity gains, and we can look at the strong return on investment within five years, then that gets built into the strategy."*

Seizing

The Chief Innovation Officer highlighted how any technological innovation must align with the broader 3PL business strategy: *"any technology, including AI, can enable and add value for our customers, yet must build on our three key business components: our people, trucking and warehousing expertise."* This observation reflects the importance of addressing customers' needs and requirements, as stated by the Head of Innovation: "*we pick themes aligned to our strategy and*

customer pain points; otherwise, they're pointless." Accordingly, the company needs to contextualise how different AI types could help capture emerging business opportunities. As reported by the Head of Technology Solutions, they *“are in the test-and-learn phase […]; we have thoughts on where we think it will bring value in terms of generative AI, predictive AI, etc. But we're not fully committed to any AI type or product now.”* Moreover, the company runs an AI solution enabler programme. This internal initiative asks employees to showcase their innovative ideas to help solve selected use cases. However, the company favours procuring off-the-shelf AI solutions products over developing solutions internally from scratch. Given ethical concerns about AI adoption, an Assurance Quality Service Cost and Innovation (AQSCI) checklist was developed to be used both internally and when assessing external AI suppliers. These ethical considerations are critical to ensure that vendors offering AI solutions have appropriate ethical policies. The Procurement Manager illustrated the company’s approach by stating *"if we're looking at a solution for a business case that might have AI, then we ask specific questions about whether they've got an ethical AI policy and how they're using AI. If they don’t satisfy our checklist, we look somewhere else.”*

To experiment with AI, the company created its Innovation Centre. It hosts events to present business use cases, also inviting startups to propose their solutions. As explained by the Product Director–Technology, “*we started with some business use cases and passed them to several vendors who were well known to us, then we tried to understand their solutions' value through a 10-week trial period.”* In 2023, the Innovation Centre involved startups to kick off projects related to four business cases (i.e., labour forecasting, labour scheduling, last-mile delivery vehicle selection, and network optimisation) which leveraged different AI types and illustrated how these can contribute to addressing specific logistics challenges.

Concerning AI Predictive Analytics, a top challenge for 3PLs is labour shortage. Therefore, one of the most pressing business opportunities concerns labour scheduling, to better cater to customer needs and address shift inefficiencies. As explained by the Operational Excellence Director, *“we run 6 to 2, 2 to 10, 10 to 6*

shifts, losing time and productivity […] and underscoring the need for AI-driven scheduling." Delivery and inventory management are also crucial to enhance delivery and stock accuracy. The company is analysing how AI algorithms could feed its daily delivery schedule and optimise delivery routes, saving fuel and ensuring on-time deliveries for both primary distribution and last-mile delivery. However, the first tests were not satisfactory, as highlighted by the Product Development and Innovation Manager: "*we did a pilot for last-mile optimisation, which gave us our first kind of experience of seeing what AI could do for us, but it wasn't scalable, and we are back to square one*."

Regarding Generative AI, the company arranged 30 Microsoft Copilot licences to test its use across different departments for generating text, suggesting edits, analysing data and documents, creating presentations, and managing emails. Some departments have massively benefited from Copilot while others are unaware or haven't found personal use (detailed accounts of use cases related to Copilot usage or non-usage across departments are offered in Appendix B). This reflects the company's approach towards "finding the right hands" for the limited resources (in this case, the number of licences) it has. As explained by the Head of Innovation, *"we have to logically determine suitable roles to justify a licence, knowing it will pay back."* Beyond Copilot, the company is testing a chatbot assistant that helps generate meeting ideas, including strategies, standard operating procedures, and creative content. The company is also exploring Generative AI tools for recruitment purposes, as these algorithms handle skill assessments, providing candidates with real-time warehouse scenarios to assess their readiness for the job. Furthermore, the company considered AI-enabled contract review tools for the procurement team. However, limited scope and high licensing cost did not justify the company-wide investment. As highlighted by the Procurement Manager – IT, "*we recently had a demo of a great solution, though it was quite expensive. We have got to weigh up the value they deliver, and while some of our complex contracts would require the legal expertise to negotiate it, the use case of the solution wasn't company-wide."*

Lastly, the company has introduced robotics to support automation. AI offers significant opportunities to improve warehouse operations' synchronisation, and

the Head of Technology Solutions acknowledged that *“the orchestration of multiple robotic technologies will increasingly need to use AI capabilities.”* This was reinforced by the Strategy Manager, who highlighted the potential for AI-driven computer vision: *"we could use AI to visualise pallets, check positioning, detect missing items, and send notifications. This would help rectify issues, predict occurrences, and maximise customer value.”* AI software can guide AMRs to streamline picking routes with minimal human intervention. Nevertheless, AI-driven Automation is not limited to physical operations but extends to back-office activities. The company already uses AI to improve activities like work allocation to employees or subcontractors, payment processing, and invoice matching. As highlighted by the Head of Innovation, “*positive AI effects not only concern robots lifting heavy boxes. AI is great for back-office, reducing 3Ds (dull, dusty, dangerous) activities like data entry or matching numbers*.”

Reconfiguring

Our interviews highlighted how AI successes motivate deeper engagement, suggesting a need for successive transformations. As reported by the Strategy Manager, “*measurable wins, like faster responses and higher optimisation, help organisations like ours build the case for wider adoption.”* However, 3PLs’ AI adoption comes with its own set of challenges, and engaging with AI highlights the need to collect higher-quality, richer data. One primary concern is data integration, due to multiple contracts and different legacy systems. As the Head of Technology Solutions explained, *“we have got old and legacy systems cobbled together over time. We must figure out how our staff can fix that mess.”* This illustrates two critical areas: the need for a cultural shift concerning AI adoption, and the importance of a robust data infrastructure to support it.

