

Artificial Intelligence in Logistics: Evidence from Slovak Enterprises

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Adoption, Embedding, and the Maturity Divide

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Data availability

The AI-ImpactSK survey dataset (Černý et al., 2026) is openly available via Zenodo under a CC BY 4.0 licence: <https://doi.org/10.5281/zenodo.20699449>

Ethics

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Use of AI tools

Data preparation and statistical analyses were performed using standard scientific software. The authors are responsible for all data, analyses, interpretations and conclusions, and have reviewed and approved the final manuscript; any use of digital assistance was confined to routine support and does not affect the integrity or originality of the scientific content.

Abstract

Artificial intelligence (AI) is widely expected to reshape logistics and supply-chain management, yet enterprise-level evidence on how firms actually deploy it remains thin, fragmented, and drawn mostly from large Western or Asian corporations. Evidence from the small, open, transition economies of Central and Eastern Europe (CEE) is almost absent, and logistics is usually folded into generic accounts of “AI in the supply chain.” This monograph addresses that gap using the AI-IMPACT survey, an organization-level study of AI adoption among enterprises operating in Slovakia (N = 816 deduplicated firms). It focuses on the 142 firms that have begun implementing or testing AI in logistics, the third most frequently named functional domain of AI application among surveyed AI users, and contrasts them with the 420 surveyed AI users that have not.

Combining descriptive, exploratory, and confirmatory methods (logistic and negative-binomial regression, exploratory factor analysis, a k-means partition, and Wilcoxon signed-rank testing), the study develops one evidence-backed argument: among these firms, adoption has run ahead of embedding. They pilot a broad portfolio of logistics AI applications, but few have converted pilots into regular operational use. The average adopter has 5.3 of 13 applications at least in pilot use and only 1.8 in regular use; 59% have none in regular use at all. A two-group partition separates a minority of “embedded” adopters (35%) from a majority of “experimenters” (65%). What most clearly distinguishes the two is organizational AI maturity, rather than firm size, sector, or perceived barriers. In a multivariate model maturity is the strongest predictor of the breadth of active deployment (incidence-rate ratio ≈ 2.5 per standard deviation), and the association holds when the two maturity dimensions that overlap with usage are removed (IRR ≈ 2.2 for the governance-and-strategy dimensions alone). Perceived benefits exceed perceived risks (Wilcoxon $p < .001$), though realized gains so far concentrate in growth, service, and productivity rather than hard cost savings, and data security is the foremost concern. Barriers, measured across the whole sample, are higher among non-adopters and predict who adopts; among adopters they do not predict how deeply AI is embedded. All relationships are cross-sectional associations, not causal effects. The monograph reads organizational AI maturity as the firm characteristic most closely tied to the move from experimentation to embedded use, and draws out the implications for managers, technology providers, and CEE digitalization policy.

Keywords: artificial intelligence; logistics; supply-chain management; technology adoption; organizational AI maturity; Industry 4.0; Slovakia; Central and Eastern Europe; enterprise survey; digital transformation

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This monograph rests on the work of many hands, and it is a pleasure to acknowledge them. Our first and greatest debt is to the AI-ImpactSK project team, whose collaboration made this study possible: for conceiving and fielding the enterprise survey, for the careful collection, cleaning, and documentation of the data, and for the many conversations that sharpened how we read it. Without their groundwork this book would have had nothing to stand on.

We are equally grateful to the enterprises and their representatives who gave their time to respond. Their willingness to describe, candidly, how they actually use artificial intelligence in their day-to-day work is what gives this study its evidentiary base, and we hope the findings repay that openness.

We thank our colleagues and home institutions for the intellectual environment in which this research took shape, and the reviewers whose questions and corrections improved the manuscript in ways large and small. Any errors that remain are, of course, our own.

Finally, and most personally, we thank our families. Their patience, encouragement, and quiet understanding through the long hours that a project like this demands were a gift we did not take for granted. This book is, in no small part, theirs as well.

Foreword

Few claims about contemporary management are repeated as confidently, or examined as rarely, as the claim that artificial intelligence is transforming the way firms move goods. The promise is everywhere; the enterprise-level evidence, especially from the smaller economies at Europe's centre, is not. This monograph is our attempt to correct that imbalance. We take a question usually answered with anecdote and isolated case study (how do real firms actually use AI in logistics?) and answer it with data, carefully, and for a setting the international literature has almost entirely overlooked.

At the heart of the book is a distinction we hold to throughout: the difference between adopting a technology and embedding it. Drawing on the AI-IMPACT survey of enterprises operating in Slovakia, and on the 142 firms that have taken AI into their logistics operations, we find that adoption has run well ahead of embedding. Firms pilot a broad portfolio of applications but convert little of it into regular operational use. The finding sits uncomfortably with the prevailing narrative of rapid digital transformation, and it is precisely the kind of finding that careful measurement, rather than enthusiasm, brings to light.

Equally important is the central association we build the book around: that what most clearly separates the firms which embed AI from those that merely experiment is not size, sector, or the barriers managers most readily name, but organizational AI maturity, the strategy, governance, data, and technology practices a firm builds around the tools it deploys. We test this claim against the obvious objections and report honestly where the evidence is strong and where it is only suggestive. We resist the language of cause and effect that a single cross-section cannot support, and we say so plainly throughout.

We have written for several audiences at once. We hope scholars will find a careful, methodologically varied treatment of a genuinely under-researched region. Managers may recognize their own organizations in the portrait of broad experimentation and shallow embedding, and find in the maturity argument a practical place to direct their effort. Policymakers concerned with the digital catch-up of Central and Eastern Europe may find their problem usefully reframed: among firms that have already adopted, the binding constraint on value is internal capability more than external obstacle.

This book is, as we describe it within, a first map of a territory drawn at the moment it began to take shape. Like any good first map, it is honest about its blank spaces and clear about where the next survey should go. We offer it to everyone trying to understand not merely whether firms are adopting artificial intelligence, but whether they are learning to use it.

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1. Introduction

1.1 From promise to practice

Few technologies have been forecast to reshape logistics as widely as artificial intelligence. Demand-sensing models that anticipate orders before they are placed, machine-learning route optimizers that reroute fleets in seconds, autonomous mobile robots that pick and pack without rest, predictive-maintenance systems that anticipate failures before they occur: these have become familiar figures in the literature on digital supply chains (Toorajipour et al., 2021; Riahi et al., 2021; Hofmann & Rüsch, 2017). The technical evidence is substantial. Machine-learning methods swept the leading positions in the M5 forecasting competition, beating statistical benchmarks by roughly a fifth (Makridakis et al., 2022); a redesigned picking algorithm cut drive distance per pick by 62% in live Amazon fulfilment centres (Allgor et al., 2023); learned heuristics now solve 500-stop vehicle-routing problems in about a second (Bai et al., 2023). Consultancies translate these advances into aggregate promises of inventory reductions of 20–30% and logistics-cost reductions of 5–20% from embedding AI in distribution operations (McKinsey & Company, 2024).

Between the demonstration and the enterprise, though, lies a wide and poorly mapped territory. Most published impact evidence comes from algorithm benchmarks, simulations, or isolated pilots; even sympathetic systematic reviews concede that firm-level studies of realized organizational impact are scarce, that the evidence concentrates in large-firm, Western, or East-Asian manufacturing settings, and that “logistics” is often subsumed within generic supply-chain management rather than examined in its own right (Culot et al., 2024; Shahzadi et al., 2024). We therefore know a good deal about what AI can do in a laboratory and rather little about what enterprises do with it, how far they get, and what separates the firms that succeed from those that stall.

This monograph tries to close part of that distance for one economy and one functional domain. It asks not whether AI can work in logistics, which the engineering literature documents at length, but how a population of real firms in a small, open, manufacturing-intensive European economy has taken AI into their logistics operations: who they are, what they apply it to, how deeply they have embedded it, how they weigh its benefits against its risks, what holds them back, and where they are heading.

1.2 The Slovak and Central European setting

The setting is Slovakia, a useful and under-studied case. Slovakia is a small, open economy whose industrial structure is unusually concentrated in manufacturing and, in particular, automotive production and its dense supplier logistics. It is the kind of economy where AI-enabled logistics might be expected to matter most, and also one where adoption lags the European frontier. Harmonized European statistics show that enterprise AI adoption in Slovakia rose across all size classes between 2021 and 2024 yet stayed below the EU-27 average throughout, with small firms moving from roughly 4% to 9% and medium firms from

7% to 16% (Eurostat, 2025; Kádárová et al., 2026). Composite digital-readiness indices place Slovakia and its Visegrád neighbours well behind Northern and Western Europe (Dobos & Bánhidí, 2024; Brodny & Tutak, 2021), and the European Commission's monitoring identifies digital-skills and ICT-specialist shortages as a brake on AI uptake (European Commission, 2024).

Almost everything known about AI in Slovak and wider CEE enterprises is either aggregate, drawn from country-level Eurostat panels and composite indices, or sector-agnostic, examining manufacturing or “enterprises in general” rather than specific operational functions. The nearest Slovak study to the present topic examines Industry 4.0 and digital technologies in logistics broadly, not AI specifically, and finds investment cost the dominant barrier (Richnák, 2022). The few studies that do isolate AI in logistics sit in neighbouring Poland or Germany and are comparative or conceptual (Panasiuk & Wiechetek, 2026; Kmiecik & Skórnóg, 2025). To our knowledge, no prior study supplies enterprise-level, logistics-specific, AI-focused evidence for Slovakia itself. This monograph aims to fill that gap.

1.3 The AI-IMPACT survey and the focal phenomenon

The evidence base is the AI-IMPACT organization-level survey, a 2025 study of AI adoption and use among enterprises operating in Slovakia. After deduplication, the analytical dataset comprises 816 firms and 621 variables organized into thematic blocks covering organizational and respondent characteristics, multidimensional AI-maturity indicators, attitudes toward AI, the status and intensity of AI use, functional areas of application, perceived impacts, and barriers (Černý et al., 2026). A pivotal question, item D3 (“In which areas of the company have you started implementing or testing AI?”), lets respondents who already use or pilot AI indicate the functional domains involved. One hundred and forty-two firms selected *Logistics*, making it the third most frequently named domain among surveyed AI users, behind marketing and sales (209) and production or manufacturing (157), and ahead of human resources, finance, ICT security, and others.

These 142 firms are the focal population of this monograph. Because the survey routed them through a dedicated logistics module, they provide unusually complete data. For each of fourteen specific logistics AI applications they reported an *adoption stage* on a graded five-point scale running from “we do not and will not use it” to “we use it actively and regularly”; they rated the significance of sixteen documented positive impacts and seven negative impacts; and, in common with all AI users, they answered batteries on AI maturity (seven dimensions), barriers (twenty items), corporate sentiment, adoption drivers, AI technology types, perceived performance effects, and workforce consequences. The 420 surveyed AI users that did not select logistics serve as a contrast group for questions about which firms bring AI into logistics in the first place.

1.4 Aim, research questions, and central argument

The aim is to produce an original, coherent, empirically grounded account of AI in Slovak logistics, useful to scholars, managers, and policymakers. Rather than treat the survey as a source of isolated facts, the monograph pursues a connected set of research questions, each

chosen because it yields a demonstrable, value-adding finding, and each answered with an appropriate descriptive or inferential method:

RQ1, Profile and determinants. Among surveyed AI-using firms, which organizational characteristics distinguish those that deploy AI in logistics from those that do not? (Chapter 5).

RQ2, Application portfolio and structure. Which specific logistics AI applications are adopted, at what stage, and do they form coherent latent capability bundles? (Chapter 6).

RQ3, Depth of embedding. How far have adopters progressed from experimentation to regular operational use, and can firms be meaningfully grouped by their embedding profile? (Chapter 7).

RQ4, The maturity association. Does organizational AI maturity track deeper, broader logistics AI deployment, and does the association survive scrutiny of how maturity is measured? (Chapter 8).

RQ5, Benefit-risk architecture. How do adopters weigh the positive and negative impacts of logistics AI, and how do these perceptions relate to realized performance and to depth of use? (Chapter 9).

RQ6, Barriers. Which barriers do firms perceive as most binding, at what point in the adoption process do they bind, and do they explain depth of deployment? (Chapter 10).

RQ7, Frontier and embedding context. Where is the forward pipeline of logistics AI heading, and how is logistics AI embedded within firms' broader AI footprint and workforce? (Chapter 11).

From these questions one argument emerges, and the monograph is organized to build and qualify it: among Slovak firms that have taken AI into logistics, adoption has run ahead of embedding, and the characteristic that most clearly separates firms that embed AI from those that merely experiment is organizational AI maturity, not size, sector, or perceived barriers. Firms pilot a wide range of logistics AI applications, but conversion into regular, value-generating operational use is the exception rather than the rule. Maturity, a firm's strategy, organization, governance, and data and technology practices around AI, is the characteristic most closely associated with crossing from experiment to routine. Because the survey observes firms at a single point in time, this is an associational claim, not a demonstrated causal mechanism; the language of "drivers" and "engines" is avoided in favour of association throughout, and Section 3.6 sets out why.

1.5 Contributions

The monograph makes four contributions. *Empirically*, it provides what is, to our knowledge, the first enterprise-level account of AI in logistics for a Central European economy, with complete graded-adoption data on fourteen applications for 142 firms. *As a measurement contribution*, it separates adoption from embedding and operationalizes the distinction with firm-level indices, in-use breadth, active-use breadth, adoption intensity, and an embedding ratio, that can travel to other settings; the pilot-to-scale gap is a familiar idea in the adoption literature (Hradecky et al., 2022; Uren & Edwards, 2023; McKinsey & Company, 2024), but it is rarely measured at this granularity for a specific function. *Theoretically*, it connects a

measured, multidimensional AI-maturity construct to concrete functional-area deployment, and tests whether that connection is an artifact of construct overlap, supplying the kind of firm-level evidence the readiness literature has called for but seldom provided (Jöhnk et al., 2021; Sadiq et al., 2021; Oldemeyer et al., 2024). *Practically*, it reframes the managerial and policy problem: among firms that have already adopted, the constraint on logistics AI value appears to be internal capability rather than the removal of external barriers.

1.6 Structure of the monograph

Chapter 2 reviews the literature across five streams, the AI-in-logistics landscape, specific applications and their documented impacts, organizational AI maturity and adoption theory, benefits, risks and barriers, and the CEE/Slovak context, and states the research gap and hypotheses. Chapter 3 describes the data, measures, derived variables, analytical strategy, and the limitations of the evidence. Chapter 4 sets the scene with a descriptive overview of AI adoption across the whole sample and positions logistics within it. Chapters 5 through 11 take the research questions in turn, moving from who adopts, through what they adopt and how deeply, to the role of maturity, how firms value AI, what constrains them, and where the field is heading. Chapter 12 synthesizes the findings, situates them against the literature, and draws out theoretical, managerial, and policy implications. Chapter 13 concludes. All numerical results are recorded in an accompanying Master Registry, all figures are provided at publication resolution, and every literature claim is logged with its source in a Literature Review Registry.

2. Background and Literature Review

This chapter situates the study within five connected streams of scholarship. The first establishes the landscape of AI adoption in logistics and supply-chain management; the second surveys evidence on specific applications and their documented impacts; the third develops the theoretical machinery of organizational AI maturity and technology adoption; the fourth examines benefits, risks, and barriers; and the fifth narrows to the Central and Eastern European and Slovak context. The chapter closes by crystallizing the research gap and stating the hypotheses that the empirical chapters test.

2.1 The landscape: AI in logistics and supply-chain management

Artificial intelligence entered supply-chain scholarship through a succession of techniques, expert systems, genetic algorithms, neural networks, agent-based systems, and fuzzy logic, applied to canonical problems of network design, forecasting, and scheduling (Min, 2010). Two decades on, the field has matured into a recognizable research programme. Systematic reviews now identify machine learning, agent-based systems, and fuzzy logic as the most-studied techniques, applied across procurement, production, and logistics or distribution, with predictive analytics, demand forecasting, inventory optimization, and transport optimization, emerging as the functions where AI delivers the clearest operational gains (Toorajipour et al., 2021). Bibliometric analyses document a steep acceleration of research after 2017, with machine learning, neural networks, and optimization forming the dominant clusters and a decisive shift toward predictive applications (Riahi et al., 2021). More recent syntheses extend the frame from Industry 4.0 to the emerging “5.0” and “6.0” visions, positioning AI as the integrative intelligence layer of digital supply chains, increasingly combined with the Internet of Things, digital twins, and blockchain (Samuels, 2025; Teixeira et al., 2025).

Conceptually, AI in logistics is best understood as one expression of a broader digitalization of logistical processes. Hofmann and Rüsçh’s (2017) foundational account of Logistics 4.0 frames it as the comprehensive interconnection of logistical processes through cyber-physical systems and autonomous, data-driven decision-making, the umbrella beneath which AI in logistics sits. The macro drivers of adoption are by now well-rehearsed: cost and speed, certainly, but increasingly resilience and competitiveness. The COVID-19 disruption proved a watershed, with multiple empirical studies finding that AI and big-data capabilities were among the digital assets most strongly associated with supply-chain resilience, demand sensing, real-time visibility, and rapid recovery (Modgil, Singh, & Hannibal, 2022; Modgil, Gupta, et al., 2022; Belhadi et al., 2021). AI has thus become a primary instrument of supply-chain risk management, supporting disruption prediction, supplier-risk scoring, and resilience, even as adoption lags the methodological state of the art (Baryannis et al., 2019).

Two features of this landscape literature matter for the present study. First, the human and organizational dimension is decisive but under-weighted: automation and AI reshape the division of labour in logistics, and worker acceptance, trust, and the broader “human factor”

are frequently the limiting conditions for autonomous logistics deployment, shifting human roles toward supervision and exception handling rather than wholesale substitution (Klumpp, 2018; Klumpp & Ruiner, 2022). Second, and most important, the literature is far richer on technique and potential than on verified enterprise adoption. The most recent and rigorous reviews state plainly that empirical, firm-level studies remain scarce and fragmented, concentrated in a few large-firm, Western, or East-Asian manufacturing contexts, leaving realized impact under-documented and logistics rarely isolated from generic supply-chain management (Culot et al., 2024; Shahzadi et al., 2024). Authoritative cross-national statistics reinforce the point: in 2024 only 13.5% of EU enterprises with ten or more employees used AI, ranging from 27.6% in Denmark to 3.1% in Romania, and adoption rose steeply with firm size, 41.2% of large versus 11.2% of small enterprises (Eurostat, 2025; OECD, 2024). Diffusion is real but rapid, uneven, and structurally tilted toward large, digitally mature firms.

2.2 Specific applications and their documented impacts

Beneath the landscape lies a granular literature on specific application families, each with its own evidence of effectiveness. *Route optimization* has been transformed by machine learning, which improves both the modelling of vehicle-routing problems and the performance of the algorithms that solve them, lowering cost and, through learned heuristics, collapsing routing latency from minutes to seconds, enabling real-time dispatch (Bai et al., 2023; Greenberg et al., 2025). Last-mile delivery, the costliest and least efficient segment, is the highest-leverage target (Giuffrida et al., 2022; Bruni et al., 2023). *Demand forecasting and inventory optimization* furnish the field's cleanest evidence: in the M5 competition every top method was a pure machine-learning model, with winners roughly 22% more accurate than a seasonal-naïve benchmark, and hybrid AI forecasting consistently improves accuracy while reducing inventory cost and raising service levels (Makridakis et al., 2022; Douaioui et al., 2024; Aamer et al., 2020; Seyedan et al., 2023).

Warehouse automation has matured around autonomous mobile robots that automate internal transport and order picking; their throughput gains come from eliminating picker travel, though realized benefits depend heavily on robot-to-picker ratios and control policies (Fragapane et al., 2021; Zhen et al., 2025). The most striking field evidence is Amazon's redesigned picking algorithm, which cut drive distance per pick by 62% in production at fulfilment-centre scale (Allgor et al., 2023); broader reviews tie warehouse robotics, IoT, and AI to higher picking accuracy, throughput, and space utilization at lower cost, while flagging integration cost and interoperability as limits (Tikwayo & Mathaba, 2023; Tubis & Rohman, 2023; Aravindaraj & Rajan Chinna, 2022). *Shipment tracking and supply-chain visibility* benefit from machine-learning estimated-time-of-arrival models that beat conventional estimators and, when coupled with IoT sensing, reduce spoilage in cold chains through condition-based rerouting (Balster et al., 2020; Müller et al., 2026). *Predictive maintenance* reduces unplanned downtime and maintenance cost relative to reactive or preventive regimes by detecting failure precursors in telemetry (Hector & Panjanathan, 2024). *Supply-chain optimization and error reduction* increasingly draw on deep-learning quality inspection and on AI for closed-loop and reverse logistics, though explainability is repeatedly identified as the bridge between technical accuracy and managerial adoption (Bhattacharya et al., 2024;

Vasan et al., 2024; Abdulrashid et al., 2024). *Drones* present the most conditional case: electric delivery drones can be fast and cost- or emission-competitive for small payloads, but outcomes are highly sensitive to payload, range, and regulation (Raghunatha et al., 2023; Eskandaripour & Boldsai Khan, 2023). Finally, *chatbots and virtual assistants* materially affect customer-service outcomes, though their value is contingent on conversational design and user characteristics (Rese & Witthohn, 2025), and generative AI is widening the natural-language service surface across logistics (Jackson et al., 2024).

