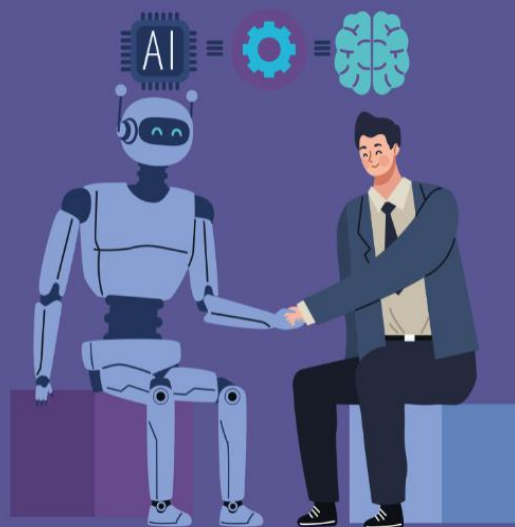




Artificial Intelligence in Production: Evidence from Slovak Enterprises

Peter Štetka & Andriana Baziuk

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*A micro-level analysis of adoption, intensity, perceived impacts,
barriers, and workforce effects*

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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 is expected to reshape how goods are made and how operational processes are run, but the firm-level evidence on what "AI in production" actually amounts to (particularly in the manufacturing-intensive economies of Central and Eastern Europe) is still thin. This monograph uses micro-data from the AI-IMPACT survey of enterprises operating in Slovakia (N = 816 organisations, fielded in 2025) to examine the firms that reported having begun implementing or testing AI in "production and operational processes" (item D3 of the questionnaire). There are 157 such firms: 19.2% of the achieved sample and 27.9% of the 562 firms that use or pilot AI in any form. For these 157 firms the survey carries a dedicated battery of seventeen concrete operational AI applications, perceived positive and negative impacts, seven AI-maturity indicators, perceived barriers, corporate sentiment, workforce effects, and full firmographic detail, which together allow a reasonably detailed, multi-angle description of production AI in one national economy.

The study combines descriptive profiling with hypothesis testing across eight lenses. Four results recur. First, production AI is not confined to the manufacturing sector: only 40.8% of the adopting firms are classified in manufacturing, with construction, ICT and a range of operationally intensive services accounting for the rest. Among the firmographic factors measured here, belonging to a goods-producing sector is the strongest correlate of adoption (46.4% of goods-producing adopters versus 19.0% of service adopters; adjusted odds ratio 3.67). Second, the factors associated with whether a firm begins production AI differ from those associated with how far it scales: sector and firm size relate to the first, while organisational AI maturity relates to the second (Spearman $\rho = 0.35$ with a multi-application intensity index; the only significant predictor in a multivariate model, which nonetheless leaves most variance unexplained). Third, firms deploy AI across a wide set of applications rather than around one flagship use case: active use is fairly even across all seventeen applications (28–41%), led by machine-learning process optimisation, quality control and energy monitoring, with predictive maintenance, often treated as the canonical case, near the bottom; this pattern holds when the analysis is restricted to goods-producing firms only. Fourth, the workforce signal leans towards job creation rather than displacement: more firms reported creating or planning new roles (19.1%) than reported or planned layoffs (11.5%), and the difference between the discordant firms is statistically significant (McNemar exact $p = .036$). Perceived benefits exceeded perceived risks (Wilcoxon $p < .001$, $r = 0.40$, robust to a goods-producing-only check); the twenty barrier items loaded on a single factor of very high internal consistency ($\alpha = .94$), led by integration complexity, skills and a notable gap in state support; and the adopters separated into a larger lower-maturity group ("Operational Experimenters", $n = 107$) and a smaller high-maturity group ("Mature Integrators", $n = 50$) deploying AI roughly twice as broadly. The adoption wave is recent: 61.1% of adopters dated their first AI project to 2024–2025.

The data are cross-sectional, self-reported and drawn from a voluntary, AI-engaged sample, so the findings are read as associations within an achieved sample rather than as causal estimates for the Slovak population; common-method variance, tested with Harman's single-factor criterion, was not dominant (largest component 26.7%). Within those bounds the monograph offers an empirically grounded account of production AI as an operational-process phenomenon that spreads across sectors along structural lines and deepens along organisational-readiness lines, and it gives Slovak and CEE policymakers firm-level evidence on where the binding constraints (skills, integration capability and public support) appear to lie.

Keywords: artificial intelligence; production and operational processes; manufacturing; technology adoption; AI maturity; Industry 4.0; SMEs; Slovakia; Central and Eastern Europe; firm-level survey

Foreword

This monograph began with a simple sense of mismatch. Few subjects generate as much noise as artificial intelligence in industry, yet when we looked for firm-level evidence on what AI in production and operational processes actually amounts to—particularly in the manufacturing-intensive economies of Central and Eastern Europe—we found surprisingly little. The public conversation is shaped by frontier exemplars and vendor case studies; the ordinary firm, deciding whether and how far to bring AI into the operational core of its business, is largely absent from it. We wrote this book to put that firm at the centre of the picture.

Slovakia is a natural place to begin. It is among the most manufacturing- and automotive-intensive economies in the world, and it sits within a region whose enterprises have repeatedly been shown to trail the European digital frontier. An economy where physical production is central but organisational and digital readiness is uneven is a revealing setting in which to watch how production AI spreads and where it stalls. Drawing on micro-data from the 2025 AI-IMPACT enterprise survey, we focus on the 157 firms that reported having begun to implement or test AI in their production and operational processes, and we examine them from eight angles—who they are, what they deploy, how far they scale, how they weigh benefits against risks, what obstacles they face, and what happens to their people.

Throughout, we have tried to let the evidence set the tone. The data are cross-sectional, self-reported and drawn from a voluntary, AI-engaged sample, and we have kept our language associational and our inferential claims modest accordingly. Readers will not find sweeping predictions here. They will find, we hope, a careful and honest account of production AI as it is currently practised in one national economy—an account that, among other things, shows AI in production reaching well beyond the manufacturing sector, deepening along lines of organisational readiness rather than firm size, and, on balance, accompanying job creation more often than job loss.

We have written for several audiences at once: managers weighing where AI fits in their operations, policymakers trying to locate the binding constraints on diffusion, and researchers seeking firm-level evidence from a part of Europe where it remains scarce. We are grateful to the enterprises that took the time to respond to the survey, to the colleagues and institutions that supported the AI-IMPACT project, and to the reviewers whose comments sharpened the argument. Any errors that remain are our own.

The authors

Bratislava, 2026

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1. Introduction

1.1 The problem and its setting

Few technologies have drawn as much simultaneous enthusiasm and alarm as artificial intelligence. In production— the making of physical goods and the operational processes around it—AI is cast at once as the engine of a fourth (and now a fifth) industrial revolution and as a threat to large numbers of jobs. Between those poles sits a less examined question: what are firms that have begun to implement or test AI in their production and operational processes actually doing? Which applications do they use rather than merely contemplate, how far have they gone, which firms are involved, what benefits and risks do they perceive, what obstacles slow them, and what happens to their workforce? These are empirical questions, and they are better answered from representative firm-level data than from frontier exemplars or vendor case studies.

The monograph takes up those questions for one economy (Slovakia) using a 2025 enterprise survey. The setting is chosen deliberately. Slovakia is among the most manufacturing-intensive and, per capita, the most automotive-intensive economies in the world, and it sits within a Central and Eastern European (CEE) region whose firms have repeatedly been shown to trail the European Union's digital frontier (Cséfalvay, 2020; Eurostat, 2025). An economy where physical production is central but organisational and digital readiness is uneven is a useful place to observe how production AI spreads and where it stalls. We do not claim that Slovakia stands in for the region; rather, it is a substantively important case whose patterns invite comparison.

The empirical anchor is a single survey item. Question D3 asked respondents in which areas of the company they had begun implementing or testing AI, offering nine options. One, "production and operational processes", was selected by 157 of the 816 firms. These 157 are the focal group. Through the survey's skip logic, exactly these firms, and only these, were routed into a dedicated module probing seventeen specific operational AI applications, seven categories of perceived positive impact and nine of perceived negative impact. The result is a self-contained block on production AI that can be combined with each firm's maturity profile, perceived barriers, sentiment, workforce decisions and firmographic identity. For brevity, the monograph follows the survey's own wording and refers throughout to "AI in production" or "production AI" — that is, AI applied within a firm's production and operational processes. The term should not be confused with the software-engineering sense of "AI in production" (a model deployed and running live, as opposed to in testing); no such distinction is intended or measured here.

The point of the exercise is to move past "how many firms use AI" toward what AI in production consists of, how far it is pursued, by whom, with what perceived consequences, and against what obstacles.

1.2 Why "production and operational processes" is the right lens

The wording of the focal item matters. The questionnaire did not ask narrowly about "factory automation" or "manufacturing"; it asked about "production and operational processes." That phrasing captures AI applied to the operational core of an organisation, the transformation of inputs into outputs and the coordination around it, whether or not the firm is classified in manufacturing. A

construction company optimising site logistics, an ICT firm automating a service-delivery pipeline, and a food producer monitoring line quality might all report AI in "production and operational processes." As the analysis shows, this is not hypothetical: most focal firms operate outside the manufacturing sector. The lens lets the study see a phenomenon—operational-process AI—that a purely sectoral classification would hide, while retaining a strong manufacturing core. One caveat, set out in the methods, is that the deep-dive battery this item triggers is itself labelled "manufacturing" in the questionnaire even though it was put to firms in every sector; the analysis returns to that point where it bears on interpretation.

1.3 Aims and analytical strategy

The aim is a coherent, evidence-based account of AI in production and operational processes among Slovak enterprises, examined from several angles. Rather than a single test, the study is organised as a sequence of lenses that move from description to explanation. The first profiles the adopters—their distribution across sectors, sizes, ownership types and ages, and where they sit within the wider AI-adoption pattern of the economy. The second maps the technology portfolio: which of seventeen applications are in active use, which are planned, and what the shape of the portfolio reveals. The third quantifies deployment intensity and breadth and asks what they are associated with, separating whether a firm begins from how far it scales. The fourth examines how adopters weigh perceived benefits against risks and the structure of those perceptions. The fifth analyses barriers and whether they form distinct dimensions or a single general factor. The sixth derives a readiness-based typology of adopters. The seventh looks at workforce outcomes—job creation versus destruction. The eighth brings the structural correlates together in a multivariate model.

Throughout, the study reports the descriptive results any survey audience expects (frequencies, distributions, cross-tabulations) while subjecting its more consequential claims to statistical testing with effect sizes, reliability and factor analysis, and regression. Research questions are stated for each lens, and where the data and prior literature support a directional prediction, a formal hypothesis is advanced and tested. Because the sample is non-random and the design cross-sectional, the language is kept associational and the inferential weight modest.