Backed by the commitment at the executive level, an open and inclusive culture towards AI is promoted through training and beyond. As explained by the Head of Data, *“the technology piece is the easy bit; the people and the culture bit are the hard bit*.” There are often misconceptions about AI’s impact on jobs, and one key aspect is the eagerness to change, fostering a culture of curiosity and continuous learning. As emphasised by the Operational Excellence Director,

“there is real fear around technology. Some people struggle with basic tablets. But motivation and investment from higher-ups have encouraged a positive direction to overcome this fear.” Skills development is a crucial aspect of the company’s approach, along with cross-functional exposure and the creation of mutual trust across different organisational levels. The Head of Data shared a revelatory example of this approach, highlighting how they *"encourage my team to attend Innovation Centre presentations with me because they are the ones working on these technologies; they need to have the best front seat view of what’s going well and what can be improved through what these vendors offer. That’s powerful exposure.”*

Nevertheless, alongside the company embracing a cultural shift to incorporate AI, our interviewees also highlighted that securing customers’ alignment with this evolving culture is equally crucial. The Product Development and Innovation Manager pointed out that “*3PLs’ business is highly competitive, and we must build confidence in customers about our AI developments to secure their commitment.”* This was reinforced by the Head of Innovation, who stressed that “*we have no data, all depends on our customers as we are executing their operations, and we need to seek their permission*.” Many interviewees stressed the importance of data integrity, highlighting the need for a consistent and robust data infrastructure. However, the 3PL industry is contract-driven, and customers’ commitment is mandatory to support further AI investments. As explained by the Chief Innovation Officer, “*before developing our data infrastructure we must ensure our customers understand and agree with our pathways*.”

Today, data readiness is critical and high-quality centralised data is crucial for AI implementation. As the Head of Data stated, *“the key to success is having the right data. You can't even start talking about AI if you haven't got the data sorted in the planning phase."* Interviews revealed the company’s strong focus on data availability and accessibility. Currently, the urgency of centralising data to foster AI is widely recognised across the organisation**,** and efforts towards data centralisation are led by the executive level. Nevertheless, a single standardised approach looks unfeasible. As highlighted by the Head of Technology Solutions, *“different customers have different characteristics and different requirements*.” To

ensure data quality and integrity as AI adoption ramps up, the company arranges weekly data quality forums to iron out data issues. As explained by the Operational Excellence Director, *"we hold weekly data quality forums, with technical and operational teams in the same call to set data model rules. Data owners and stewards manage this process."* However, as data's importance for AI grows, the company's current plans include building a centre of excellence for common themes across different departments and businesses (i.e., different customers). As highlighted by the Head of Data, *"we're implementing a hybrid model, with centralised capabilities for strategic needs and standardised reporting to meet 80% of business requirements. Local users – our customer contracts – handle the remaining 20% for site-specific needs. We're developing a data and reporting centre of excellence to support this, ensuring consistency while allowing flexibility for individual contracts."* Better and stronger data contribute to reinforcing customer relationships and to developing awareness across the organisation, helping to overcome misconceptions about AI. As highlighted by the Head of Innovation, "*better data can tell sophisticated stories, making new opportunities emerge and leading to higher awareness of what could be done next. In leveraging data to gain insight into organisations, leaders often fall prey to misconceived answers. These misconceptions can obscure the bigger picture, overlooking opportunities to improve flawed processes. As 3PL leaders, we must go beyond such misconceptions to build on the new knowledge that AI promotes*."

Discussion

Today, AI represents a powerful driver of transformation within the logistics industry (Durach and Gutierrez, 2024; Richey et al., 2023). However, 3PLs are struggling to keep pace with technological development, and very few have successfully adopted AI in logistics operations (Jackson et al., 2024; Baglio et al., 2025). We leveraged the dynamic capabilities theory (Teece et al., 1997) to explore how 3PLs can approach AI opportunities, as it highlights firms' abilities to face phenomena that are currently evolving like tumultuous technological

advancements and digital transformation (Warner and Wager, 2019; Herold et al., 2024). The theory emphasises the importance of adapting to changing environments responsively, purposefully, and efficiently by developing three higher-order capabilities: sensing, seizing, and reconfiguring (Helfat et al., 2007; Teece, 2018). It also argues that higher-order capabilities are based on microfoundations (Teece, 2007; Eisenhardt et al., 2010; Schilke et al., 2018), yet the formalisation of microfoundations of dynamic capabilities is still underdeveloped (Wagner and Kurpjuweit, 2024). Scholars have mainly focused on digital transformation in the context of digital procurement (Wagner and Wager, 2019; Herold et al., 2024), and few studies have explored dynamic capabilities' microfoundations in logistics (Eriksson et al., 2022).

We built on these contributions to elaborate the extant theory and identify micro-foundations supporting 3PLs amid rising digitalisation and AI adoption (Figure 3). We also identified a set of boundary conditions to contextualise how 3PLs can sense and seize AI opportunities, as well as reconfigure their resources. These boundary conditions delimit implications according to firms' resources (i.e., tangible or intangible assets at their disposal), organisational culture (i.e., organisational beliefs and principles) and organisational structure (i.e., how activities are orchestrated) (Schilke et al., 2018). Specifically, they concern the type of activities included within the logistics scope but also the peculiarities of the 3PLs' competitive environment (e.g., average contracts' duration and data sparsity) and the crucial commitment needed from 3PLs' customers, influencing multiple micro-foundations spanning different higher-order dynamic capabilities.

