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EXPLORING BARRIERS TO THE ADOPTION OF ARTIFICIAL INTELLIGENCE IN THE TRANSPORTATION SECTOR IN THE CONTEXT OF INDUSTRY 5.0: A QUALITATIVE EXPERT-BASED STUDY

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This study investigates barriers to the adoption of Artificial Intelligence (AI) in the transportation and logistics sector within the context of Industry 5.0, emphasizing human centricity, sustainability, and system resilience. A qualitative expert-based research approach was applied using asynchronous email interviews with 54 experts representing transport operators, logistics service providers, SMEs, public sector institutions, technology providers, and academia from multiple countries. The analysis identified eight interrelated categories of barriers affecting AI implementation in transport systems, including data quality and integration issues, infrastructure limitations, financial constraints, lack of human competencies, managerial challenges, psychological resistance, ethical and safety concerns, and regulatory uncertainty. SME specific challenges were further examined using Latent Dirichlet Allocation, confirming the central role of data, competences and resource constraints. The findings indicate only partial alignment of current AI initiatives with Industry 5.0 values and provide implications for intelligent transport systems, transport safety, and policy development.

Keywords: Artificial intelligence adoption, transport and logistics systems, Industry 5.0, intelligent transport systems, SMEs

1. Introduction

The accelerating digital transformation of logistics and transportation has intensified interest in technologies such as AI, cyber-physical systems, and automation, which are central to the evolution from Industry 4.0 toward the human-centric, sustainable, and resilient paradigm of Industry 5.0. Recent studies emphasize that Industry 5.0 requires a deeper integration of advanced technologies with human expertise, shifting the focus from pure automation toward augmentation, adaptability, and social value (Monferdini *et al.*, 2025). Parallel research demonstrates that disruptive tools – including artificial intelligence (AI), and data-driven systems, and intelligent robotics – are increasingly embedded in logistics and supply chain operations as organizations pursue higher levels of efficiency and sustainability (Nicoletti and Appolloni, 2024).

Within this framework, transportation and logistics systems are expected to become more intelligent, collaborative, and environmentally responsible. However, many organizations—particularly SMEs—continue to face substantial technological and organizational constraints during digital transition (Osieczko-Potoczna, 2024; Marchenko *et al.*, 2023). These constraints reflect limited financial and human resources, insufficient IT infrastructure, skill shortage, and heightened vulnerability to rapidly evolving technological demands. At the same time, structural disruptions and insufficient digital integration across logistics networks reinforce the strategic importance of advanced technologies such as AI for building resilient and adaptable transport systems (Pan *et al.*, 2025). Research on Industry 5.0 further highlights the critical role of human-technology collaboration and human-centric system design, underscoring that advanced technologies can enhance operational resilience when positioned as support for human expertise rather than as mechanisms of full automation (Hajzargarbashi *et al.*, 2025). Moreover, the integration of Industry 5.0 principles is increasingly viewed as an enabler of broader sustainability goals across logistics ecosystems (Kasinathan *et al.*, 2022).

Despite this expanding body of research on digital transformation and Industry 4.0/5.0 transitions, several limitations remain evident. Existing studies highlight the role of digital technologies, automation, AI, and cyber-physical systems in transforming logistics and transportation (Nicoletti and Appolloni, 2024; Pan *et al.*, 2025; Hassan *et al.*, 2024). They also stress that Industry 5.0 demands deeper human–technology collaboration, sustainability-oriented decision-making, and enhanced system resilience (Leng *et al.*, 2022; Kasinathan *et al.*, 2022; Alojaiman, 2023). While such works provide conceptual frameworks and technological perspectives, they offer limited evidence on how these transformations are experienced in transportation settings and how organizations navigate barriers to AI adoption in practice.

From a theoretical perspective, the adoption of artificial intelligence in transportation systems can be interpreted through established technology acceptance frameworks, particularly the Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT). TAM explains adoption through perceived usefulness and ease of use, while its extensions—TAM2 (Venkatesh and Davis, 2000) and TAM3 (Venkatesh and Bala, 2000)—incorporate additional factors such as social influence and determinants of user behaviour. UTAUT further integrates these perspectives, emphasizing performance expectancy, effort expectancy, social influence, and facilitating conditions (Venkatesh *et al.*, 2003). Prior research shows that even advanced technologies may fail without user acceptance, highlighting the importance of behavioural and organizational factors. However, these frameworks remain underexplored in the context of AI adoption in transportation within Industry 5.0. Therefore, they provide a valuable lens for analysing the barriers identified in this study.

The research gap concerns three areas. First, existing studies do not provide qualitative, practitioner-level evidence on how barriers to AI adoption manifest in transport operations; current work remains largely conceptual or quantitative and lacks systematic expert-based insights (Nicoletti and Appolloni, 2024; Osieczko-Potoczna, 2024). Second, although Industry 5.0 literature emphasizes human-centricity, augmentation, and socio-technical integration, empirical understanding of how these principles influence AI-related decisions in transportation is limited (Leng *et al.*, 2022; Nahavandi, 2019; Alojaiman, 2023). Third, the literature insufficiently examines SME-specific vulnerabilities—such as limited digital maturity, resource constraints, and organizational resistance—despite SMEs’ pivotal role in transport and logistics networks (Fernández *et al.*, 2024; Osieczko-Potoczna, 2024).