1.4 Contributions

The contribution is, first, empirical: a detailed firm-level portrait of production AI in a CEE economy on which micro-level evidence remains scarce. Second, it is interpretive: the study documents, and confirms in this setting, that production AI reaches well beyond the manufacturing sector—an operations-management point made in the broader literature but rarely shown at firm level in CEE—and it distinguishes the correlates of beginning AI in production from the correlates of scaling it. Third, it is practical: the results point Slovak and CEE policymakers and managers toward where the binding constraints on production AI (skills, integration capability and public support) appear to lie, and toward the workforce implications of its diffusion. These contributions are offered in proportion to a 157-firm cross-sectional study; they are not claims to settle the questions they raise.

1.5 Structure of the monograph

Chapter 2 develops the conceptual background, drawing on the literatures on smart manufacturing and Industry 4.0/5.0, technology-adoption theory, organisational AI maturity, technology acceptance, barriers to adoption, and the economics of automation and employment, and it states the research questions and hypotheses. Chapter 3 describes the data and methods, including the dataset, the focal group, the derived indices, the statistical procedures and the data's limitations. Chapters 4 through 11 present the eight lenses. Chapter 12 draws the findings together and connects them to theory and the CEE policy context. Chapter 13 sets out implications, limitations and directions for further work, and concludes.

2. Conceptual background and theoretical framing

This chapter situates the study within six interlocking literatures and derives, from each, the research questions and, where warranted, the hypotheses that organise the empirical chapters. The literatures are: AI and machine learning in manufacturing and the Industry 4.0/5.0 paradigm; the determinants of firm-level technology and AI adoption; organisational AI maturity and readiness; technology acceptance and the perception of benefits and risks; barriers to AI adoption; and the economics of automation and employment. A final section addresses the Central and Eastern European context that conditions the whole.

2.1 AI in production: from smart manufacturing to Industry 5.0

The application of AI to production is not new in conception, but it has accelerated sharply in scope and maturity. Machine learning has long been recognised as well suited to manufacturing because it can accommodate the high dimensionality, complexity and dynamic behaviour of production data across design, quality control, maintenance and scheduling tasks (Wuest, Weimer, Irgens, & Thoben, 2016). Deep learning extended this reach, with convolutional architectures proving especially capable in vision-based inspection and other data-intensive smart-manufacturing tasks (Wang, Ma, Zhang, Gao, & Wu, 2018). Kusiak's (2017, 2018) influential statements positioned data-driven analytics and the integration of physical assets with sensing, computation and predictive modelling as the substance of "smart manufacturing." A systematic review by Jan and colleagues (2023) consolidated the field, showing that production-AI applications cluster into a recognisable set of domains (predictive maintenance, quality control, process optimisation, scheduling and fault diagnosis) and that manufacturing use cases tend to deliver the highest measured impact on cost.

These applications are conventionally housed within the Industry 4.0 paradigm, whose design principles (interconnection, information transparency, decentralised decisions and technical assistance, realised through cyber-physical systems) were articulated by Hermann, Pentek and Otto (2016) and whose "nine pillars" of enabling technologies furnish the standard taxonomy (Rüßmann et al., 2015). Several applications have matured into research fields in their own right: machine-learning-based predictive maintenance (Çınar et al., 2020; Achouch et al., 2022), deep-learning surface-defect detection that now outperforms both rule-based machine vision and manual inspection (Bhatt et al., 2021), digital twins as virtual-physical mirrors for simulation and control (Tao, Zhang, Liu, & Nee, 2019), and machine learning for the optimisation of analytically intractable production processes (Weichert et al., 2019). More recently, the policy-driven Industry 5.0 framing has reoriented this agenda from a purely efficiency-centric logic toward human-centricity, sustainability and resilience (Breque, De Nul, & Petridis, 2021; Maddikunta et al., 2022; Ghobakhloo et al., 2022)—a shift that raises the human and environmental consequences of production AI, its workforce and energy effects among them, to first-order concerns.

Two points frame the present study. First, production AI is a set of distinct applications rather than a single technology, so a serious empirical account has to measure the set, not a monolith. Second, the literature's centre of gravity, exemplified by the prominence of predictive maintenance, reflects the concerns of capital-intensive manufacturing, and whether the portfolios of ordinary firms in a mixed economy mirror that emphasis is an open question. This motivates the second research question.

Research Question 1 (Landscape). Who are the firms that have begun implementing or testing AI in production and operational processes, and how is production AI distributed across sectors and firm characteristics in the Slovak economy?

Research Question 2 (Portfolio). Which specific AI applications do production-AI firms actually use, plan, or ignore, and does the portfolio centre on a dominant application or spread across many?

2.2 Determinants of firm-level AI adoption: structure and the size–sector logic

A large body of work treats the adoption of AI and advanced digital technologies as organisational technology adoption, theorised most durably through the Technology–Organization–Environment (TOE) framework (Tornatzky & Fleischer, 1990) and Rogers' (2003) Diffusion of Innovations. These lenses direct attention to the technological, organisational and environmental conditions that enable or constrain adoption, and to attributes such as relative advantage, compatibility and complexity that govern diffusion speed. Two structural regularities recur with unusual consistency. The first is the firm-size gradient: larger firms adopt AI at markedly higher rates, a pattern attributed to greater financial resources, risk tolerance and complementary intangible assets (Katz & Jung, 2025; Hong & Kim, 2024; Czarnitzki, Fernández, & Rammer, 2023). The OECD (2025a) documents that the share of large firms using AI is roughly three times that of small firms, and analyses of analytics adoption in manufacturing reach the same conclusion (Brynjolfsson & McElheran, 2019). The second is sectoral heterogeneity: AI adoption varies enormously across industries, with skill-intensive service sectors such as information and professional services typically adopting earliest (Bonney et al., 2024; OECD, 2025b). Reviews integrating TOE and Diffusion of Innovations confirm organisational size, resources, AI strategy and top-management support as recurring determinants (Khanfar et al., 2024; Sánchez, Calderón, & Herrera, 2025).

A complementary strand stresses that AI is increasingly an operations-management technology that diffuses beyond the factory into services, product development and supply chains (Mithas, Chen, Saldanha, & De Oliveira Silveira, 2022; Toorajipour, Sohrabpour, Nazarpour, Oghazi, & Fischl, 2021), while evidence on robots and advanced automation shows adoption concentrated among large, internationalised, productive firms (Stapleton & Webb, 2020). Together these strands imply that whether a firm extends AI into production is shaped first by structural position—being in a goods-producing or operationally intensive activity, and being large enough to command the resources—rather than by softer attitudinal factors. This yields the study's first directional hypotheses.

Research Question 3 (Determinants). What structural and organisational factors distinguish firms that extend AI into production from other AI adopters that do not?

Hypothesis 1 (Size). Among AI adopters, the probability of extending AI into production increases with firm size.

Hypothesis 2 (Sector). Among AI adopters, firms in goods-producing sectors are more likely than service-sector firms to extend AI into production, and this association is the strongest of the structural correlates measured.

2.3 Organisational AI maturity and the intensification margin

If structural factors relate to whether a firm begins, a distinct literature suggests that organisational capability relates to how far it goes. AI maturity models describe organisational AI capability as a staged progression—from no AI-supportive culture, vision or data infrastructure to optimised, institutionalised deployment—across dimensions such as strategy, organisation, technology, data, ethics and privacy (Sadiq, Safie, Abd Rahman, & Goudarzi, 2021; Alsheibani, Cheung, & Messom, 2019). Closely related work on organisational AI readiness identifies multidimensional preconditions (strategic alignment, resources, knowledge, culture and data) that determine whether firms can move AI beyond isolated pilots into sustained use (Jöhnk, Weißert, & Wyrski, 2021; Pumplun, Tauchert, & Heidt, 2019). The theoretical underpinning is the firm's absorptive capacity—its ability to recognise, assimilate and apply new external knowledge as a function of prior related knowledge (Cohen & Levinthal, 1990; Zahra & George, 2002)—and, more broadly, its dynamic capabilities for reconfiguring competences in changing environments (Teece, Pisano, & Shuen, 1997). An integrated AI capability that combines tangible, human and intangible assets predicts firm performance beyond mere adoption (Mikalef & Gupta, 2021), and realising AI value is shown to depend on staged capability-building and leadership commitment rather than on technology acquisition alone (Brock & von Wangenheim, 2019; Davenport & Ronanki, 2018; Chatterjee, Rana, Dwivedi, & Baabdullah, 2021). Maturity-model research on Industry 4.0 likewise treats data and analytics capability as the dimension along which advanced manufacturers deepen their use of intelligent technologies (Wagire, Joshi, Rathore, & Jain, 2021; Berghaus & Back, 2016).

The implication is a separation that, to our knowledge, has not been cleanly shown for production AI at firm level: structural factors should relate to the adoption margin (whether AI enters production at all), whereas organisational maturity should relate to the intensification margin (how broadly and deeply the firm deploys). The present data, which carry both a multi-application intensity measure and a seven-dimension maturity profile for every focal firm, allow that separation to be examined directly—with the caveat that the maturity battery measures AI readiness rather than absorptive capacity in the strict sense, so the link to that theory is suggestive.

Research Question 4 (Intensity). Among production-AI firms, what is associated with variation in the intensity and breadth of deployment?

Hypothesis 3 (Maturity–intensity). Among production-AI firms, organisational AI maturity is positively associated with the intensity and breadth of production-AI deployment, and is a stronger correlate of intensity than firm size.

2.4 Perceived benefits, risks, and technology acceptance

Whether firms adopt and deepen technology use depends not only on objective conditions but on perceptions. The technology acceptance tradition—from the Technology Acceptance Model (Davis, 1989) to the Unified Theory of Acceptance and Use of Technology (Venkatesh, Morris, Davis, & Davis, 2003)—establishes perceived usefulness, or performance expectancy, as the primary driver of acceptance, typically dominating perceived ease of use. Applied to organisational AI, this implies that adopters who proceed do so because they perceive benefits as exceeding risks. The production-AI literature catalogues concrete benefits—reduced downtime and maintenance cost, longer equipment life, shorter process times, more efficient use of materials and energy, and better

coordination (Çınar et al., 2020; Liu, Qian, Yang, & Yang, 2022)—alongside concrete risks such as false detections, high implementation cost, data-quality dependence and the hazards of automated decisions. The acceptance perspective predicts a net-positive perception among firms that have begun deployment, and how those perceptions are structured, as a few interpretable dimensions or as global evaluations, bears on how managers reason about production AI.

Research Question 5 (Benefit–risk). How do production-AI firms weigh the perceived benefits and risks of AI in production, and what is the latent structure of those perceptions?

Hypothesis 4 (Benefit dominance). Among production-AI firms, perceived benefits of production AI exceed perceived risks.

2.5 Barriers to AI adoption

A large applied literature catalogues the barriers that impede AI and Industry 4.0 adoption, especially among small and medium-sized enterprises (SMEs). Recurring obstacles include high investment and operating cost, scarce internal expertise and an acute AI-skills shortage, immature IT infrastructure, the complexity of integrating AI into existing systems, poor data quality and availability, uncertainty over legal and ethical aspects, and insufficient public support (Raj, Dwivedi, Sharma, Lopes de Sousa Jabbour, & Rajak, 2020; OECD, 2025a; Horani et al., 2023; Mikalef, Fjørtoft, & Torvatn, 2019). Studies proximate to the present setting find that CEE manufacturing SMEs are constrained above all by financial limits, scarce digital expertise and short-term strategic horizons (Horváth & Szabó, 2019), and TOE-based work identifies state support as a significant adoption determinant whose absence operates as a barrier (Sánchez et al., 2025). Whether such barriers are experienced as distinct, separable constraints, amenable to targeted intervention, or as a single, diffuse sense of difficulty is an open and consequential question.