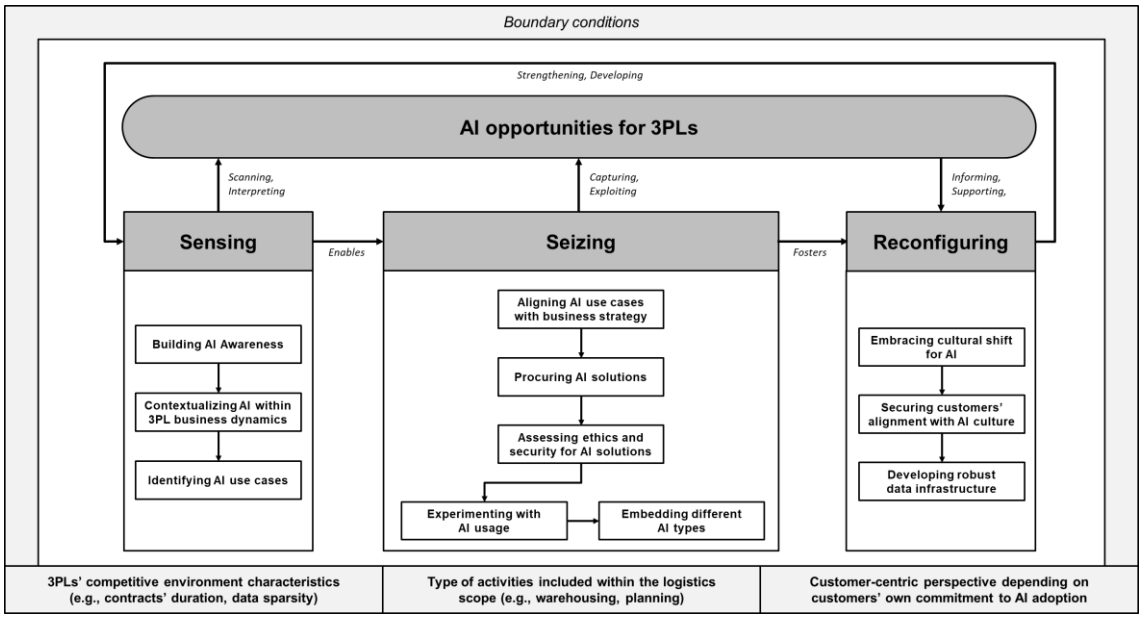

Figure 3. Higher-order dynamic capabilities and their micro-foundations in the context of AI adoption in the 3PL industry. Source: authors' own elaboration.

Conceptualising micro-foundations of 3PLs' dynamic capabilities related to AI

Findings suggest that sensing AI opportunities builds on the increasing awareness and commitment at the executive level, which sets the strategic goals shaping the company's business direction (including the orientation towards technologies like AI). 3PLs traditionally leveraged a functional use of technology, while AI offers broader perspectives than the implementation of Warehouse Management Systems or Transport Management Systems (Marchet et al., 2017). AI can enable market differentiation, but the fierce competition within the 3PL industry makes customers' involvement paramount to help 3PLs contextualise AI within their peculiar business dynamics. Our study elaborates on "digital scouting" (i.e., scanning technological and customer-centric trends) (Wagner and Wager, 2019; Herold et al., 2024) to acknowledge how 3PLs' commitment to AI needs to be matched with specific customers' requirements, also considering the contracts' duration to ensure the viability of the necessary investments. 3PLs execute highly heterogeneous services on behalf of multiple customers, all with bespoke requirements and different commercial models (Marchet et al., 2017).

AI can promote efficient and effective understanding between 3PLs and their clients, supporting the development of tailor-made 3PL services (Baglio et al., 2025). The commitment to a customer-centric approach can guide technological choices and strengthen customer relationships, potentially leading to extended contracts and bringing customers to accept innovative solutions. Identifying these opportunities then leads to developing business cases for value-added applications, prioritising AI use cases based on the potential impact (e.g., ROI). Accordingly, we formulate a first proposition:

P1: In business contexts characterized by fierce competition and limited contractual duration, sensing AI opportunities requires adequate executive awareness and significant customers' involvement.

Sensing AI opportunities directly enables seizing those opportunities related to distinct types of AI tools (i.e., Predictive Analytics, Generative AI, and AI-driven Automation). Executive decisions and customers' requirements inform the creation of business cases (like improving inefficient labour scheduling) aligned with the overall business strategy. 3PLs can shortlist and evaluate external suppliers offering AI tools, prioritising vendors who can offer proprietary software that enables effective integration with 3PLs' existing systems. Our findings suggest that a "buy" off-the-shelf procurement strategy for AI is currently more suitable than internal development, helping to reduce cost and avoid massive internal efforts to develop AI solutions. However, procuring AI solutions critically depends on assessing security and ethical implications – going beyond the assessment of internal or external solutions to set a proper speed of execution (Wagner and Wager, 2019). Testing and piloting AI solutions in controlled environments allow experimentation with AI, being akin to "rapid prototyping" (Herold et al., 2024) before embedding different AI types into business routines. Case findings illustrate the vast potential of AI Predictive Analytics to address labour shortages and enhance operational efficiency, in line with previous scholars (e.g., Richey et al., 2023; Mediavilla et al., 2022). Generative AI can be leveraged to enhance knowledge sharing and content creation (Durach and

Gutierrez, 2024), while robotics reflects the growing importance of AI-driven Automation (Rainer et al., 2025). Beyond robotics, findings also illustrate the potential for AI to automate “dull, dusty, and dangerous” activities like matching numbers or data entry within back-office operations, thereby reducing errors and improving efficiency. A second proposition follows:

P2: Seizing AI opportunities involves multiple AI types and spans from enhanced predictions to contents creation and back-office automation, yet success critically depends on the security and ethical implications of the procured solutions.

However, assets realignment is needed to ensure that firms’ resources are deployed following the detected changes and sensed opportunities (Kähkönen et al., 2023). Reconfiguring capability builds on “redesigning internal structures” and “improving digital maturity” (Herold et al., 2024), including workforce development. Resource reconfiguration often requires overcoming resistance to change (Schilke et al., 2018); in the context of AI adoption by 3PLs, it starts by acknowledging the fears and misconceptions about AI’s impact on jobs. An open and inclusive culture is required since AI's impact on labour can create huge friction due to job displacement and job elimination (Chen et al., 2020; Klumpp, 2017). The company's approach to training and cross-functional exposure aligns with fostering a culture of continuous learning to adapt to the evolving technological space. In this context, it becomes critical to engage with workers to discuss how technology adoption does not entail job-replacing consequences. Given the increasing labour shortages within the industry, AI could support the logistics workforce by handling routine and time-intensive tasks, allowing human workers to focus on complex and value-added activities. Instead of being a threat to people, AI becomes a contributor to enhanced job satisfaction, addressing labour shortages without reducing employment opportunities. Moreover, this open-minded culture is needed to embrace innovation processes and fully benefit from the adoption of new technologies (Baglio et al., 2025). We thus argue:

P3: Developing a learning-focused and inclusive culture towards AI is necessary to strengthen workers' engagement and foster technological and physical assets reconfiguration for AI adoption.