In response to these gaps, this study delivers an empirically grounded analysis designed to extend current understanding of AI adoption challenges in the transportation sector. This study contributes to the growing body of research on Industry 5.0 and AI-enabled transportation by offering one of the first qualitative, expert-driven analyses of the barriers that hinder AI adoption in the transport sector. Drawing on insights from specialists representing logistics firms, SMEs, public-sector organizations and academia, the study provides context-sensitive evidence that complements predominantly conceptual and quantitative work in this field. It advances current knowledge by (1) identifying and thematically organizing the technological, organizational and ethical challenges constraining AI implementation; (2) elucidating how Industry 5.0 principles—such as human-centricity, sustainability and resilience—influence expert perspectives on AI readiness; and (3) highlighting SME-specific vulnerabilities that remain underexplored in existing literature. The findings offer a grounded understanding of the conditions shaping AI adoption in transportation, supporting more informed decision-making among practitioners and policymakers. Importantly, while the identified barriers may appear consistent with general digitalization challenges reported in prior studies, this study contributes by revealing how these barriers manifest, interact, and reinforce each other within the specific context of transportation and logistics systems under Industry 5.0 conditions. In particular, the findings demonstrate that these barriers are not isolated but form interconnected structures, where data-related issues, competence gaps, and resource constraints jointly shape AI adoption outcomes. Moreover, the study provides context-specific, expert-based insights into how these barriers influence human-centricity, sustainability, and system resilience, which remain underexplored in existing literature.

2. Theoretical background

Global logistics and supply chains are undergoing a profound transformation driven by climate imperatives, geopolitical tensions and recurrent disruptions (Pan *et al.*, 2025). Monferdini *et al.* (2025) add that the shift from Industry 4.0 to Industry 5.0 brings new opportunities and challenges, requiring a deeper understanding of how successive industrial revolutions reshape logistics. Industry 5.0 and Society 5.0 are conceptualized as responses to the limitations of technology-driven Industry 4.0 and traditional production

systems, refocusing attention on human well-being, sustainability, and resilience (Nahavandi, 2019; Xu *et al.*, 2021; Leng *et al.*, 2022; Alojaiman, 2023). Emerging digital technologies, such as artificial intelligence (AI), the industrial Internet of Things (IIoT), cloud computing, and digital twins, are viewed as key enablers of this human-centric, sustainable paradigm (Kasinathan *et al.*, 2022; Matenga and Mpofu, 2023). In logistics, these developments coalesce in the concept of Logistics 5.0, which combines advanced AI foundation models with sustainable practices to mitigate logistics' environmental footprint (Nicoletti and Appolloni, 2024).

Santhi and Muthuswamy (2022) show that supply chains increasingly rely on AI, IIoT, and blockchain to address challenges of data visibility, trust, and coordination. They argue that simple digitization must give way to interconnected, data-driven ecosystems. Similarly, Pan *et al.* (2025) emphasize that AI, machine learning, digital twins, and blockchain are propelling logistics toward Supply Chain 4.0 and 5.0. The transition toward Industry 5.0 requires building on the technological foundations of Industry 4.0, including IIoT-enabled smart technologies and emerging data-driven approaches which recent studies identify as key enablers in enterprise management and service operations (Babkin *et al.*, 2023; Marchenko *et al.*, 2023; Monferdini *et al.*, 2025). This technological continuity also extends to intralogistics, where automated solutions and IIoT-driven monitoring systems support real-time information flow and more intelligent internal transport (Mustapić *et al.*, 2023; Osieczko-Potoczna, 2024; Pizoń *et al.*, 2024). Building on these technology-centric foundations, Industry 5.0 is framed as a value-driven paradigm combining AI, big data analytics, and human-centric design with sustainability and resilience (Xu *et al.*, 2021; Leng *et al.*, 2022). Accordingly, Logistics 5.0 integrates foundation models, digital twins, IIoT, blockchain, and green logistics to realize human-centric, sustainable logistics systems (Nicoletti and Appolloni, 2024).

Despite advances in digital technology, logistics operations remain exposed to lead-time uncertainty, terminal disruptions, labor shortages, and geopolitical instability, which complicates the deployment of advanced digital tools (Pan *et al.*, 2025). Even when technologies are available, organisations struggle to align Industry 4.0 solutions with Industry 5.0 values; system heterogeneity, data privacy concerns, skill shortages, and the complexity of embedding human-centric values into technology result in persistent adoption gaps (Monferdini *et al.*, 2025). Studies of intralogistics cite obstacles including employee resistance, insufficient digital skills, high implementation costs, interoperability issues, cybersecurity concerns, and difficulty scaling AMR fleets (Pizoń *et al.*, 2024). In transport, a lack of suitable technology, high investment costs, regulatory compliance requirements, and integration complexity, along with resistance to change, remain major impediments (Nicoletti and Appolloni, 2024). SME-focused research highlights financial, infrastructural, and skill constraints, along with cultural resistance and data privacy/security concerns, as central barriers to digital transformation (Fernández *et al.*, 2024); this pattern reinforces that AI adoption is a multi-dimensional process shaped by financial, technological, organisational, regulatory, and socio-cultural constraints (Leng *et al.*, 2022; Fernández *et al.*, 2024).