Research Question 6 (Barriers). Which barriers most constrain production-AI firms, and do barriers decompose into distinct dimensions or form a single general factor?

Hypothesis 5 (Barriers–intensity). Among production-AI firms, perceived barrier severity is negatively associated with deployment intensity.

2.6 Automation, AI, and the workforce

Perhaps no aspect of production AI is more contested than its effect on employment. The task-based framework holds that automation displaces labour from routine tasks while complementing it in non-routine ones, generating polarisation and skill-biased reallocation (Acemoglu & Autor, 2011; Acemoglu & Restrepo, 2019). The displacement is real and measurable—industrial robots reduce local employment and contribute to wage inequality (Acemoglu & Restrepo, 2020, 2022)—but it is only half of the ledger. The same framework, and a growing body of firm- and country-level evidence, shows that new technologies also reinstate labour by creating new tasks and roles (Acemoglu & Restrepo, 2018, 2019); that robot-adopting firms expand their own employment even as they displace rivals (Acemoglu, Lelarge, & Restrepo, 2020); that economy-wide effects can be net-neutral when service-sector creation offsets manufacturing losses (Dauth, Findeisen, Suedekum, & Woessner, 2021); and that robots can raise productivity and wages without reducing total employment (Graetz & Michaels, 2018; Bessen, 2019). Contemporary evidence on AI specifically points toward augmentation: machine learning reconfigures task bundles within jobs rather than

eliminating whole occupations (Brynjolfsson & Mitchell, 2017), generative AI raises the productivity of less-experienced workers most (Brynjolfsson, Li, & Raymond, 2025; Noy & Zhang, 2023), and AI's lowering of prediction cost raises the value of complementary human judgment (Agrawal, Gans, & Goldfarb, 2019). Cross-country evidence finds no overall negative association between AI exposure and employment (Georgieff & Hye, 2022). Whether a given firm's deployment creates or destroys jobs is thus theoretically indeterminate and has to be settled empirically; the firm-level augmentation evidence suggests, at adopting firms specifically, a tilt toward creation.

Research Question 7 (Workforce). Is AI in production associated with job creation, job destruction, or neither among adopting firms?

Hypothesis 6 (Net augmentation). Among production-AI firms, the incidence of AI-related job creation exceeds the incidence of AI-related layoffs.

2.7 The Central and Eastern European context

The study's setting is itself salient. Slovakia is among the world's most automotive-intensive economies, and its manufacturing core makes it a useful case for production AI (GLOBSEC, 2021). Yet the CEE region shows a persistent digital and AI-adoption gap relative to the EU frontier: in 2024 only 13.5% of EU enterprises used AI, with CEE states near the bottom of the distribution (Eurostat, 2025), and Slovakia scores below convergence expectations on the Digital Economy and Society Index (European Commission, 2022). Regional robotisation has surged, but in a dependence-driven pattern tied to foreign-owned automotive value chains rather than indigenous catching-up (Cséfalvay, 2020), and analyses of the Visegrád Four find domestic firms outside automotive lagging in digital integration (Vakulenko, Bogdanova, & European Commission, 2020; Gyimesi, 2021). Recent evidence confirms that Slovak enterprises' AI adoption, while rising across all size classes between 2021 and 2024, remained below the EU27 average (Kádárová et al., 2026). This configuration—economically central physical production combined with uneven organisational readiness, under the binding new framework of the EU AI Act (European Parliament & Council of the European Union, 2024) and the national Digital Transformation Strategy 2030 (Ministry of Investments, Regional Development and Informatization of the Slovak Republic, 2019)—makes Slovakia an informative case for understanding where production AI diffuses and where it stalls.

Together these literatures yield seven research questions and six hypotheses, summarised in Chapter 3 (Table 1) and examined across Chapters 4-11. The survey's design—routing production-AI adopters into a dedicated deep-dive module—allows all of them to be addressed within one internally consistent dataset.

3. Data and methods

3.1 The AI-IMPACT survey dataset

The empirical basis of the monograph is the AI-IMPACT Survey Dataset (Slovakia), an organisation-level survey of the adoption and use of artificial intelligence among enterprises operating in Slovakia, fielded in 2025. The publicly released analytical dataset comprises 816 organisations and 621 variables organised into thematic blocks that mirror the questionnaire's logic: characteristics of the organisation and respondent; multidimensional indicators of AI maturity; corporate attitudes toward AI; the status and intensity of AI adoption; functional areas of application and their evaluation; and perceived barriers. The dataset integrates several variable types—categorical indicators, ordinal maturity items, Likert-scale items, and binary variables derived from multiple-choice questions—supplemented by technical metadata. The final file of 816 cases is a deduplicated version of a larger raw export of 1,086 complete responses; in line with the dataset documentation and the requirements of this study, all analyses use the clean comma-separated file so that each company is represented once. The data were collected under a project co-funded by the European Union and are distributed under a Creative Commons Attribution 4.0 licence with a structured data dictionary and bilingual (Slovak/English) questionnaires.

A central design feature, and the one that makes this study possible, is the survey's skip logic. Many items were displayed only to respondents for whom they were relevant, conditional on earlier answers. Missing values in content variables therefore arise predominantly from routing rather than from item non-response: a firm that does not use AI was never shown the deep-dive modules, and its blanks on those modules are structurally meaningful absences rather than refusals. This property is exploited directly in constructing the focal population.

3.2 The focal population: production-AI adopters

The study's focal population is defined by a single questionnaire item. Question D3 ("In which areas of the company have you started implementing or testing AI?") presented respondents with nine non-exclusive options. The option of interest (rendered in the English questionnaire as "Production and Operational Processes") corresponds to dataset variable AIAareas_2B. Exactly 157 firms selected it. These 157 firms are the focal population analysed throughout; they represent 19.2% of all 816 surveyed organisations and 27.9% of the 562 firms that use or pilot AI in any area.

Two features of this definition deserve emphasis. First, the item was shown only to firms that use or pilot AI (those answering the gateway question A_{use} with one of its three "use/test" categories); planners and non-adopters were never offered it. The focal population is therefore, a subset of active AI users, and "production-AI adoption" throughout this monograph means current implementation or testing of AI in production and operational processes, not mere intention. Second, the survey's skip logic routed exactly and only these 157 firms into a dedicated deep-dive module. Verification confirmed a one-to-one correspondence: all 157 focal firms answered the deep-dive battery, and no non-focal firm did. The focal item thus functions as the gateway to a self-contained block comprising seventeen specific production-AI applications (variable group ManAreas), seven perceived positive

impacts (Manpositive), and nine perceived negative impacts (Mannegative). This clean routing is what permits the internally consistent characterisation that follows.

One terminological feature of the instrument warrants clarification. Although the gateway item D3 is phrased broadly as "production and operational processes", the deep-dive battery it triggers is titled, in the questionnaire, in terms of "manufacturing" (for example, "In what areas of manufacturing does your company use AI?"). That battery was nonetheless administered to every firm selecting the gateway item, regardless of sector, and its constituent items describe generic operational applications—process optimisation, quality control, inventory and supply-chain optimisation, energy monitoring, predictive analytics, and an AI decision-support copilot, among others—that apply to operational processes well beyond classical factory production. Non-manufacturing respondents thus answered these items in relation to their own production and operational processes. This dual framing, a broad gateway and a manufacturing-labelled but operationally generic deep dive, should be borne in mind when interpreting the analysis, and it is noted again among the limitations in Section 3.6.

To enable comparison, two reference groups are used throughout: the 405 "other AI adopters" (the contrast group), firms that use or pilot AI but did not select production and operational processes, and, where relevant, the full sample of 816 firms.

3.3 Variables and derived measures

Beyond the focal item and the deep-dive module, the analysis draws on the following variable groups.

Firmographics. Sector (18 categories following the standard economic classification), firm size (four employee bands: micro <10, small 10–49, medium 50–249, large 250+), annual net sales (six bands), ownership (private Slovak, foreign registered in Slovakia, state-owned, mixed), firm age (under 5, 5–10, 11+ years), and respondent managerial level.

AI maturity. Seven ordinal items (1–5), each capturing a stage of organisational AI maturity along a distinct dimension: culture and mindset, strategy, organisation, technology, data, ethics and privacy. A composite maturity score was computed as the mean of the seven dimensions; its internal consistency is excellent (Cronbach's $\alpha = .89$). These items capture organisational AI readiness (strategy, structures, data practices, culture and governance) rather than absorptive capacity in the strict sense of prior related knowledge or R&D stock; the maturity construct is treated here as a readiness proxy, and the theoretical links to absorptive capacity in Chapter 2 are used in that spirit.

Production-AI deployment. The seventeen substantive ManAreas applications use a five-point intensity scale (1 = do not use and do not plan to; 2 = considering for the more distant future; 3 = plan to use within two years; 4 = use in pilot/occasional form; 5 = use actively and regularly). From these, three measures were derived: a Production-AI Intensity Index (the mean of the seventeen items, 1–5); a breadth count (the number of applications in active use, i.e. rated 4 or 5); and a regular-use count (rated 5). The "Other" eighteenth option was excluded from the indices. Because the scale places planning anchors (levels 2–3) and usage anchors (levels 4–5) on one axis, the mean index blends intention with behaviour and is treated as an ordinal summary; the breadth and regular-use counts, clean dichotomies of active use, are given weight alongside it.

Perceived impacts. Seven positive-impact and nine negative-impact items, each rated 1–5 for perceived significance. Composite benefit and risk means were computed (Cronbach's alpha =.90 and .91), along with a net-benefit score (benefit mean minus risk mean).

Barriers. Twenty items rated 1–5 for barrier severity; a composite barrier-severity mean was computed (Cronbach's alpha =.94).

Corporate sentiment. Eight agreement items (1–5); after reverse-coding the four negatively worded items, a positive-sentiment composite was formed (alpha =.64, acceptable for a short, mixed-direction attitudinal scale). Its modest reliability attenuates the coefficients in models where sentiment enters as a predictor, which is borne in mind when those coefficients are interpreted.

Workforce. Two binary items capturing whether AI implementation has led to, or is planned to lead to, layoffs and new job creation.

Context. Year of first AI project, decision-making mode, information sources, factors that convinced management, and AI technology types used (seven types rated 1–5).

