Oh my, AI! How to foster Artificial Intelligence maturity for third-party logistics service providers?[1]

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Abstract

Frame of the research. *Artificial Intelligence (AI) is increasingly seen as a transformative force across the logistics industry, including third-party logistics service providers (3PLs). However, the academic literature reveals a limited understanding of how 3PLs can develop their AI maturity to capture the emerging opportunities.*

Purpose of the paper. *The study explores AI adoption within the 3PL industry by leveraging the dynamic capabilities theory.*

Methodology. *Empirical insights were collected through a single case study at a leading British 3PL, comprising 10 qualitative interviews and 2 on-site visits. Abductive reasoning guided iterative comparisons between empirical material and theory to understand how 3PLs sense and seize AI opportunities and reconfigure their processes during transformation.*

Results. *Sensing AI opportunities depends on developing robust AI awareness and actively involving customers to incorporate their perspective; seizing involves using AI to improve labour forecasting, scheduling, and back-office automation. Companies must also reconfigure resources by fostering a cultural shift and building a robust data infrastructure to support AI efforts. Building on these findings, an exploratory framework is proposed to assess 3PLs' AI maturity level and the related dynamic capabilities.*

Research limitations. *The reliance on a single case study design inherently limits external validity, restricting the applicability of the study's findings to a wider population of logistics and supply chain contexts.*

Managerial implications. *The study focuses on 3PLs to examine how they can navigate the complexities of AI adoption and develop their AI maturity, offering rich empirical insights into the synergies among the human workforce, technological tools, and physical assets.*

Originality of the paper. *Existing research has only recently begun to explore how 3PLs approach AI adoption. The study elaborates and contextualises the dynamic capabilities theory with respect to AI-driven opportunities for 3PLs, showing how sensing, seizing, and reconfiguring capabilities manifest in 3PL operations. By providing original insights into adopting AI tools, it offers a pathway to sense and seize AI-driven capabilities and reconfigure resources through AI adoption.*

Key words: *3PL; artificial intelligence; AI; dynamic capabilities*

1. Introduction

Over the last few decades, the increasing focus on core competencies has led many companies to outsource their logistics operations to third-party logistics service providers (3PLs), leveraging 3PLs' expertise to handle transport management, warehousing, and distribution on their behalf (Cozzolino, 2009; Sink and Langley, 1997). Nowadays, the logistics industry is on the brink of a revolutionary transformation driven by advancements in Artificial Intelligence (AI) (Richey *et al.*, 2023; Dang *et al.*, 2025). AI is a branch of computer science that attempts to understand the essence of intelligence and produce a new machine that mimics human intelligence (Bettiol *et al.*, 2021; Jackson *et al.*, 2024). AI is increasingly considered a transformative force within the logistics industry (Helo and Hao, 2022), showing great potential to ease repetitive tasks with minimal human input but also analyse raw data to identify solutions to problems which require significant human input/intervention (Durach and Gutierrez, 2024; Pournader *et al.*, 2021).

Although AI has emerged as a top technological priority for organisations over the last few years, with promising supply chain use cases (Guida *et al.*, 2023; Hendriksen, 2023), the available literature has paid limited attention to its implications for 3PLs (Dang *et al.*, 2025). AI tools can enable 3PLs to improve decision-making, optimise operations, and adapt to increasingly complex and volatile supply chain environments (Richey *et al.*, 2023; Pournader *et al.*, 2021). Recent industry surveys indicate that shippers are likely to switch logistics providers based on AI capabilities, and failing to develop AI readiness could erode competitiveness (NTT Data, 2025). However, many 3PLs struggle to clearly understand the opportunities AI tools may offer (Cannas *et al.*, 2024; Prataviera *et al.*, 2026). Although they risk becoming obsolete or losing competitive advantage if they fail to adopt AI, 3PLs have not yet developed the necessary competencies to reconfigure their operational processes in response to AI innovations, displaying limited AI maturity (Kmiecik, 2023; Jackson *et al.*, 2024). Building on dynamic capabilities theory, which emphasises the importance of an organisation's ability to adapt to changing environments by integrating and reconfiguring resources (Teece *et al.*, 1997), this study aims to address the following research question:

How can 3PLs develop their dynamic capabilities to foster AI maturity?

Building on abductive reasoning, we developed a single case study in collaboration with a leading British 3PL provider, leveraging empirical insights from 10 qualitative interviews with managerial-level stakeholders across different departments and 2 on-site visits. We iteratively compared our empirics with extant theoretical knowledge to elaborate on how 3PLs can leverage their dynamic capabilities to sense and seize AI opportunities, as well as to reconfigure their resources to capture them. Findings highlight that sensing critically depends on AI awareness and understanding, as well as customer involvement, while seizing mainly involves leveraging AI to improve labour forecasting/scheduling and automating back-office activities. Nevertheless, companies also need to reconfigure their resources through fostering a cultural shift and developing a robust data infrastructure to support AI efforts. Building on these findings, an exploratory framework is proposed to assess 3PLs' AI maturity level and evaluate their dynamic capabilities throughout their AI journey.