Industry 5.0 scholarship highlights human-centricity, sustainable development, human capital investment, and inclusive growth as key pillars of the emerging paradigm (Marchenko *et al.*, 2023). Empirical studies show that firms adopt sustainable logistics and transport practices to advance decarbonization and meet Net Zero targets under Industry 5.0's sustainability agenda (Trstenjak *et al.*, 2023; Pan *et al.*, 2025). Human workers remain central, with a focus on safety measures, skill development, and human-robot collaboration; for example, employees work alongside robots and AMRs in intralogistics to enhance safety and stabilize operations (Trstenjak *et al.*, 2023; Osieczko-Potoczna, 2024; Pizoń *et al.*, 2024). Resilience is strengthened through human-centric cobotic platforms that keep operators in the loop, supported by deep-learning-enhanced interaction and adaptive cyber-physical systems that enable flexible responses to unforeseen situations (Sheikh *et al.*, 2024).

SMEs face distinctive, often disproportionate challenges in integrating AI and advanced digital technologies into logistics and transport operations. Studies of intralogistics automation find that SMEs encounter major financial and skills barriers to implementation, frequently forcing reliance on external funding and support programmes (Osieczko-Potoczna, 2024; Pizoń *et al.*, 2024). Broader analyses confirm that SMEs' restricted financial capacity, insufficient digital skills, inadequate technological preparedness, and limited resource access make the transition to digitised production and logistics far more difficult than it is for larger firms (Fernández *et al.*, 2024). These constraints create major obstacles to AI-driven intralogistics and transport solutions, as necessary infrastructure upgrades, integration complexity, and capability gaps compound investment pressures (Pizoń *et al.*, 2024). Accordingly, recent research emphasizes the need for industrial solutions engineered for easy implementation and affordability in SMEs,

directly targeting the financial and organisational barriers hindering technology adoption in smaller firms (Sheikh *et al.*, 2024).

Industry 5.0 literature frames AI as a tool for augmentation rather than full automation. Empirical studies of production platforms show that labour-intensive tasks can be automated while human operators supervise the process, exemplifying an augmentation-oriented approach of close human–machine collaboration (Sheikh *et al.*, 2024). Similarly, intralogistics studies report that autonomous mobile robots take over repetitive transport tasks without replacing human operators, allowing employees to focus on higher-value activities (Pizoń *et al.*, 2024). At the logistics system design level, Industry 5.0 is associated with a shift from pure automation to human–technology integration, giving greater importance to ergonomics, human factors and the design of effective human–machine interfaces (Monferdini *et al.*, 2025; Lagorio *et al.*, 2023). In this view, AI-driven decision-support tools augment managerial and operational decision-making, reinforcing Industry 5.0’s vision of collaborative human–AI logistics systems (Nicoletti and Appolloni, 2024; Shahidzadeh and Shokouhyar, 2025;).

Overall, Industry 4.0 and Industry 5.0 are portrayed as complementary dimensions of an ongoing techno-social evolution reshaping logistics, transport, and production systems. Rather than supplanting Industry 4.0’s technology-centric advances, Industry 5.0 is seen as an evolutionary shift toward human-centred, sustainable, and resilient industrial ecosystems that will guide future technological and societal development (Xu *et al.*, 2021; Leng *et al.*, 2022). This evolution calls for new management paradigms and decision-making tools to balance sustainability, resilience, and economic performance in global logistics (Pan *et al.*, 2025). Combining Industry 4.0 automation with the human-centred principles of Industry 5.0 is increasingly presented as essential for developing logistics systems that are more efficient, sustainable, and aligned with human and organisational needs (Monferdini *et al.*, 2025). Within this vision, AI and advanced autonomous systems enhance sustainable, efficient, and human-centric production, while human–machine cooperation enables more adaptive and humanised manufacturing systems that improve productivity and sustainability and, as noted by Nahavandi (2019), may create more jobs than they displace.

3. Methods and process

This study adopts a qualitative, exploratory and expert-based research design aimed at understanding how specialists and practitioners perceive the barriers to adopting AI in the transportation and logistics sector within the framework of Industry 5.0. The methodological approach is grounded in the use of asynchronous email interviewing, a technique increasingly recognised in qualitative research for its flexibility, its ability to generate reflective and detailed responses, and its suitability for engaging geographically dispersed or time-constrained expert groups (Harris *et al.*, 2024; Dahlin, 2021; Ratislavová and Ratislav, 2014). Prior research emphasises that asynchronous email interviews offer substantial advantages, including flexibility, elimination of scheduling constraints, enhanced opportunities for thoughtful reflection, and the production of text-based data that require no transcription (Harris *et al.*, 2024; Amri *et al.*, 2021). These features make the method particularly suitable for studies involving international experts in complex socio-technical domains.

3.1. Sampling

A purposive sampling strategy was used to ensure participation of experts with substantive experience in AI applications, logistics and transport operations, SME digitalisation, and Industry 5.0-related initiatives. Participants were recruited from logistics and transport firms, SMEs, public-sector organisations, technology providers, and academic or research institutions. The sample was designed to include different stakeholder perspectives on AI adoption in transportation and logistics. Academic experts were included because of their cross-sectoral knowledge of AI, digital transformation, and Industry 5.0. Logistics service providers were treated as sector-specific actors, whereas SMEs were distinguished as a size-based category to capture the specific constraints of smaller firms. Some overlap between categories was possible; therefore, respondents were classified according to their primary professional role. This strategy is consistent with qualitative approaches that prioritise information-rich cases and expert knowledge when examining complex technological or organisational issues (Harris *et al.*, 2024). The final dataset included 54 expert responses from eight countries (Latvia, Croatia, Austria, Spain, Slovenia, Poland, Tunisia, and Hungary), providing diverse and cross-national perspectives on AI readiness, organisational constraints, and human-centric considerations in the transport and logistics sector.