3.4 Statistical procedures

The analysis combines descriptive methods with hypothesis testing; given the non-random sample, the latter is treated as hypothesis-consistent evidence rather than confirmation in the strict sense. Descriptive results are reported as frequencies, percentages, means and standard deviations, with 95% Wilson confidence intervals for key proportions. Group comparisons between the focal and contrast groups use the chi-square test of independence with Cramér's V for categorical associations, and the Mann–Whitney U test (with effect size $r = Z/\sqrt{N}$) for ordinal comparisons, given the ordinal, non-normal nature of the Likert and maturity items. Comparisons across more than two groups use the Kruskal–Wallis test with epsilon-squared. Associations among ordinal and continuous measures use Spearman's rank correlation. The paired comparison of perceived benefits and risks uses the Wilcoxon signed-rank test. Where multiple related comparisons are made (for example, across the seven maturity dimensions or twenty barriers), Holm's correction is applied and corrected p-values are reported.

Three multivariate techniques are used. First, exploratory factor analysis (principal-axis factoring with varimax rotation) assesses the latent structure of the impact and barrier batteries; the number of factors is determined by Horn's parallel analysis and cross-checked against the eigenvalue-greater-than-one rule, with sampling adequacy verified by the Kaiser–Meyer–Olkin (KMO) statistic and Bartlett's test of sphericity. For the twenty-item barrier battery the case-to-item ratio (about 8:1) is below the conventional 10:1 guideline, so its dimensionality result is reported as indicative rather than definitive; the seven- and nine-item impact batteries are comfortably above the guideline. Second, k-means cluster analysis on the standardised seven AI-maturity dimensions derives an empirical typology of adopters (with intensity, breadth and perceived benefit held out as external validators) and the number of clusters is selected by the silhouette criterion. Third, ordinary-least-squares and binary logistic regression model, respectively, the intensity of production-AI deployment and the probability of being a production-AI adopter; for the logistic model, discrimination is assessed by the area under the receiver-operating-characteristic curve (AUC) and fit by McFadden's pseudo- R^2 . All analyses were conducted in Python (pandas, SciPy, statsmodels, scikit-learn and factor-analyzer).

Two safeguards are reported. Because every measure is self-reported by one respondent on one instrument, common-method variance is a concern; it was assessed with Harman's single-factor test, in which the largest unrotated component across the perceptual batteries accounts for 26.7% of the variance, below the 50% threshold conventionally treated as a warning sign, though this does not rule out method bias entirely. And because the study runs one set of pre-specified hypotheses alongside a larger number of exploratory bivariate comparisons, the six hypotheses are treated as the confirmatory core and other associations, especially those with p-values near .05, are read as exploratory and interpreted cautiously. The full numerical output is recorded in an accompanying Master Results Registry, and all figures are provided at publication resolution.

Table 1. Research questions, hypotheses, and statistical tests.

Research question	Hypothesis	Focus	Methods
RQ1 Landscape	—	Who adopts production-AI; distribution by sector/size	Frequencies, chi-square, Cramér's V, Wilson CI
RQ2 Portfolio	—	Which applications are used/planned/ignored	Descriptive ranking, intensity scale
RQ3 Determinants	H1 size (+), H2 sector (+)	What distinguishes production-AI adopters	Logistic regression, OR, AUC
RQ4 Intensity	H3 maturity (+)	Drivers of deployment intensity/breadth	Spearman, Kruskal-Wallis, OLS
RQ5 Benefit-risk	H4 benefit > risk	Weighing of benefits vs risks; latent structure	Wilcoxon, EFA, parallel analysis, alpha
RQ6 Barriers	H5 barriers (-) intensity	Leading barriers; dimensionality	Mann-Whitney, EFA, Spearman
RQ7 Workforce	H6 creation > layoffs	Job creation vs destruction	McNemar, chi-square, logistic

3.5 The AI-adoption landscape of the sample

Before turning to the focal population, it is useful to situate it within the broader sample, both to provide the standard survey overview readers expect and to make the focal group's position legible. Among the 816 firms, AI engagement is substantial: 16.5% report using AI in multiple areas, 26.5% in several specific processes, and 25.9% are testing or piloting, so that 68.9% are AI users or pilots, while 15.1% neither use AI nor plan to, and the remainder plan future adoption. Across the nine application areas of question D3, marketing and sales is the most common locus of AI (selected by 25.6% of all firms and 37.2% of adopters), followed by production and operational processes (19.2% and 27.9%) and logistics (17.4% and 25.3%); management, human resources, ICT security, finance and research and development follow. Production and operational processes is thus the second most common functional home for AI in the sample, behind only the customer-facing marketing function—an early indication that, among AI-engaged firms in this sample, operational-process AI is a common rather than a marginal undertaking.

Table 2. AI adoption status and application areas, full sample (N = 816).

Category	n	Share
AI adoption status		
Use - multiple areas	135	16.5%
Use - specific processes	216	26.5%
Testing/piloting	211	25.9%
Plan < 1 year	59	7.2%
Plan <2 years	29	3.6%
Plan 3 years+	43	5.3%
No & no plan	123	15.1%
AI application area (% of adopters)		
Marketing & Sales	209	37.2%
Production & Operational Processes	157	27.9%
Logistics	142	25.3%
R&D & Innovation	121	21.5%
Human Resources	100	17.8%
Management	91	16.2%
ICT security	78	13.9%
Finance	75	13.3%
Other	44	7.8%

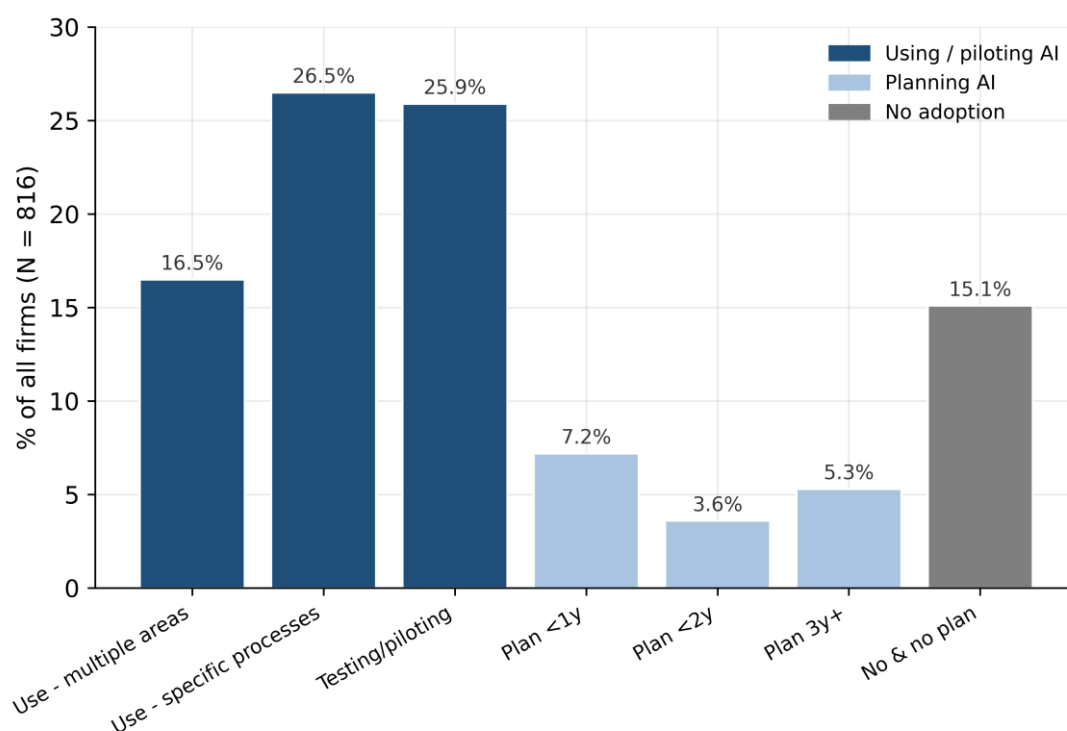


Figure 1. AI adoption status across the full sample of 816 Slovak enterprises.

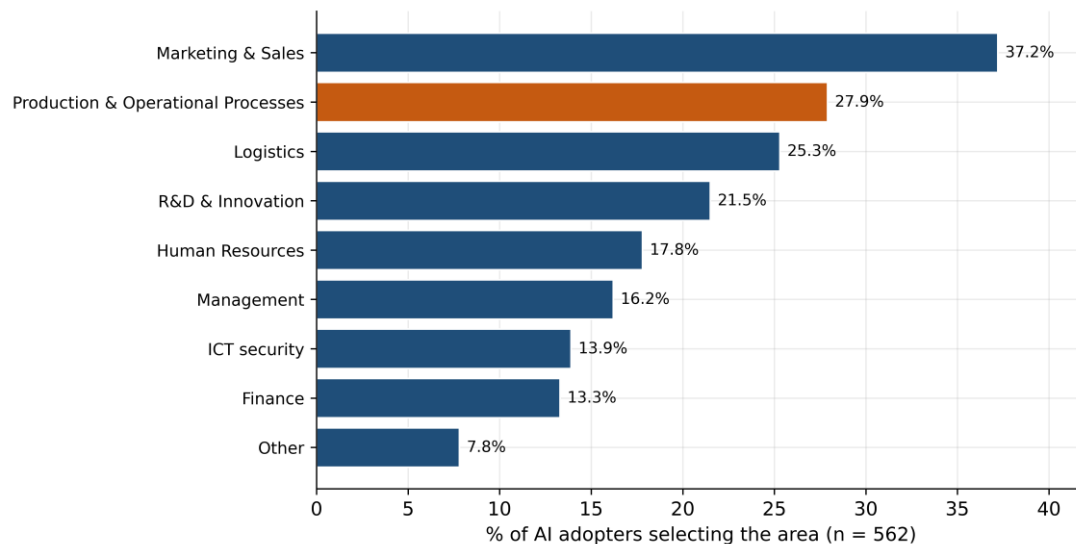


Figure 2. AI application areas among AI adopters (n = 562), with production and operational processes highlighted.

3.6 Limitations of the data

A candid account of the dataset's limitations is a precondition for responsible interpretation, and the constraints below qualify every result that follows.

First, the data are cross-sectional. They capture a single moment in 2025 and cannot establish causal direction. When the analysis reports that maturity is associated with deployment intensity, this is a contemporaneous association consistent with—but not proof of—a causal pathway; reverse and reciprocal influences are plausible and cannot be excluded.

Second, all measures are self-reported by a single respondent per organisation. This introduces the familiar risks of common-method variance (mitigated, on Harman's test, but not removed), social-desirability bias, and key-informant error. Although respondents were predominantly managers positioned to know their firm's AI activities, perceptions of maturity, impact and barriers are subjective. The workforce items, in particular, conflate realised and planned actions ("has led to, or do you plan to").

Third, the focal measure is a binary self-classification. A firm's selection of "production and operational processes" reflects its own interpretation of that phrase; the breadth that makes the lens valuable also introduces heterogeneity in what respondents counted as production AI. Relatedly, the deep-dive battery is labelled "manufacturing" in the questionnaire even though it was administered to adopters from every sector; while its items are operationally generic, the manufacturing framing may have shaped how some respondents (particularly those in services) construed them.

Fourth, the focal sample size (n = 157), while ample for the descriptive and bivariate analyses and adequate for the regressions and the impact factor analyses, is modest for fine-grained sub-group comparisons and underpowered for weak associations; cells defined by the intersection of small sectors and size bands can become sparse, and such results are reported with appropriate caution and confidence intervals.