The study contextualises the dynamic capabilities theory in relation to AI-driven opportunities for 3PLs, contributing to the literature by illustrating how 3PLs can systematically improve their AI maturity and develop the dynamic capabilities needed to innovate, digitise, and respond to the complexities of modern supply chains. By specifically considering the perspective of 3PLs, this study elucidates how these organisations can sense and seize AI-driven opportunities, reconfigure resources to navigate the complexities of AI adoption, and develop their AI maturity.

The remainder of the paper is organised as follows. Section 2 provides an overview of the relevant academic literature, followed by Section 3, which details our methodological approach. The study's findings are described in Section 4, before discussing their implications in Section 5 and summarising the contribution to knowledge and managerial practice in the concluding remarks.

2. Related literature

2.1 From transport and warehousing to Artificial Intelligence: the evolution of 3PLs

Logistics services are essential in the smooth flow of materials, information, and money within supply chains (Lieb *et al.*, 1993; Cozzolino, 2009). By ensuring an efficient flow of goods and services from point to point, businesses can meet customer demand and create a competitive advantage (Marchet *et al.*, 2017). However, conducting logistics operations efficiently and effectively can be expensive, further diverting businesses' focus from their core competencies and the primary ways they create their competitive advantage (Selviaridis and Norrman, 2015). Therefore, companies increasingly outsource logistics operations to third-party logistics service providers (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). At first, logistics outsourcing was motivated by the need to reduce cost and lead times and avoid heavy investment (Razzaque and Sheng, 1998). It started with services such as transport and warehousing (Sink and Langley, 1997), then evolved into integrating logistics into their client systems and providing tailored solutions to meet specific requirements (Selviaridis and Norrman, 2015). Today, many firms are outsourcing logistics activities to reduce overheads and supply chain complexity, increase capacity, and retain the benefits of operational efficiency, flexibility, and higher customer satisfaction (Prataviera *et al.*, 2021).

Although 3PLs emerged as essential players in streamlining supply chain operations, the rising digitalisation has significantly affected their business and opened up significant opportunities to add value to client services (Mathauer and Hofmann, 2019). 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). As we venture deeper into the digital age, the emergence of large language models like ChatGPT suggests we are on the brink of a significant technological upheaval driven by AI, which can potentially revolutionise logistics and supply chain management (Richey *et al.*, 2023; Dang *et al.*, 2025). AI refers to the ability of a machine to reason, solve problems, and adapt to its environment (Bettiol *et al.*, 2021; Chen and Chen, 2022), simulating and performing tasks that typically require human intelligence, such as logical reasoning, learning, and problem-solving (Iansiti and Lakhani, 2020; Patrizi *et al.*, 2021). In the supply chain context, AI tools can process vast amounts of data generated across supply chains to provide actionable insights, helping managers make informed decisions regarding procurement, manufacturing, and distribution (Hendriksen, 2023; Cannas *et al.*, 2024).

2.2 AI tools: Predictive analytics, generative AI, and AI-driven automation

AI tools can be classified into different types based on their cognitive ability, i.e., their capacity to learn, understand, and make decisions based on data and experiences. This classification discloses three overarching types of AI tools: predictive analytics, generative AI, and AI-driven automation.

Predictive analytics tools help predict future activities (Mediavilla *et al.*, 2022). AI predictive analytics models enable more accurate demand forecasting, optimise inventory, reduce stockouts, and provide predictive maintenance of equipment, helping reduce downtime (Woschank *et al.*, 2020). 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).

Generative AI tools enable content generation with limited predictive capabilities, focusing on original content rather than acting on existing elements (Hendriksen, 2023). Natural language processing models can handle customer inquiries and resolve issues autonomously through chatbots powered by generative AI (Durach and Gutierrez, 2024). Chatbots can enhance operational efficiency by automating routine tasks, providing real-time updates and assisting in decision-making processes (Pfaff, 2023). Generative AI opportunities also relate to conversational interface and knowledge discovery, supporting organisational and administrative tasks (Durth *et al.*, 2023).

Lastly, AI-driven automation involves using AI to automate various logistics processes (Richey *et al.*, 2023). Logistics automation usually entails adopting physical robots, such as 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 that provide efficient material transport within logistics facilities. They can navigate throughout the warehouse, retrieve products from their locations, and deliver them to the picking stations, thereby improving picking efficiency. AI can reinforce logistics automation and improve warehousing operations, reducing errors and increasing throughput by enhancing precision and adaptability. Given the rising shortage of qualified supply chain personnel, including people working in transport and warehousing operations (Klumpp, 2017; Phares and Baltrop, 2022), AI could help solve labour shortages. However, the broader impact of AI on labour demand is under discussion as it might lead to job displacement (Chen *et al.*, 2020).