3.2. Recruitment

Following recommended procedures for asynchronous qualitative recruitment (Harris *et al.*, 2024), invitations were distributed through professional associations, academic networks related to AI and Industry 5.0, and direct contacts with logistics and transport organisations. Each invitation contained a description of the study purpose, confidentiality assurances, and instructions for participation. Only individuals who confirmed their willingness to take part received the interview prompts. Data collection occurred between September and November 2025.

3.3. Data collection

In line with methodological guidelines for asynchronous email interviewing (Dahlin, 2021; Ratislavová and Ratislav, 2014), participants received a set of open-ended prompts aligned with the research questions. To reduce interpretive ambiguity, the interview materials clarified that AI technologies referred broadly to data-driven and learning-based solutions supporting prediction, optimisation, automation, or decision-making in transport and logistics. Participants were selected on the basis of relevant professional experience in AI, digitalisation, logistics, transport operations, or Industry 5.0-related initiatives. The interview contained the following items:

1. What are the main barriers to adopting AI technologies in the logistics/transportation sector within the framework of Industry 5.0?
2. How do experts assess the current level of strategic alignment between AI initiatives in logistics/transportation and the core values of Industry 5.0 (human-centricity, sustainability, resilience)?
3. What are the sector-specific challenges for SMEs in integrating AI into logistic/transport processes?

Participants were encouraged to provide reflective, detailed responses similar in depth to traditional qualitative interviews. The asynchronous format enabled participants to respond at their own pace, minimising scheduling constraints and allowing for thoughtful articulation of professional experience—benefits consistently highlighted in methodological literature (Harris *et al.*, 2024; Dahlin, 2021).

3.4. Methods used

The responses to RQ1 were analysed using a grounded theory approach, first applying open coding and then axial coding to identify the main themes. This approach has been applied in prior studies to analyse expert opinions (Mozelius *et al.*, 2024) and is also considered appropriate for data collected through asynchronous communication tools (Bonfim, 2025). During the open coding phase, the researchers systematically broke the data into discrete units to identify meaningful data extracts, initial codes, and emerging categories. In the subsequent axial coding phase, these elements were reassembled and integrated into more abstract, conceptually coherent categories. For RQ2, we employed manual coding for the synthesis of experts' alignment opinions. For RQ3, we employed a topic analysis, using the Latent Dirichlet Allocation (LDA) method. The application of this method enabled us to uncover the latent topic structure embedded in the text data, thereby enhancing our understanding of both the content and the underlying relationships present within the textual information (Pan and Xu, 2023; Sharma *et al.*, 2022). In addition, the analysis considered potential relationships across responses to the three research questions. This cross-question comparison made it possible to identify recurring patterns between perceived barriers to AI adoption, the assessment of alignment with Industry 5.0 values, and SME-specific constraints. In particular, the analysis showed that data-related, competence-related, and financial barriers were not isolated themes, but reappeared across all three questions and were linked to weaker alignment with the human-centric dimension of Industry 5.0.

4. Results and discussion

4.1. Main barriers to adopting AI technologies in the logistics/transportation sector

During open coding, 26 distinct codes emerged from the data (answers to RQ1), representing initial concepts identified across the responses. Through axial coding, these 26 codes were synthesized and organized into 8 central categories (Table 1), establishing relationships and patterns among the initial codes. The eight categories identified were: Data issues, Ethical/safety concerns, Financial constraints, Infrastructure issues, Lack of human competencies, Managerial issues, Psychological barriers, and Regulatory barriers.

Table 1. Axial coding results (Source: own elaboration)

Open codes	Category
Data issues (low quality, heterogeneity)	Data issues
Data silo	
Fragmentation of data (supply chain fragmentation result)	
Ethical concerns	Ethical/safety concerns
Sustainability concerns	
Limited transparency of AI	
Cybersecurity concerns	
Long-term investment with unknown result	Financial constraints
High investment costs	
Legacy systems	Infrastructure issues
Insufficient IT infrastructure	
Inconsistent infrastructure	
Integration issues	
Lack of human training	Lack of human competences
Competences shortage	
Too fast technological change to follow by human	
Lack of AI strategy	Managerial issues
Lack of understanding of the nature of AI projects (iterations)	
Leadership mindset	
Processes too simple to change	
There is no one-do-all model	Psychological barriers
Lack of trust for AI technology	
Fear of becoming obsolete	
Resistance to change	Regulatory barriers
Inadequate legal framework	
Regulatory and political instability	

Although the identified categories of barriers are consistent with those reported in prior digitalization and AI adoption studies, the results highlight their strong interdependencies and context-specific configuration within transportation and logistics systems. Rather than functioning as isolated constraints, the barriers form a mutually reinforcing system, where, for example, data-related issues, infrastructure limitations, and competence gaps collectively shape implementation outcomes. This systemic perspective extends existing literature by demonstrating how general digitalization challenges operate in a transport-specific and Industry 5.0-oriented context.