Two lessons follow. First, documented impacts are robust but framed almost entirely in technical terms, accuracy, latency, distance, cost, and reported by researchers rather than rated by adopting firms. Even leading reviews concede that many deployments, especially of generative AI, remain at prototype stage and “rarely report system-wide KPIs” (Jackson et al., 2024). Second, the evidence is siloed by application: almost no study measures how a single population of enterprises perceives the significance of AI across a *full portfolio* of logistics applications at once. That is precisely the gap the present graded-adoption and perceived-impact data fill.

2.3 Organizational AI maturity, readiness, and adoption theory

Why do otherwise comparable firms differ so sharply in how far they take AI? The dominant answers come from three theoretical traditions. The *Technology–Organization–Environment* (TOE) framework holds that adoption is shaped jointly by technological, organizational, and environmental contexts (Tornatzky & Fleischer, 1990), and has been applied productively to AI adoption in manufacturing, services, insurance, and logistics technologies such as automated warehousing and blockchain (Chatterjee et al., 2021; Gupta et al., 2022; Hao et al., 2020; Ganguly & Kumar, 2024). *Diffusion of innovations* contributes the perceived attributes of innovations and the adopter categories that govern the pace of spread (Rogers, 2003). And the *resource-based* and *dynamic-capabilities* views explain why value, once a technology is available, accrues unevenly: sustained advantage flows from valuable, rare, inimitable, non-substitutable resources and from a firm’s capacity to integrate, build, and reconfigure competences, with absorptive capacity, the ability to recognize, assimilate, and apply new knowledge, a precondition for converting AI into capability (Barney, 1991; Teece et al., 1997; Cohen & Levinthal, 1990).

On these foundations a more specific construct has grown: organizational *AI readiness* or *AI maturity*. Jöhnk, Weißert, and Wyrski (2021) show that AI readiness is inherently multidimensional, spanning strategy, culture, data, organizational structure, and ethics. A complementary body of work demonstrates that AI *capability*, itself a multidimensional bundle of tangible, human, and intangible resources, predicts firm performance, often mediated by a data-driven culture (Mikalef & Gupta, 2021; Fosso Wamba et al., 2024; Chowdhury et al., 2023). Prerequisites such as absorptive capacity, prior digitalization, and firm size repeatedly emerge as enablers (Kinkel et al., 2022), and readiness gaps are shown to stall AI at the experimentation stage (Hradecky et al., 2022; Uren & Edwards, 2023). For the present argument, the more relevant strand is recent work linking readiness not merely to adoption but to the *scope and depth* of deployment: resource orchestration drives the

breadth and depth of AI in manufacturing SMEs (Peretz-Andersson et al., 2024), internal digital capability dominates external factors in European SMEs (Arroyabe et al., 2024), and deployment scope tracks data and strategy readiness in public organizations (Neumann et al., 2024). The realized value of AI, in short, depends on complementary resources and capabilities rather than on the technology alone (Enholm et al., 2022).

Yet the maturity literature has two persistent weaknesses that this study addresses. First, maturity models proliferate but are rarely validated, and most embed large-firm assumptions ill-suited to the SMEs that dominate European economies (Sadiq et al., 2021; Oldemeyer et al., 2024). Second, and more consequentially, the empirical link runs mostly from maturity to *intention* or to *generic firm performance*; very few studies connect measured, multidimensional maturity to *concrete functional-area deployment*, to whether and how deeply a firm actually uses AI in a specific operational domain such as logistics. Establishing that link is a central theoretical objective of this monograph.

2.4 Benefits, risks, and barriers

A fourth stream weighs the upside and downside of logistics AI. On the *benefit* side, syntheses tie AI to efficiency, decision quality, and new capabilities through automational, informational, and transformational mechanisms (Enholm et al., 2022; Wamba-Taguimdje et al., 2020), with sustainability an increasingly prominent theme: AI-driven route and load optimization, energy-efficient operations, and emissions monitoring deliver measurable fuel and CO₂ reductions (Frikha & Mrad, 2025; El jaouhari et al., 2025). Industry estimates put the operational prize at inventory reductions of 20–30% and logistics-cost reductions of 5–20% (McKinsey & Company, 2024).

On the *risk* side, the literature catalogues opacity and the black-box problem, accountability and privacy, bias, error propagation, over-automation, and workforce displacement (Dwivedi et al., 2021; Ghosh, 2025). A distinct behavioural literature shows that these risks are not merely technical: human trust in AI is fragile and shaped by transparency and reliability, opaque or unreliable systems erode trust and provoke disuse even when they outperform humans, over-trust breeds complacency, and people abandon algorithms faster than humans after equal errors, the phenomenon of algorithm aversion (Glikson & Woolley, 2020; Hoff & Bashir, 2014; Dietvorst et al., 2015). The lack of transparency in AI recommendations is therefore simultaneously a risk and an adoption barrier, which is why explainability is repeatedly proposed as the bridge to adoption (Nimmy et al., 2022).

On the *barrier* side, tertiary and systematic studies converge on a recurring set: high cost and limited financing, shortages of skilled personnel, poor data quality and availability, integration with legacy IT, weak strategy, organizational resistance, and, newly, regulatory compliance, as the EU AI Act imposes binding obligations on high-risk systems with penalties up to €15 million or 3% of turnover (Hangl et al., 2022; Shahzadi et al., 2024; European Parliament & Council, 2024). These barriers fall disproportionately on SMEs: only about 6.9% of European SMEs have adopted AI, with digital skills, infrastructure, firm size, and internationalization the decisive determinants, and skill gaps cited by 63% of employers as the single biggest barrier to transformation (Segarra-Blasco et al., 2025; Arroyabe et al.,

2024; World Economic Forum, 2025). Third-party logistics providers, specifically, struggle to identify viable AI use cases amid fragmented data and heterogeneous customer needs, and capture value only by building dynamic capabilities to sense, seize, and reconfigure around AI (Pratavia et al., 2026).

What is missing is integration. Benefits, risks, and barriers are studied in separate literatures and rarely co-measured in a single firm-level instrument, still less for logistics specifically. The literature also exhibits a marked asymmetry, quantified benefit optimism dominates, while risks appear mostly as conceptual cautions seldom rated by adopters themselves (Hangl et al., 2022). A survey that asks the same firms to rate positive impacts, negative impacts, and barriers in parallel can therefore test directly whether benefit optimism outweighs risk salience and whether barriers actually constrain deployment.

2.5 The Central European and Slovak context

The fifth stream localizes these questions. Enterprise AI adoption in CEE is consistently below the EU average and structurally gated by digital readiness rather than firm scale. In a study of 478 manufacturing firms across Slovakia, Slovenia, and Croatia, only 18.4% used AI software in at least one production area, and firm size, supply-chain role, and technology intensity did *not* predict AI use, whereas Industry 4.0 readiness did (Kovič et al., 2024). Slovak enterprise AI adoption rose between 2021 and 2024 but stayed below the EU-27 average every year, with no stable aggregate AI-productivity link, implying that gains depend on complementary organizational, skills, and institutional investment (Kádárová et al., 2026; Eurostat, 2025). Composite digital-readiness and digital-maturity analyses place Slovakia and its Visegrád neighbours well behind the European frontier, with wide intra-CEE disparities (Dobos & Bánhidi, 2024; Brodny & Tutak, 2021; Vrchota & Pech, 2019), and the European Commission's Digital Decade monitoring flags below-average integration of cloud, big data, and AI among Slovak SMEs alongside skills shortages (European Commission, 2024).

On logistics specifically, the evidence thins to almost nothing. Richnák (2022) shows that Industry 4.0 and digital technologies are implemented in Slovak logistics, most strongly in production logistics across all firm sizes, and that investment cost is the single greatest barrier, but the study concerns digital technologies broadly rather than AI. Entrepreneurial orientation is significantly linked to effective AI integration across 136 Visegrád chemical SMEs (Hruby, 2025); Slovak firms are only partially prepared for Industry 4.0, constrained by labour structure and digital-skills shortages (Grenčíková et al., 2019, 2021); and the nearest AI-in-logistics readiness work sits in Poland and Germany (Panasiuk & Wiechetek, 2026; Filina-Dawidowicz et al., 2026; Kmiecik & Skórnóg, 2025). No prior study supplies enterprise-level, logistics-specific, AI-focused evidence for Slovakia itself.

2.6 Research gap and hypotheses

Synthesizing across the five streams, the gap this monograph addresses is sharply defined. The technical literature establishes that AI works in logistics but reports impact in laboratory terms; the adoption literature establishes that readiness matters but links it to intention or

generic performance rather than to functional-area deployment; the benefit–risk–barrier literatures run in parallel and are rarely integrated for logistics; and the regional literature documents CEE’s adoption lag only in the aggregate. Missing is an enterprise-level account that, for a specific economy and a specific function, (a) profiles who adopts, (b) maps what they adopt and how deeply, (c) tests whether measured AI maturity drives depth of deployment, and (d) integrates perceived benefits, risks, and barriers. This study supplies exactly that for AI in Slovak logistics.

From the gap and the theory, six testable hypotheses follow, organized around the central thesis that adoption has outrun embedding and that maturity is the decisive divide:

H1 (determinants). Among Slovak AI-using firms, the probability of deploying AI in logistics increases with organizational AI maturity and is elevated in logistics-intensive sectors (manufacturing; transportation and storage), net of firm size.

H2 (maturity → depth). Among logistics adopters, organizational AI maturity positively predicts the breadth of *actively* used logistics AI applications, over and above firm size and sales.

H3 (benefit > risk). Logistics adopters rate the positive impacts of AI as significantly more important than the negative impacts, indicating net benefit optimism.

H4 (barrier paradox). Perceived barriers do *not* meaningfully distinguish logistics adopters from other AI users, nor predict the depth of logistics AI deployment; the binding constraint is internal capability rather than perceived external obstacles.

H5 (latent structure). The portfolio of logistics AI applications is internally coherent, dominated by a single general adoption-propensity dimension while admitting an interpretable secondary distinction between physical supply-chain and customer-facing/cognitive applications.

H6 (embedding gap). A large majority of adopters remain at the experimentation stage, with few applications in regular active use, such that firms separate into a minority of “embedded” adopters and a majority of “experimenters” distinguished chiefly by maturity.

The remainder of the monograph tests these hypotheses and assembles the answers into a single account of AI in Slovak logistics.

3. Data and Methods

3.1 The AI-IMPACT survey and dataset

The empirical basis of this monograph is the AI-IMPACT survey, an organization-level study of the adoption and use of artificial intelligence among enterprises operating in Slovakia (Černý et al., 2026). The publicly released analytical dataset contains responses from 816 organizations after deduplication of multiple representations of the same company; a “raw” reference export of 1,086 complete cases is also available but is not used here, because each company should appear once in adoption analyses. The instrument comprises 95 questions decomposed into 621 variables, organized into seven thematic blocks that mirror the questionnaire’s skip logic: company and respondent characteristics; organizational AI maturity; AI adoption and utilization; functional areas of AI application and their evaluation; barriers to implementation; corporate sentiment toward AI; and supplementary company information. The dataset integrates categorical indicators, ordinal maturity items, Likert-type significance scales, and binary multiple-choice variables, supplemented by technical metadata.

A defining feature of the instrument is its extensive skip logic. Respondents were routed to question batteries only when prior answers made them relevant, so the great majority of missing values in content variables are structural, they reflect non-applicability rather than item non-response. The gateway item, *Aluse*, sorts firms into current users and testers (AI used in multiple areas; in several specific processes; or being piloted), planners (intending to adopt within one, two, or three-plus years), and non-adopters. Only current users and testers were shown item D3 (“In which areas of the company have you started implementing or testing AI?”), and only firms selecting a given functional area were shown that area’s detailed module. This routing is analytically convenient: every firm answering the logistics module had, at D3, reported that it has begun implementing or testing AI in logistics, and the modules yield complete data. Throughout, “adopter” is a defined shorthand for this group, firms that have started implementing or testing AI in logistics, and not a claim that all are in full operational use; much of the analysis concerns how far short of full use most of them fall.

3.2 Focal population and contrast group

Of the 816 firms, 562 are current AI users or testers. Among these, 142 selected *Logistics* at item D3 and thereby form the **focal population** of this monograph. The 420 AI users who selected other functional areas but not logistics constitute the **contrast group** used to identify the determinants of logistics adoption (Chapter 5). The remaining 254 firms, 131 planners and 123 non-adopters, were not shown D3 and are therefore outside the adoption analyses, though the planner subsample informs the discussion of the forward frontier. Because the 142 focal firms answered mandatory array questions within the logistics, maturity, barrier, and sentiment modules, the focal data are effectively complete: every logistics application, positive and negative impact, barrier, and maturity item has a valid response for all 142 firms.

3.3 Measures and derived variables

AI maturity. Seven single-item maturity dimensions (strategy, culture, organization, technology, data, ethics, and privacy) were each rated on a five-point scale of increasing sophistication (for strategy, for example, from “no AI vision or strategy in place” to “strategy is recognized as industry-leading”). A composite maturity score was computed as the mean of the seven dimensions (Cronbach’s $\alpha = .88$), standardized for use in regression models. Two of the seven dimensions warrant a measurement caveat: the technology item asks “how does your organization use AI technologies?” and the data item asks how prepared the organization is “to work with data for AI purposes.” Both are partly outcomes of AI usage rather than purely antecedent conditions, so a composite that includes them overlaps conceptually with the deployment outcomes it is later used to predict. To guard against this, Chapter 8 re-estimates the key model with a reduced, governance-and-strategy composite that drops these two items (and, in a stricter variant, retains only strategy, organization, ethics, and privacy); because each dimension is a single item, dimension-level differences are also interpreted with caution and the composite is treated as the reliable unit.

Logistics AI applications (LOGareas). For each of fourteen logistics applications, respondents reported an *adoption stage* on a graded five-point scale: 1 = “we do not and will not use it”; 2 = “considering for the more distant future (more than two years)”; 3 = “plan to use within the next two years”; 4 = “already using in pilot form / occasionally”; and 5 = “using actively and regularly.” Thirteen substantive applications were retained for firm-level indices (the fourteenth, “Other,” was analyzed descriptively only). From these graded stages we derived four firm-level indices: **in-use breadth** (count of applications at stage ≥ 4 , i.e., at least piloted), **active-use breadth** (count at stage 5, i.e., in regular use), **adoption intensity** (mean stage across the thirteen applications), and an **embedding ratio** (active-use breadth divided by in-use breadth, the share of a firm’s adopted applications that have reached regular use). These indices operationalize the distinction between adoption and embedding that organizes the monograph.

Perceived impacts. Adopters rated the significance of sixteen documented *positive* impacts (e.g., shorter delivery times, fuel savings, warehouse automation, lower CO₂) and seven potential *negative* impacts (e.g., faulty deliveries, inventory dropping below critical levels, loss of sensitive logistics data, lack of transparency) on a five-point significance scale (1 = “not at all significant” to 5 = “very significant”). Two further positive-impact items carried in the dataset without documented question wording in the codebook were excluded from the scale for transparency. Firm-level means were computed for positives ($\alpha = .93$) and negatives ($\alpha = .93$), and a **net perceived benefit** index as their difference.

Barriers and sentiment. Twenty barrier items were rated on a five-point scale whose anchors run from “not a barrier” (1) through a neutral “no impact” midpoint (3) to “a very significant barrier” (5), and were averaged into a barrier index ($\alpha = .95$). The scale is therefore bipolar with a neutral centre rather than a simple intensity gradient, so a mean near 3 indicates barriers perceived as close to neutral rather than “moderately binding”; treating the index as equal-interval is a simplification. Eight corporate-sentiment statements were rated for agreement ($\alpha = .58$, reflecting deliberately mixed-direction items, so the composite is reported descriptively only).

Performance impact, technologies, drivers, and workforce. Adopters rated the perceived direction of change in thirteen performance indicators since (or expected from) AI implementation on a five-point scale from “significant decrease” to “significant increase”; the extent of use of seven AI technology types; the importance of nineteen adoption drivers; and binary indicators of AI-related layoffs and newly created positions, together with how the adoption decision was made.

Firmographics. Firm size (four employee bands), net sales (six bands), ownership (Slovak private, foreign, state, mixed), age (three bands), sector (NACE-aligned, eighteen categories), and respondent managerial level were used as covariates and descriptors.

3.4 Analytical strategy

The analysis proceeds from description to confirmation. *Descriptive* analyses profile the full sample and the focal population, including adoption-stage distributions and ranked item profiles. *Reliability* analysis (Cronbach’s α) validates the multi-item scales. *Exploratory factor analysis* (EFA) on the thirteen application stages, with Kaiser–Meyer–Olkin and Bartlett adequacy tests, parallel analysis for factor retention, and oblimin rotation, examines latent structure (H5). A *k-means partition* of standardized application-stage profiles, with the number of clusters chosen by the silhouette criterion, summarizes the population as a small number of strata (H6); the partition is read as a description of a continuum, not as evidence of natural kinds, and the silhouette value is reported so the reader can judge how clean the separation is. *Confirmatory* models then test the hypotheses: a binary **logistic regression** estimates the correlates of logistics adoption among the 562 AI users (H1); a **negative-binomial regression** (chosen over Poisson because the active-use breadth count is overdispersed) estimates the association between maturity and the breadth of active deployment among the 142 adopters (H2). Because that count has many zeros (59% of adopters), the negative-binomial result is checked against a two-part (hurdle) formulation that separates whether a firm has any regular use from how much, and against composites that drop the usage-laden maturity items (see Chapter 8). A **Wilcoxon signed-rank test** compares positive and negative impact ratings within firms (H3); **Mann–Whitney** tests, Spearman correlations, and a full-sample adoption-margin logistic model evaluate where barriers bind (H4). Effect sizes (odds ratios, incidence-rate ratios, Cohen’s d_z , rank correlations) and 95% confidence intervals are reported throughout. Given the number of tests, p-values are interpreted descriptively rather than as strict accept/reject thresholds; the primary confirmatory results (H1–H4) are also reported with Benjamini–Hochberg false-discovery-rate-adjusted q-values, and exploratory comparisons (the EFA, the dimension-by-dimension correlations, and the typology) are read as hypothesis-generating. Variance-inflation factors are reported to confirm the regression predictors are not collinear. All results are logged in the accompanying Master Registry; all figures are provided at 600 dpi.

3.5 Reliability and validity

The multi-item scales display strong internal consistency: maturity $\alpha = .88$, positive impacts $\alpha = .93$, negative impacts $\alpha = .93$, barriers $\alpha = .95$, and the thirteen application stages $\alpha = .92$.

High internal consistency shows that the items in each scale hang together; it does not by itself establish that a scale measures the intended construct, and the maturity caveat above applies. The application battery is highly factorable (KMO = .91; Bartlett's test $p < .001$), supporting the latent-structure analysis. As an external benchmark, the survey's aggregate adoption picture is consistent with independent European statistics, in which Slovak enterprise AI adoption sits below the EU average and is concentrated among larger and more digitally mature firms (Eurostat, 2025; Kovič et al., 2024).

3.6 Limitations of the data

Sound interpretation requires that the limitations of the evidence be stated plainly. *First*, the design is **cross-sectional**: the survey observes firms at a single point in 2025, so the relationships reported, notably between maturity and depth of deployment, are associational, not causal. A mature firm may deploy AI more deeply, deeper deployment may build maturity, or both may be driven by an unobserved factor such as managerial quality; the data cannot adjudicate, and the language of “drivers” and “engines” throughout should be read as theoretically motivated association rather than established causation.