Fifth, the survey is not a simple random sample of a fully enumerated population frame, and, as is typical of voluntary enterprise surveys, firms already engaged with AI are likely over-represented; the

micro (<10 employees) band is effectively absent from the adopter pool. Population-level prevalence figures should therefore be read as descriptive of the achieved sample rather than as unbiased national estimates, even as the internal comparisons that carry the study's main arguments remain valid.

Sixth, a small number of value labels in the source data retain bilingual residue, and the forward-looking "plan" battery (Manplan) was routed to a separate population of prospective adopters rather than to the focal firms; consequently, forward orientation for the focal group is captured through the planning levels embedded in the ManAreas intensity scale itself rather than through a separate planning module. These features were identified during data preparation and handled explicitly.

None of these limitations is disqualifying, but together they counsel interpretive restraint: the monograph's claims are offered as well-evidenced descriptions of, and associations within, a large achieved sample of Slovak enterprises, not as causal estimates for a precisely defined population.

4. The adopter landscape: who pursues AI in production

Who, in concrete terms, pursues AI in production? This chapter (addressing Research Question 1) profiles the 157 focal firms against the 405 other AI adopters and examines Hypotheses 1 and 2 at the bivariate level; the multivariate test, which separates size from sector, is held back to Chapter 11. The chapter's main descriptive point is what might be called the sectoral paradox of production AI: the activity is most common in goods-producing sectors, yet most of the firms doing it operate outside manufacturing as conventionally classified.

4.1 A firmographic profile

The focal firms differ from other AI adopters on some dimensions and resemble them on others. The clearest contrasts are size, sector and ownership; age and respondent profile differ more modestly.

Table 3. Firmographic profile: production-AI firms vs other adopters vs full sample (column %).

Characteristic	Production-AI (n=157)	Other adopters (n=405)	All (N=816)
— Size —			
Small (10-49)	19.7%	27.9%	27.2%
Medium (50-249)	23.6%	30.9%	30.1%
Large (250+)	56.7%	41.2%	42.6%
— Sector —			
Agriculture	0.0%	1.0%	0.9%
Mining	0.6%	0.2%	0.5%
Manufacturing	40.8%	16.8%	24.6%
Electricity/Gas	0.6%	1.7%	1.6%
Water/Waste	0.6%	0.7%	0.9%
Construction	11.5%	3.7%	6.9%
Vehicle repair/trade	2.5%	2.7%	2.2%
Transport/Storage	5.1%	9.9%	8.0%
Accommodation/Food	2.5%	4.7%	4.0%
ICT	12.1%	13.8%	10.7%
Finance/Insurance	5.7%	11.9%	8.9%
Real estate	0.6%	1.5%	1.5%
Professional/Sci/Tech	4.5%	4.9%	4.0%
Admin/Support	4.5%	6.4%	5.0%
Public admin	0.0%	1.2%	0.9%
Education	0.0%	3.2%	2.5%
Health/Social	3.2%	4.4%	5.0%
Other	5.1%	11.1%	12.0%
— Ownership —			
Private Slovak	37.6%	45.4%	47.9%
Foreign (in SK)	49.7%	41.7%	40.0%
Mixed	12.7%	12.8%	12.1%

— Firm age —			
5-10 years	27.4%	38.0%	30.4%
11+ years	72.6%	62.0%	69.6%

On size, production AI is more often the business of larger firms. Large firms (250+ employees) make up 56.7% of the focal group but 41.2% of other adopters and 42.6% of the sample; small firms (10–49) are 19.7% of focal firms against 27.9% of other adopters. The micro band (<10 employees) is effectively absent from the adopter pool and so from the focal group. A chi-square test on the three populated size bands shows the size distributions differ ($\chi^2(2) = 10.96$, $p = .004$, Cramér's $V = 0.13$), a small-to-moderate association consistent with Hypothesis 1.

On sector, the focal group is more manufacturing-intensive than the comparison group: 40.8% are in manufacturing, against 16.8% of other adopters (for manufacturing versus non-manufacturing among adopters, $\chi^2(1) = 34.86$, $p < .001$, Cramér's $V = 0.25$). The same figure carries the seed of the paradox, since 40.8% manufacturing means 59.2%, a clear majority, of production-AI firms are not manufacturers. Construction (11.5%), ICT (12.1%), finance and insurance (5.7%), transport and storage (5.1%) and a tail of service activities make up the bulk.

On ownership, the focal firms are somewhat more often foreign-owned: foreign companies registered in Slovakia are 49.7% of the focal group against 41.7% of other adopters and 40.0% of the sample, with private Slovak firms correspondingly fewer (37.6% versus 47.9%). This direction is what the regional literature would lead one to expect, given the role of foreign-owned, automotive-anchored value chains in carrying advanced production technology into CEE (Cséfalvay, 2020). It should be read cautiously, however: the ownership association is not statistically significant ($\chi^2(2) = 3.24$, $p = .20$), so it is at most a suggestive tendency rather than an established difference.

The focal firms are also a little older and more established (72.6% have operated for 11+ years versus 62.0% of other adopters; $\chi^2(1) = 5.17$, $p = .023$, a difference to read as exploratory given the number of comparisons made), and their questionnaire was somewhat more often completed by top managers (21.0% versus 17.0%). Sales-band differences are weak and not significant once size is accounted for.

4.2 The sectoral paradox

Two facts sit side by side: production AI is most common in goods-producing sectors, yet most firms doing it are not manufacturers. This is not a contradiction so much as a feature of how an operational technology spreads through a mixed economy, and it is clearest when one computes, for each sector, the share of that sector's AI adopters who extend AI into production and operations.

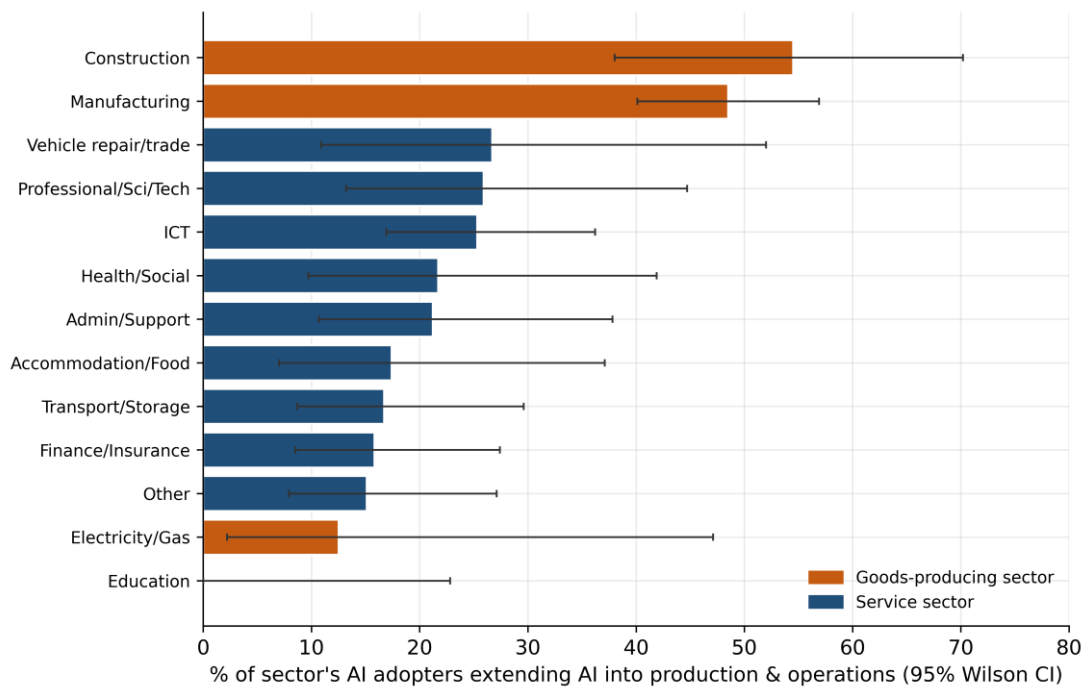


Figure 3. Production-AI adoption rate by sector, expressed as the share of each sector's AI adopters that extend AI into production and operational processes.

Table 4. Production-AI adoption rate among AI adopters, by sector.

Sector	Prod-AI / adopters	Rate	95% CI
Construction	18/33	54.5%	[38.0, 70.2]
Manufacturing	64/132	48.5%	[40.1, 56.9]
Vehicle repair/trade	4/15	26.7%	[10.9, 52.0]
Professional/Sci/Tech	7/27	25.9%	[13.2, 44.7]
ICT	19/75	25.3%	[16.9, 36.2]
Health/Social	5/23	21.7%	[9.7, 41.9]
Admin/Support	7/33	21.2%	[10.7, 37.8]
Accommodation/Food	4/23	17.4%	[7.0, 37.1]
Transport/Storage	8/48	16.7%	[8.7, 29.6]
Finance/Insurance	9/57	15.8%	[8.5, 27.4]
Other	8/53	15.1%	[7.9, 27.1]
Electricity/Gas	1/8	12.5%	[2.2, 47.1]
Education	0/13	0.0%	[0.0, 22.8]

The rates show a gradient. The highest are in construction (54.5%) and manufacturing (48.5%), followed by a middle band of vehicle trade and repair (26.7%), professional and scientific activities (25.9%) and ICT (25.3%), and then a tail of service sectors near 15-22%. Education records no production-AI adopters. That construction edges out manufacturing is worth pausing on: construction is a goods-producing, project-based, operationally intensive activity in which AI applied to site logistics, scheduling, quality and equipment monitoring maps naturally onto "production and

operational processes," even if it is rarely the first sector mentioned in discussions of AI in manufacturing.

Grouping sectors into goods-producing activities (agriculture, mining, manufacturing, utilities, water and waste, and construction—the primary and secondary sectors) versus services makes the pattern explicit: 46.4% of goods-producing adopters extend AI into production, against 19.0% of service-sector adopters ($\chi^2(1) = 44.84$, $p < .001$, Cramér's $V = 0.28$). Among the firmographic factors measured here, goods-producing sector membership is the strongest correlate of production-AI adoption—though one should not read "strongest correlate" as "complete explanation," since the survey did not measure, for instance, capital intensity, R&D, or prior automation stock.

The paradox resolves through the composition of the adopter pool. Goods-producing sectors adopt at a high rate but are outnumbered in the economy by service firms, so even a moderate service-sector rate (19.0%) applied to a large service base yields, in absolute terms, most of the production-AI population. Production AI is, in this sample, a goods-producing phenomenon by propensity and a cross-sector one by incidence. That duality is the empirical basis for the operational-process reading developed later: what the survey captures is AI applied to the operational core of organisations, wherever that core involves the transformation and coordination of physical or quasi-physical processes.

4.3 The size gradient and its interpretation

The size gradient deserves a precise reading. Among adopters, the share extending AI into production rises with size: 21.5% of small adopters, 22.8% of medium adopters and 34.8% of large adopters.