Financial constraints represent a critical barrier to AI adoption that is deeply interconnected with deficiencies in complementary resources, including inadequate infrastructure, workforce capacity gaps, and managerial uncertainty regarding investment outcomes. Experts repeatedly stressed that “*implementing AI typically requires a significant cost*” and that “*the main barriers are high upfront costs and limited budgets*”. These costs are not limited to acquiring software and hardware; they also encompass “*subsequent maintenance of this infrastructure*” and “*upfront investments in (...) cybersecurity, and workforce development*”. The challenge is particularly acute in legacy environments, where “*the most visible obstacle is the high cost of implementation, particularly when it comes to integrating AI with older systems that many companies still rely on*”. Uncertain economic returns further intensify these cost-related concerns. As several experts noted, “*companies often hesitate because the return on investment is unclear*”, and some AI “*technologies (...) have a long payback period if there aren’t millions of orders per day*”, creating persistent “*uncertainty about return on investment*”. In this context, managerial risk aversion becomes a reinforcing barrier, resulting in “*reluctance to incur costs associated with innovative solutions*.” Taken together, high initial and ongoing expenditures, difficulty integrating AI with legacy systems, and ambiguous payback horizons combine to make financial risk a major impediment to strategic investment in AI in logistics and transportation.

Infrastructure constraints represent a significant barrier closely intertwined with financial limitations. Many organizations face the dual challenge of investment costs and technical compatibility: *"many companies fear high investment costs and difficulties in integrating new solutions with existing IT systems and technical infrastructure"* and *"AI requires integration with existing IT systems in the company, and such integration is not always possible without a lot of work and financial resources."* Legacy systems constitute a particularly acute problem. Experts highlighted that *"outdated IT systems that do not work with modern analytics tools are also a problem"* and that *"legacy system integration"* presents substantial obstacles. The core issue is that *"advanced technologies cannot function efficiently without a solid foundation. In many cases, organizations rush to implement new systems without first ensuring that the underlying infrastructure is capable of supporting them."* This manifests as *"limited interoperability between older and newer IT systems"* and *"difficulties with the compatibility of AI technology with the systems used in the company."* Infrastructure deficiencies cascade into additional problems, particularly affecting data quality. As experts noted, *"data comes from many unrelated systems: ERP, TMS, WMS, IoT devices and is often incomplete, varies in structure, or is incompatible."* This fragmentation reflects the underlying technical architecture problem: without modernized, interoperable infrastructure, organizations cannot achieve the data standardization and integration necessary for effective AI implementation.

Data-related barriers emerged as the most pervasive obstacle to adopting AI technologies in logistics and transportation. Experts stressed that *"the introduction of AI in logistics and transport as part of Industry 5.0 is hampered by fragmented data"* and that existing datasets are *"poor quality"*, *"not standardized"*, and *"difficult to access"*. They further noted that *"another difficulty is integrating data from various sources"*. These challenges are amplified by structural characteristics specific to logistics: *"AI needs a complete picture to make our supply chains stronger, but right now, every company keeps its data locked away in its own silo"*. As another expert observed, *"the logistics ecosystem involves multiple stakeholders—manufacturers, carriers, warehouses, and customers - often using incompatible data systems. This makes it difficult to collect, share, and analyze data at scale, which limits the potential of AI for predictive analytics, optimization, and decision support"*. Together, these accounts underscore that without coordinated efforts toward data standardization, interoperability, and secure data sharing, even advanced AI solutions will struggle to deliver their promised benefits in this sector.

Human competence deficiencies emerge as a multifaceted barrier to AI implementation in logistics and transportation. At a fundamental level, *"skills shortages in the workforce (...) complicate the transition to human-centred collaboration"* and as experts admit *"many employees lack digital skills"*. A critical challenge involves the human-machine interface: *"AI technologies are based on data, and humans often use not data, but information in the broad sense, which they are unable or unwilling to communicate to the computer"*. The sector faces shortages of specialized expertise. Experts highlighted *"shortage of specialists combining logistics and AI knowledge"* and *"a shortage of professionals with the right skills to manage AI systems"*, with particular gaps in *"shortages of AI, data analysis, and cybersecurity specialists"*. These deficiencies extend to management levels, where there is a *"small number of (...) managers who have developed digital competences and can properly lead the team during the implementation of such technologies in the company."* The broader labour market offers limited relief: *"few available employees with appropriate education and experience in the labour market."*

Workforce development through training is essential yet underutilized. As one expert emphasized, *"we need to shift our focus from replacing people to empowering them, but that requires building trust and retraining our entire workforce to collaborate with smart technology - a massive task we're only just beginning to tackle."* However, as another expert noticed, *"training is not always prioritized"*. Training's importance extends beyond technical skill acquisition - it also mitigates psychological resistance: *"the lack of AI expertise (...) will create a certain resistance to change the existing systems and many stakeholders might be skeptical in the AI adoption"*.