Overall, logistics research highlights specific applications that enable end-to-end supply chain visibility, warehouse optimisation, predictive maintenance and last-mile routing (Pournader *et al.*, 2021). The discussed examples underscore the breadth of AI's impact across planning and operational optimisation (Hendriksen, 2023). Nevertheless, barriers to AI adoption in logistics include difficulties in integrating new AI solutions with legacy systems, a shortage of personnel with the necessary digital skills, and high initial investment costs (NTT Data, 2025). Addressing these hurdles requires attention to data quality and governance as well as organisational change management (Durach and Gutierrez, 2024).

2.3 Dynamic Capabilities Theory and AI development in logistics

Dynamic capabilities are the firm's ability to integrate, build, and reconfigure internal competencies 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).

In the logistics industry, this theory is increasingly used to explain and predict how firms respond to rapid technological advancements and evolving customer demands (Li *et al.*, 2024; Ciceri *et al.*, 2026). AI is emerging as a driving force of digital transformation, offering 3PLs significant potential to enhance their business operations by improving decision-making and automating processes (Richey *et al.*, 2023). However, the strategic integration of AI into logistics operations requires the development of specific capabilities and competencies (Jackson *et al.*, 2024). Sensing in the AI context involves identifying how AI tools can unlock new opportunities, while seizing requires embedding these technologies into business operations. Reconfiguring, then, involves restructuring internal processes and systems to fully leverage AI's potential (Prataviera *et al.*, 2026).

Previous scholars argue that companies can start by identifying potential business use cases or opportunities where AI might generate improvements (Hendriksen, 2023; Herremans, 2021), then focus on the planning stage, highlighting critical steps such as accessing available data sources and identifying their use within the company (Wagner, 2020). However, implementing AI requires not only the right technology but also consideration for the people working alongside it. The continuous advancement in computing power and data availability has facilitated the maturation of AI, enabling efficient and robust human-AI collaboration (Jackson *et al.*, 2024). Human-AI collaboration depends on several critical factors, including the flexible integration of AI into workflows, support for human sensemaking, and the maintenance of human control over AI systems (Hendriksen, 2023). Organisations must equip their workforce with the necessary skills to leverage AI tools effectively, though this is not a one-off training exercise but rather 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, as well as the importance of data management and organisational culture in driving AI maturity (Dhamija and Bag, 2020). Previous scholars formalised AI maturity as the level of development and sophistication in an organisation's utilisation of AI tools and capabilities (Chen *et al.*, 2021). Companies usually utilise maturity models to assess the capabilities of technologies and improve their ability to apply them, considering dimensions such as culture/mindset, data maturity, ethics, organisation and processes, and technological development (Comuzzi and Patel, 2016; Sonntag *et al.*, 2024).

3. Methodology

3.1 Research design

This study aims to explore how 3PLs can build their AI maturity. The dynamic capabilities theory is leveraged as it examines the foundation of enterprise-level competitive advantage in regimes of rapid (technological) change (Teece, 2007). As 3PLs experience the tumultuous evolution of the AI types around them, their ability to sense, seize, and reconfigure their internal processes becomes crucial for harnessing AI. Given the study's exploratory nature and the need to capture in-depth insights, a qualitative case study approach is employed to cope with contemporary practices and challenges (Ketokivi and Choi, 2014). As units of analysis, we considered AI-related capabilities supporting AI adoption within 3PLs.

A single-case study research design was adopted to conduct exploratory research focused on better understanding a nascent phenomenon, examining a specific setting to gather rich and detailed data, and generating deep insights into the phenomenon (Voss *et al.*, 2002). Although a single-case approach can reduce transferability, it allows for the investigation of an unexplored phenomenon (Flyvbjerg, 2006), as demonstrated by the scarcity of empirical studies that delve into the real-world implementation of AI by supply chain managers and enterprises (Moretto *et al.*, 2024). A leading British 3PL provider was considered a rare example of an organisation actively 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 (e.g., transport route optimisation and warehouse automation software). The selected 3PL can be considered a critical or revelatory case because it is among the first providers to experiment extensively with AI initiatives, offering insights that could illuminate broader industry dynamics, despite the inherent limitations of a single-case design. The case offered unique potential to explore AI adoption within 3PLs' logistics processes (Flyvbjerg, 2006), enabling us to examine the current business landscape and identify ways to create opportunities for customer value enhancement. Despite its initial commitment to AI, the company is still at the beginning of its AI journey, revealing unique opportunities to examine how to further develop AI-related capabilities.