Although AI represents a transformative opportunity to build on existing systems and address complex logistics challenges (Hendriksen, 2023), a customer-centric perspective is needed to consistently scrutinise the value delivered to current and prospective clients (Cichosz et al., 2020). 3PLs handle logistics operations on behalf of their customers and must ensure customers' commitment to potential AI developments. Leveraging advanced tools has become essential for success in the industry (Jazairy et al., 2024) but 3PLs need to build customers' trust to protect their contracts and extract the maximum value from AI initiatives. Furthermore, securing customers' alignment with a renewed AI culture is instrumental in developing a robust data infrastructure that supports and promotes AI efforts. As stressed by the company's Head of Innovation, 3PLs must "*win the customers' commitment before any change in infrastructure*". Our findings highlight the importance of reconfiguring resources by investing in data infrastructure, fostering information sharing, and tightening links with customers (Zhou et al., 2023). Creating a centralised data infrastructure and establishing clear data governance policies are needed for both data quantity (amount) and quality (structured nature) (Richey et al., 2023). Better and stronger data contribute to reinforcing customer relationships and to developing awareness across the organisation, allowing for overcoming misconceptions about AI. This suggests the activation of a virtuous spiral, promoted by AI, towards dynamic capabilities' evolution:

P4: Securing customers' alignment with AI initiatives can sustain AI adoption over time through building robust data infrastructure, creating a virtuous AI-enabled learning cycle, yet it critically depends on customers' own commitment to AI adoption.

Research implications

3PLs find themselves amid an industry-wide digital transformation led by the adoption of AI tools, which can help improve process efficiency and extract new insights from data, adding significant value for customers. Given the lack of empirical studies guiding AI adoption (Moretto et al., 2024), we conducted a single case study with a leading British 3PL and leveraged the dynamic capabilities theory to explore how 3PLs can approach AI-driven opportunities and address the rising digitalisation in modern supply chains.

From an academic viewpoint, the study contextualises the theory to elaborate on the extant literature about rising digitalisation in supply chains (e.g., Wagner and Wager, 2019; Herold et al., 2024), formalising micro-foundations for higher-order dynamic capabilities in the context of AI adoption by 3PLs. The study also identifies boundary conditions for theory elaboration and offers a set of research propositions, emphasising the crucial influence of customer dynamics wherein any technological initiative for 3PLs, including AI adoption, is heavily impacted by customers' expectations and involvement.

Moreover, previous scholars have highlighted the need to carefully examine AI strategic and managerial implications within supply chain management (Handfield et al., 2019; Guida et al., 2023; Durach and Gutierrez, 2024). This study formalises AI implications for 3PLs and sketches a pathway for AI adoption, offering rich empirical insights into exploring the synergies among human workforce, technological tools, and physical assets. By focusing on 3PLs and deepening their business dynamics, we illustrate how they should prioritise purchasing off-the-shelf AI solutions rather than committing huge resources to internal development. 3PLs should cultivate strategic partnerships with AI vendors to maximise learning opportunities and increase effectiveness in operations, with particular interest towards labour forecasting and scheduling. Given the typical fragmented structure of customer contracts within the industry, prioritising the completion of a centralised data infrastructure and establishing clear data governance policies emerge as pivotal elements.

Research limitations

The reliance on a single case study design inherently limits external validity and transferability beyond a British 3PL at an early adoption stage. Nevertheless, our analysis discloses opportunities to conduct multiple case studies and generalise the study's findings to a wider population of logistics and supply chain contexts. Future work could involve other 3PLs (within and outside the UK) and investigate other types of organisations to explore the interplay among higher-order capabilities with rising AI adoption. Scholars could build further on the dynamic capabilities theory to elaborate on the microfoundations identified in this study and compare contextualised findings across different industries. Moreover, the dynamic and fast-evolving nature of AI presents another challenge. Specific findings, such as the current non-use of Generative AI's capabilities for demand forecasting, may become outdated quickly. Longitudinal studies could run a periodic readiness assessment of dynamic capabilities related to various applications in logistics (Durach and Gutierrez, 2024). Lastly, the study does not delve into the opportunities presented by integrating diverse types of AI, such as AI-driven Automation using historical data to feed AI Predictive Analytics tools (Jazairy et al., 2025). This gap presents another promising area for future research, to investigate the synergies and novel applications arising from such combinations within the context of 3PL businesses, including the relationships that might exist between individual dynamic capabilities and specific AI types.

Prompting future theoretical developments: a research agenda for 3PLs' AI-related dynamic capabilities

Previous studies have suggested that dynamic capabilities are linked to each other, with sensing capability enabling seizing capability, and this latter fostering resource reconfiguration (Wagner and Wager, 2019; Herold et al., 2024). This study contextualised the interplay among dynamic capabilities for 3PLs, confirming that scanning opportunities are a precondition for exploitation (Schilke et al., 2018). Identifying and prioritising use cases leads to better engagement with AI, while initial successes motivate deeper engagement (Herold et al., 2024). Experimenting with AI usage and its wider adoption (i.e., seizing) can reveal the

need for broader transformations, fostering resource reconfiguration. Developing a robust data infrastructure is instrumental in improving data quality, displaying high potential related to AI adoption (Jazairy et al., 2025). Better data not only helps improve logistics operations but also makes new opportunities emerge, strengthening sensing capabilities.

If dynamic capabilities reflect the ability to create, deploy, and protect the intangible assets supporting long-run business performance (Teece, 2007), our case suggests the existence of a virtuous spiral where dynamic capabilities allow for capturing AI opportunities but are also reinforced by AI adoption. AI adoption emerges as an evolving process that integrate multiple micro-foundations, shaped by boundary conditions such as resources, culture, structure, and customer commitment. 3PLs' success depends not only on technological readiness but also on relational, organizational, and cognitive factors. In Figure 4, we combined our empirics (whose boundaries are shown with a dotted red line) with prior conceptual work (Richey et al., 2023; Jackson et al., 2024) to envision this evolving process and formalise potential evolutionary patterns of dynamic capabilities driven by AI adoption. Given the limitations of our empirical analysis, in Table III we developed a set of exemplary research questions which pinpoint what remains unknown beyond this study, laying the foundation for a research agenda oriented at prompting further theoretical developments.