Second, all measures are **self-reported perceptions** from a single respondent per firm. Adoption stages, impact significance, and especially the performance-change items reflect managerial perception rather than audited operational data; common-method bias and social-desirability pressures (for instance, optimism about benefits) cannot be excluded. The performance-impact items denominated in “days” (inventory, receivables, and payables turnover; decision-making time) are additionally ambiguous, because respondents may read “decision-making speed” as improving even as the underlying days metric is framed to decrease; these items are interpreted cautiously and the analysis foregrounds the unambiguous growth, productivity, and service indicators.

Third, the **sampling frame and representativeness** of the AI-IMPACT survey are not fully characterized in the public documentation, and the focal population is defined by self-selection into AI use and then into logistics; the 142 firms are therefore not a random sample of Slovak logistics operations but a purposive population of logistics AI adopters. Findings describe this population and the mechanisms within it; they do not support unconditional national prevalence estimates. The focal n of 142, while ample for the main models, limits the power of finely subdivided analyses and the number of covariates that can be estimated stably, which is why sparse categories (e.g., state ownership, micro-firms, very young firms, all essentially absent among adopters) were collapsed or omitted.

Fourth, several constructs are **single-item** (each maturity dimension; ownership; age), trading depth for breadth of coverage; and the questionnaire's skip logic, while it produces clean within-module data, means that comparisons across the user, planner, and non-adopter groups must respect the fact that different groups answered different questions. *Finally*, direct identifiers and identifying free-text responses were removed for anonymity, so the analysis cannot incorporate firm-level register data (e.g., audited financials) that might sharpen the firmographic picture. These limitations bound the claims that follow; within

those bounds, the consistency, internal coherence, and theoretical interpretability of the results give grounds for confidence.

4. The Landscape of AI Adoption in Slovak Enterprises

Before turning to logistics specifically, it is worth situating the focal population within the broader pattern of AI adoption captured by the survey. This chapter offers a descriptive overview of the 816-firm sample and positions logistics among the functional domains of AI application.

4.1 A workforce of users, planners, and abstainers

The 816 Slovak enterprises distribute across the AI adoption spectrum in instructive proportions (Figure 1). A clear majority, 562 firms, or 68.9%, are current users or testers: 135 report using AI in multiple areas, 216 in several specific processes, and 211 are testing or piloting. A further 131 firms (16.0%) are planners who intend to adopt within one to three-plus years, and 123 (15.1%) are non-adopters with no plans to adopt. That roughly seven in ten responding firms already use or pilot AI in *some* form is far higher than the national enterprise average reported by Eurostat (2025); the gap is a direct consequence of the survey's purposive focus and a reminder that the sample over-represents the digitally engaged segment of the economy. The analytically important point is internal: even among these engaged firms, a large share sits at the testing stage (211 of 562 users are piloting rather than operating), foreshadowing the experimentation plateau that the logistics data will make precise.

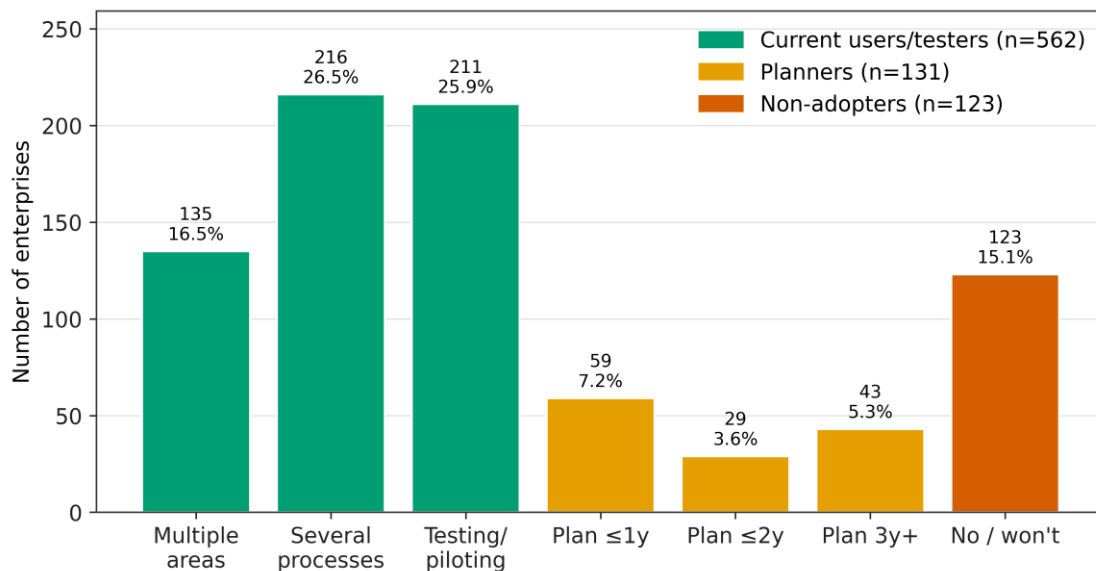


Figure 1. Distribution of AI adoption stages across the Slovak enterprise sample ($N = 816$), grouped into current users/testers, planners, and non-adopters.

4.2 Where AI lands: the functional geography of adoption

Among the 562 users and testers, item D3 reveals where in the organization AI has actually been put to work (Figure 2). Marketing and sales lead by a wide margin (209 firms, 37.2% of users), followed by production or manufacturing (157, 27.9%). **Logistics ranks third (142, 25.3%)**, ahead of research, development and innovation (121), human resources (100), management and administration (91), ICT security (78), and finance (75). The prominence of logistics is notable in its own right: in an economy where AI is most visible in the customer-facing and shop-floor domains, a quarter of AI-using firms have nonetheless taken AI into the movement, storage, and coordination of goods. Logistics is neither a marginal nor a universal domain of AI application in Slovakia, it is a substantial, mainstream, but far-from-saturated frontier, which is exactly what makes it an informative case for studying the transition from adoption to embedding.

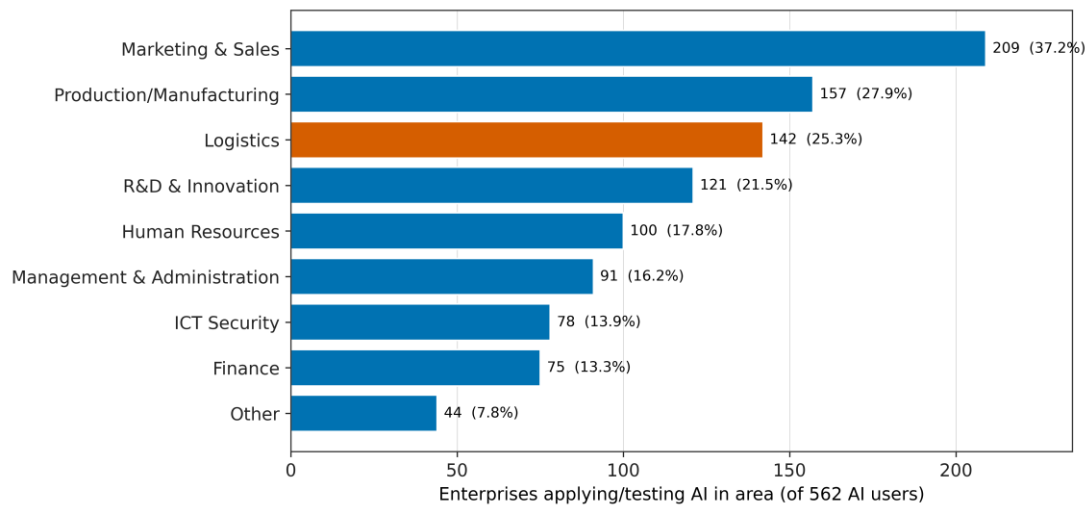


Figure 2. Functional areas of AI application among Slovak AI users ($n = 562$); logistics, the focus of this monograph, is highlighted.

A first hint that logistics AI is rarely a standalone undertaking also appears here. The functional areas are not mutually exclusive, firms could select several, and logistics adopters typically did. As Chapter 11 documents in detail, the 142 logistics adopters apply AI across an average of 2.86 functional areas, more than double the 1.35 of other AI users. Logistics AI, in other words, tends to arrive in firms that are already deploying AI across several functions; it is a marker of broader digital engagement rather than an isolated experiment.

4.3 The shape of the focal population

The 142 logistics adopters are, by construction, a selected and comparatively capable slice of the Slovak enterprise population, and their firmographic profile bears this out (developed fully in Chapter 5). They skew large and established: none is a micro-firm of fewer than ten employees, 63 employ 250 or more, and 89 have operated for eleven years or more, with none younger than five years. Ownership splits almost evenly between domestic private

firms (59) and foreign-owned firms registered in Slovakia (62), with 21 of mixed ownership and no purely state-owned enterprises. Sectorally, manufacturing dominates (51 firms), followed by transportation and storage (21), information and communication (15), and a long tail across construction, professional services, finance, and others. This is the established, mid-to-large, privately or foreign-owned, manufacturing-and-transport core of the Slovak economy, the segment in which one would expect logistics AI to take root first, and a useful population in which to ask how far that rooting has actually gone.

Their AI experience is recent. The modal year of first AI project is 2024 (55 firms), followed by 2025 (31) and 2023 (23); only a handful began before 2020. The logistics AI story in Slovakia is therefore overwhelmingly a story of the last three years, a young phenomenon caught, in this survey, near the moment of its emergence. That youth is part of what makes the embedding question so pointed: these firms have adopted quickly, but adoption is recent enough that the slower work of embedding may not yet have caught up. The chapters that follow show that, for most of them, it has not.

5. Who Adopts AI in Logistics? Profile and Determinants

This chapter answers RQ1 and tests H1. It first profiles the 142 logistics adopters in detail and then asks, through a multivariate model, what distinguishes them from the 420 AI users who have not taken AI into logistics. The answer reframes a common intuition: logistics AI adoption is not principally a story about firm size.

5.1 A firmographic portrait

The 142 logistics adopters are concentrated in the larger and more established strata of the Slovak enterprise population (Figure 3). On size, the distribution is striking for what is absent: there are no micro-firms at all. Forty-four percent of adopters (63 firms) employ 250 or more people, 32% (45) employ 50–249, and 24% (34) employ 10–49. Net sales follow suit, with 43 firms in the €2–10 million band and another 50 above €10 million. On age, every adopter has operated for more than five years and 89 of 142 (63%) for eleven years or more. Ownership divides almost evenly between domestic private firms (42%) and foreign-owned firms registered in Slovakia (44%), with mixed ownership accounting for the remaining 15% and state ownership essentially absent. This profile is consistent with the broader European finding that AI adoption is structurally tilted toward larger, older, resource-rich firms (Eurostat, 2025; Rammer et al., 2022), and with the specific CEE observation that adoption concentrates in the established industrial core (Kovič et al., 2024).

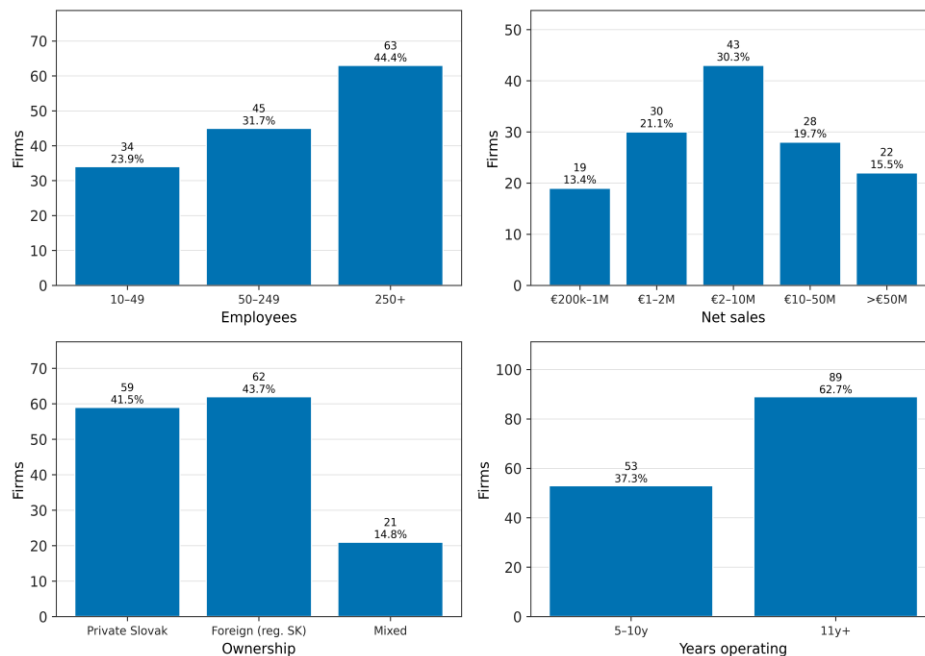


Figure 3. Firmographic profile of the 142 logistics AI adopters by employee size band, net-sales band, ownership type, and years in operation.

Sectorally, logistics AI adoption is anchored in manufacturing and transport (Figure 4). Manufacturing alone accounts for 51 of the 142 adopters (36%), reflecting Slovakia's industrial structure and the dense inbound and outbound logistics of its automotive and supplier base. Transportation and storage, the logistics sector proper, contributes 21 firms (15%), information and communication 15, and a long tail spans construction (12), professional and scientific activities, finance, public administration, and others. The breadth of this tail is itself informative: AI in logistics is not confined to logistics-sector firms but is pursued wherever goods must be moved and coordinated, from manufacturers managing supplier flows to service firms managing distribution.

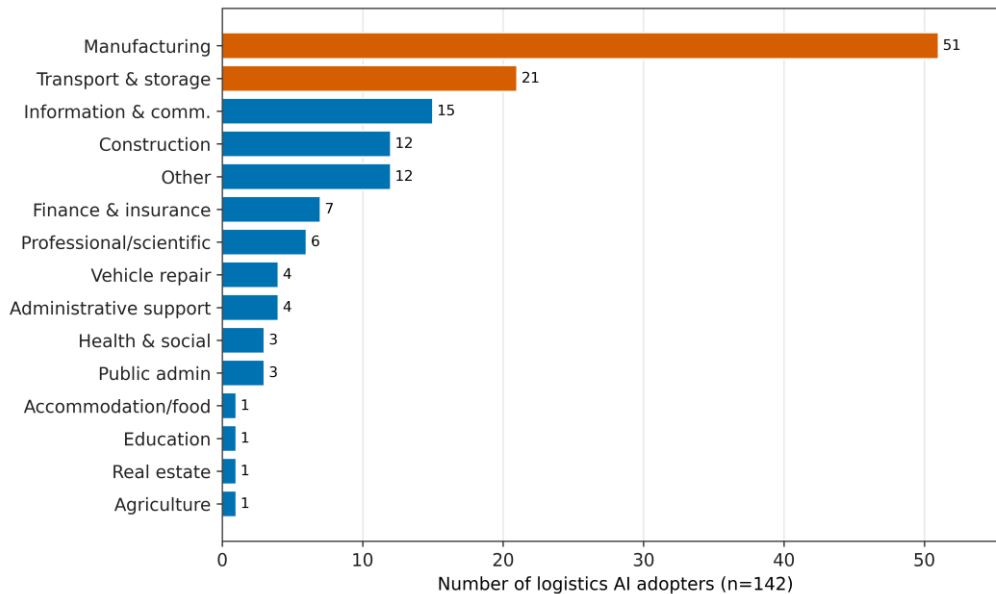


Figure 4. Sectoral distribution of the 142 logistics AI adopters; manufacturing and transportation & storage (highlighted) dominate.

In their overall AI posture, the adopters lean toward production rather than mere experimentation: 33 use AI in multiple areas, 44 in several specific processes, and 65 are testing or piloting. They are, then, somewhat more advanced as AI users than the average, but, as later chapters show, advanced *general* AI use does not guarantee deep *logistics* AI use.

5.2 A modest maturity edge

Do logistics adopters differ from other AI users in organizational AI maturity? At the level of simple comparison, the edge is real but modest (Figure 5). Across all seven maturity dimensions, logistics adopters score slightly higher than other AI users, with a composite of 2.99 versus 2.85 on the five-point scale. The largest gaps appear on strategy (2.89 vs. 2.72), technology (3.14 vs. 2.96), and ethics (2.89 vs. 2.74), but none of the individual dimensions reaches conventional significance in a two-group test, and the composite difference is only marginal (Mann–Whitney $p = .08$). Taken alone, this might suggest maturity matters little. The multivariate analysis that follows shows why that inference would be premature: maturity's role becomes clearer once other characteristics are held constant, and, as Chapter

8 shows, its stronger association is with the *depth* of deployment among adopters rather than with the binary fact of adoption.

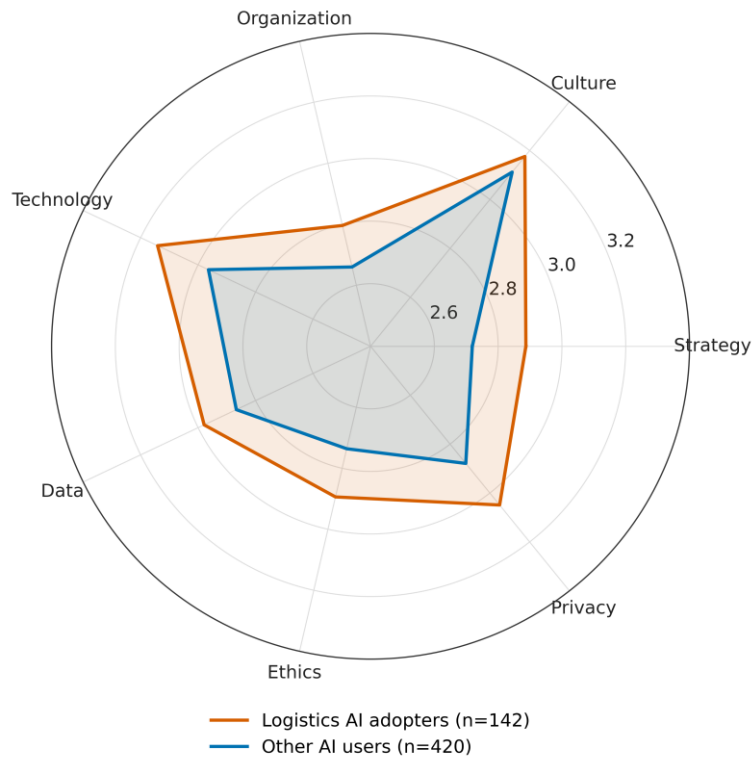


Figure 5. AI maturity profiles of logistics adopters ($n = 142$) versus other AI users ($n = 420$) across the seven maturity dimensions.

The maturity profile is also uneven in a theoretically sensible way. Adopters score highest on culture (3.18) and technology (3.14), the experiential, tool-level dimensions that accumulate through use, and lowest on organization (2.80) and strategy (2.89), the structural, deliberate dimensions that require management design. This pattern, in which firms acquire AI tools and a positive disposition faster than they build the organizational scaffolding and strategy to govern them, recurs throughout the monograph and is, the analysis will argue, the proximate reason that so many adopters stall before embedding.

5.3 Determinants of logistics AI adoption

To identify what distinguishes logistics adopters from other AI users net of confounds, a binary logistic regression was estimated on all 562 AI users, with logistics adoption as the outcome and standardized maturity, firm size, net sales, AI-use depth, foreign ownership, state/mixed ownership, manufacturing-sector membership, transportation-and-storage membership, and firm age as predictors (Figure 6; full coefficients in Master Registry, Table T18). The model is significant overall (likelihood-ratio $\chi^2 = 43.9$, $p < .001$) though modest in fit (McFadden pseudo- $R^2 = .069$), as is typical of adoption models in which much of the variation is idiosyncratic.

The model qualifies the common assumption that logistics-AI adoption is mainly a matter of firm size. Sector is the strongest correlate: firms in manufacturing have 3.6 times the odds of logistics AI adoption (OR = 3.57, 95% CI [2.19, 5.82], $p < .001$), and firms in transportation and storage 3.7 times the odds (OR = 3.67, 95% CI [1.92, 7.00], $p < .001$), relative to other sectors. Logistics AI adoption is, as one would expect, concentrated in the sectors whose value chains are most logistics-intensive. Organizational AI maturity comes next: each standard-deviation increase in composite maturity is associated with 1.4 times the odds of taking AI into logistics (OR = 1.40, 95% CI [1.13, 1.74], $p = .002$), holding sector and size constant. Firm size, by contrast, is **not a significant predictor** once maturity, sales, and sector are included (OR = 0.86, 95% CI [0.63, 1.17], $p = .34$); the same is true of net sales, ownership, AI-use depth, and firm age. The two sector effects and the maturity effect all survive Benjamini–Hochberg correction across the confirmatory set (Master Registry, Table T28); the size null should be read as absence of a detectable association in this model rather than positive evidence that size is irrelevant, since size also shapes which firms enter the sample at all (no adopter employs fewer than ten people).