The shortages in competences might strengthen psychological barriers among logistics and transportation stakeholders – especially employees and management. Experts emphasized that *"resistance to change and limited trust in AI further complicate the transition to human-centred collaboration"*. Employee resistance was frequently linked to perceived job threats: *"emerging resistance from employees to the implementation of new technologies, fear of job loss and replacement by artificial intelligence"*. One of our experts noticed that this pattern is not new: *"this issue (resistance to change) was already present during the transition to Industry 4.0 (...) it is especially evident among people who have already experienced one or more technological transitions. Many of them feel that the additional effort required for adaptation is not reflected in their salaries or benefits. Others believe they have already contributed enough throughout their careers and wish to retire peacefully without facing another major paradigm shift"*. Fears around job security fuel this reluctance, as *"employees are often concerned about job security"* and *"employees may perceive AI as a threat to their jobs rather than as a tool to augment their capabilities, leading to reluctance"*

in adoption.” Additional everyday constraints like “*lack of time to engage due to daily tasks*” and “*lack of understanding of project goals and insufficient preparation*” - further reduce willingness to participate in AI initiatives. Trust in technology is another critical dimension: experts pointed to “*lack of trust in algorithms*” and “*limited trust in process automation - some managers fear excessive dependence on technology*”. These concerns are shared across hierarchies, as “*employees and management fear job losses or excessive process automation*”. Overall, psychological barriers - rooted in fear of job loss, change fatigue, limited understanding, and low trust - form a powerful barrier to the adoption of AI that can be potentially limited with proper training programmes and changes in organizational culture.

Organizational issues constitute another barrier to AI adoption in logistics and transportation, cutting across strategy, governance, and project management practices. Experts pointed to “*lack of understanding that many IT tasks in AI implementation (...) are achieved after several iterations*”, which leads managers to expect immediate, deterministic outcomes rather than experimental, incremental progress. This is reinforced by “*management’s lack of time to engage in as-is diagnosis, requirement analysis, and solution design*” and a transactional mindset - “*thinking in terms of ‘I pay = I demand,’ while real Industry 4.0/5.0 implementation requires partnership and engagement of multiple stakeholders*” - that undermines collaborative innovation. Weak internal organization further constrains implementation, with “*poor process organization (lack of proper people assignment, supervision, responsibility division)*” and the tendency “*to automate chaotic processes instead of organizing them first*”. Strategically, “*many firms lack a clearly defined digitization strategy or innovation culture, which slows adoption of new solutions*”. In such contexts, some managers perceive “*no need due to simplicity of processes*” and there is a persistent “*lack of awareness of potential*” and “*lack of awareness of the business benefits of AI among management*”. Finally, “*there is also a lack of understanding of innovative projects -potential failure, need for cooperation, need for real change, not just tool delivery*”, which results in under-resourced, tool-centric initiatives that fall short of the transformative organizational change required for effective AI deployment.

Ethical considerations and safety issues constitute significant obstacles to AI implementation in logistics and transportation. Experts emphasized that “*ethical concerns (...) slow down adoption, as Industry 5.0 requires human centric and sustainable solutions*” and stressed the importance of regulatory frameworks, noting that “*the lack of appropriate legal regulations and ethical standards also matters, as these could ensure the safe implementation of AI*”. A critical concern raised by multiple experts involves algorithmic transparency. The operation of “*AI algorithms as ‘black boxes’*” undermines stakeholder trust in AI-driven systems, limiting their acceptance and adoption (“*we can’t expect an experienced truck driver or warehouse manager to blindly trust a ‘black box’ AI that tells them what to do*”). Beyond that, cybersecurity and data protection emerged as paramount issues. Experts warned that “*companies increasingly fall victim to cyberattacks (e.g., ransomware), which becomes a critical issue for AI*”. The logistics sector’s handling of sensitive information intensifies these risks: “*this sector uses the personal data of many drivers and clients, which forces the owner to protect these data.*” Furthermore, the sector’s inherent safety requirements compound these challenges, as “*this field has a lot of safety requirements to meet.*” Collectively, these concerns - regulatory gaps, algorithmic opacity, cybersecurity vulnerabilities, and data protection obligations - must be addressed before ethical and safe AI deployment can occur in logistics and transportation.

The problem begins with macroeconomic instability: experts noted “*unstable political and economic conditions*” that create an unfavourable environment for long-term technology investments, compounded by “*regulatory uncertainty regarding responsibility for decisions made by AI systems, which hinders broader implementation*”. The sector faces deficiencies in AI-specific legislation. Experts highlighted a “*lack of legal regulations (...) regarding the use of AI in companies, or use in transport such as autonomous trucks (heavy goods vehicles)*”, leaving firms without clear guidance on permissible AI applications. Where regulations do exist, they remain inadequate for emerging technologies: “*regulatory frameworks are not fully adapted to technologies such as autonomous vehicles or drones, creating uncertainty for firms that might otherwise adopt them*”. Cross-border operations become even more complex, as there is “*lack of harmonization of law (...) where carriers operate*”. Existing regulations are frequently vague creating practical implementation obstacles. Companies encounter “*unclear regulations regarding algorithmic responsibility*” and face “*ambiguity of the AI Act in practical logistics implementation*”. More broadly, “*regulatory frameworks regarding data privacy, ethical AI use, and liability in autonomous decision-making remain underdeveloped in many regions, creating uncertainty for companies*”. Specific compliance tensions include: “*difficulties ensuring compliance with data protection and transport regulations*” and “*GDPR limitations in the processing of telematics and operational data*”. Collectively, regulatory instability, legislative gaps, jurisdictional fragmentation, and ambiguous frameworks create a climate of legal uncertainty that might deter investment in AI technologies in the logistics and transportation sector.