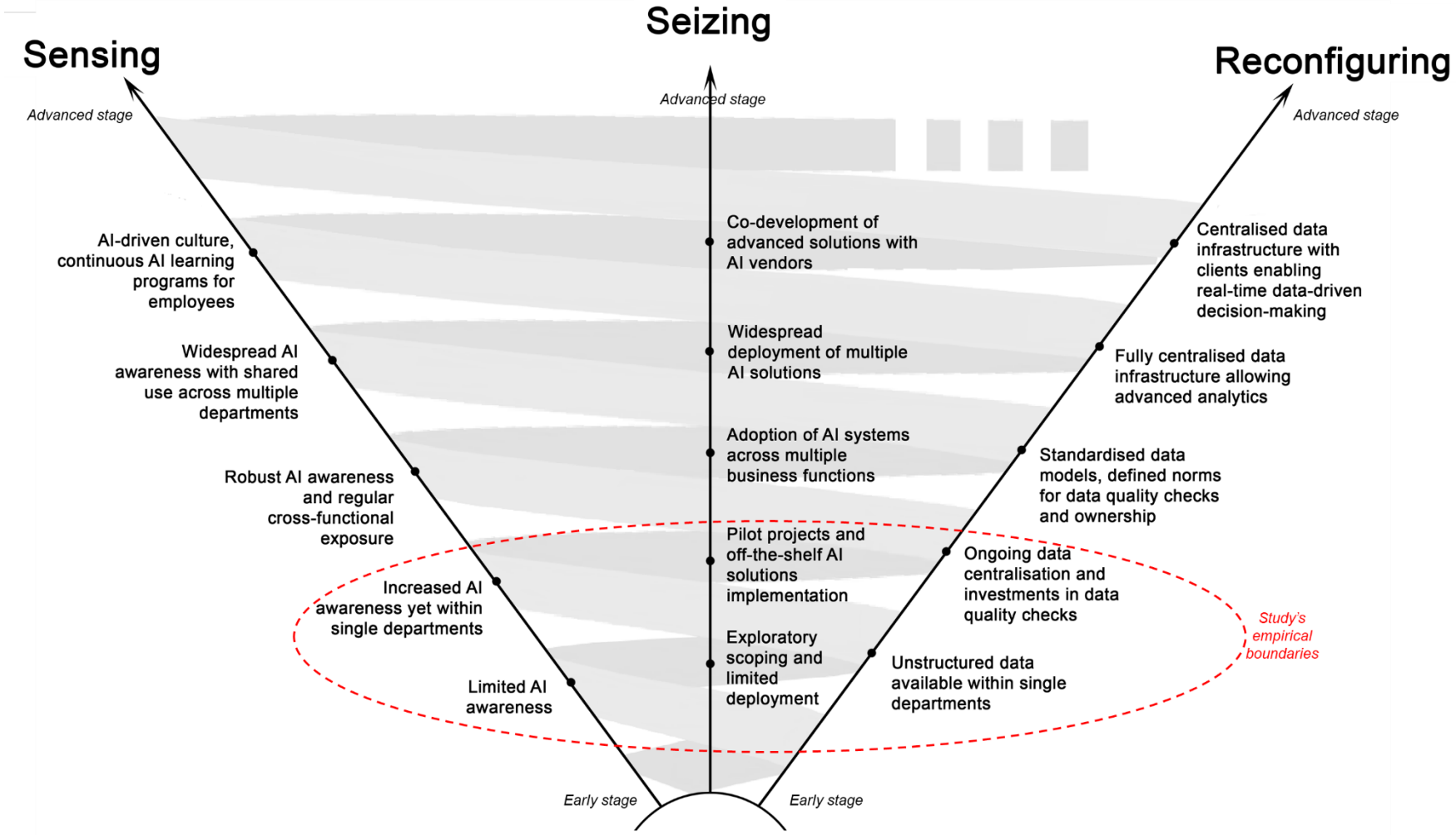

Figure 4. AI-driven evolutionary patterns for 3PLs' dynamic capabilities. Source: authors' own elaboration.

Dynamic capabilities	Future evolutionary patterns	Exemplary research questions
Sensing	Robust AI awareness and regular cross-functional exposure	*How to share AI competencies across multiple functions and logistics processes?*
		How to build cross-functional AI competencies within an evolving competitive environment?
	Widespread AI awareness with shared use across multiple departments	*How to ensure consistency in AI interpretation and understanding across multiple departments?*
		How to consolidate cross-functional AI knowledge that is transferable across multiple customers?
	AI-driven culture, continuous AI learning programs for employees	*How to maintain trust towards AI and overcome fears about technology replacing human work?*
		How to design AI continuous learning programmes balancing internal awareness and external commitment from customers?
Seizing	Adoption of AI systems across multiple business functions	*How to successfully integrate distinct AI solutions deployed by multiple vendors?*
		How to ensure AI interoperability and alignment across multiple functions?
	Widespread deployment of multiple AI solutions	*How to determine the best degree of human intervention for each logistics-related AI application?*
		How to leverage Generative AI tools to strengthen predictive and automation applications for logistics purposes?
	Co-development of advanced solutions with AI vendors	*How to set up governance structures with AI vendors to manage data availability, especially for advanced solutions?*
		How to strengthen advanced analytics applications by embedding human expertise from multiple stakeholders (employees, customers, AI vendors)?
Reconfiguring	Standardised data models, defined norms for data quality checks and ownership	*How to define standardised data models and norms across multiple stakeholders for different logistics activities?*
		How to contractually and legally govern commercially sensitive data?
	Fully centralised data infrastructure allowing advanced analytics	*How to coordinate investments in AI infrastructure from various stakeholders?*
		How to share benefits resulting from AI infrastructure developments?
	Centralised data infrastructure with clients enabling real-time data-driven decision-making	*How to promote customers' involvement to address insufficient data and information and foster AI adoption?*
		How to establish and maintain centralised data structures shared with customers?