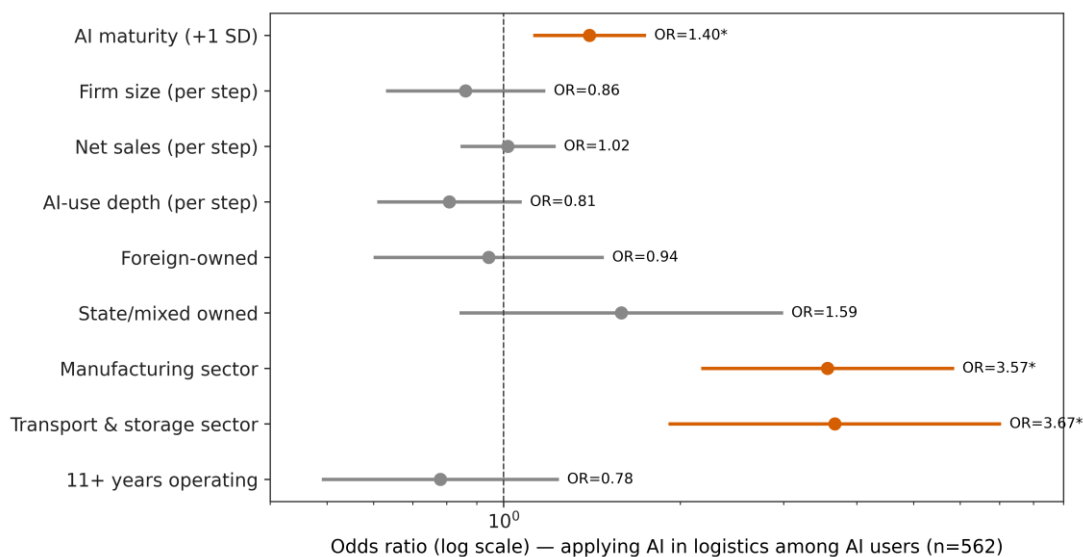


Figure 6. *Determinants of logistics AI adoption among AI users (n = 562): odds ratios with 95% confidence intervals from a logistic regression. Significant predictors (p < .05) are highlighted.*

The substantive message is that whether a firm adopts AI in logistics is associated mainly with its sector and, secondarily, with its organizational maturity, but not with its size once those are accounted for. This is consistent with Kovič et al.'s (2024) CEE finding that Industry 4.0 readiness, rather than firm size or supply-chain role, predicted AI use in manufacturing. Since size does not track even whether firms adopt, the larger differences in how deeply they deploy will have to be explained by something else, and Chapter 8 argues that maturity is the best candidate. H1 is supported: in this model maturity and logistics-intensive sectors are associated with higher adoption, net of size. The remainder of the monograph turns from who adopts to the harder question of who embeds.

6. The Logistics AI Application Portfolio and Its Latent Structure

Having established who adopts, the analysis turns to *what* they adopt. This chapter answers RQ2 and tests H5. It first maps the adoption stage of fourteen specific logistics AI applications, then examines whether those applications form coherent latent capability bundles.

6.1 A portfolio mapped by adoption stage

The defining analytical asset of the AI-IMPACT logistics module is that it records, for each application, not a binary “used / not used” but a graded adoption stage from rejection through consideration and planning to pilot and regular use. Figure 7 displays the full portfolio, with applications ordered by the share of adopters that have reached at least pilot use. Three features stand out.

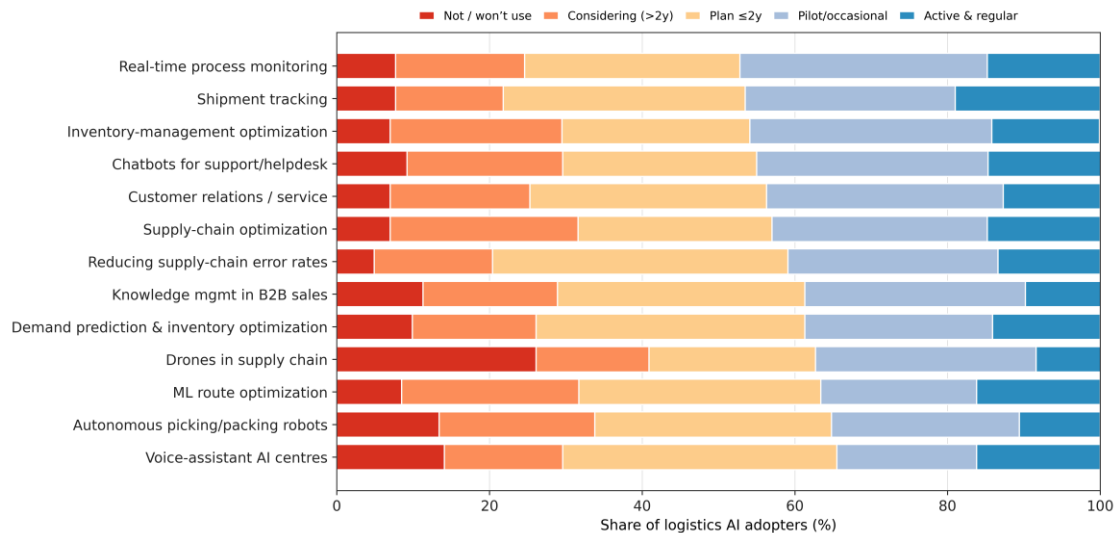


Figure 7. The logistics AI application portfolio: distribution of adopters ($n = 142$) across five adoption stages for thirteen applications, ordered by in-use share.

First, the data-centric monitoring and visibility applications lead. Real-time monitoring of logistics processes (47.2% at least in pilot use), shipment tracking (46.5%), and inventory-management optimization (45.8%) head the portfolio, followed by chatbots for support (45.1%) and customer relations (43.7%). These are, broadly, the applications that ride on data a firm already collects and impose the least disruption on physical operations, the natural entry points to logistics AI. Shipment tracking is also the single most *deeply* adopted application, with 19.0% of firms using it actively and regularly, the highest active-use rate in the portfolio.

Second, the capital-intensive and frontier physical applications trail. Voice-assistant AI centres (34.5% in use), autonomous picking-and-packing robots (35.2%), machine-learning route optimization (36.6%), and drones in the supply chain (37.3%) occupy the bottom of

the distribution. Drones are the clear outlier on the downside: more than a quarter of adopters (26.1%) reject them outright, by far the highest rejection rate in the portfolio, reflecting the conditional, regulation-bound economics that the technical literature documents for UAV logistics (Raghunatha et al., 2023; Eskandaripour & Boldsai Khan, 2023).

Third, and most important for the monograph's thesis, **active and regular use is uniformly low across the entire portfolio**. Even the most deeply embedded application, shipment tracking, reaches regular use in fewer than one firm in five, and most applications are actively used by only 9–16% of adopters. The modal experience of a logistics AI application in Slovakia is not regular operation and not rejection, but a middle zone of piloting, planning, and consideration. Table 1 records the underlying figures.

Table 1. Adoption-stage profile of thirteen logistics AI applications among adopters ($n = 142$). "In use" = pilot or active; "Active" = regular use; "Pipeline" = considering or planning.

Application	Mean stage	Active %	In-use %	Pipeline %	Reject %
Real-time process monitoring	3.30	14.8	47.2	45.1	7.7
Shipment tracking	3.36	19.0	46.5	45.8	7.7
Inventory-management optimization	3.23	14.1	45.8	47.2	7.0
Chatbots for support / helpdesk	3.21	14.8	45.1	45.8	9.2
Customer relations / service	3.24	12.7	43.7	49.3	7.0
Supply-chain optimization	3.19	14.8	43.0	50.0	7.0
Reducing supply-chain error rates	3.29	13.4	40.8	54.2	4.9
Demand prediction & inventory optimization	3.17	14.1	38.7	51.4	9.9
Knowledge management in B2B sales	3.08	9.9	38.7	50.0	11.3
Drones in the supply chain	2.79	8.5	37.3	36.6	26.1
ML route optimization	3.13	16.2	36.6	54.9	8.5
Autonomous picking/packing robots	2.99	10.6	35.2	51.4	13.4
Voice-assistant AI centres	3.07	16.2	34.5	51.4	14.1

The portfolio thus presents a paradox that the next chapter resolves: breadth of engagement is considerable, most firms are doing *something* with most applications, but depth of embedding is thin. Adopters have spread themselves widely and shallowly across the logistics AI landscape.

6.2 The latent structure of the portfolio

Are these thirteen applications adopted independently, or do they cohere? The question matters both methodologically (can the portfolio be summarized by a few dimensions?) and substantively (do firms build *bundles* of related capabilities?). The application battery is highly suitable for factor analysis (KMO = .91; Bartlett's test of sphericity $p < .001$) and internally very consistent ($\alpha = .92$).

Parallel analysis, which compares observed eigenvalues against the 95th percentile of eigenvalues from random data, points clearly to one factor: only the first eigenvalue exceeds its random benchmark (6.88 versus 1.67), while the second (1.15) falls below its benchmark (1.49) and is statistically indistinguishable from noise. The first unrotated component alone accounts for about 53% of the total item variance (Figure 8). The portfolio, in other words, is essentially one-dimensional. That is a substantive result: logistics AI adoption behaves largely as a single general propensity rather than a set of separable choices, with firms that adopt one application tending to adopt across the board. A single dominant dimension is consistent with the maturity account developed in Chapter 8, a common organizational capacity expressing itself across applications. It is worth being honest that a one-factor solution cannot, on its own, distinguish that reading from a simpler one in which a single respondent's general disposition toward AI inflates the correlations among all the items (the common-method concern noted in Section 3.6).

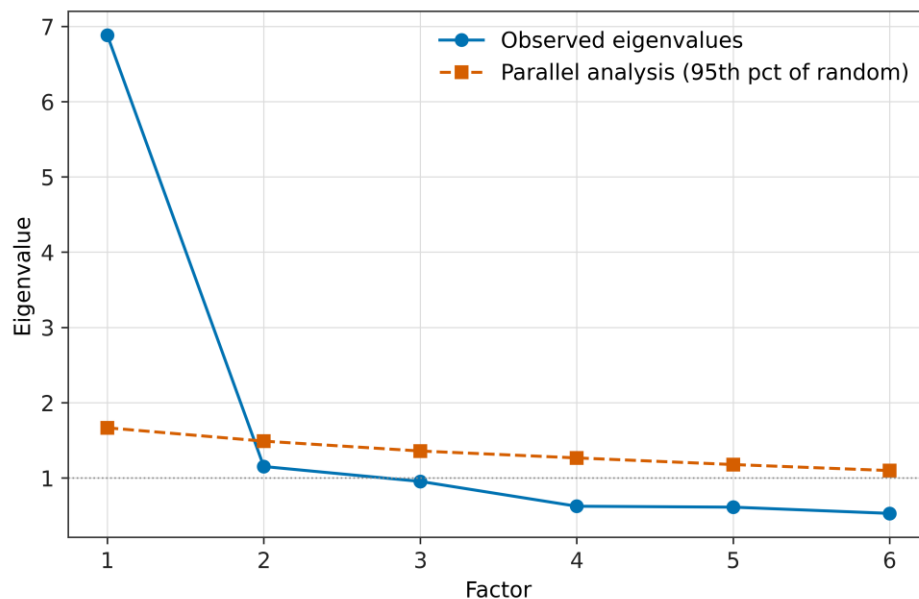


Figure 8. Scree plot of observed eigenvalues against the 95th-percentile eigenvalues from parallel analysis, indicating one dominant factor underlying the thirteen logistics AI applications.

Beneath that dominant general factor lies a weaker secondary structure that is worth describing even though parallel analysis does not warrant retaining it. Forcing a two-factor oblimin solution, purely as an interpretive aid, separates two families of applications (Figure

9). Because the items are five-point ordinal adoption stages treated here as continuous, a polychoric-correlation extraction would be more exact; the Pearson-based solution is reported as a description rather than a confirmed dimensional model. The first factor loads on **customer-facing and cognitive** applications: chatbots (.84), voice-assistant centres (.81), customer relations (.74), supply-chain error reduction (.69), inventory management (.61), and B2B knowledge management (.61). The second loads on **physical supply-chain** applications: autonomous robots (.81), route optimization (.81), supply-chain optimization (.65), shipment tracking (.65), demand-and-inventory prediction (.63), and real-time monitoring (.49). Drones load weakly on both (.33 / .29), consistent with their peripheral, contested status. Both facets are internally reliable (customer-facing/cognitive $\alpha = .89$; physical supply-chain $\alpha = .88$) and, because the rotation is oblique and the factors are correlated, they sit beneath the single higher-order general factor identified by parallel analysis.

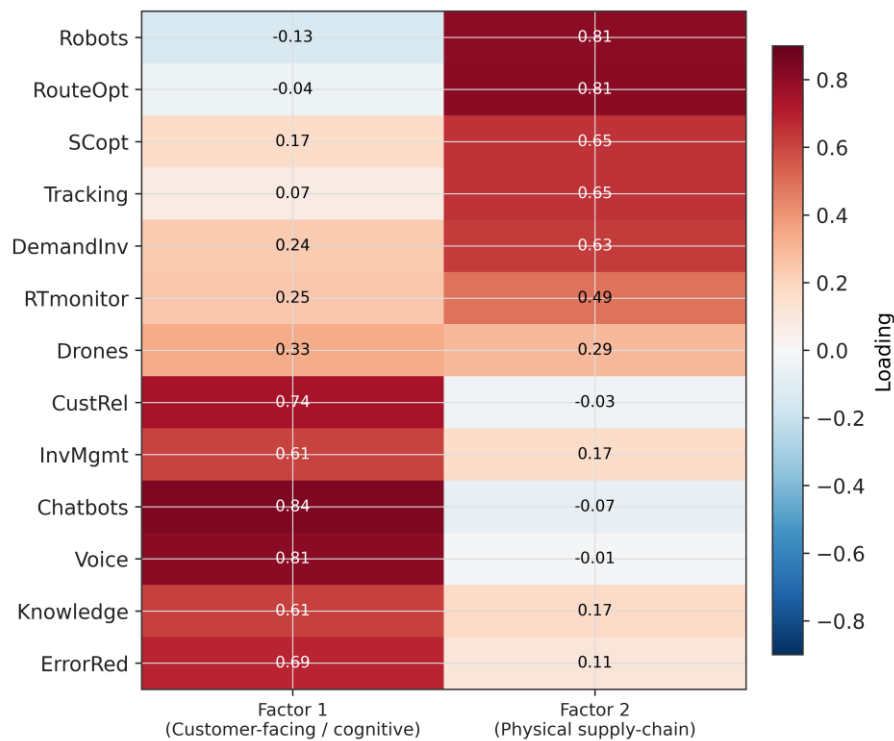


Figure 9. Oblimin-rotated factor loadings of the thirteen logistics AI applications on two correlated facets, customer-facing/cognitive (F1) and physical supply-chain (F2).

H5 is therefore only partly supported. Its first part, a dominant general adoption-propensity dimension, is confirmed; its second part, a physical-versus-cognitive split, exists only as a weak, rotation-dependent pattern that the retention criterion does not endorse. The unidimensional result is, if anything, the more useful of the two for the argument that follows: it says firms do not specialize in one family of applications at the expense of the other but move across the whole portfolio together, more capable firms further along on every front and less capable firms behind on all of them. The portfolio behaves like a single ladder that firms climb as a whole, which is why the question taken up next, how high they have climbed, is the one that matters.

7. Adoption Without Embedding: The Experimentation Plateau and a Firm Typology

This chapter develops the monograph’s central claim and tests H6. It distinguishes adoption from embedding, quantifies the gap between them, and shows that Slovak logistics AI adopters fall along a continuum that is usefully summarized as two strata: a minority that has embedded AI in regular operations and a majority still in experimentation.

7.1 The embedding gap

The graded adoption scale makes a distinction that binary adoption measures cannot: the difference between having an application, at least in pilot use, and embedding it in regular operations. The contrast is large (Figure 10). The average adopter has 5.3 of thirteen logistics AI applications at least in pilot use (in-use breadth) but only 1.8 in active, regular use (active-use breadth). The median firm has four applications in use and none in regular active use. Across the population, 59.2% of adopters have no application at all in regular operational use, even though 81.7% have at least one in pilot use. The embedding ratio, the share of a firm’s in-use applications that have reached regular use, averages 0.24 (median 0.05). For every four logistics AI applications a firm has brought in-house, roughly one, on average, has crossed into regular operation. This gap is not an artifact of where the threshold for “embedded” is set. The plateau is defined by treating only the top scale point (stage 5, “active and regular use”) as embedding, while “in use” includes the pilot/occasional stage 4. Relaxing the threshold does not dissolve it: even counting any pilot or occasional use, the mean firm reaches just 5.3 of thirteen applications and 18.3% reach none, so a clear majority of the portfolio sits below regular use under either definition. The substantive picture, broad trial and thin routine use, is robust to the cut-point.

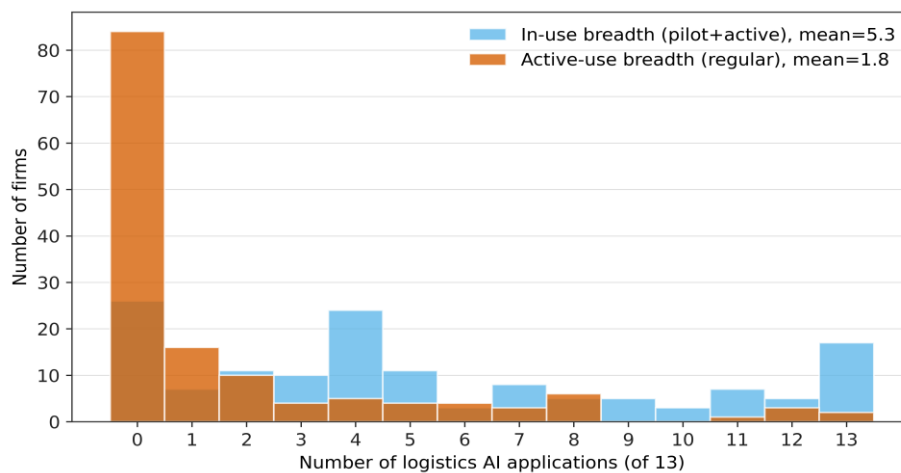


Figure 10. The embedding gap: distributions of in-use breadth (pilot or active) and active-use breadth (regular use) across the 142 adopters. The leftward shift of the active-use distribution is the experimentation plateau.

This is the **experimentation plateau**: a population that has adopted widely but embedded narrowly. The pattern is consistent with, and gives precise enterprise-level shape to, the readiness literature's observation that AI initiatives frequently stall before operational integration (Hradecky et al., 2022; Uren & Edwards, 2023), and with the practitioner finding that the overwhelming majority of distributors explore AI while only a small minority scale it (McKinsey & Company, 2024). It also reframes the survey's own headline: that "a quarter of AI users apply AI in logistics" is true but, taken alone, misleading. Most of those applications are pilots, trials, and plans. The decisive managerial question in Slovak logistics is not whether to adopt — many firms have — but whether and how to cross from pilot to practice.

The plateau is not a measurement artifact of a demanding scale. The same firms that report sparse regular use report extensive pipeline activity: across applications, between 37% and 55% of firms sit in the considering-or-planning band (Chapter 11). The middle of the distribution is genuinely occupied, which is why the population is better described as mid-progression than as either embedding or rejecting.

7.2 Two strata of adopters

If most firms experiment and few embed, can the population be usefully grouped? A k-means partition of the standardized thirteen-application stage profiles, with the number of clusters chosen by the silhouette criterion, returns a two-cluster solution (silhouette = 0.29 for $k = 2$, the maximum over $k = 2-5$). A silhouette of 0.29 indicates weak separation, and the value falls as k rises, both of which point to a single continuum rather than two natural kinds; k-means always returns a partition, so these clusters should be read as a convenient two-stratum summary of that continuum and not as discrete types (Figures 11 and 12; Master Registry, Table T22). With that caveat, the two strata differ markedly on the variables that matter.