4.2. The sector-specific challenges for SMEs in integrating AI into logistic/transport processes

To validate and deepen our understanding of the thematic relationships within expert responses regarding SME-specific barriers to AI adoption in logistics and transportation, we employed Latent Dirichlet Allocation (LDA), a computational topic modelling technique. Manual qualitative analysis using open and axial coding initially identified three dominant thematic clusters: costs, data, and competencies. LDA was subsequently applied to reduce analyst subjectivity and bias (Alqazlan *et al.*, 2025) by computationally validating these manually-derived themes and revealing latent relationships among topics. As an unsupervised exploratory learning method, LDA requires specification of the number of topics to extract (Palacios *et al.*, 2020). Grounding this hyperparameter selection in empirical observations from manual coding, we set the number of topics to three, aligned with our qualitative findings. The initial text corpus consisted of 3,008 words. Following preprocessing, including the removal of standard stop words and researcher-defined domain-specific stop words (e.g., “industry,” “5.0,” “businesses,” “SMEs,” and “AI”), the final analytical corpus was reduced to 1,516 words. The resulting topic model yielded keyword clusters for each identified topic, presented in the figure below (Fig. 1).

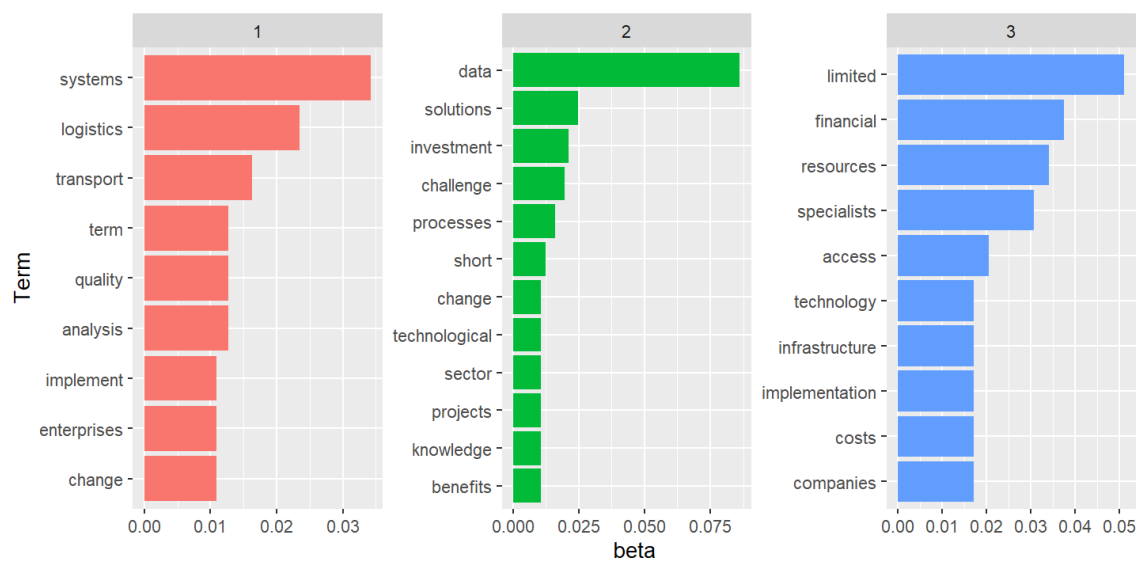


Figure 1. Sector-specific challenge for SME - main topics keyword
Source: own elaboration

Topic 1 centres on "systems" ($\beta = 0.034$), the highest-weighted term across all topics, followed by keywords including "logistics," "transport," "term," "quality," "analysis," "implement," "enterprise." And "change". This topic appears to capture issues related to logistics and transport systems, particularly in the context of operational change and implementation processes within organizations. It suggests a system-level perspective on logistics transformation, underlying unique barriers associated with it. Topic 2 is dominated by the term "data" ($\beta = 0.083$), followed by secondary terms including "solutions," "investment," "challenge," "processes". This cluster represents the challenges surrounding data quality and integration that underpin effective AI deployment. The co-occurrence of "data", "change", and "investment" reflects experts' recognition that data-related obstacles are not merely technical issues but require substantial organizational change and financial commitment to address. Topic 3 is characterized by "limited" ($\beta = 0.051$) and "financial" ($\beta = 0.037$) as leading terms, combined with "resources," "specialists," "access," "infrastructure," "technology," "implementation," "costs," and "companies." This cluster captures the resource scarcity - financial limitations, insufficient infrastructure, restricted access to specialists from the field. The co-occurrence of "limited," "financial," "resources," and "infrastructure" reveals that SMEs face interconnected resource deficits that constrain all aspects of AI adoption.

The obtained results are similar to the outcome from the manual coding approach (similar barriers were revealed). At the same time, the topic modelling results suggest that these barriers are closely interrelated rather than fully discrete. In particular, data-related challenges appear to require investment and organizational change, while the limited budgets and restricted access to specialists typical of SMEs may further intensify these constraints.