The research approach is based on abductive reasoning (Kovacs and Spens, 2005). Abductive reasoning focuses on the search for suitable theories for an empirical observation through "theory matching" or "systematic combining" (Dubois and Gadde, 2002). By leveraging abductive reasoning, this research bridged empirical findings with previous knowledge and the dynamic capabilities theory. The abductive research process began by reviewing available academic literature to develop a broader understanding of AI's strategic opportunities and adoption within the 3PL industry (Kovács and Spens, 2005). Supply chain magazines and other secondary sources were also analysed to contextualise the academic insights through a practitioner lens, strengthening the study's practical relevance. Next, in-depth empirical insights were collected, analysed, and systematically combined with the existing literature, specifically in relation to the dynamic capabilities theory.

3.2 Data collection

Data were collected through semi-structured interviews with 10 senior managerial stakeholders and 2 on-site visits at one of the company's primary distribution centres. Informants were selected based on their potential to provide details about the investigated unit of analysis. In more detail, interviewees included all senior stakeholders who would be decision-makers or influencers in AI adoption, namely two Executive Board Members, five members of the Senior Leadership Group, and three Heads of Department. Semi-structured interviews were conducted between April 2024 and June 2024 (either in person or online through Microsoft Teams). On-site visits in May and July 2024 provided contextual understanding and first-hand insights into the company's technological landscape and operational processes. Each interview lasted 45 to 60 minutes. Interviewees were provided with consent forms before the interview and were assured that their information would be confidential and anonymous (Voss *et al.*, 2002). Each participant was asked to sign the consent form, and the forms were stored in a secure location. All the interviews were recorded and transcribed verbatim to ensure accuracy, and backup files of each transcript were maintained to safeguard against accidental deletions within the main files. Transcripts were condensed and returned to our interviewees for fact-checking and accuracy verification. All the interviewees were consistently available to answer questions or provide additional contextual information needed for our analysis. Primary data collected through semi-structured interviews were triangulated with academic and grey literature, including reports from Gartner and other global firms, which provided additional insights into the current state of AI applications in logistics and supply chain management. In addition to interviews, the research includes observations from two visits to the Innovation Centre and the primary distribution centre. These visits offered on-field insights into the technologies used in warehousing and transport operations, allowing firsthand observation of the impact of AI adoption on both front-end (e.g., goods receiving, picking, packing, labelling) and back-end activities. Those observations represented a source of original disciplinary knowledge that is fruitful for exploring technological innovations and the implementation of advanced technologies, such as AI. Notes from the visit were taken down manually or recorded and later transcribed to capture details of the various stimuli; some photographs were taken of in-development technologies to document the near future of technological advancement. Lastly, the study's findings and implications were returned to interviewees for fact-checking and accuracy verification.

3.3 Data analysis

Data analysis included familiarising and preparing the data, generating initial codes, searching for themes, and reviewing/defining them (Braun and Clarke, 2006). To clean the data collected from the semi-structured interviews and site visits, each transcript was read thoroughly, followed by familiarisation with the data to take notes and record early impressions from each interview (Voss *et al.*, 2002). Data analysis 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. In practice, we progressed from empirically driven codes (1st order concepts) to more conceptual categories (2nd order themes) which were then further abstracted to overarching themes (aggregate dimensions) explicitly linked to the extant theory and its core capabilities (sensing, seizing, reconfiguring), enabling an iterative process where empirics and theory inform each other (Kovács and Spens, 2005).

In more detail, the process began by examining the interview transcripts to identify key phrases, codes, and ideas related to AI adoption and the emerging opportunities. Consistent with our abductive reasoning, 1st order concepts were inductively derived from interviewees' perceptions and insights. Based on the semi-structured interviews and on-site visits, this initial set of codes was developed from interview quotes. 1st order concepts reflected the interviewees' experiences and perspectives and were then compared for pattern matching, being grouped into broader 2nd order themes. The level of detail within the transcripts helped organise data into more conceptual categories. For example, a 2nd order theme named "AI Awareness" emerged from 1st order concepts such as "Acknowledging AI 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 the formalisation of the 2nd order theme "Embedding different AI types". 2nd order themes were further consolidated into overarching aggregate dimensions to capture the essence of the company's dynamic capabilities towards AI adoption. For example, "3PL Dynamics" emerged as an important 2nd order theme, reflecting the 3PLs' specific business environment and the importance of liaising effectively with customers. Careful consideration was given to which aggregate dimension best fit the 2nd order theme, and "Sensing" was selected because it most accurately reflects how customers influence AI decisions, as customer dynamics significantly shape the identification of new business opportunities for 3PLs. Overall, three aggregate dimensions were formalised in accordance with the established literature about dynamic capabilities (e.g., Teece *et al.*, 1997) for theory matching (Dubois and Gadde, 2002).