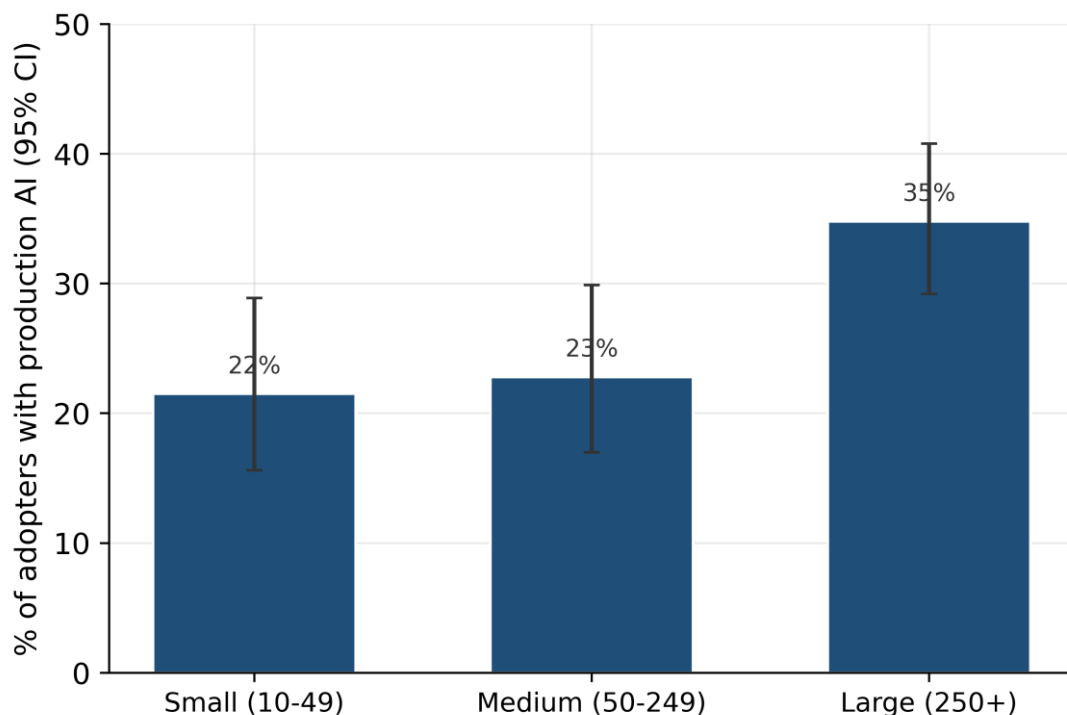


Figure 4. Production-AI adoption rate by firm size band, among AI adopters.

This is consistent with the firm-size advantage repeatedly found in AI and advanced-technology adoption, where larger firms command the resources, risk tolerance and specialised personnel that production AI tends to require (OECD, 2025a; Katz & Jung, 2025; Brynjolfsson & McElheran, 2019). What size is associated with, however, is whether a firm crosses into production AI, not how intensively it deploys once across: as Chapter 6 shows, among the 157 firms that have crossed, deployment intensity is statistically unrelated to size. Size, on this evidence, relates to the decision to begin rather than to the depth of deployment—a distinction the bivariate gradient alone cannot reveal.

4.4 Production AI within the firm's wider AI footprint

Is production AI pursued in isolation or as part of a broader AI effort? Because D3 allowed multiple selections, one can count how many other application areas each focal firm reported. On average they reported AI in 1.45 other areas, most often logistics (30.6% of focal firms—an operational adjacency), marketing and sales (22.3%) and R&D. At the same time, 42.7% of focal firms named production and operational processes as their only AI area.

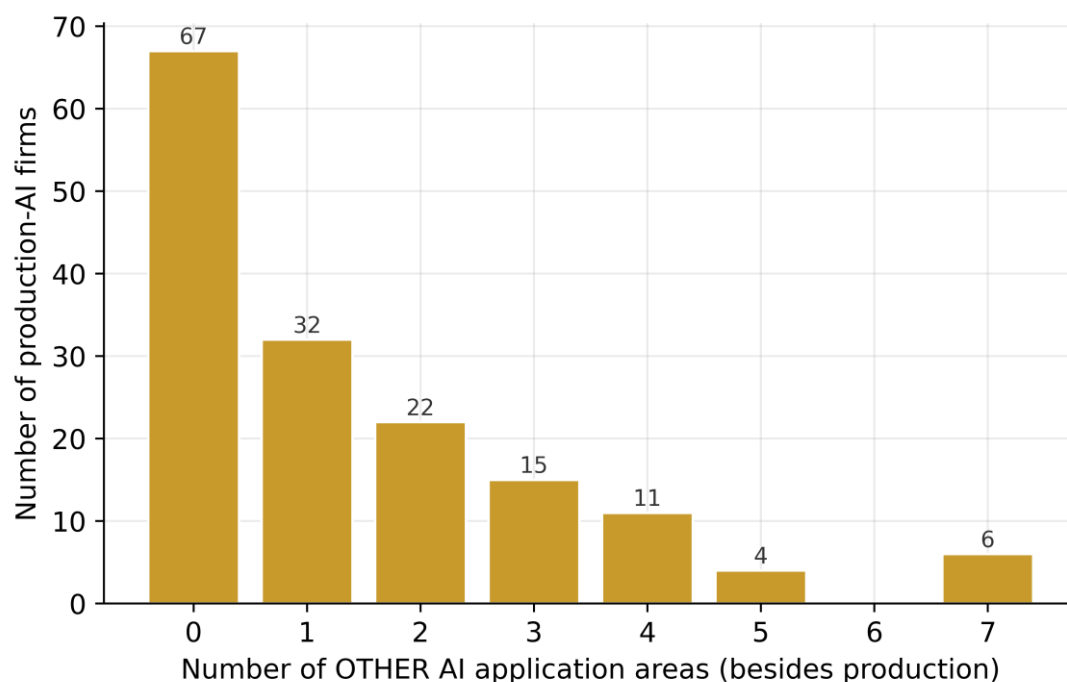


Figure 5. Distribution of the number of additional AI application areas (besides production) among production-AI firms.

The split is informative. For a large minority, production is the single entry point for AI (a focused, operationally motivated deployment) while for the majority it sits within a wider programme that most often extends into logistics. The pattern anticipates the readiness typology of Chapter 9, where a narrow, single-area orientation tends to go with lower maturity and a broad, multi-area orientation with higher maturity. It also fits the operational-process reading: the most common companion to production AI is not a customer-facing function but logistics, the other half of the operational core.

To summarise, the focal firms are disproportionately large, established, and more often foreign-owned, and disproportionately, but far from exclusively, in goods-producing sectors. Goods-producing membership is the strongest firmographic correlate of adoption (46.4% versus 19.0%) and

firm size a secondary one, both bearing on whether firms begin. Because service firms greatly outnumber goods producers, however, most production-AI firms are not manufacturers; the activity is best understood as operational-process AI spread across the economy along a goods-producing gradient. Hypotheses 1 and 2 hold at the bivariate level; their multivariate test follows in Chapter 11.

5. The technology portfolio: what AI in production consists of

Chapter 4 established who pursues production AI; this chapter (Research Question 2) asks what they actually do with it. It maps the seventeen specific applications the deep-dive module probed, separating active use from planning and non-engagement, and characterises the underlying technology types. The picture is of a wide set of applications used at moderate and fairly even rates rather than a deployment built around one dominant use case—and, against the emphasis of much of the technical literature, predictive maintenance sits among the least-used applications, not the most.

5.1 The adoption map

For each application, respondents reported their engagement on the five-point intensity scale described in Chapter 3. Combining the two highest levels (pilot/occasional and active/regular) gives a share in active use; the two middle levels (considering; planning within two years) give a planning share; the lowest gives a not-on-the-agenda share.

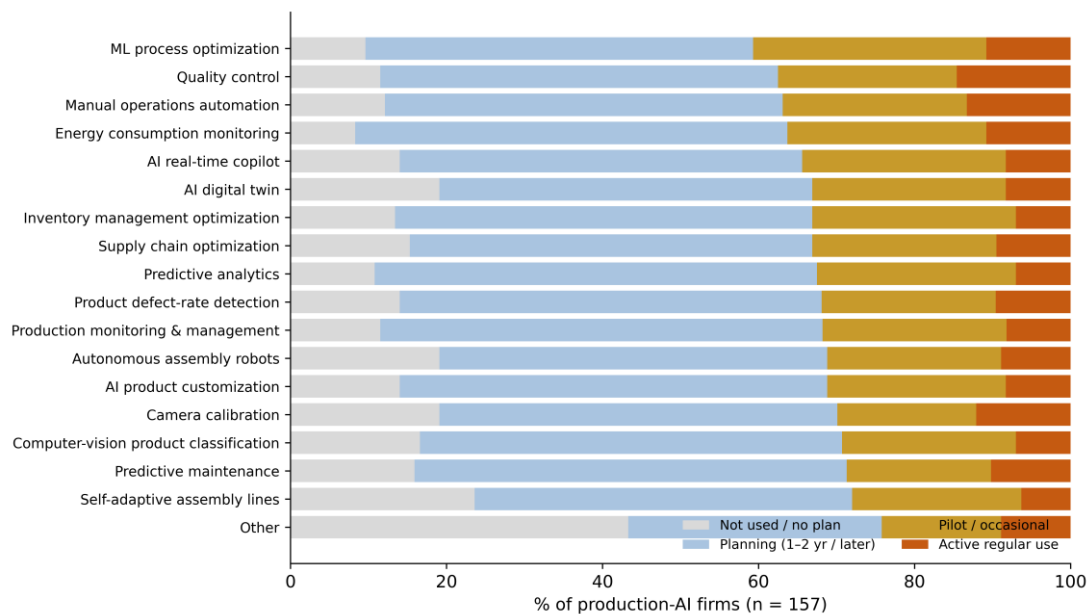


Figure 6. Technology adoption map for the seventeen production-AI applications, showing the distribution of firms across non-engagement, planning, pilot, and regular use.

Table 5. Adoption of seventeen production-AI applications (n = 157).

Application	Mean (1-5)	Active use (4-5)	Planning (2-3)	Not on agenda (1)
ML process optimization	3.08	40.8%	49.7%	9.6%
Quality control	3.10	37.6%	51.0%	11.5%
Manual operations automation	3.05	36.9%	51.0%	12.1%
Energy consumption monitoring	3.10	36.3%	55.4%	8.3%
AI real-time copilot	2.95	34.4%	51.6%	14.0%

Inventory management optimization	2.92	33.1%	53.5%	13.4%
Supply chain optimization	2.90	33.1%	51.6%	15.3%
AI digital twin	2.82	33.1%	47.8%	19.1%
Predictive analytics	2.92	32.5%	56.7%	10.8%
Production monitoring & management	2.99	31.8%	56.7%	11.5%
Product defect-rate detection	2.89	31.8%	54.1%	14.0%
Autonomous assembly robots	2.79	31.2%	49.7%	19.1%
AI product customization	2.89	31.2%	54.8%	14.0%
Camera calibration	2.83	29.9%	51.0%	19.1%
Computer-vision product classification	2.80	29.3%	54.1%	16.6%
Predictive maintenance	2.78	28.7%	55.4%	15.9%
Self-adaptive assembly lines	2.67	28.0%	48.4%	23.6%

Three features stand out. First, active use is moderate and tightly bunched: across all seventeen applications it ranges from 28.0% to 40.8%. The most actively used are machine-learning process optimisation (40.8%), quality control (37.6%), automation of manual operations (36.9%) and energy-consumption monitoring (36.3%); the least are self-adaptive assembly lines (28.0%), predictive maintenance (28.7%) and computer-vision product classification (29.3%). The whole spread is about thirteen percentage points. With $n = 157$ and overlapping confidence intervals, the rank order of adjacent applications should not be over-read—but the flatness itself, the near-absence of a standout application, is the substantive point.