Table III. Future research agenda. Source: authors' own elaboration.

Sensing development relates to how AI shapes the organisational culture and identity, including and beyond technological advancements (Jaiswal et al., 2022). 3PLs can start investigating AI opportunities without formal AI processes and with limited awareness, yet early AI applications can increase AI awareness and develop sensing within single departments and through regular cross-functional exposure to AI initiatives. In our case, the company aimed to embrace a workplace culture of innovation and openness towards AI. The case showcases remarkable efforts to identify AI potential, primarily at the executive level. However, executive awareness has not yet translated into AI competencies across the organisation. This reflects companies' struggles with building AI competencies across and beyond their organisations, often owing to hesitancy about technology replacing human work. Further opportunities thus exist to develop sensing due to widespread awareness built on specific solutions that are implemented across multiple departments and involving customers, aiming at an AI-driven culture where workers are both proactive actors and reactive recipients of AI evolution with continuous-learning programmes (Cannas et al., 2024).

If seizing corresponds to capturing the sensed opportunities (Teece, 2018), 3PLs can first pursue an exploratory scoping of AI types, usually through deployment in robotics and/or automation (Richey et al., 2023). This can be followed by pilot projects, characterised by the implementation of off-the-shelf AI solutions offered by external vendors. This aligns with our case, due to structures and initiatives developed by the company to support AI adoption (e.g., the Innovation Centre). However, seizing development could require the adoption of AI systems across multiple business functions, potentially encompassing a broader use of Generative AI (Gezdur and Bhattacharjya, 2025). A widespread deployment of AI solutions for logistics could then extend to predictive and automation applications, until becoming industry leaders able to build from scratch advanced AI tools co-developed with AI vendors (Sonntag et al., 2024).

Reconfiguring capability then needs to be developed to incorporate the successful identification and calibration of technological and market opportunities, the judicious selection of technologies and product attributes, and the commitment of financial resources to investment opportunities (Schilke et al.,

2018). When firms rely on unstructured data available across multiple systems within single departments, lacking data integrity and consistency, reconfiguring capability is limitedly developed (Sonntag et al., 2024). This capability evolves thanks to data centralisation efforts and investments in data quality checks, as illustrated in the case findings. Ongoing efforts in data centralisation to create a robust and consistent data repository stress the critical role of data in AI-driven logistics. However, firms should build standardised data models and establish norms for data quality checks, pursuing a fully centralised data structure that enables advanced analytics related to predictive and generative AI purposes. Ultimately, the reconfiguring capability will build on an AI-driven culture (cf. sensing) and solid vendor relationships (cf. seizing) and leverage the cultural shift to create a centralised data infrastructure shared with customers to enable real-time data-driven decision-making.

By systematically combining empirical findings with the extant theory and suggesting evolutionary patterns for dynamic capabilities, this study offers a pathway to sense and seize AI-driven opportunities and reconfigure resources to address rapid technological changes. By illustrating how dynamic capabilities could evolve through progressive AI adoption, we hope the could be viewed as an “opening-up exercise”, enabling researchers to critically interrogate the available literature and generate new ways of thinking.

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Appendix A – Interview Questionnaire

The primary purpose of this study is to explore how Artificial Intelligence (AI) can impact and transform third-party logistics service providers (3PLs). Please note that the interviews will be recorded and transcribed for research purposes. An informed consent form will be sent to guarantee confidentiality, trustworthiness, and transparency.

General questions for all interviewees

1. On a high level, how do you envision AI, particularly AI, which can help forecast demand and create content, transforming the 3PL space over the next five years?
2. What are the most significant challenges and opportunities in adopting AI?
3. How do you see the inclusion of AI in business operations impacting the skills and capabilities required of your workforce? Are there any strategies you think are essential for training employees for these new technologies?

Specific questions for individual interviewees

Chief Innovation Officer

1. What do you think your customers are or will be asking from you regarding services? Specifically, how can AI give a competitive advantage that will help it win business?
2. On a high level, how do you and your EMT team prioritise AI initiatives against other innovative technologies at a high level?

Head of Innovation

1. What is your vision for the AI strategy at your company?
2. How do you ensure AI initiatives align with the overall business goals?
3. What partnerships or collaborations are you pursuing to enhance AI capabilities?

4. Given your service offerings (warehousing, transport, packaging, and return recovery), where do you think AI could potentially have the most significant impact on operations?
5. What role does change management play in ensuring the successful adoption of AI at your company?

Head of Technology Solutions

1. What key AI tools do you believe will be most impactful for yours' and your customers' operations? How can the use of AI help your organisation win business?
2. How would you address the integration of AI with existing technology systems?
3. What are the main technical challenges you may face when implementing AI solutions?
4. Let's imagine five years from now. How would AI solutions' scalability and sustainability would have developed?

Strategy Manager

1. How does AI feature in the company's long-term strategic plan?
2. What frameworks or methodologies do you use to assess the potential impact of AI initiatives?
3. How do you balance the need for innovation with operational stability and efficiency?
4. What role do external trends and market conditions play in shaping or creating the urgency of your AI strategy?

Product Director Technology

1. How do you see AI influencing product development and innovation at your company?
2. How would you prioritise which AI projects to pursue from a product perspective?
3. Are there any customer needs or problems you aim to solve with AI-driven products? If yes, what may they be?

4. What skills do you need in your team to embrace AI, and what gaps do you currently identify?

Head of Data

1. What is the role of data management and analytics in supporting AI initiatives at your company?
2. How do you ensure data quality and integrity for AI applications?
3. What are the biggest data-related challenges one would encounter when implementing AI solutions?
4. How do you manage data privacy and security concerns related to AI?

Operational Excellence Director

1. Which AI tools would have the most significant impact on your company's operational efficiency?
2. How can AI enhance operational efficiency, productivity, and excellence?
3. What processes or operations do you think will benefit most from AI integration?
4. How do you measure the impact of AI on operational performance?

Head of Robotics Solutions

1. From a Robotics and Automation perspective, what are the most promising applications of AI within logistics operations?
2. How would you approach integrating AI with robotics to optimise logistics processes?
3. What are the critical challenges in deploying AI-powered robotic solutions?
4. When considering the balance between predictive, generative and automation-based AI, which one would bring the most value to the company's current services? Why?