4.3. The current level of strategic alignment between AI initiatives in logistics/transportation and the core values of Industry 5.0

Generally, most experts identify only a partial, medium level of strategic alignment between AI initiatives in logistics and transportation and the core values of Industry 5.0. Most experts agree that “AI technologies are mainly launched to improve efficiency and reduce costs”. However, they emphasize that “while many organizations have embraced AI to improve efficiency, optimize routes, and reduce operational costs, fewer have systematically aligned these efforts with the broader principles of human-centricity, sustainability, and resilience”. Critical perspectives also exist, suggesting that current developments diverge significantly from Industry 5.0 assumptions: “business plans are more focused on efficiency, accelerating work, not reducing the burden and quality of work, which is the opposite of putting the human at the center”. It should also be underlined that experts observe a pattern related to firm size: “exceptions include large logistics operators implementing AI that supports rather than replaces workers, but in SMEs, alignment with Industry 5.0 values is still marginal”. Furthermore, they note that alignment varies across different dimensions: “the progress is uneven, with sustainability being the area where alignment is strongest”.

To capture the overall assessment of alignment, we applied a three-point scale (low, medium, high). The same scale was used to evaluate three individual dimensions when experts referred to them separately (Fig. 2). The results indicate that sustainability represents the most aligned dimension, although some experts stress that this progress is largely unintentional: “where we’re seeing the best progress, almost by accident, is in sustainability. AI-powered route optimization is a perfect example - the primary goal is to save money on fuel, but the fantastic side effect is a smaller carbon footprint”. Similar tendencies are observed with respect to resilience: “AI is increasingly being used to improve efficiency, for optimization, cost reduction, and predictive maintenance - which does support (...) resilience goals”. In contrast, the human-centric dimension shows much weaker alignment: “it affects workplace ergonomics and human-machine cooperation to a lesser degree” and “there is still a lack of strong emphasis on the human aspect at the center”. In summary, alignment with Industry 5.0 principles remains uneven. It tends to be stronger in larger companies, yet efficiency and cost reduction continue to serve as the primary drivers. While sustainability and resilience goals often align with these motivations, the human-centric dimension still lags behind.

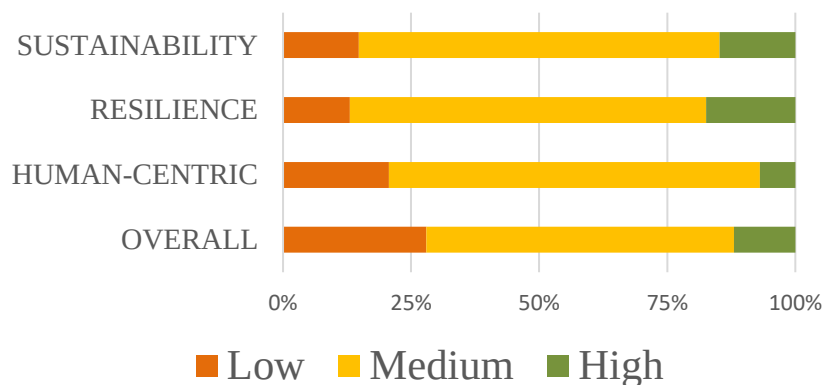


Figure 2. The experts' assessment of strategic alignment between AI initiatives in logistics/transportation and the core values of Industry 5.0
Source: own elaboration

4. Conclusions

This study examined barriers to AI adoption in transportation and logistics in the context of Industry 5.0 using asynchronous email interviews with 54 experts representing multiple stakeholder groups and countries. The analysis identified eight interrelated categories of barriers affecting AI implementation: data issues, infrastructure limitations, financial constraints, lack of human competencies, managerial issues, psychological barriers, ethical and safety concerns, and regulatory uncertainty. Expert accounts indicate that these barriers are mutually reinforcing rather than independent. Data-related problems, including fragmentation, limited standardization, and difficulties with integration across systems and partners, emerged as the most pervasive constraint and were frequently linked to infrastructure readiness and investment capacity.

The SME-focused analysis confirms a concentrated set of challenges. Topic modelling revealed three core and connected themes: data, limited resources and system-level obstacles. The results further suggest that addressing data quality and integration issues requires both financial investment and specialised expertise, both of which remain constrained in SMEs.

The study also indicates that the current strategic alignment between AI initiatives in transport and logistics and Industry 5.0 values is generally partial. Experts largely perceived AI as being implemented primarily to increase efficiency and reduce costs. Sustainability benefits are often achieved indirectly through optimisation applications, while resilience is supported through predictive and preventive approaches. In contrast, human centricity remains the weakest dimension of alignment, with limited emphasis on augmentation-oriented design and human-oriented work improvements. Differences by firm size were noted, with larger operators more frequently deploying AI to support rather than replace workers, while alignment in SMEs remains marginal (Monferdini *et al.*, 2025; Nicoletti and Appolloni, 2024; Nahavandi, 2019).

From a practical perspective, the results suggest that improving AI readiness in transportation requires coordinated actions targeting data governance and interoperability, legacy infrastructure constraints, workforce development, and managerial capabilities for iterative implementation. Regulatory clarity concerning responsibility, data use, and cross-border compliance remains an important enabling condition for broader adoption.

Declaration of Generative AI and AI-assisted technologies in the writing process:

During the preparation of this manuscript, ChatGPT (OpenAI) was used in order to improve the clarity of language and refine the structure of the text. No AI tools were employed for generating scientific results, analyses, or data. After using this tool, the content was carefully reviewed and edited, and full responsibility for the publication remains with the author.

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