Embedded adopters number 49 firms (34.5% of the population). They combine high adoption intensity (mean stage 4.1 of 5), broad active use (4.5 applications in regular use on average), and higher AI maturity (composite 3.64). Their net perceived benefit is also numerically higher (0.72). AI is woven through their logistics operations across many applications rather than merely trialled.

Experimenters number 93 firms (65.5%). Their adoption intensity sits near the scale midpoint (2.66) and their active-use breadth is close to nil (0.38 applications in regular use). Their AI maturity is lower (2.65) and their net perceived benefit lower too (0.22). These firms hold logistics AI applications in pilots and plans but have embedded almost nothing in regular operation.

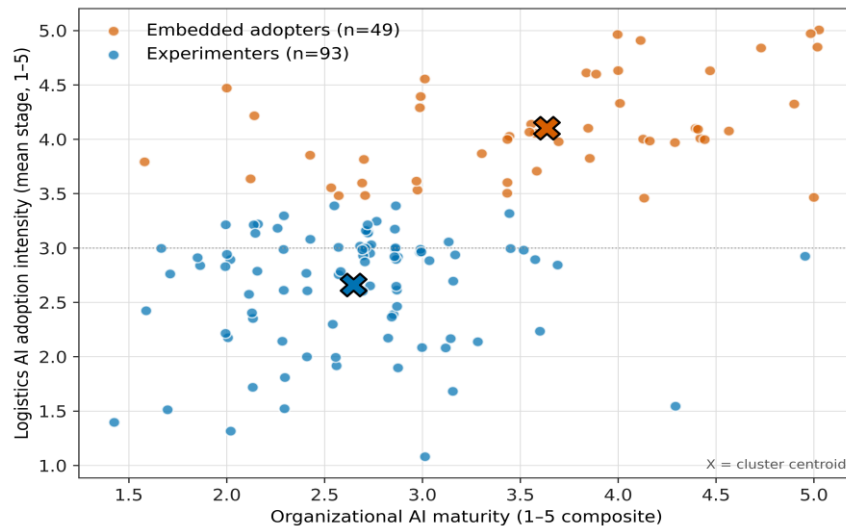


Figure 11. The two strata in the space of organizational AI maturity and logistics AI adoption intensity. Embedded adopters (higher maturity, higher intensity) and experimenters overlap but have distinct centroids (marked X).

The most informative fact about this partition is what does not separate the strata. The two groups are nearly identical in firm size: 40.8% of embedded adopters and 46.2% of experimenters employ 250 or more people, so if anything large firms are slightly over-represented among the experimenters. The line between embedding and experimenting is not a line between large and small firms. It tracks organizational AI maturity instead. The maturity gap between the strata is almost a full scale point (3.64 versus 2.65), it is visible on every maturity dimension (Figure 12), and a Mann–Whitney test confirms it is large and highly significant (rank-biserial $r = .64$, $p < .001$), in contrast to the net-benefit difference, which is not significant ($p = .11$; Section 7.3). The strata are defined partly on the same stage variables that make up adoption intensity, so the intensity and breadth contrasts are in part built in; the maturity contrast is not, because maturity is measured by a separate battery, which is what makes it the substantively interesting difference.

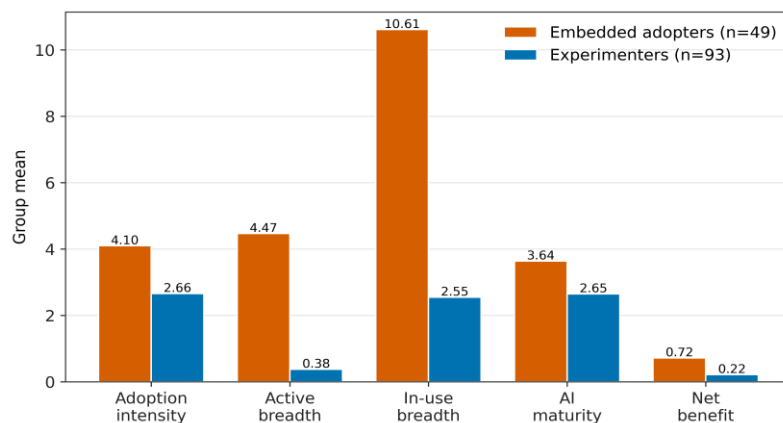


Figure 12. Profile comparison of embedded adopters and experimenters across adoption intensity, active-use breadth, in-use breadth, AI maturity, and net benefit. The groups differ on every dimension except firm size; the maturity difference is statistically significant, the net-benefit difference is not.

7.3 Interpreting the divide

A few observations sharpen the interpretation. The partition is best read as graded. The silhouette of 0.29 describes strata that overlap rather than separate cleanly, consistent with a developmental process in which firms move along a maturity gradient rather than belonging to fixed groups. The boundary between experimenter and embedded adopter is a threshold firms can cross, not a wall, and that is the more hopeful reading of the plateau. The gradient aligns with the uneven maturity profile noted in Chapter 5. Experimenters are not uniformly immature; like the population as a whole, they tend to have acquired AI tools and a favourable culture while lagging on strategy and organization. What they lack is the structural and strategic maturity associated with embedded routines, the organization and strategy dimensions on which the whole population scores lowest. On this reading, embedding is tied less to technology than to management. The gradient is also associated with how firms appraise AI, though this evidence needs care. Embedded adopters report numerically higher net perceived benefit than experimenters (0.72 versus 0.22), but that difference is not statistically significant (Mann–Whitney $p = .11$), because perceived benefits and perceived risks both rise with engagement and partly cancel. Perceived positive impact alone tracks active-use breadth more strongly (Spearman $\rho = .61$) and maturity moderately ($\rho = .47$). This correlation should be treated as suggestive rather than as independent confirmation, because the same respondent rated both deployment and impact on adjacent items, so a firm that has deployed more may simply report more benefit (a common-method and motivated-reasoning concern). With that qualification, the embedded and experimenter strata differ not only in what they do but in how favourably they judge what AI delivers. The experimenters sit in a familiar position from the adoption literature: real sunk effort in pilots, modest realized returns so far, and some risk of disillusionment if the move to regular use does not come.

This answers RQ3 and supports H6, with the qualification that the two groups are strata of a continuum rather than discrete types: a large majority of adopters remain experimenters, a minority have embedded AI, and the two are separated mainly by maturity rather than size. It also sets up the next chapter. If maturity is what distinguishes embedded adopters from experimenters at the group level, it should also predict the depth of logistics AI deployment in a firm-level model. It does, and the association holds up under scrutiny.

8. Maturity and the Depth of Embedding

The previous chapter showed that organizational AI maturity, not firm size, separates embedded adopters from experimenters at the group level. This chapter tests the same relationship at the firm level, answering RQ4 and testing H2. It asks whether measured AI maturity is associated with the breadth of active logistics AI deployment once firm size, sales, sectoral position, and general AI-use depth are held constant, and then asks how far that association survives the obvious objections: that the maturity measure overlaps with the outcome, that the count is dominated by zeros, and that an unobserved common cause might produce both. The association is the strongest in the model and holds up under each of these checks, though, being cross-sectional, it remains an association rather than a demonstrated effect.

8.1 Maturity and the breadth of active use

The outcome is active-use breadth: the count, from zero to thirteen, of logistics AI applications a firm uses actively and regularly. The count is overdispersed, its variance (9.8) far exceeding its mean (1.8), so a negative-binomial model is used in preference to Poisson. Predictors are standardized composite maturity, firm size, net sales, AI-use depth, and membership in the transportation-and-storage and manufacturing sectors. Incidence-rate ratios (IRRs) and 95% confidence intervals appear in Figure 13 and Master Registry Table T19.

A one-standard-deviation increase in organizational AI maturity is associated with about 2.5 times the rate of actively used logistics AI applications (IRR = 2.46, 95% CI [1.84, 3.29], $p < .001$), holding size, sales, AI-use depth, and sector constant. This is the largest association in the model by a clear margin. General AI-use depth carries a positive but only marginal association (IRR = 1.33, $p = .085$). Sector membership, which mattered for whether a firm adopts (Chapter 5), is not associated with how broadly it actively deploys once maturity is included (manufacturing IRR = 1.00; transport IRR = 0.64, *n.s.*). The sectoral logic that draws firms into logistics AI does not, by itself, account for depth; maturity is the variable that does. Variance-inflation factors for the predictors are low (all below 1.5; Table T29), so the estimates are not distorted by collinearity, and the maturity coefficient survives Benjamini-Hochberg correction across the confirmatory set ($q < .001$; Table T28).

Firm size carries a negative and marginal coefficient (IRR = 0.66, 95% CI [0.45, 0.98], $p = .04$). The confidence interval almost touches one, the result does not survive false-discovery correction ($q = .05$), and conditioning on a maturity measure that itself rises with usage can induce exactly this kind of suppression. We therefore report it as a weak, specification-sensitive association and do not build an interpretation on it; the earlier draft's speculation about smaller firms being "more agile" is set aside as untested. An OLS model on adoption intensity gives the same overall picture, with maturity the dominant and highly significant predictor.

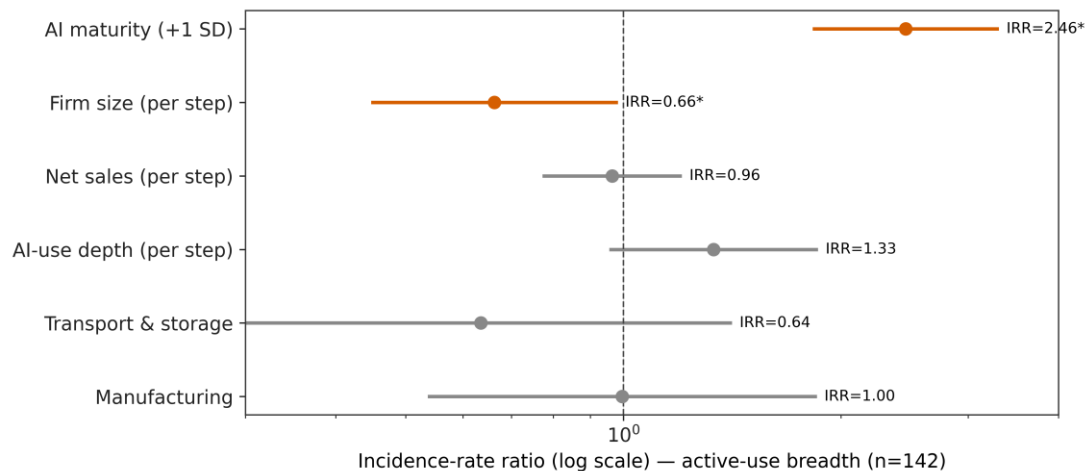


Figure 13. Negative-binomial regression of active-use breadth on organizational AI maturity and controls ($n = 142$): incidence-rate ratios with 95% confidence intervals. Maturity is the largest association in the model.

8.2 Three objections, and what the data say to them

The maturity association is strong, but three objections could deflate it. Each can be examined directly, and the association survives all three.

The first objection is **construct overlap**. As Section 3.3 noted, two of the seven maturity dimensions are partly definitions of AI usage: the technology item asks how the organization uses AI technologies, and the data item asks how prepared it is to work with data for AI. A maturity composite that includes them could predict deployment partly because it *is* a measure of deployment. To test this, the model was re-estimated with composites that progressively exclude the usage-laden items. Dropping technology and data leaves the association essentially intact ($IRR = 2.34$, $p < .001$); using only the four governance-and-strategy dimensions, strategy, organization, ethics, and privacy, which are antecedent rather than usage-defined ($\alpha = .83$, correlated .96 with the full composite), the association is $IRR = 2.17$, 95% CI [1.63, 2.87], $p < .001$ (Master Registry, Table T25). The relationship attenuates modestly, from 2.46 to 2.17, but does not collapse. Whatever maturity is doing here, it is not merely a relabelling of how much AI the firm already runs; the governance and strategy a firm has built around AI is associated with deeper deployment over and above its existing tooling.

The second objection is that the count is **dominated by zeros**: 59% of adopters have no application in regular use, so a single overdispersed count model is effectively explaining variation among the embedded minority. A two-part (hurdle) formulation separates the two questions a firm faces. In the first part, a logistic model for whether a firm has *any* application in regular use, maturity is associated with more than two and a half times the odds of crossing that threshold ($OR = 2.64$, $p < .001$). In the second part, a count model among the 58 firms that have crossed it, maturity is still associated with breadth ($IRR = 1.62$, $p < .001$). Maturity

therefore matters at both margins, the move from no regular use to some, and the move from some to broad, which is reassuring given how much of the sample sits at zero.

The third objection is **reverse causation and common cause**, and it cannot be dismissed, only stated honestly. The data are a single cross-section. Higher maturity may support deeper deployment; deeper deployment may build maturity; or a third factor, most plausibly the quality and commitment of management, or a firm's general level of digital sophistication, may produce both at once and reproduce every correlation reported here. Because maturity and deployment are reported by the same respondent on one instrument, common-method variance is an additional reason the association could be inflated. The structural-composite and hurdle checks reduce some of these concerns but cannot resolve the direction of causation. This is why the chapter speaks of maturity as the strongest *correlate* of embedding rather than its cause, and why the practical reading offered later is conditional rather than mechanistic.

8.3 Which dimensions of maturity, and how much to make of them

Every maturity dimension is positively correlated with active-use breadth, and the composite correlates most strongly of all (Spearman $\rho = .48$, $p < .001$), which is why the composite, rather than any single dimension, is the unit the analysis relies on (Figure 14). Among the individual dimensions, the correlations are uniformly positive and close together: ethics ($\rho = .43$), technology (.41), data (.39), organization (.38), privacy (.37), strategy (.34), and culture (.30). Because each dimension is measured by a single item, with the measurement error that implies, differences of two or three hundredths between them at $n = 142$ are well within noise, and the ranking should not be over-read.

The earlier draft made something of a “leading role” for the ethics dimension; that reading is withdrawn. The defensible statement is narrower and still useful: the dimensions act together rather than substituting for one another, and the data and technology dimensions, prominent here, are the ones the supply-chain literature most often identifies as preconditions for AI value (Nguyen et al., 2018; Dubey et al., 2020; Enholm et al., 2022), while the governance and strategy dimensions, on which the population scores lowest, are the ones whose absence the construct-overlap check (Section 8.2) shows still matters.

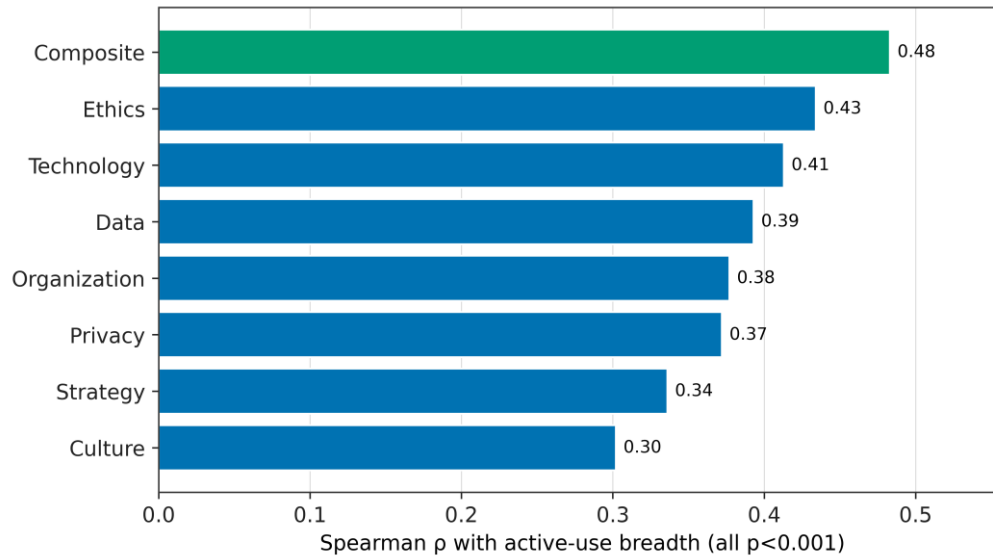


Figure 14. Spearman correlations of each AI-maturity dimension, and the composite, with active-use breadth (all $p < .001$). The dimensions are uniformly and similarly correlated; the composite is the reliable unit.

8.4 A pattern of associations, read cautiously

The pieces assembled so far form a consistent pattern. Maturity is associated with the odds of adopting AI in logistics (Chapter 5); more strongly, it is associated with the breadth of active deployment among adopters (this chapter); and active deployment is, in turn, associated with a more favourable appraisal of AI's impact (Chapters 7 and 9). The correlation matrix of firm-level indices (Master Registry, Table T23; Figure 26) shows the shape of it: maturity correlates with active-use breadth ($\rho = .48$) and in-use breadth ($\rho = .49$), the embedding indices correlate strongly with one another, and perceived positive impact rises with both maturity ($\rho = .47$) and active-use breadth ($\rho = .61$). Net perceived benefit, by contrast, correlates only weakly with embedding, because perceived risk rises alongside perceived benefit, and perceived risk and barriers sit in a separate group of their own.

Read as a causal chain, this configuration is what the dynamic-capabilities and AI-readiness literatures would predict, with maturity the complementary capability that converts an available technology into embedded use (Teece et al., 1997; Enholm et al., 2022; Peretz-Andersson et al., 2024). Read conservatively, which is how the cross-sectional design requires it to be read, it is a coherent set of contemporaneous associations consistent with that theory and with at least one alternative (a common managerial-quality cause). H2 is supported in the sense that matters for this study: among adopters, maturity is the firm characteristic most closely and most robustly associated with the breadth of active logistics AI use. The practical question this raises, whether the binding constraint on logistics AI value is internal capability or external obstacle, is taken up directly in the next two chapters.

9. The Benefit–Risk Architecture

How do Slovak logistics adopters weigh the upside and downside of AI, and does that calculus connect to what they actually experience? This chapter answers RQ5 and tests H3. It shows that adopters are net optimists, positive impacts significantly outweigh negative ones, but that their optimism is concentrated, realistic, and tempered by a clear-eyed concern about data security.

9.1 Perceived positive impacts

Adopters rated sixteen documented positive impacts of logistics AI on a five-point significance scale. The profile is uniformly favourable but far from uncritical (Figure 15). The most significant perceived benefits are operational and planning-oriented: more efficient maintenance planning (mean 3.77), inventory optimization (3.77), warehouse automation (3.75), and faster response to changes in demand and the market (3.75). A second tier covers shipment-sorting accuracy and speed, scanning accuracy, and shorter delivery times. The lowest-rated positives, though still above the scale midpoint, are the sustainability and fleet-efficiency items: reduced CO₂ emissions (3.47) and fewer vehicle breakdowns (3.54). That the planning and automation benefits outrank the sustainability benefits is consistent with the drivers analysis (Chapter 11), in which cost reduction and process automation dominate the motives for adoption, and with the broader finding that environmental gains, while real, are rarely the primary rationale for logistics AI (Frikha & Mrad, 2025).

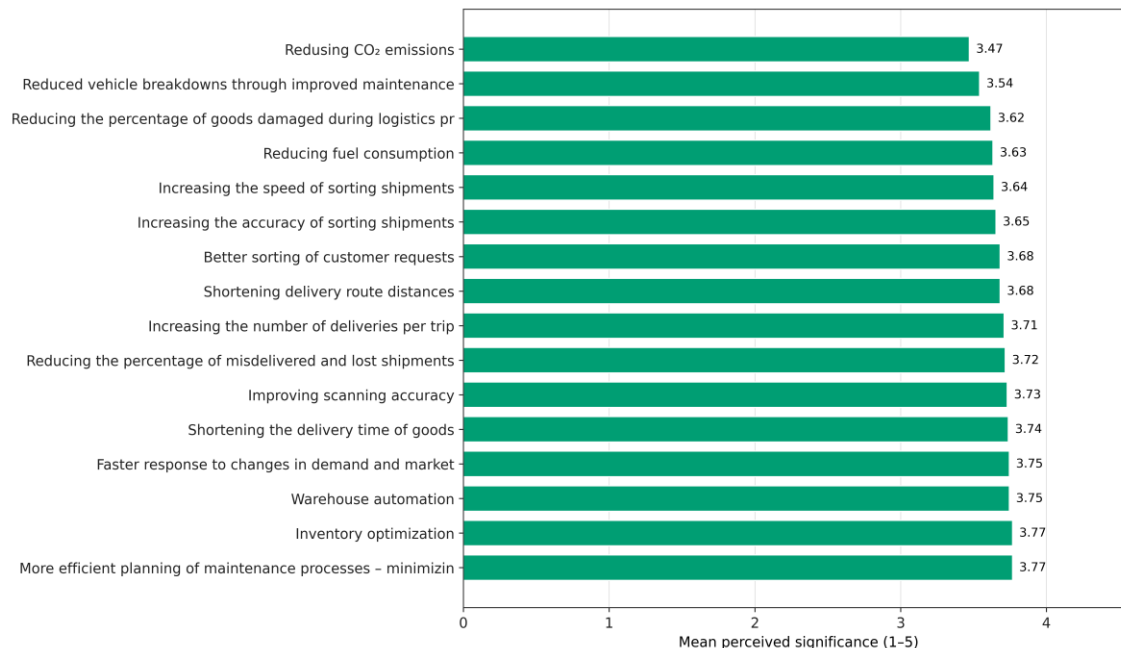


Figure 15. Perceived significance of sixteen positive impacts of logistics AI among adopters ($n = 142$), ranked by mean rating on a five-point scale.