Moreover, during data analysis, additional insights emerged regarding the interdependencies among dynamic capabilities arising from AI adoption. We identified 1st order concepts describing how scanning AI opportunities is a precondition for exploitation, or how initial tests reveal the need for deeper transformations. Customer involvement primarily relates to sensing, but it also influences implementation choices and affects seizing through prioritisation. Similarly, data infrastructure development concerns reconfiguring capabilities, yet it also unfolds as an enabler for sensing and seizing. Since the three dynamic capabilities emerge as analytically distinct but empirically intertwined, we combined our empirical data and their analysis with recent academic literature about AI capabilities in logistics and supply chain management (Richey *et al.*, 2023; Jackson *et al.*, 2024) and drew on knowledge from closely related research domains focusing on AI maturity (e.g., Sonntag *et al.*, 2024), which refers to the level of development and sophistication in an organisation's utilisation of AI tools and capabilities (Chen *et al.*, 2021). This approach stimulated fruitful cross-fertilisation, in which new combinations for AI development and maturity levels were developed through a blend of established theoretical models and concepts derived from confronting reality (Dubois and Gadde, 2002). We challenged our findings and compared the emerging patterns about AI adoption against the available literature, developing an exploratory framework to assess AI maturity and 3PLs' related dynamic capabilities with respect to organisational processes, culture and competence, data maturity, and technological adoption (Comuzzi and Patel, 2016; Sonntag *et al.*, 2024).

4. Findings

4.1 Sensing

The importance of AI innovation is driven by the strong 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*". With this commitment at the executive level, the company set out to understand and explore AI potential by creating an Innovation team, which led discussions on AI awareness and understanding by focusing on defining what AI capabilities meant to the 3PL business. The company created an Innovation Centre to host events where business use cases are presented, also inviting startups to propose their solutions. In 2023, the Innovation Centre explored services from AI startups across four clear use cases: labour forecasting, labour scheduling, last-mile delivery vehicle selection, and network optimisation. As explained by the Head of Innovation: "*there were big use cases, and we invited around ten big and small companies to pitch. This was for us to explore and not invest money into something built from scratch*". Therefore, the company was able to embark on an AI learning phase. Moreover, the company encourages home-grown talent through its AI solution enabler programme. This internal initiative asks employees to showcase their innovative ideas to help solve selected use cases.

However, interviews also revealed the critical importance of the business dynamics between 3PLs and their customers. The company owns only about 40% of its truck fleet and an even smaller share of its distribution warehouses, relying heavily on its customers' behaviour. Interviews revealed how deeply customers are integrated into the company's business, including their influence on AI adoption, and multiple stakeholders highlighted that customer interest is a critical driver in AI exploration. However, there is a gap between customer expectations and their understanding of AI applications. As reported by the Chief Innovation Officer, "*our customers want us to use AI but don't know what they want us to do with it*". Therefore, major customers talk with senior executives to inform them about the latest AI tools they may be implementing. This also involves customers contributing to the Innovation Centre's selection criteria for testing specific technologies.

4.2 Seizing

Any technological innovation, including AI developments, needs alignment with the broader business strategy. The first step is to identify use cases. Based on the identified use cases, business cases are developed, as initiatives require a strong return on investment (ROI). Regarding predictive analytics, the company developed business use cases to justify investments in AI initiatives or tools that may alleviate business challenges and improve predictive capabilities. For example, a top challenge in the 3PL industry is a labour shortage. Accordingly, one of the most pressing opportunities concerns labour scheduling, which is crucial for workforce optimisation to better cater to customer needs and address shift inefficiencies. Delivery and inventory management are also crucial to enhance delivery and stock accuracy. The company is currently analysing how machine learning algorithms could feed their daily delivery schedule and optimise delivery routes, saving fuel and ensuring on-time deliveries for both primary distribution and last-mile delivery.

Regarding Generative AI, the company recently arranged licences for 30 Microsoft Copilot users to test its use across different departments. It assists workers in generating text, suggesting edits, analysing/searching for data and documents, creating presentations, and managing emails. Findings showed a wide range of responses, with specific departments benefiting substantially from Copilot while others remain unaware of its potential or have not yet identified a personal use case. This reflects the company's approach to "finding the right hands" for the limited number of licences it has. Beyond Copilot, the company is testing a chatbot assistant that helps generate meeting ideas, including strategies, standard operating procedures, and creative content. Moreover, the company is exploring Generative AI tools for recruitment, as their algorithms handle skill assessments and provide candidates with real-time warehouse scenarios to assess their job-readiness. Furthermore, the company considered an AI-enabled contract review tool for the procurement team. However, its limited scope and high licensing cost didn't justify the company-wide investment.