Second, active use is shallow as well as bunched. The "active use" figure pools pilot/occasional use with regular use; if one isolates regular, embedded use (the top scale point), the shares fall to between 6.4% and 14.6%, averaging 9.4%, and are flatter still. So while a moderate minority of firms are doing something with each application, genuinely routine use of any one of them is uncommon. "Portfolio" here means broad, mostly shallow engagement—wide piloting rather than committed multi-application deployment.

Third, non-engagement is low: the share for which a given application is entirely off the agenda is mostly 8–24%, so firms tend to have nearly the whole catalogue at least under consideration. The mean intensity across applications sits below the scale midpoint (the intensity index averages 2.91 on the 1–5 scale; see Chapter 6), consistent with firms that have begun but are still early in their trajectories.

5.2 The shape of the portfolio and predictive maintenance

The flat active-use profile matters because it cuts against the way the technical literature is organised. Reviews of production AI tend to centre on a few flagship applications, with predictive maintenance as the canonical, most-developed case (Çınar et al., 2020; Achouch et al., 2022). One might therefore expect a real adopter population to concentrate its active use there. In these data, predictive maintenance ranks sixteenth of seventeen in active use (28.7%), behind process optimisation, quality control and energy monitoring. A plausible reason is that predictive maintenance is demanding in its prerequisites (instrumented equipment, historical failure data, integration with maintenance-planning systems) which the capital-intensive exemplars of the

literature possess but many ordinary firms do not, whereas lower-threshold applications such as generic process optimisation, quality checks, operations automation and energy monitoring are easier to begin.

Because 59% of the focal firms are outside manufacturing, one should ask whether this ranking is an artefact of administering a manufacturing-flavoured battery to non-manufacturing firms (some of whom may have read items such as "autonomous assembly robots" as not applicable and recorded them as merely "considered"). It is not. Restricting the analysis to the 85 goods-producing focal firms (those for whom every item is squarely relevant) leaves the pattern intact: active use remains moderate and fairly flat, and predictive maintenance still sits last of the seventeen (32.9%). The low standing of predictive maintenance, relative to its prominence in research, is therefore not a mixed-economy measurement effect but a feature of how these firms have actually begun.

The reading to take from this is modest. It is not that predictive maintenance is unimportant, but that the centre of gravity of the academic and vendor literature, calibrated to advanced discrete and process manufacturing, is an imperfect guide to what production AI looks like across a typical national economy, where accessible, low-threshold applications come first and the data- and integration-hungry ones lag.

5.3 Use versus pipeline

Looking at each application's mix of current use and planning sharpens the sense of direction, with one caveat: because both come from the same five-point item, "planning" (levels 2–3) and "use" (levels 4–5) are not independent measures, so the observation that planning shares exceed use for every application is partly built into the scale and should not be read as a precise forecast.

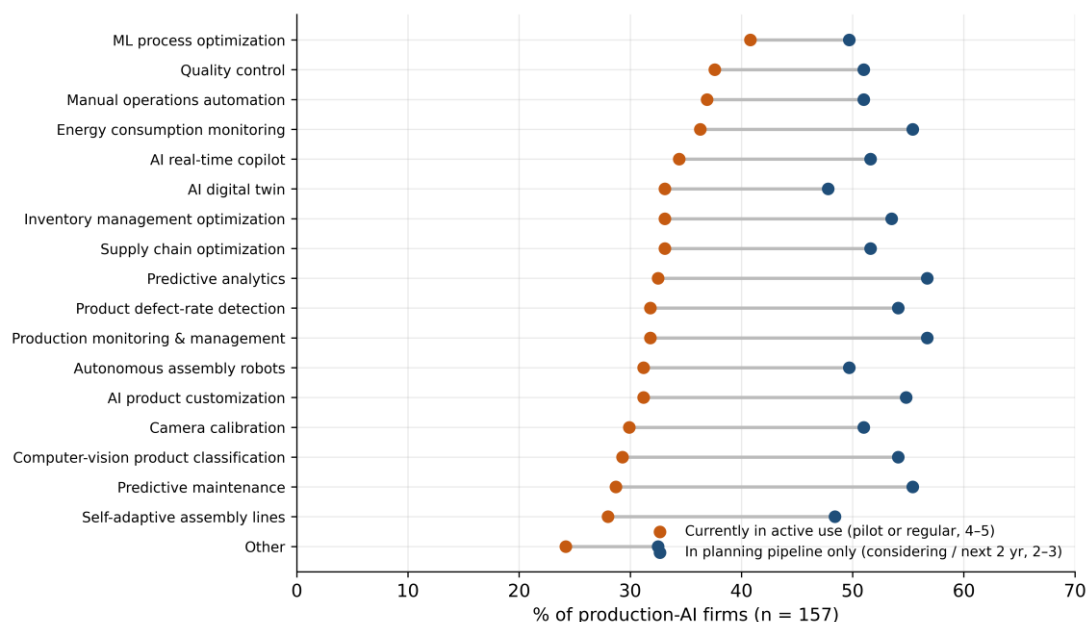


Figure 7. Current active use versus planning-pipeline share for each of the seventeen production-AI applications.

With that caveat, the applications combining higher current use with a large planning share (process optimisation, quality control, operations automation, energy monitoring) are the natural near-term growth areas. Applications such as predictive maintenance, predictive analytics and production

monitoring show modest current use alongside large planning shares (around 55–57%), marking them as candidates to mature next as firms accumulate data and integration capability. The most capital- and integration-intensive applications (self-adaptive lines, autonomous robots, digital twins, camera calibration) carry the largest not-on-the-agenda shares (19–24%), which is where greater readiness or external support would be needed.

5.4 Underlying technology types and the recency of adoption

Beneath the application layer is the question of which AI technology types firms use. The survey probed seven on a 1–5 usage scale. One limitation should be stated up front: this battery is firm-wide, not specific to the production domain, so a production-AI firm reporting heavy chatbot use is likely describing its marketing or service AI rather than anything on the shop floor. The ranking is therefore about the firm's overall AI toolkit, not its production toolkit specifically.

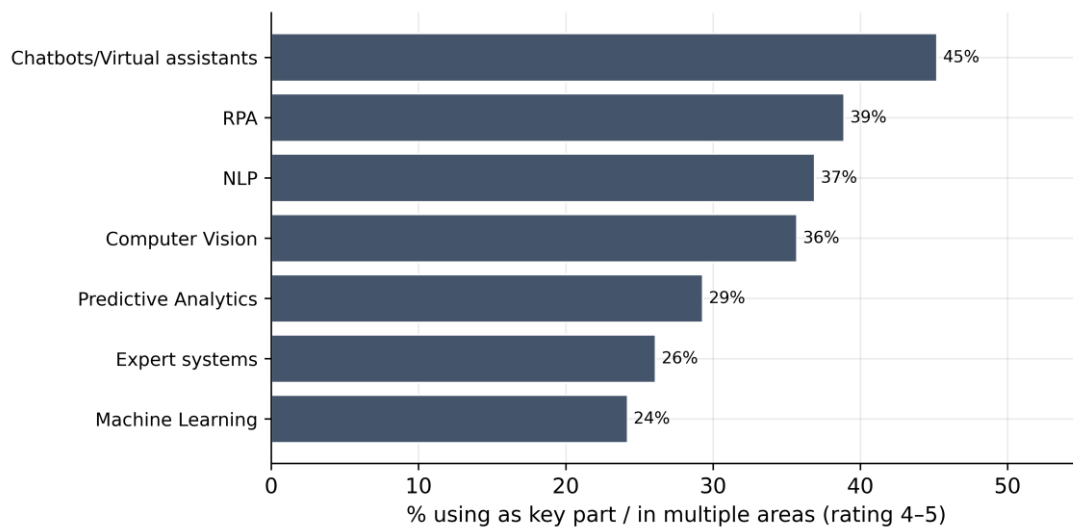


Figure 8. AI technology types used by production-AI firms, share rating each as a key part of processes or used in multiple areas (4–5).

Table 6. AI technology types used by production-AI firms ($n = 157$).

Technology type	Mean (1-5)	Key/multi-area (4-5)	Any use (3-5)
Chatbots/Virtual assistants	3.18	45.2%	70.7%
RPA	2.93	38.9%	59.9%
NLP	2.96	36.9%	65.0%
Computer Vision	2.96	35.7%	64.3%
Predictive Analytics	2.80	29.3%	56.7%
Expert systems	2.66	26.1%	51.6%
Machine Learning	2.75	24.2%	56.1%

With that in mind, the most embedded technologies are chatbots and virtual assistants (45.2% rate them key or multi-area), robotic process automation (38.9%), natural-language processing (36.9%)

and computer vision (35.7%); machine learning in the narrow sense (24.2%) and expert systems (26.1%) trail. The prominence of accessible, conversational and automation tools reflects the broad, often generative-AI-flavoured character of the current adoption wave; the more specialised machine-learning capabilities that underpin the most advanced production applications remain comparatively shallow.

The wave is recent. Among the focal firms the median year of the first AI project is 2024, 61.1% date it to 2024 or 2025, 73.2% to 2023 or later, and only 8.3% began before 2020.

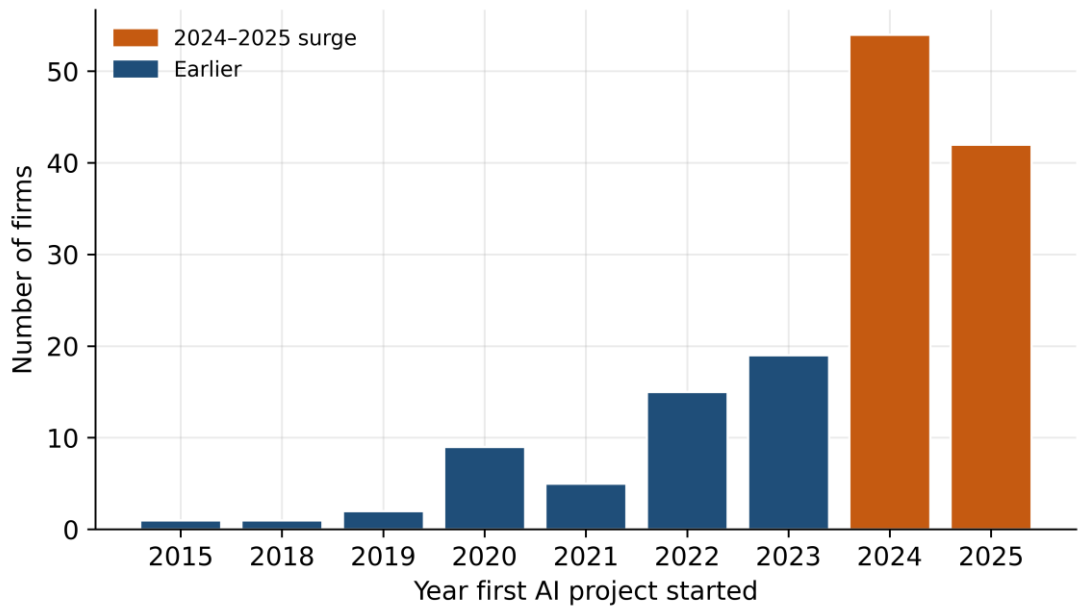


Figure 9. Distribution of the year of first AI project among production-AI firms, with the 2024–2025 surge highlighted.