Procurement Manager

1. How does your company evaluate and select vendors for services (by extension, AI services)? What criteria are most important in your decision-making process?

2. In the potential future, in procuring AI services, do you anticipate using similar techniques to evaluate AI service vendors? What challenges do you foresee in procuring AI services?
3. How do you currently segment and prioritise vendors based on their offerings, and what factors influence your segmentation strategy?
4. Can you describe any existing or planned partnerships with AI vendors, and how do these partnerships align with the company's strategic goals?

Concluding remarks

I would like to thank you for your time today. Before we wrap up, could you please describe AI solutions that have already been implemented within the organisation? Please elaborate on how these solutions have impacted the operations and overall efficiency of the logistics processes.

Appendix B – Copilot use cases across different departments

Department	Use cases description through quotes
Strategy	*"Co-pilot is extremely handy. It helps me write excellent emails and saves time. While working with legal on merger documents, I've handled 2,000-3,000 files. Co-pilot easily searched for specific topics like automation, found me relevant documents, and provided summaries."*
Procurement	*"To be fair, I have used it to do some high-level generation for risk factors within contracts, which did save me time. I have used it for meeting note insights, too."*
Technology Solutions	*"I use it because we are generating spec documents, we are generating sales documents, we are doing many meetings, a lot of my calendar is meetings with various people, so it's used for generating meeting notes and insights."*
Innovation Centre	*"Used it across the board to improve productivity, helps with meeting notes, searching for things and documents, allowing us to reduce two to five hours a week."*
Operations	*"I haven't used it, but I do; it's been used in procurement and HR for productivity or brainstorming. Even recent graduates are using it for meeting notes and other things. Seems like a time saver."*
Data	*"In my team, it's mostly for personal productivity. It still needs to be more effective in Excel or Power BI. I haven't seen much benefit for data and reporting personally."*
Robotics	*"Not aware of any use cases, nor have I used it."*

Appendix C – Data structure and corresponding representative quotes

Representative quotes	1st order codes	2nd order themes	Aggregate dimensions
AI is a buzzword, our board's talking about it, our executive board is talking about… it's been a little bit of a buzzword for a while, yet it's difficult to narrow down what is true AI and what's just some pretty clever coding.	Acknowledging AI as a buzzword beyond general hype	Building AI awareness	Sensing
We segmented AI for our purpose into generative, which is obvious; predictive (decisions for the future); and automation (e.g., robotics mimicking human behaviour).	Segmenting different types of AI (generative, predictive, automation)		
We started talking to all our big vendors and customers to see what they are doing about AI in logistics; how do they see the world... and we quite quickly figured out a lot of people were at a similar stage to us.	Collecting scattered knowledge of AI capabilities in different business contexts		
It's hard because we're not maturing our thinking around it... There's a whole world of, is it hype, is it reality, how do you ensure you're going to get good value from it? Innovation is hard without knowing what problems we are trying to solve and what limitations AI still has.	Understanding AI's limitations and challenges		
Customers are asking for solutions to their problems, including those that might be underpinned by AI innovations, as AI brings us the option to solve customer problems in a quick and efficient manner.	Addressing customer pain points with AI solutions	Contextualizing AI within 3PL business dynamics	
We're excited about AI because our customers are excited about AI. And everything we need to do has to be of value to customers. So even if it's something back of the house in our back office, it will only be done if it adds value to customers.	Responding to customer interest in AI capabilities		
We've changed, particularly under our new CEO's leadership, so creating the role I am in and an Innovation Centre... is part of us being more technology oriented as well as an operational service provider. However, we're a fragmented business made up of contracts: it can bring complexities that other organisations don't face when they're trying to introduce new technology.	Differentiating services through AI-driven innovations		

Even when our customers want us to use AI, they don't know what they want us to do with it. We should ask the correct question: not "how could we use AI", but rather "what problems do we think AI can help us with"."	Balancing customer expectations with AI readiness		
AI will be a significant piece of business analytics for 3PLs. As an example, 30 co-pilot licences, £30 a month, we were willing just to pay that. Two million to work out how we could schedule our labour better, that's not going to be ideal for us... that's high risk.	Assessing AI business cases for value-added applications	Identifying AI use cases	
We look at business case options, and then if there's something that has massive productivity gains, and we can look at the strong return on investment within five years, then that gets built into the strategy. I would probably take that top-down approach and say, okay, well, if I reduce fuel usage by 1%, that's a lot bigger saving for us in the 3PL business transport is crucial than 1% on something else	Prioritising AI use cases based on potential impact		
We pick themes aligned to our strategy and customer pain points; otherwise, they're pointless. Any technology, including AI, can enable and add value for our customers yet must build on our three key business components: our people, trucking and warehousing expertise.	Aligning AI use cases with overall business strategy	Aligning AI use cases with business strategy	Seizing
We defined our business around generative AI, predictive AI, and then AI automation. That was how we broke it down for logistics use cases because each of them provided unique value propositions for the business we are in. We have thoughts on where we think AI will bring value in terms of generative AI, predictive AI, etc. But we're not fully committed to any AI type or product now.	Contextualising AI types (predictive, generative, automation) for logistics		
"buy" off-the-shelf procurement strategy for AI is currently more suitable than internal development, helping reduce cost and avoiding massive internal efforts to develop AI solutions. For example, we had one company in our Innovation labs who could answer the small vehicle/large vehicle question [the one where in last-mile delivery, do we send a large vehicle or a small one, saving costs] using Google Maps and machine vision. On the other hand, building internally from scratch would	Assessing buy vs. build decisions for AI capabilities	Procuring AI solutions	