Lastly, the company has invested heavily in robotics for automation. While older distribution centres use non-AI robotics, newer facilities employ advanced AMRs for efficient, adaptable routing with minimal human intervention. In this respect, the Head of Robotics Solutions explained, "*we currently have more QR-based AMRs, but we're exploring collaborative mobile robots for greater flexibility and impact without zonal restrictions*". AMRs can map the area autonomously or be guided by a handler using an RFID-based wearable. Then, AI software optimises the robot's route through machine learning algorithms to reach the pickers efficiently. However, investment in proprietary AI software to strengthen robotics is highly critical as AI offers significant opportunities for better optimisation and synchronisation. Nevertheless, AI-driven automation is not limited to physical operations but also extends to back-office activities. The company already leverages AI to improve the quality of activities such as employee or subcontractor work allocation, payment processing, and invoice matching.

4.3 Reconfiguring

Developing AI capabilities and integrating them into the 3PL business presents its own set of challenges. One primary concern is integration, particularly given multiple contracts and different legacy systems. Backed by executive-level commitment, an open and inclusive culture towards AI is highly encouraged. One key aspect is the eagerness to change, supported by the Leadership buy-in. As emphasised by the Operational Excellence Director, "*there's real fear around technology. But motivation and investment from the higher up have encouraged a positive direction to overcome this fear*". Skill development and continued learning are crucial aspects of the company's cultural approach, along with cross-functional exposure and the creation of mutual trust across different organisational levels. Moreover, due to numerous ethical concerns related to AI adoption, an Assurance, Quality, Service, Cost, and Innovation (AQSCI) checklist was developed for internal use and to assess external AI suppliers. These ethical considerations are critical to ensure that vendors offering AI solutions have appropriate ethical policies.

Nevertheless, data readiness is critical, and high-quality centralised data is crucial for AI implementation. Interviews revealed the company's strong focus on data availability and accessibility. Many interviewees stressed the importance of data integrity, highlighting the need for a consistent and robust data infrastructure. Without it, AI (as well as other technologies) would have a limited impact. Currently, the urgency of centralising data to foster AI is strongly felt across the organisation, and efforts to centralise data are led by the executive level. To ensure data quality and integrity as AI adoption ramps up, the company holds a weekly data quality forum to iron out data issues. To maintain data security, data is provided to internal stakeholders and vendors on a role-based basis. However, as the importance of data to AI grows, stakeholders recognise the challenges posed by decentralised operations. As acknowledged by the Strategy Manager, "*we've got lots of data across the business that sits isolated. Our best use case is convergence - combining these datasets to extract value from a holistic view*".

5. Discussion

The dynamic capabilities theory suggests that companies need to develop the ability to integrate, build, and reconfigure competencies and resources to create, deploy, and protect the intangible assets that support superior long-run business performance (Teece, 2007). The theory also emphasises the importance of adapting to changing environments (Teece *et al.*, 1997). Today, AI represents a powerful driver of transformation within the logistics industry (Durach and Gutierrez, 2024; Richey *et al.*, 2023). However, the existing literature offers limited insights into how 3PLs can understand and leverage AI's potential across their operations (Jackson *et al.*, 2024; Prataviera *et al.*, 2026). Our findings suggest that enhanced sensing of AI-driven opportunities is driven by increasing awareness and commitment at the executive level, which sets strategic goals to extract the maximum value from AI initiatives by building customer trust. The commitment to a customer-centric approach seems crucial, as customer involvement helps guide technological choices and strengthens customer relationships, potentially leading to extended contracts and helping customers understand solutions they may not be aware of.

Sensing AI opportunities directly influences the ability to seize opportunities across different types of AI tools (i.e., predictive analytics, generative AI, and AI-driven automation). Executive decisions inform the creation of a business use case, which is usually driven by customers' needs, such as improving inefficient labour scheduling, thereby identifying strategic opportunities for 3PLs. Our findings suggest that adopting an off-the-shelf "buy" procurement strategy for AI is currently more suitable than internal development, helping reduce costs and avoid the massive internal effort required to develop these solutions. After identifying strategic opportunities, 3PLs can shortlist and evaluate external suppliers offering AI tools, prioritising those that can provide proprietary software enabling effective integration with 3PLs' existing systems. Operationally, the case findings illustrate the vast potential of 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. Beyond robotics, the findings also illustrate the potential for AI to automate tasks such as number matching and data entry in back-office operations, reducing errors and improving efficiency.

However, our analysis also highlights two critical areas for reconfiguration that underpin AI capabilities. First, AI's impact on labour prompts debate and potentially creates significant frictions due to job displacement and elimination (Chen *et al.*, 2020; Klumpp, 2017). Therefore, an open and inclusive culture is required to enable a cultural shift towards AI adoption. It becomes critical to engage with workers to discuss how technological adoption does not encompass work-replacing consequences for humans. Instead of being a threat to people, AI becomes a contributor to enhanced job satisfaction, addressing labour shortages without reducing employment opportunities. Moreover, prioritising the completion of a centralised data infrastructure and establishing clear data governance policies are fundamental steps, as high-quality, well-managed data is critical (Zhou *et al.*, 2023).