9.2 Perceived negative impacts

The seven negative-impact items reveal a coherent risk hierarchy (Figure 16). The single most significant perceived risk is **the loss of sensitive logistics data** (mean 3.39), followed by elevated error rates in logistics processes (3.37), inventory dropping below critical levels (3.35), and faulty deliveries to customers (3.24). The lowest-rated risk is the lack of transparency in AI recommendations (3.16), notable because the academic literature treats opacity and the black-box problem as central (Nimmy et al., 2022; Glikson & Woolley, 2020). Slovak adopters, by contrast, worry less about *understanding* their AI than about its concrete operational failure modes: data breaches, mistakes, and stockouts. This is the risk perception of operators, not of ethicists, a focus on tangible disruption to the physical flow of goods rather than on epistemic transparency.

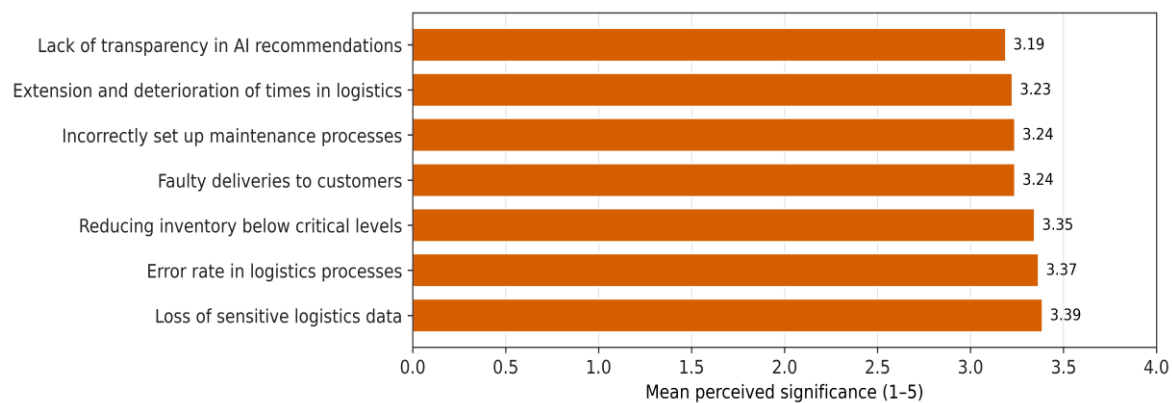


Figure 16. Perceived significance of seven negative impacts of logistics AI among adopters ($n = 142$), ranked by mean rating. Loss of sensitive data is the foremost concern.

The salience of data security deserves emphasis because it is actionable. It echoes the integration and data-sharing concerns documented for logistics AI elsewhere (Cerchione et al., 2026; Filina-Dawidowicz et al., 2026) and points to a concrete lever: investments in data governance and security are not merely compliance costs but enablers of adoption, addressing the risk that adopters themselves rank highest.

9.3 Benefit optimism, formally tested

Do positives outweigh negatives within firms? They do, significantly. The firm-level mean positive-impact rating (3.68) exceeds the mean negative-impact rating (3.29) by 0.39 of a scale point, and a Wilcoxon signed-rank test confirms the difference is highly significant ($p < .001$), with a small-to-moderate effect size (Cohen's $d_z = 0.43$). Some 62.0% of adopters rate positives above negatives, against 38.0% who rate them equal or lower (Figure 17). H3 is supported: adopters are net benefit optimists.

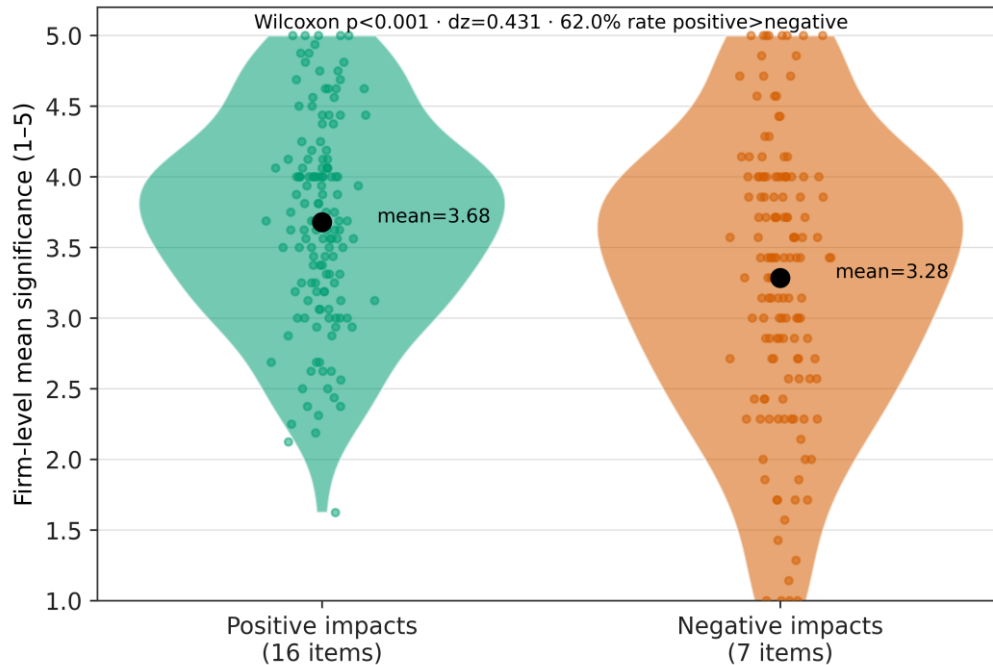


Figure 17. Firm-level distributions of mean positive- and mean negative-impact ratings ($n = 142$). Positives significantly exceed negatives (Wilcoxon $p < .001$), but both sit clearly above the scale midpoint.

Three qualifications keep this from being read as naïve techno-optimism. The first is about selection: a population that chose to adopt AI is close to guaranteed to judge its benefits greater than its risks, so H3 is best understood as a description of how committed adopters weigh the trade-off, not as a test of whether AI's benefits exceed its risks in general. The second is about magnitude: the margin is moderate, with more than four in ten firms not rating benefits above risks, and the negative-impact mean of 3.29 sits above the scale midpoint, so adopters take the risks seriously even as they judge the benefits greater. This is the profile of a population weighing a real trade-off rather than one swept up in hype, consistent with the literature's view that AI value is real but contingent and risk-laden (Enholm et al., 2022; Dwivedi et al., 2021). The third concerns the perceptual link to embedding. Net perceived benefit relates only weakly to depth of use, because perceived risk rises alongside perceived benefit and the difference partly cancels; perceived positive impact alone tracks active-use breadth more strongly ($\rho = .61$). That correlation is best treated as suggestive rather than as independent evidence for the maturity argument, since the same respondent rated both deployment and impact, and a firm that has deployed more has every reason to report more benefit.

9.4 Perceived performance impact: where the value lands

Perceived significance is one thing; perceived effect on the firm's own performance is another. Adopters rated the direction of change in thirteen performance indicators attributable to AI. Interpreted with attention to the direction in which each indicator improves, the pattern is revealing (Figure 18). On **outcome and growth** indicators, a

majority of adopters report improvement: financial result (57.0% report a favourable increase), labour productivity (57.7%), customer-service quality (56.3%), operating cash flow (55.6%), and revenue (54.9%). On **cost** indicators, which are denominated unambiguously, favourable change is much rarer: only 23.2% report reduced material and energy costs and 21.8% reduced personnel costs. (Inventory turnover, reported favourable by 13.4%, is one of the days-denominated items flagged in Section 3.6 as ambiguous, and is not leaned on here.) The modal response on the cost metrics is “no change,” and a non-trivial minority report cost increases, consistent with an investment phase in which AI is being paid for before it pays for itself.

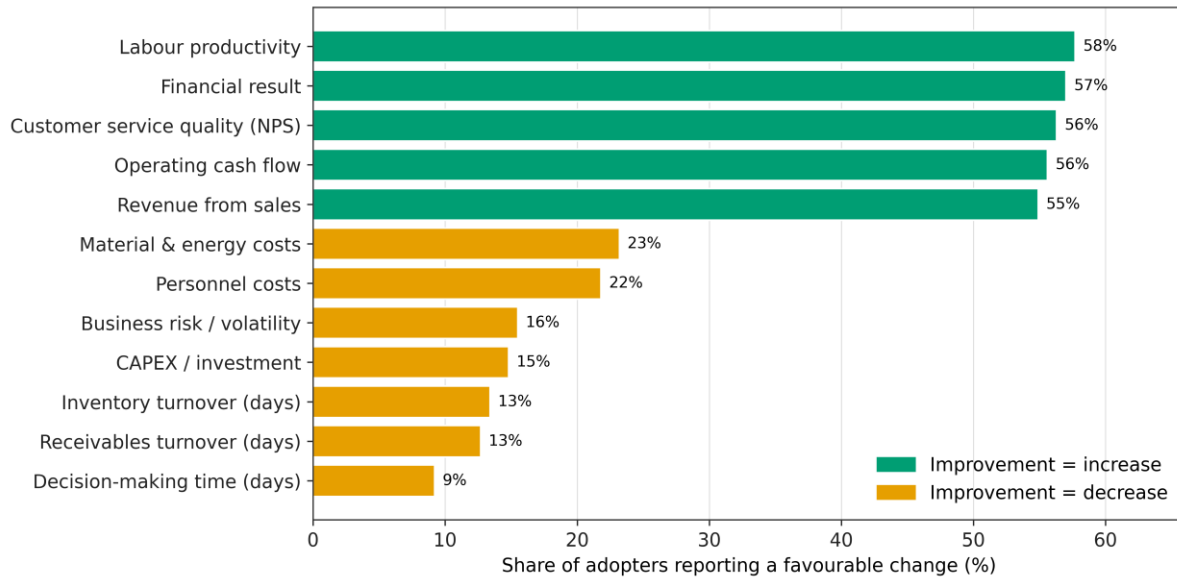


Figure 18. Share of adopters reporting a favourable change in each performance indicator attributable to AI ($n = 142$). Growth, productivity, and service gains lead; hard cost savings lag.

This asymmetry, growth and service gains reported while cost savings are not, fits the picture of a population still largely in the experimentation stage, though the cross-sectional data show only a single moment and cannot themselves establish a sequence. A reading consistent with the rest of the monograph is that responsiveness, quality, and decision-making gains are perceived earlier than the harder efficiency savings, which require deeper operational integration. It is also a caution against the consultancy narrative of immediate 20–30% inventory and cost reductions (McKinsey & Company, 2024): among these mostly recent, mostly experimental adopters, such savings are reported as not yet realized. Whether they materialize as firms embed AI more deeply is a question only longitudinal data could answer. (The four performance items denominated in “days” are not emphasized here, for the reasons set out in Section 3.6.)

10. Where Barriers Bind: The Adoption Margin, Not the Embedding Margin

A natural explanation for the experimentation plateau is that firms are held back by external barriers: cost, skills, data, regulation. This chapter tests that explanation, answering RQ6 and testing H4. The result is more precise than a simple yes or no. Barriers do matter, but they bind at the point of *adoption*, separating firms that take up AI from those that do not, rather than at the point of *embedding*, among firms that have already adopted. The earlier draft called the within-adopter null a “barrier paradox”; the fuller analysis here shows it is not a paradox but a two-stage pattern.

10.1 The barrier profile among adopters

Logistics adopters rated twenty potential barriers to AI implementation. The scale runs from “not a barrier” (1) through a neutral “no impact” midpoint (3) to “a very significant barrier” (5), so it is bipolar with a neutral centre rather than a simple intensity gradient. Read correctly, the adopter profile is one of barriers perceived as close to neutral (Figure 19).

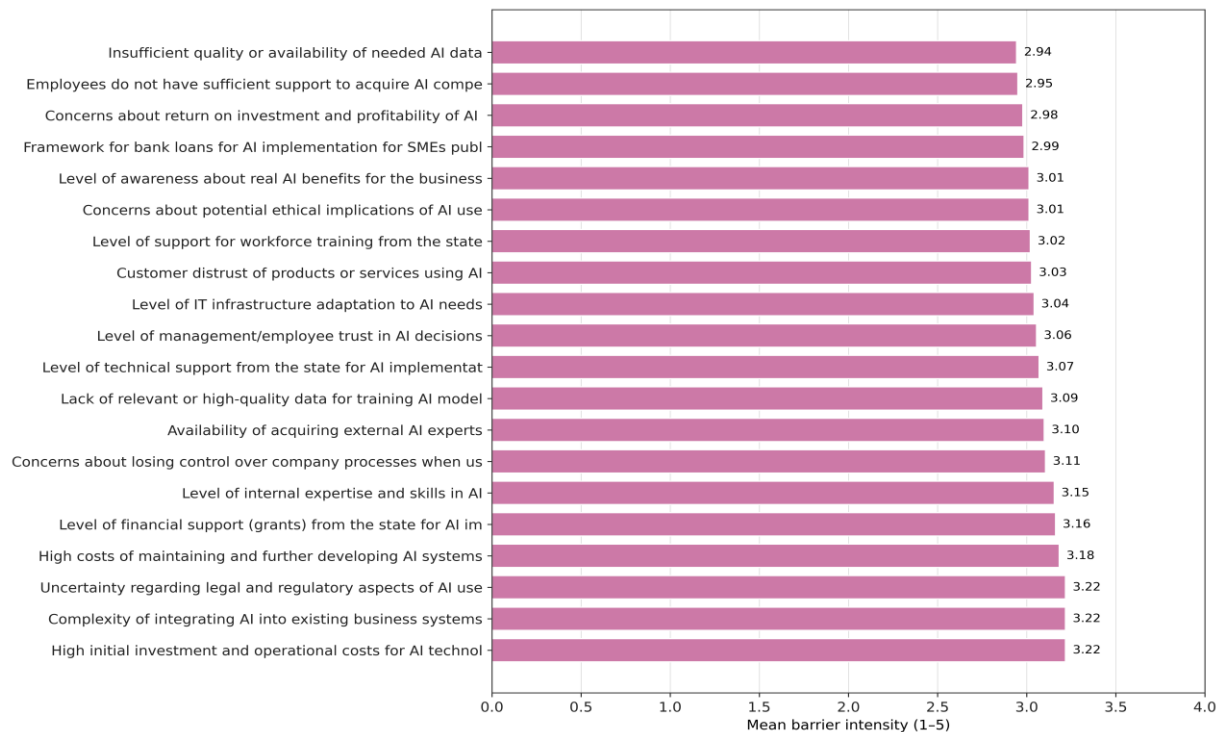


Figure 19. Perceived barriers to AI implementation among logistics adopters ($n = 142$), twenty items ranked by mean rating. The five-point scale is anchored at “not a barrier” (1), “no impact” (3), and “a very significant barrier” (5).

The overall mean is 3.08, just above the “no impact” midpoint, and the items cluster in a narrow band with none standing out as strongly binding. The highest-rated obstacles are the

familiar ones from the adoption literature: the cost of implementation and technology, shortages of qualified personnel and AI skills, data availability and quality, and integration with existing systems (Hangl et al., 2022; Shahzadi et al., 2024; Arroyabe et al., 2024). The lowest-rated concern employee resistance and doubts about the usefulness of AI, which makes sense for firms that have already decided AI is worthwhile.

That cost, skills, and data top the list matches the Slovak and CEE evidence, in which investment cost is repeatedly the foremost obstacle to digital and Industry 4.0 adoption in logistics (Richnák, 2022) and skills shortages constrain AI uptake across the region (European Commission, 2024; Grenčíková et al., 2019). The barrier *profile*, then, is exactly what the literature would lead one to expect. What is informative is where in the adoption process these barriers actually bite.

10.2 Barriers gate adoption; they do not predict depth

If barriers drove the experimentation plateau, two things should hold among adopters: firms perceiving higher barriers should deploy AI less deeply, and logistics adopters should perceive lower barriers than other AI users. Neither does. Within the 142 adopters, the barrier index is uncorrelated with active-use breadth (Spearman $\rho = .03$, $p = .76$): firms that report high barriers embed neither more nor less than firms that report low ones. And logistics adopters and other AI users perceive barriers at essentially the same level (3.08 versus 3.12; Mann–Whitney $p = .83$). Among firms that have already adopted, in other words, the perceived barrier a firm reports tells us nothing about how far it has got.

It would be a mistake to conclude from this that barriers do not matter. The within-adopter null is a range-restriction result: every firm in this sample already cleared the barriers far enough to adopt, so the remaining variation in their perceived barriers is decoupled from what they go on to achieve. To see whether barriers operate at the adoption margin, one has to look outside the adopter population, and the AI-IMPACT survey makes that possible because the barrier and maturity batteries were answered by all 816 firms, including the planners and non-adopters who never reached the logistics module. Across the full sample, barriers clearly do gate adoption (Figure 20). Mean perceived barriers rise monotonically as firms move away from adoption, from 3.11 among AI users to 3.35 among planners to 3.50 among non-adopters (Kruskal–Wallis $p < .001$). In a logistic model of whether a firm is an AI user, controlling for maturity, size, and sector, each standard-deviation increase in perceived barriers is associated with markedly lower odds of being an adopter (OR = 0.64, $p < .001$), while AI maturity is associated with much higher odds (OR = 6.48, $p < .001$; Master Registry, Table T27). Maturity, correspondingly, falls steeply across the same groups, from 2.88 among users to 2.14 among planners to 1.27 among non-adopters.

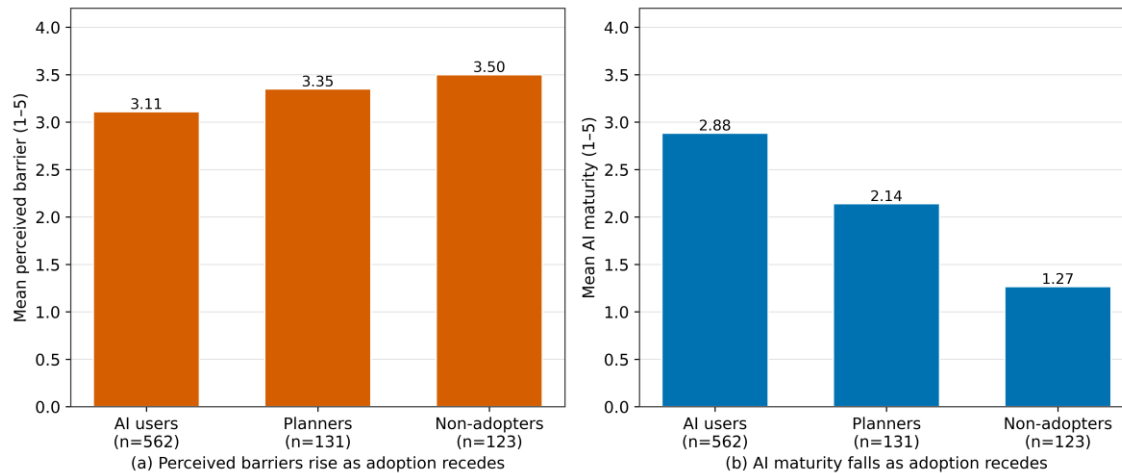


Figure 20. *The adoption margin (N = 816): perceived barriers rise, and AI maturity falls, as firms move from adoption through planning to non-adoption. Barriers and immaturity gate adoption; among adopters, barriers no longer predict depth.*

The picture is therefore a two-stage one. Barriers, and low maturity, separate the firms that adopt AI from the firms that do not. Once a firm has crossed that threshold, its remaining perception of barriers no longer tracks how deeply it embeds AI in logistics; what tracks depth is maturity (Chapter 8). H4 is supported in this refined form: barriers do not distinguish logistics adopters from other AI users, and do not predict depth of deployment among adopters, but they are not inert in the wider process, they bind at adoption rather than at embedding.