have costed us millions, which isn't what we are looking for.			
We passed use cases to several vendors who were well known to us… then we tried to understand their solutions' value through a 10-week trial period, experiencing what AI could do for us.	Evaluating AI vendors and solutions		
If we're looking at a solution for a business case that might have AI, then we ask specific questions about whether they've got an ethical AI policy and how they're using AI.	Evaluating ethics and security challenges related to AI	Assessing ethics and security for AI solutions	
If we're onboarding a new supplier, they'd have to do a number of assessments around data protection and IT security, and that would be reviewed by the data protection team and the IT team. If AI solutions don't' satisfy our ethics and security checklist, we look somewhere else.	Ensuring AI solutions meet security and compliance requirements		
We started with some business use cases and had four or five, then we went with the ones we thought we had the most value. We invited at the Innovation Centre around about 10 companies, big and small, to pitch... so we could see what they could do.	Conducting AI tests and proofs of concept at the Innovation Centre	Experimenting with AI usage	
We did a pilot for last-mile optimisation, which gave us our first kind of experience of seeing what AI could do for us, but it wasn't scalable, and we are back to square one.	Piloting AI solutions in controlled environments		
We operate with something like 180 sites. They operate across individual client contracts. So, anything you bring in, trying to scale it across all of those... you almost have to do it piecemeal.	Scaling successful AI initiatives across the organisation		
Labour forecasting is a big thing. Currently, you know, we need dynamic and automated solutions rather than someone sitting with an Excel sheet. We are starting to get into more of the proactive predictive side of things with AI now.	Applying AI Predictive Analytics to labour forecasting/scheduling	Exploring different AI types	
Addressing the final-mile delivery question [big vehicle/small vehicle vs routing] gave us our first real experience of AI in action, where AI can be 40 percent better at route planning…	Enhancing AI-driven route and distribution (including last-mile delivery)		
Some departments have massively benefited from Copilot while others are unaware or haven't found personal use. I have heard good feedback from the ones on the pilot program, its mainly being used for admin work, but there have been great productive strides being	Experimenting with Copilot for productivity gains		

made. We must logically determine suitable roles to justify a license, knowing it will pay back.			
Generative AI used in the meetings helps generate new content, helping us work through tedious tasks. So, it does generate new content, which is very useful. I think we could probably use more of that around the business to create business ideas and talking points.	Exploring generative AI for content creation and analysis		
AI automation, which is AI that mimics human activity and includes robotics for us. Positive AI effects not only concern robots lifting heavy boxes. AI is great for back-office, reducing 3Ds (dull, dusty, dangerous) activities like data entry or matching numbers; things like image recognition, speech recognition, invoice matching and anything admin related.	Using AI to automatise data entry and other back-office activities		
I think one has a fear of AI's impact on jobs, and people can see that it has a negative impact, so we are trying to tackle that. People can get scared of it, you know, they think they're taking our jobs.	Addressing fears and misconceptions about AI's impact on jobs	Embracing cultural shift for AI	Reconfiguring
I think, being curious, it's just that, which I feel is important to approach AI transformation. We need people with the right attitude, because then you can teach them thing.	Fostering a culture of curiosity and continuous learning		
The technology piece is the easy bit, the people and the culture bit are the hard bit. There's real fear around technology. Some people struggle with basic tablets. But motivation and investment from the higher up have encouraged positive direction to overcome this fear.	Informing existing workforce on AI concepts and applications		
We must build confidence in customers about our AI developments to secure their commitment. The biggest challenge is always the people, because not everyone gets technology…	Building confidence in customers about AI developments	Securing customers' alignment with AI culture	
We have no data, all depends on our customers as we are executing their operations, and we need to seek their permission. Before developing our data infrastructure, we must ensure our customers understand and agree with our pathways.	Securing customers' commitment		
The key for success is having the right data in the right place. You can't even start talking about AI if you haven't got the data sorted.	Appreciating the need for good data foundations for AI	Developing robust data infrastructure	

We're implementing a hybrid model, with centralised capabilities for strategic needs and standardised reporting to meet 80% of business requirements. Local users, our customer contracts, handle the remaining 20% for site-specific needs. We're developing a data and reporting centre of excellence to support this, ensuring consistency while allowing flexibility for individual contracts. Focus on the data platform, get that to a good point, and then you can start layering your AI models over the top of it.	Building centralised data warehouses and platforms		
We hold weekly data quality forums, with technical and operational teams in the same call to set data model rules. Data owners and stewards manage this process. If your data's not accurate, if your data's not accessible, if your data not structured appropriately, then you limit your ability to use some of these tools to the full potential.	Improving data quality		
Interpreting AI opportunities is fundamental for us to understand what could be done. We're doing a lot - are we doing enough?	Scanning AI opportunities is a pre-condition for exploitation	Sensing → Seizing	Dynamic capabilities evolution
AI will eventually be a significant piece of business analytics for 3PLs. Initial use cases will develop to focus first on efficiency improvements for low-hanging fruit like back office administrative functions and warehouse operations.	Identifying and prioritising use cases leads to better engagement with AI		
Data isn't created equal. How can we know if we're asking the right questions? To be effective, data needs context. Contexts illuminate what to do next.	Contextual awareness suggests next steps to capture business opportunities		
Measurable wins, like faster responses and higher optimisation, help organisations like ours build the case for wider adoption.	AI successes motivate deeper engagement	Seizing → Reconfiguring	
In the short term, AI mainly concerns a test&learn approach for early trials, to improve understanding including the ethical aspects. In the long term, AI relates to developing functional use cases that improve business performance yet requiring some transformations.	Initial test&learn illuminates the need for deeper transformations		
AI types help paint a more complicated relationship between variables, unlocking the complexity of the emerging data and the needs to collect better and deeper data.	Engaging with AI highlights which other data will also be necessary		
Better data can tell sophisticated stories that help businesses improve their operations, making new opportunities	Better data develops awareness across the organisation	Reconfiguring → Sensing	

emerge and leading to higher awareness of what could be done next.			
Most of our data are actually our customers'; robust data management will reinforce their confidence, leading to better understanding their requirements (current and future)	Better data reinforces customers' relationships		
In leveraging data to gain insight on organisations, leaders often fall prey to misconceived answers. These misconceptions can obscure the bigger picture, overlooking opportunities to improve flawed processes. As 3PL leaders, we must go beyond such misconceptions to build on the new knowledge that AI promotes.	Better data allows for overtaking misconceptions about AI		