Moreover, our findings illustrate that dynamic capabilities are analytically distinct but empirically intertwined. Our analysis illustrates that sensing involves understanding how AI tools can unlock new opportunities, while seizing requires embedding those tools into business operations. Reconfiguring, then, involves restructuring internal processes and systems to fully leverage AI's potential. However, it also suggests that sensing capability enables seizing capability, and the latter fosters resource reconfiguring. Scanning opportunities is a precondition for exploitation, while identifying and prioritising use cases leads to better engagement with AI, and initial successes motivate deeper engagement with technologies. Experimenting with AI (i.e., seizing) helps reveal the need for broader transformations and requires resource reconfiguration. Developing a robust data infrastructure improves data quality, indicating a high potential to strengthen sensing capabilities and accelerate AI adoption.

5.1 Depicting an Exploratory Framework for 3PLs' AI Maturity

Based on insights from qualitative interviews and the literature review, an original exploratory framework to display and assess 3PLs' AI maturity and the related dynamic capabilities is presented in Figure 1. 3PLs' success depends not only on technological readiness but also on relational, organisational, and cognitive factors (Dang *et al.*, 2025). We thus combined our empirical work and prior conceptual work to envision future patterns of AI adoption by 3PLs, proposing five maturity levels of dynamic capabilities driven by AI adoption that merge empirical findings with established concepts from the extant literature on AI maturity (Comuzzi and Patel, 2026; Sonntag *et al.*, 2024). At the first level, termed the Initial Explorer (L1), 3PLs begin investigating AI opportunities without formal AI processes and with limited awareness. At this level, they can sense new opportunities through scanning, learning, and interpreting activities. 3PLs can host AI pilots as they progress to Focused Pilot (L2), thereby increasing their AI awareness while evaluating solutions from external AI suppliers. This corresponds to the preliminary seizing of AI opportunities: once a new (technological or market) opportunity is sensed, it must be addressed through new products, processes, or services (Teece, 2018). The journey continues to become a Structured Implementer (L3), encompassing widespread AI awareness across organisational departments and the implementation of AI tools across different business areas. At this level, reconfiguring capabilities are developed to incorporate the successful identification and calibration of technological and market opportunities, the judicious selection of technologies and product attributes, the design of business models, and the commitment of financial resources to investment opportunities. This is reflected in the case by the company's ongoing efforts to centralise data and build a centre of excellence, which emerges as critical for future AI success. Advanced Integrator (L4) follows, marked by AI being deeply integrated into multiple business areas, deployment across various applications, and the emergence of an AI-driven culture with solid vendor relationships. This level corresponds to mature sensing and seizing capabilities, while the highest level of overall maturity is a Transformed Organisation (L5), where employees lead AI-based innovation. In this scenario, the 3PL becomes an AI industry leader with robust reconfiguration capabilities that embrace a deep cultural shift. Accordingly, the distinction between L4 and L5 lies in how AI reshapes the organisational culture and identity, rather than in technological advancements (Jaiswal *et al.*, 2022).

Fig. 1: Exploratory framework to assess 3PLs' AI maturity level and the related dynamic capabilities

Level	Organisational Processes	Culture and Competence	Data Maturity	Technological Adoption	Dynamic Capabilities Maturity
Initial Explorer (L1)	No formal AI processes, mostly exploratory scoping through programs	Limited AI awareness, primarily at the managerial level	Unstructured data across multiple systems or business units	Limited AI technology deployment such as in robotics and automation	Sensing ●○○ Seizing ○○○ Reconfiguring ○○○
Focused Piloter (L2)	Pilot projects underway through programs, evaluation of vender performance	Increased AI awareness of applications; some departments using AI tools (e.g., Copilot)	Ongoing data centralisation efforts and investments in data quality checks	Implementation of off- the-shelf AI solutions and investment in robotics	Sensing ●○○ Seizing ●○○ Reconfiguring ●○○
Structured Implementer (L3)	Focus on procuring through established procurement norms and scalability of AI vendors	Widespread AI awareness, regular cross-functional exposure to AI initiatives	Standardised data model, defined norms for data quality checks and ownership	Facilitation of AI systems across multiple business functions; widespread use of generative Al	Sensing ●●○ Seizing ●○○ Reconfiguring ●○○
Advanced Integrator (L4)	Strong vendor relationships, built through trust in technology	Continuous AI learning programs for employees	Fully centralised data infrastructure (e.g., data centres) allowing advanced analytics	Widespread deployment of AI solutions across predictive, generative and automation applications	Sensing ●●● Seizing ●●○ Reconfiguring ●●○
Transformed Organisation (L5)	Fully integrated information for sharing AI processes between 3PLs, allowing for continuous optimisation	Al-driven culture, employees driving AI- based innovation or Al-first mindset	Real-time data-driven decision-making, allowing for industry- Leading AI initiatives	Industry leaders in introducing built- from- scratch AI technologies, including advanced robotics and cognitive technologies	Sensing ●●● Seizing ●●● Reconfiguring ●●●