10.3 Reconciling the two stages

Two readings make sense of why barriers gate the first stage but not the second. The first is statistical, the range restriction already described: among committed adopters, the variance in perceived barriers that remains is small and largely unrelated to outcomes. The second is substantive, and complements the maturity finding. A mature organization may experience a given obstacle, a data-quality problem, an integration challenge, as a solvable engineering task, while a less mature one experiences the same obstacle as a wall; on this reading perceived barriers are partly filtered through capability, which is consistent with the European-SME evidence that internal digital capability outweighs external environmental factors in AI adoption (Arroyabe et al., 2024) and with the resource-orchestration account of AI breadth and depth (Peretz-Andersson et al., 2024). The managerial and policy implication, developed in Chapter 12, follows from the two-stage structure rather than from a flat claim that “barriers do not matter.” Measures that lower cost, skills, and data barriers, the standard instruments of digitalization policy, plausibly help firms reach the adoption threshold, where the full-sample evidence shows barriers bind. What the evidence does not support is the expectation that the same measures will, by themselves, move firms from pilots to embedded use, because among adopters, depth is associated with internal maturity rather than with the barriers those measures target. Crossing the experimentation plateau is a different problem from reaching the starting line, and calls for different tools.

11. The Forward Frontier and Functional Embedding

The preceding chapters described a present in which adoption has run ahead of embedding. This chapter looks outward and forward, answering RQ7. It maps where the logistics AI frontier is heading, places logistics AI within firms' broader AI footprint and technology stack, identifies the motives behind adoption, and examines its consequences for the workforce. Together these views suggest that the experimentation plateau is a stage in an active, broadening process rather than a terminus.

11.1 The use–plan frontier

Because the adoption scale records planning as well as use, the forward pipeline of each application can be read directly. Figure 21 plots every application by its current in-use share against its forward pipeline, the share of firms considering or planning it, with marker colour showing active-use rate and size showing rejection. The picture is one of broad forward intent. For almost every application the pipeline is large: between 37% and 55% of firms are considering or planning each one, and among firms not yet using a given application, the majority sit in that pipeline rather than rejecting it. Reducing supply-chain error rates has the highest forward momentum (91.7% of non-users are in the pipeline), followed by supply-chain optimization, customer relations, and inventory management, all above 87%.

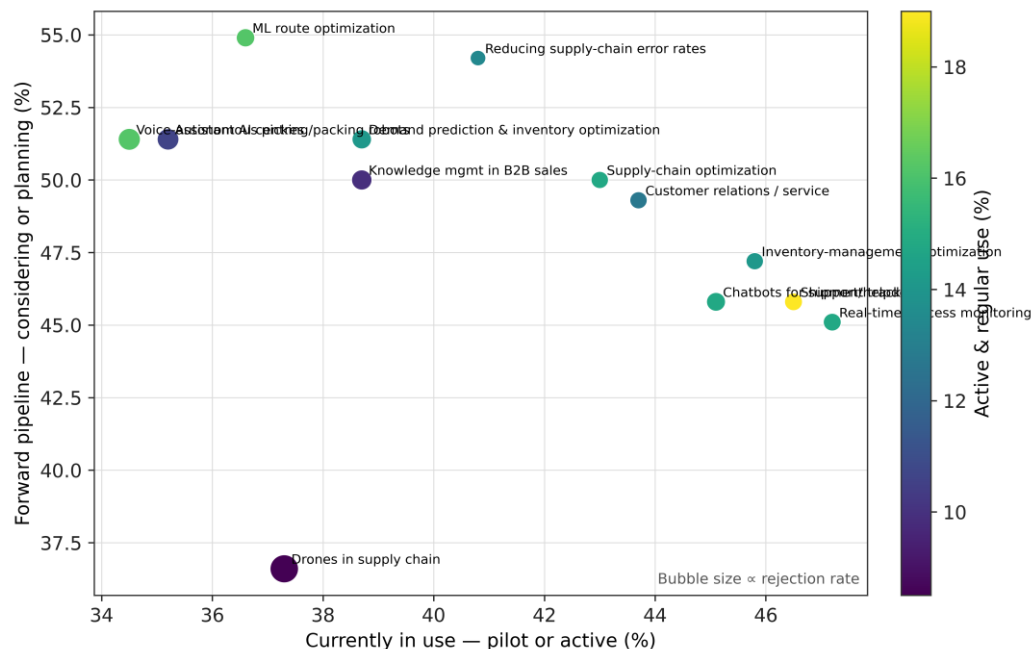


Figure 21. The use–plan frontier: each logistics AI application positioned by current in-use share and forward pipeline (considering or planning). Colour encodes active-use rate; bubble size encodes rejection rate.

One application breaks the pattern. Drones combine the lowest momentum (58.4%) with by far the highest rejection rate (26.1%), marking them as the portfolio’s genuinely contested technology, a niche application whose conditional economics and regulatory friction lead a quarter of firms to rule it out, as the technical literature anticipates (Raghunatha et al., 2023; Eskandaripour & Boldsaikhan, 2023). For everything else, the pipeline is full, which suggests the plateau is not a ceiling so much as a stage. If the firms now considering and planning these applications follow through, and build the maturity to embed rather than merely trial them, the active-use rates that today sit below 20% could rise considerably. The forward frontier is open; whether Slovak firms cross it depends on the capability question this monograph has documented. One caution applies throughout this section: for the capital-intensive physical applications in particular (autonomous robots, drones, voice-assistant centres), a self-reported adoption stage is more likely to capture familiarity or intent than verified operation, so their stage figures should be read with more caution than those for software applications such as tracking or chatbots.

11.2 Logistics AI within a broader AI footprint

Logistics AI is rarely a firm’s only AI venture. The 142 adopters apply AI across an average of 2.86 functional areas, more than double the 1.35 of surveyed AI users that did not select logistics. Logistics adoption is thus a marker of broad digital engagement, and the pattern of co-adoption is informative (Figure 22). Measured by lift, co-occurrence relative to chance, logistics AI is most associated with ICT security (lift 1.57), human resources (1.54), and finance (1.48), followed by R&D, management, and production. In raw terms, a third of logistics adopters also use AI in production or manufacturing (33.8%) and in marketing and sales (35.2%).

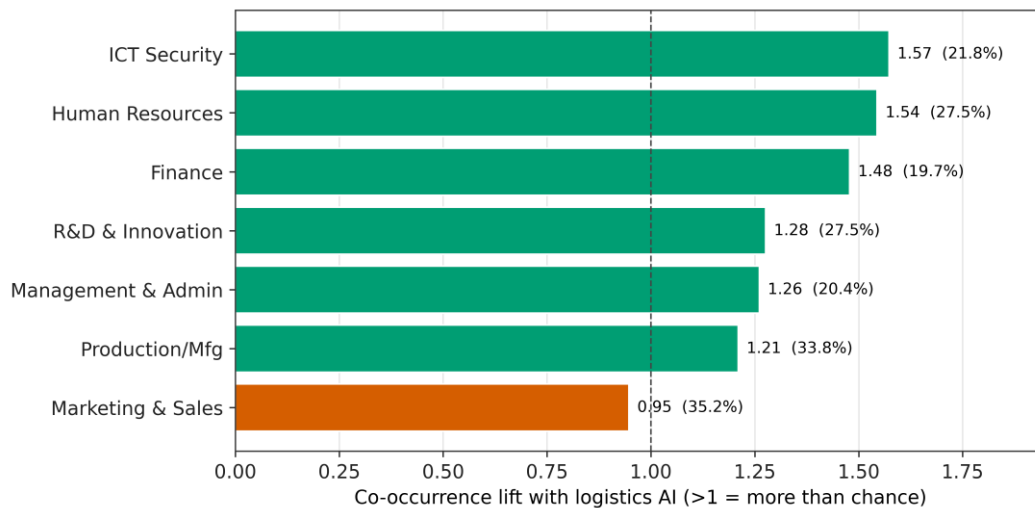


Figure 22. Co-occurrence of logistics AI with other functional domains among AI users: lift (relative to chance) and the share of logistics adopters also using AI in each domain.

The lift pattern is suggestive. Logistics AI co-occurs most with the infrastructural functions, ICT security, HR, finance, that underpin a firm’s capacity to run AI at all, rather than with the

customer-facing functions where AI is most common in absolute terms (marketing, where lift is below one because marketing AI is near-ubiquitous regardless). This is the footprint of firms building a broad digital-operations capability, of which logistics AI is one expression, and it reinforces the general-factor finding of Chapter 6 at the level of the firm's whole AI portfolio: the same organizational capacity that drives broad adoption within logistics seems to drive broad adoption across functions.

11.3 The technology stack and the motives

What technologies underpin logistics AI, and why do firms adopt? The technology stack is broad and led mostly by packaged rather than bespoke AI (Figure 23). The technologies used as a core part of processes or across multiple areas are, in order, chatbots and virtual assistants (43.0% of adopters), computer vision (41.5%), predictive analytics (39.4%), robotic process automation (36.6%), expert systems (35.2%), natural-language processing (34.5%), and, last, custom machine learning and deep learning (31.7%). That bespoke ML trails packaged applications such as chatbots and computer vision is consistent with the experimentation plateau: firms adopt AI they can buy and deploy quickly before they build the in-house data-science capability that custom ML requires. (As elsewhere, “computer vision” here may include relatively standard quality-control cameras and scanning, so the figure is best read as a self-reported breadth of AI-labelled tooling rather than a precise technology census.)

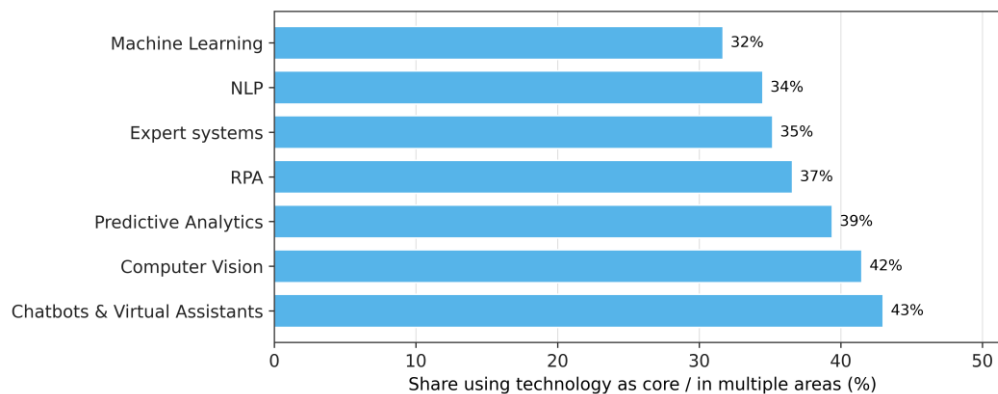


Figure 23. AI technology types underpinning logistics AI: share of adopters using each as a core technology or across multiple areas ($n = 142$).

The motives are operational (Figure 24). The drivers that most convinced management to adopt are the desire to reduce costs (mean 3.94), to automate business processes (3.91), to increase efficiency (3.89), to speed innovation (3.83), and to make faster, more accurate decisions (3.82). Cost and efficiency, rather than strategic positioning or customer experience, are the leading motives, which makes the unrealized cost savings documented in Chapter 9 worth restating: firms adopt logistics AI mainly to cut cost and raise efficiency, yet it is the cost and efficiency gains that most of them have not yet seen. The gap between the motive for adoption and the realized return is the experimentation plateau viewed from the standpoint of managerial expectation.

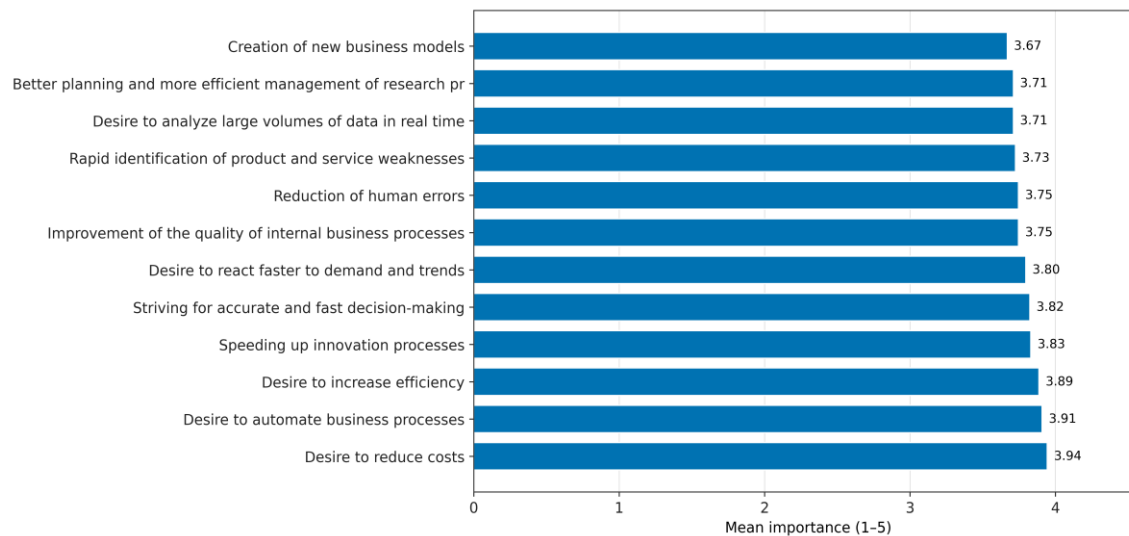


Figure 24. Drivers that convinced management to adopt AI, ranked by mean importance ($n = 142$). Cost reduction, automation, and efficiency lead.

11.4 Governance, workforce, and sentiment

Three further views round out the picture. On *governance*, respondents reported how the adoption decision was made. The most common mode was a decision taken at the level of a single department, such as IT, innovation, or marketing (56 firms), followed by a decision made by company leadership or top management (37), a collaborative process across departments (27), and a decision by an individual key manager or expert (21). The distribution is mixed rather than pointing to any single governance model: departmental and leadership decisions together account for most cases, while cross-departmental collaboration is comparatively uncommon, which is consistent with the population's relatively low scores on the organization dimension of maturity.

On the *workforce*, the evidence runs against a simple displacement narrative. Only 11 of 142 adopters report AI-related layoffs, while 17 report creating new AI-related positions, a net positive job balance among adopters. This is in line with the logistics-employment literature's finding that AI and robotics shift human roles toward supervision and exception handling rather than effecting wholesale substitution (Klumpp & Ruiner, 2022), and with macro projections that AI will both displace and create roles, on balance reshaping rather than shrinking employment (World Economic Forum, 2025). On *sentiment*, adopters broadly agree that AI matters to their company's future and competitiveness, with more measured views on whether their organization is adequately prepared, a profile that mirrors the substance of this monograph: firms believe in AI's importance while acknowledging they have not yet built the maturity to realize it.

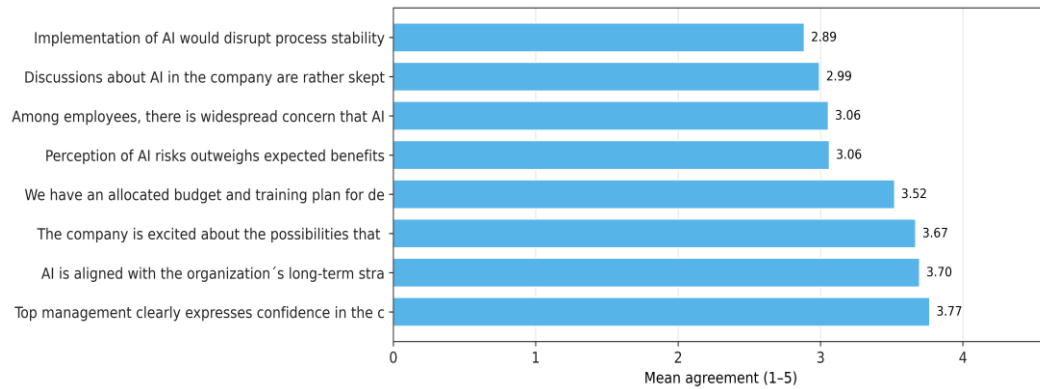


Figure 25. Corporate sentiment toward AI among logistics adopters, eight statements ranked by mean agreement ($n = 142$).

11.5 A synthesis of associations

The firm-level indices that organize the monograph form a coherent web of associations, summarized in the correlation matrix of Figure 26. Maturity, adoption intensity, in-use breadth, active-use breadth, and perceived positive impact cohere positively, with correlations of roughly .47 to .87 among them. Perceived risk and the barrier index, by contrast, form a separate, loosely linked group that is essentially uncorrelated with maturity and embedding, the statistical counterpart of the two-stage barrier result of Chapter 10. The matrix is a compact portrait of the monograph's argument: maturity, depth of embedding, and perceived benefit move together, while perceived barriers among adopters stand apart.

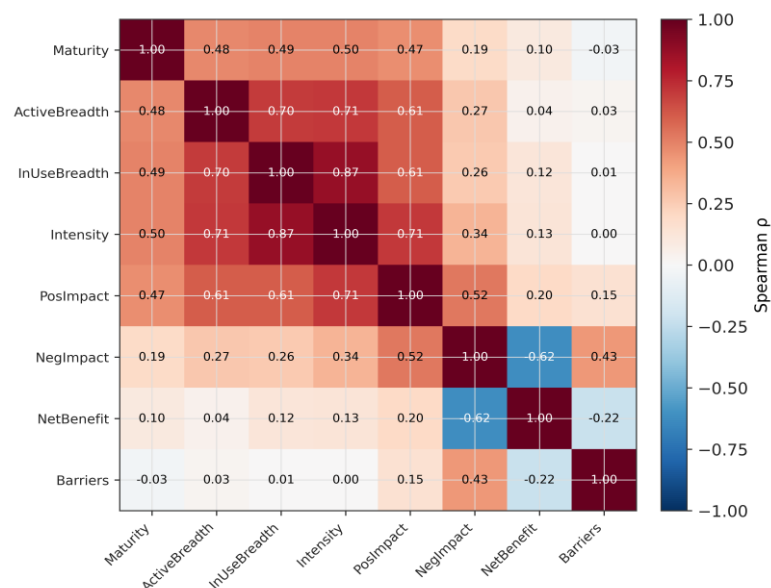


Figure 26. Spearman correlation matrix of the principal firm-level indices among logistics adopters ($n = 142$). Maturity, the embedding indices, and perceived positive impact cohere; perceived risk and barriers form a separate group.

The recency of the phenomenon bears restating. The overwhelming majority of these AI ventures began in 2023, 2024, or 2025 (Figure 27). Logistics AI in Slovakia is young, and the experimentation plateau documented here is in part the plateau of a field still in its first years. Whether it becomes a launching point or a resting point depends on the slow construction of maturity that the evidence identifies as the characteristic most closely tied to embedding.

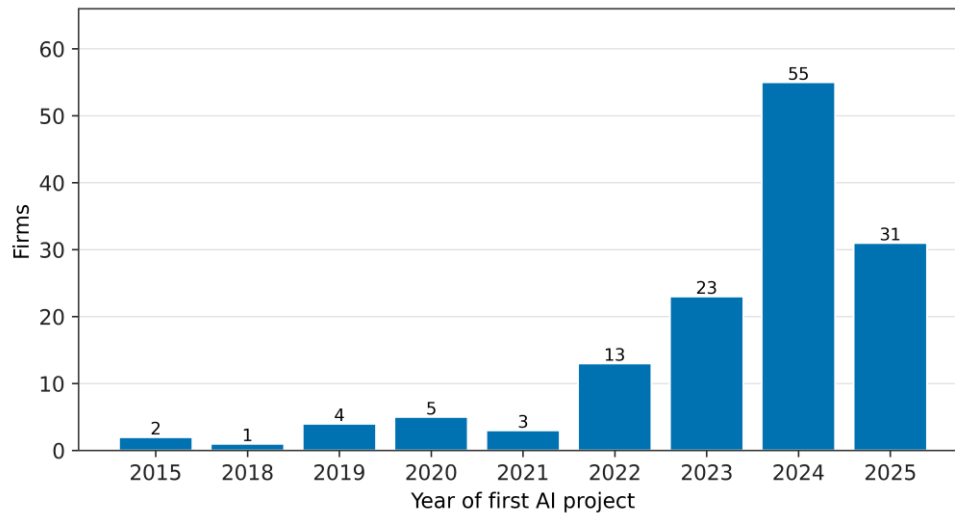


Figure 27. *Year of first AI project among logistics adopters (n = 142): a phenomenon concentrated in 2023–2025.*

12. Discussion

The empirical chapters answered seven research questions and tested six hypotheses with descriptive, exploratory, and confirmatory methods, and subjected the central claim to the obvious objections. This chapter draws the threads together. It restates the argument in the associational terms the design supports, sets out the contributions in scope, situates the findings against the literature, and confronts the limitations that bound the claims.