Source: our elaboration (Note: black circles in the column "Dynamic Capabilities Maturity" indicate increasing maturity levels)

6. Concluding remarks

3PLs find themselves amid an industry-wide digital transformation driven by the adoption of AI tools, which can improve process efficiency and extract valuable insights from data, adding tremendous value to their customers. This study leveraged the dynamic capabilities theory to explore how 3PLs can develop the sensing, seizing, and reconfiguring capabilities needed to innovate and respond to the complexities of modern supply chains. A single case study conducted within a leading British 3PL offered rich insights into how leveraging AI potential is a crucial capability for 3PLs. Moreover, an exploratory framework is proposed to assess 3PLs' AI maturity and their related dynamic capabilities, merging empirical findings with the extant literature on AI maturity. Therefore, the study sketches a pathway for AI adoption by 3PLs, offering rich empirical insights into the synergies among the human workforce, technological tools, and physical assets.

6.1 Theoretical implications

From an academic viewpoint, the study contextualises the dynamic capabilities theory within the realm of AI adoption in logistics. Accordingly, it can offer two theoretical contributions. By showing how sensing, seizing and reconfiguring capabilities manifest in 3PL operations, the study suggests that developing AI maturity in 3PLs requires more than deploying technology. Findings highlight that AI maturity is built through cultivating sensing, seizing and reconfiguring capabilities across customer engagement, predictive applications, and organisational transformation. Moreover, the study emphasises the pivotal role of customer involvement in sensing AI opportunities-an aspect often underemphasised in the dynamic capabilities literature. Second, the study provides original insights into adopting AI tools, offering a pathway to sense and seize AI-driven capabilities and reconfigure resources to address technological changes. To this end, it proposes an exploratory framework for 3PLs' AI maturity that integrates capability development with organisational and cultural readiness. The framework merges categories taken from the extant literature on AI maturity with contextual insights, building on recent work (e.g., Jackson *et al.*, 2024; Prataviera *et al.*, 2026) to suggest that 3PLs' AI-related challenges could be framed within organisational processes, culture and competence, data maturity, and technological adoption. Due to its limited empirical foundations, this framework also offers promising opportunities for further testing and refinement. At the same time, dynamic capabilities theory privileges internal resource orchestration and may underplay structural or power-related constraints. Therefore, alternative perspectives such as the resource-based view or information processing theory could complement the analysis offered in this study.

6.2 Managerial implications

For managers, the study exposes how 3PLs can navigate the complexities of AI adoption and develop their AI maturity. To sense AI opportunities effectively, 3PLs should cultivate organisation-wide awareness of AI technologies and co-create solutions with customers, recognising that customer expectations shape which opportunities will generate value. Since the most promising early gains from AI adoption lie in predictive labour scheduling and automation of administrative tasks, managers can seize such opportunities by piloting these applications and measuring their impact to build momentum and learn before scaling. Nevertheless, successful AI adoption requires reconfiguration beyond technology, including fostering a culture that embraces experimentation and investing in data infrastructure and governance to enable AI solutions. To this end, the exploratory framework proposed here serves as a diagnostic tool for scholars and practitioners to assess readiness and identify avenues for improvement. Findings suggest that 3PLs should cultivate strategic partnerships with AI vendors to maximise learning opportunities and increase operational effectiveness, with particular interest in labour forecasting and scheduling. Given the typical fragmented business structure of customer contracts in the 3PL industry, fostering an AI-positive culture from the top down is crucial, with leadership championing this change and encouraging implementation and testing at all levels. Similarly, prioritising the completion of a centralised data infrastructure and establishing clear data governance policies are fundamental steps for successful AI adoption.

7. Research limitations and future research directions

The reliance on a single case study design inherently limits external validity, restricting the applicability of the study's findings to a wider population of logistics and supply chain contexts. However, our analytical approach followed rigorous procedures to strengthen internal and construct validity, including selecting respondents based on their potential to provide details about the investigated unit of analysis and returning all collected data to respondents for fact-checking and accuracy verification. Future work could investigate other contexts (e.g., involving 3PLs outside the UK) and elaborate single case findings to explore the transition across the different levels of the proposed exploratory framework for AI maturity and examine how it manifests in alternative settings.

Moreover, specific findings may quickly become outdated due to the rapid pace of technological evolution in the field. However, this limitation highlights an opportunity for future research, including periodic assessments of dynamic AI capabilities and their readiness for various logistics applications (Durach and Gutierrez, 2024). Lastly, the study did not consider different AI types simultaneously, while future research could investigate the synergies and novel applications arising from such combinations within the context of 3PL businesses. Such investigations could also help illuminate the interdependencies characterising the relationships among the different 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.

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