12.1 The argument restated

The monograph set out to explain how a population of Slovak enterprises has taken AI into logistics, and it arrives at one connected account. Among these firms, adoption has run ahead of embedding. A quarter of surveyed AI users have brought AI into logistics, the third most common functional domain, and they pilot a broad portfolio of applications: the average adopter has more than five of thirteen applications at least in pilot use. But conversion into regular operational use is the exception. The average adopter uses fewer than two applications regularly, the median uses none, and almost three in five have nothing in regular operation at all. The field is wide and shallow.

The difference between depth and breadth is not random. Adopters fall along a continuum, usefully summarized as a minority of embedded adopters (35%) who have woven AI through their logistics operations and a majority of experimenters (65%) still in pilots, and the characteristic that most clearly separates them is organizational AI maturity. Maturity is associated with the odds of adopting AI in logistics ($OR = 1.40$ per standard deviation), and more strongly with depth: a one-standard-deviation increase is associated with about 2.5 times the rate of actively used applications, the largest association in the model, and the relationship holds when the two maturity dimensions that overlap with usage are removed ($IRR \approx 2.2$ for the governance-and-strategy dimensions alone) and at both stages of a hurdle model. What does not explain the divide is just as important. Firm size does not predict adoption once other characteristics are accounted for, and the embedded and experimenter strata are nearly identical in size. Perceived barriers, among adopters, neither distinguish them from other AI users nor predict how deeply they deploy. All of these are cross-sectional associations, not demonstrated effects, and a common managerial-quality cause remains a live alternative; within those limits, the evidence points inward, to organizational maturity, rather than outward, to size or to the barriers firms most readily name.

The argument is reinforced from several directions. The application portfolio is essentially one-dimensional, consistent with a single organizational capacity expressing itself across many applications (Chapter 6). The benefit-risk appraisal is net-positive but realistic, with realized gains so far in growth and service rather than the cost savings that motivate adoption and would require deep integration (Chapter 9). Logistics AI sits within a broad, infrastructure-anchored AI footprint and a packaged-technology stack, a pattern consistent with firms adopting deployable AI more readily than they develop bespoke capability (Chapter 11). And the firm-level indices cohere maturity, embedding, and perceived benefit move together, while perceived risk and barriers form a separate group (Chapter 11). The

two-stage barrier result completes the picture: barriers and low maturity gate adoption across the full sample, but among adopters' depth is associated with maturity, not barriers (Chapter 10).

12.2 Contributions, in scope

The monograph contributes to three conversations, and it is worth being precise about how much each contribution claims.

The first contribution is empirical and regional. To our knowledge this is the first enterprise-level account of AI in logistics for a Central European economy, with complete graded-adoption data for 142 firms across fourteen applications. Where prior Slovak and CEE evidence is aggregate (Eurostat, 2025; Dobos & Bánhidi, 2024; Kádárová et al., 2026) or sector-agnostic (Kovič et al., 2024; Grenčíková et al., 2019), and where the nearest logistics-specific work sits in Poland or Germany (Panasiuk & Wiechetek, 2026; Kmiecik & Skórnóg, 2025), this study turns the region's documented "below-average adoption" into concrete operational, perceptual, and organizational evidence for one economy.

The second contribution is one of measurement rather than concept, and it is important not to overstate it. The idea that firms stall between pilot and production is not new: it is the pilot-to-scale gap of the practitioner literature (McKinsey & Company, 2024), the stalled-at-experimentation finding of the readiness literature (Hradecky et al., 2022; Uren & Edwards, 2023), and, further back, the implementation-to-assimilation distinction long familiar in information-systems research on technology diffusion. What this study adds is granular measurement: graded-stage data on a thirteen-application portfolio for a specific function, and a small set of portable firm-level indices, in-use breadth, active-use breadth, adoption intensity, and an embedding ratio, that make the gap visible and comparable. Binary adoption indicators, which dominate enterprise-AI statistics (Eurostat, 2025), cannot see the difference between a firm running thirteen applications in production and a firm trialling one; the graded indices can, and the gap between adoption and embedding may prove a more informative indicator of digital progress than adoption rates alone.

The third contribution is theoretical, and it is the one the robustness work was designed to protect. The AI-readiness literature has established that readiness is multidimensional (Jöhnk et al., 2021) and that AI capability predicts performance (Mikalef & Gupta, 2021; Fosso Wamba et al., 2024), but it has mostly linked maturity to adoption intention or generic performance, with maturity models that are largely unvalidated and skewed to large firms (Sadiq et al., 2021; Oldemeyer et al., 2024). This study connects a measured, multidimensional maturity construct to concrete functional-area deployment, and then tests whether that connection is an artifact of the maturity measure overlapping with the outcome. It is not: the association survives removing the usage-laden dimensions and survives a two-part specification. That is a modest but genuine addition, evidence that the governance and strategy a firm builds around AI, not merely its existing tooling, is associated with how deeply it deploys, at a granularity the readiness literature has rarely reached. The claim is associational, and the cross-sectional design means it stops short of demonstrating that maturity causes embedding.

12.3 Relation to the literature

The findings sit alongside the reviewed scholarship while sharpening several of its claims. The experimentation plateau gives enterprise-level shape to the practitioner observation that most firms explore AI while few scale it (McKinsey & Company, 2024) and to the readiness literature's account of stalled initiatives (Hradecky et al., 2022). The prominence of data-centric monitoring and visibility applications at the top of the portfolio matches the supply-chain literature's identification of forecasting, inventory, and tracking as the functions where AI delivers earliest (Toorajipour et al., 2021; Makridakis et al., 2022; Balster et al., 2020). The contested status of drones mirrors the conditional economics the UAV-logistics literature documents (Raghunatha et al., 2023). The greater salience of data-security risk over opacity, among these operators, is a useful corrective to an academic literature centred on the black box (Nimmy et al., 2022; Glikson & Woolley, 2020): firms running goods worry first about concrete failure modes. And the two-stage barrier result connects the diffusion literature's emphasis on perceived obstacles (Rogers, 2003) with the readiness literature's emphasis on internal capability, by locating barriers at the adoption margin and capability at the embedding margin.

12.4 Practical and policy implications

For *managers*, the reading the evidence supports is that, among firms that have already adopted, depth of value in logistics AI is associated with organizational maturity rather than with the accumulation of more pilots. The firms further along are not the largest or those reporting the fewest obstacles but those that have built strategy, organization, data practice, and governance around AI. A logistics leader with several stalled pilots might therefore look first at internal conditions, an absent strategy, weak data governance, no operating model for AI in production, rather than at external cost or vendor limits. The population's uneven maturity profile points to where attention may pay off: Slovak adopters score relatively well on culture and technology and least well on organization and strategy, which are also the dimensions whose absence the construct-overlap check showed still matters for depth.

For *technology providers*, the lead of packaged over bespoke AI and the prominence of chatbots, computer vision, and predictive analytics indicate real demand for deployable, low-integration AI. The plateau is a caution, though: selling pilots is not the same as creating embedded value, and providers that help customers move from pilot to production, and that address the data-security concern adopters rank highest, are better placed to convert a wide pipeline into regular use.

For *policymakers*, the two-stage structure of the barrier result is the relevant finding, and it cuts two ways. Across the full sample, barriers and low maturity do gate adoption, so the standard instruments of digitalization policy, support for cost, skills, and data, plausibly help firms reach the adoption threshold, which is where those barriers bind. What the evidence does not support is the expectation that the same instruments will, on their own, move firms from pilots to embedded use, because among adopters' depth is associated with maturity rather than with the barriers those instruments target. Policy aimed at *embedding*, as distinct from *adoption*, would give more weight to managerial capability, AI governance, and

organizational change, the slower investments the evidence ties to depth. These implications are drawn from a purposive sample of Slovak firms that have already engaged with AI; they are offered for a manufacturing-intensive economy whose competitiveness leans on logistics, but they describe the adopter population studied here rather than the national firm population, and their extension to the wider Visegrád region awaits the comparative work set out in Chapter 13.

12.5 Limitations and threats to validity

The limitations of Section 3.6 bound these conclusions and are restated here for the claims they most affect. The *cross-sectional* design means the maturity–embedding relationship, however strong and theoretically motivated, is associational; reverse causation, where embedding builds maturity, and a common cause such as managerial quality cannot be excluded, and the causal-sounding shorthand of earlier drafts has been replaced with associational language throughout. The robustness checks address some specific threats, construct overlap in the maturity measure and the zero-inflated count, but they cannot establish direction of causation. The *self-report, single-respondent* design invites common-method bias, which is a particular concern for the maturity–deployment and perceived-impact–deployment correlations, where the same respondent rated both sides on one instrument; the “days”-denominated performance items are additionally ambiguous and were de-emphasized. The *purposive focal population*, firms that self-selected into AI use and then into logistics, supports claims about mechanisms within this population but not unconditional national prevalence estimates, and the focal n of 142, ample for the main models, limits finer subgroup analysis; the population includes small and medium firms but no micro-firms, so “SME” should be read with that exclusion in mind. Several constructs are *single-item*, which is why the analysis relies on composites and declines to rank the maturity dimensions. The *k-means partition* is a description of a continuum, not evidence of natural kinds, and the *two-factor EFA* is reported as a weak, non-retained secondary pattern beneath a dominant single factor. What offsets these constraints is not any single estimate but the convergence of many analyses, several of them designed to attack the central claim, on one coherent and internally consistent account.

13. Conclusion

This monograph set out to give an empirically grounded account of artificial intelligence in Slovak logistics, drawing on the AI-IMPACT enterprise survey and the 142 firms that have begun implementing or testing AI in their logistics operations. Across nine analytical views and six hypotheses, and after a deliberate effort to attack the central claim, one argument held: among these firms, adoption has run ahead of embedding, and organizational AI maturity, rather than firm size, sector, or the barriers adopters most readily name, is the characteristic most closely associated with the move from experimentation to embedded use.

The evidence is layered and mutually reinforcing. Logistics is the third most common domain of AI application among surveyed AI users, and its adopters are the established, mid-to-large, manufacturing-and-transport core of the economy. They pilot a broad portfolio of applications, led by the data-centric monitoring, tracking, and inventory tools that form the natural entry points, but they embed little: the average adopter has more than five applications in pilot use and fewer than two in regular use, and 59% have none in regular use at all. This gap divides adopters into a minority of embedded firms and a majority of experimenters, separated by almost a full point of AI maturity but barely at all by size, and the maturity difference is statistically robust where the size and net-benefit differences are not. In a firm-level model, maturity is the strongest correlate of the breadth of active deployment, and the association survives removing the maturity dimensions that overlap with usage and survives a two-part specification. Perceived barriers, measured across the whole sample, are higher among non-adopters and gate adoption; among adopters they do not predict depth, which is associated with maturity instead. Adopters judge AI's benefits to exceed its risks while taking the risks seriously, and their realized gains so far are in growth, productivity, and service rather than the cost savings that motivated adoption. The forward pipeline is broad, the phenomenon is young, and whether the plateau becomes a launching point is, on the evidence here, tied to the slow construction of maturity.

The contributions follow from this account and are offered in scope. Empirically, the study provides what is, to our knowledge, the first enterprise-level account of AI in logistics for a Central European economy. As a measurement contribution, it separates adoption from embedding and equips the distinction with portable firm-level indices, deepening rather than inventing the familiar pilot-to-scale idea. Theoretically, it links a measured maturity construct to concrete functional-area deployment and shows the link is not merely an artifact of how maturity is measured. Practically, it reframes the problem of CEE digitalization in two stages: barriers and immaturity gate adoption, but among firms that have adopted, the constraint on logistics AI value is internal capability more than external obstacle. The claims are associational, bounded by a cross-sectional, self-reported, purposive sample, and stated as such.

Future research

Four directions would extend the work. *Longitudinal* data are the priority: re-surveying these firms would turn the cross-sectional maturity–embedding association into evidence on

sequence and direction, and would show whether today's experimenters cross the plateau or abandon their pilots. *Objective outcome measures*, audited operational and financial data linked to firm registers, would test whether the perceived benefits reported here translate into measured performance, and whether the cost savings firms expected eventually arrive. *Comparative designs* across the Visegrád economies would establish whether the maturity association generalizes beyond Slovakia and would set the region's embedding gap against the EU frontier with one instrument. And *mechanism-focused qualitative work* inside embedded adopters and stalled experimenters would open the question this survey can only frame: the concrete organizational practices, governance routines, and data capabilities through which maturity is built and pilots become production. Each builds on what this study provides, a detailed and honest first map of AI in Slovak logistics, drawn at the moment the territory began to take shape.

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Appendices

Appendix A. Synthesis of Research Questions, Hypotheses, and Outcomes

The monograph organized its empirical work around seven research questions and six hypotheses. Table A1 summarizes the question, the method used to address it, the principal quantitative result, and the outcome. Together the rows constitute the evidentiary backbone of the maturity-divide thesis.

Table A1. Research questions, hypotheses, methods, key results, and outcomes.

RQ / H	Question or hypothesis	Method	Key result	Outcome
RQ1 / H1	Are maturity and logistics-intensive sectors associated with the odds of adopting AI in logistics, net of size?	Logistic regression (n = 562)	Maturity OR = 1.40 (p = .002); manufacturing OR = 3.57; transport OR = 3.67; size n.s.; all survive FDR	Supported
RQ2 / H5	Do logistics AI applications form coherent latent structure?	EFA, parallel analysis (n = 142)	One dominant factor (~53% total variance) confirmed; physical vs. cognitive split weak and not retained by parallel analysis	Partially supported
RQ3 / H6	Do adopters separate into strata distinguished by maturity, not size?	k-means partition (n = 142)	Two strata of a continuum (silhouette 0.29): embedded 35% (maturity 3.64) vs. experimenters 65% (2.65); maturity difference significant (r = .64, p < .001), size near-identical	Supported (as strata)
RQ4 / H2	Is maturity associated with the breadth of active deployment?	Negative-binomial + robustness (n = 142)	Maturity IRR = 2.46 (p < .001), largest in model; survives dropping usage-laden items (IRR 2.17) and a hurdle specification; VIF ≤ 1.4; FDR q < .001	Supported (associational)
RQ5 / H3	Do perceived positives outweigh perceived negatives?	Wilcoxon signed-rank (n = 142)	Positive 3.68 > negative 3.29; p < .001; d _z = 0.43; 62.0% pos > neg (selection-bounded)	Supported
RQ6 / H4	Where do barriers bind — adoption or depth?	Mann-Whitney, Spearman, full-sample logit (n = 142 / 816)	Among adopters: barrier × depth ρ = .03 (n.s.). Full sample: barriers gate adoption (OR = 0.64; group means 3.11/3.35/3.50, p < .001)	Supported (two-stage)

RQ7	Where is the frontier heading and how is logistics AI embedded in the broader firm?	Descriptive frontier, co-occurrence	Pipeline 37–55% per application; 2.86 vs. 1.35 functional areas; net-positive jobs	Answered
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Four of the six hypotheses (H1–H4 in their refined forms, and H3) are supported; H5 is partially supported, with one confirmed factor and a weak, non-retained secondary split; H6 is supported in the sense that the population is usefully summarized as two strata of a continuum rather than two discrete types. The analyses were designed in part to attack the central claim, and they converge on one coherent, associational account: a population that has adopted broadly, embedded narrowly, and is differentiated mainly by organizational AI maturity.

Appendix B. Glossary of Derived Firm-Level Measures

The analysis introduced several derived measures to operationalize the adoption-versus-embedding distinction. They are defined here for reuse.

In-use breadth. The number of the thirteen substantive logistics AI applications a firm has reached at least pilot use (adoption stage ≥ 4). Range 0–13; mean among adopters 5.33.

Active-use breadth. The number of applications a firm uses actively and regularly (stage 5). Range 0–13; mean 1.79; median 0. The primary dependent variable in the depth-of-embedding models.

Adoption intensity. The mean adoption stage across the thirteen applications (1–5). Mean 3.16. A continuous summary of how far, on average, a firm has progressed across its portfolio.

Embedding ratio. Active-use breadth divided by in-use breadth — the share of a firm's adopted applications that have reached regular use. Mean 0.24. The single clearest scalar expression of the experimentation plateau: on average only a quarter of adopted applications are regularly used.

Composite AI maturity. The mean of seven maturity dimensions (strategy, culture, organization, technology, data, ethics, privacy), each rated 1–5 ($\alpha = .88$). Standardized for regression.

Net perceived benefit. Mean positive-impact rating (16 items) minus mean negative-impact rating (7 items). Mean +0.39 among adopters.

Barrier index. Mean of twenty barrier items, each rated 1–5 ($\alpha = .95$). Mean 3.08.

Appendix C. Survey Item Inventories and Descriptive Summaries

This appendix provides the descriptive reference for the principal logistics-module batteries, complementing the figures in the main text. All means are on five-point scales among the 142 logistics adopters. Full numerical detail is recorded in the accompanying Master Registry of Results.

C.1 Logistics AI applications (adoption stage, 1 = will not use ... 5 = active & regular)

Shipment tracking (3.36) · Real-time process monitoring (3.30) · Reducing supply-chain error rates (3.29) · Customer relations / service (3.24) · Inventory-management optimization (3.23) · Chatbots for support / helpdesk (3.21) · Supply-chain optimization (3.19) · Demand prediction & inventory optimization (3.17) · ML route optimization (3.13) · Knowledge management in B2B sales (3.08) · Voice-assistant AI centres (3.07) · Autonomous picking/packing robots (2.99) · Drones in the supply chain (2.79).

C.2 Positive impacts (sixteen documented items; perceived significance, 1–5)

More efficient maintenance planning (3.77) · Inventory optimization (3.77) · Warehouse automation (3.75) · Faster response to demand/market changes (3.75) · Shorter delivery times (3.74) · Improved scanning accuracy (3.73) · Reduced misdelivered/lost shipments (3.72) · More deliveries per trip (3.71) · Shorter delivery route distances (3.68) · Better sorting of customer requests (3.68) · Increased sorting accuracy (3.65) · Increased sorting speed (3.64) · Reduced fuel consumption (3.63) · Reduced damaged goods (3.62) · Reduced vehicle breakdowns via improved maintenance (3.54) · Reduced CO₂ emissions (3.47). Overall positive-impact mean 3.68 ($\alpha = .93$).

C.3 Negative impacts (perceived significance, 1–5)

Loss of sensitive logistics data (3.39) · Error rate in logistics processes (3.37) · Reducing inventory below critical levels (3.35) · Incorrectly set maintenance processes · Faulty deliveries to customers (3.24) · Extension/deterioration of logistics times · Lack of transparency in AI recommendations (3.16). Overall negative-impact mean 3.29 ($\alpha = .93$).

C.4 AI technology types (share using as core / across multiple areas)

Chatbots & virtual assistants (43.0%) · Computer vision (41.5%) · Predictive analytics (39.4%) · Robotic process automation (36.6%) · Expert systems (35.2%) · Natural-language processing (34.5%) · Machine learning / deep learning (31.7%).

C.5 Leading adoption drivers (importance, 1–5)

Desire to reduce costs (3.94) · Desire to automate business processes (3.91) · Desire to increase efficiency (3.89) · Speeding up innovation processes (3.83) · Striving for accurate and fast decisions (3.82).

C.6 Perceived performance impact (share reporting favourable change)

Labour productivity (57.7%) · Financial result (57.0%) · Customer-service quality / NPS (56.3%) · Operating cash flow (55.6%) · Revenue (54.9%) · Material & energy costs reduced (23.2%) · Personnel costs reduced (21.8%) · Business risk reduced (15.5%) · Inventory turnover improved (13.4%).

C.7 Organizational AI maturity (mean, 1–5)

Culture (3.18) · Technology (3.14) · Privacy (3.05) · Data (2.98) · Strategy (2.89) · Ethics (2.89) · Organization (2.80). Composite 2.99 ($\alpha = .88$).