This concentration, in line with the broader rise in enterprise AI engagement after accessible generative tools spread, helps explain the early-stage, broad-but-shallow portfolio: most of these firms are one or two years into their AI work. It also means the snapshot captures a fast-moving target, so the planning shares above are better read as appetite than as a schedule.

To sum up, production AI in this sample is a wide and still-shallow set of applications rather than a deployment concentrated on a dominant one. Active use is moderate (28–41%) and fairly uniform, regular embedded use is uncommon (around 9% on average), predictive maintenance is among the least-used despite its prominence in the literature (a pattern that survives restricting to goods-producing firms), the underlying technology mix is led by accessible tools, and the whole phenomenon is recent. That breadth-without-depth raises the question Chapter 6 takes up: what is associated with how intensively a firm deploys once it has begun?

6. Adoption intensity and what it is associated with

Chapters 4 and 5 described who pursues production AI and what their portfolios contain. This chapter (Research Question 4) turns from the fact of adoption to its degree. It builds measures of deployment intensity and breadth, looks at their distribution, and asks what they are associated with. The recurring result is that the firm characteristics linked to whether a firm begins production AI are not the ones linked to how far it scales: sector and size relate to the first, organisational AI maturity to the second. The two margins are separable, though (as the closing section stresses) this is a contemporaneous association in cross-sectional data, not a demonstrated mechanism.

6.1 Measuring intensity and breadth

Two measures capture degree of deployment. The Production-AI Intensity Index is the mean of a firm's ratings across the seventeen applications on the 1–5 scale, summarising average depth. The breadth count is the number of applications a firm has in active use (rated 4 or 5). As noted in Chapter 3, the 1–5 scale mixes planning with usage anchors, so the index is treated as an ordinal summary and the breadth count, a clean count of applications actually in use, is given equal weight.

Table 7. Descriptive statistics for production-AI deployment indices and composites (n = 157).

Measure	Mean	SD	Min	Median	Max
Production-AI Intensity Index (1-5)	2.91	0.87	1.00	2.88	5.00
Breadth: applications in active use (0-17)	5.60	5.60	0.00	4.00	17.00
Composite benefit (1-5)	3.59	0.87	1.00	3.71	5.00
Composite risk (1-5)	3.24	0.83	1.00	3.22	5.00
Net benefit (benefit - risk)	0.35	0.88	-3.00	0.13	3.05
AI maturity composite (1-5)	2.91	0.91	1.14	2.71	5.00
Positive sentiment (1-5)	3.29	0.60	2.00	3.12	5.00
Barrier severity (1-5)	3.08	0.76	1.00	3.05	5.00

The intensity index averages 2.91 (SD = 0.87), below the scale midpoint, consistent with the early-stage character noted in Chapter 5; its distribution is broad and roughly symmetric.

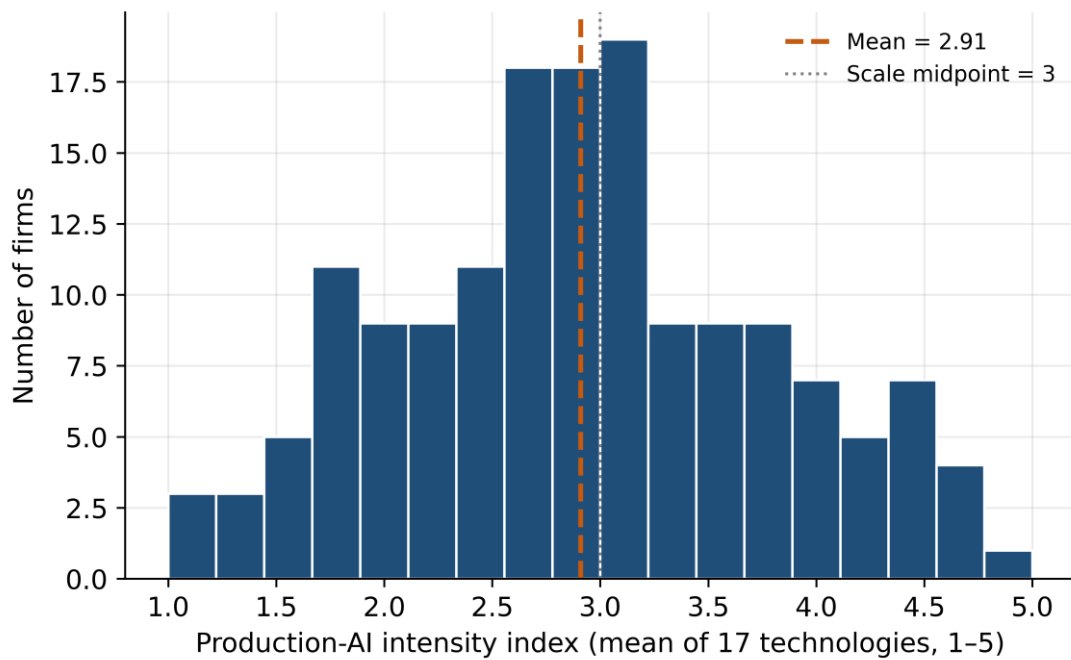


Figure 10. Distribution of the Production-AI Intensity Index across the 157 focal firms.

Breadth is more telling. On average, focal firms have 5.6 of the seventeen applications in active use, but the distribution is very dispersed ($SD = 5.6$ – the standard deviation happens to equal the mean here, reflecting genuinely wide variation rather than a transcription error) and right-skewed, with a median of 4.

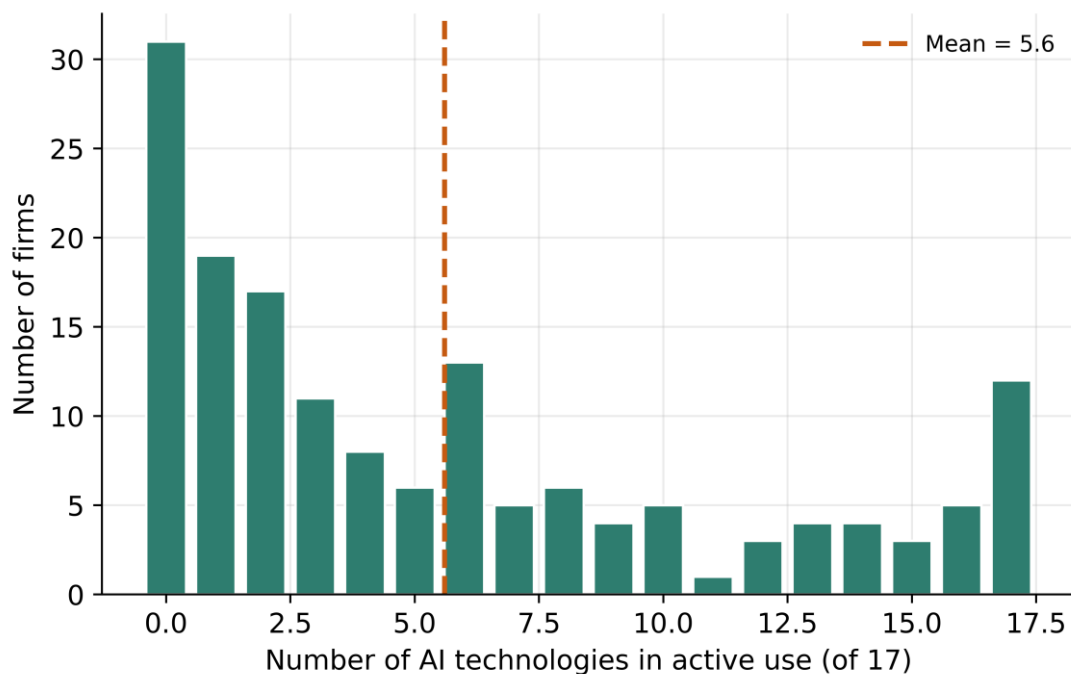


Figure 11. Distribution of the number of production-AI applications in active use (breadth) across focal firms.

Two features matter. At one end, 19.7% of focal firms have zero applications in active use: they selected production and operational processes as an area where they had begun implementing or testing AI, yet rate every specific application at the considering or planning level rather than at pilot

or regular use. These are intenders—firms past the self-identified threshold of "doing AI in production" but not yet running any single application. At the other end is a group of broad deployers with nine or more applications in use. The category "production-AI adopter" thus contains very different firms, which is why the intensity and breadth measures are needed to tell them apart, and which sets up the typology of Chapter 9.

6.2 What intensity is not associated with: size, sector and barriers

The natural first guess, that the firm characteristics linked to adoption also track its intensity, turns out to be largely wrong, instructively so. Firm size, linked to adoption (Chapter 4), is unrelated to intensity among adopters: a Kruskal–Wallis test across the three size bands is non-significant ($H = 2.56$, $p = .28$, $\epsilon^2 = 0.004$) and the Spearman correlation of size with intensity is essentially zero ($\rho = 0.03$, $p = .71$). The same holds for sales ($\rho = -0.09$, $p = .25$). Perceived barrier severity is likewise unrelated to intensity ($\rho = -0.01$, $p = .87$), a near-zero estimate examined further in Chapter 8. Sector exerts a modest influence: intensity differs across the three best-represented sectors (manufacturing, ICT, construction; $H = 8.33$, $p = .016$), with construction firms deploying somewhat more intensively than ICT firms, but the effect is small and does not survive in the multivariate model below.

These are partly null results, and at $n = 157$ the study cannot detect weak associations: it has reasonable power only for correlations of about $|\rho| \geq 0.20$, so "no significant association" between size and intensity means the data show no detectable link, not that one is ruled out. The barrier–intensity estimate ($\rho = -0.01$) is close enough to zero to be read as a genuine absence; the size result is better described as undetected. Either way, the structural factors tied to whether a firm begins do not visibly track how far it goes.

6.3 What intensity is associated with: AI maturity

What does track intensity is organisational AI maturity. The composite maturity score correlates positively with intensity (Spearman $\rho = 0.35$, $p < .001$) and breadth ($\rho = 0.36$, $p < .001$): firms further along the maturity dimensions deploy production AI both more deeply and more widely.

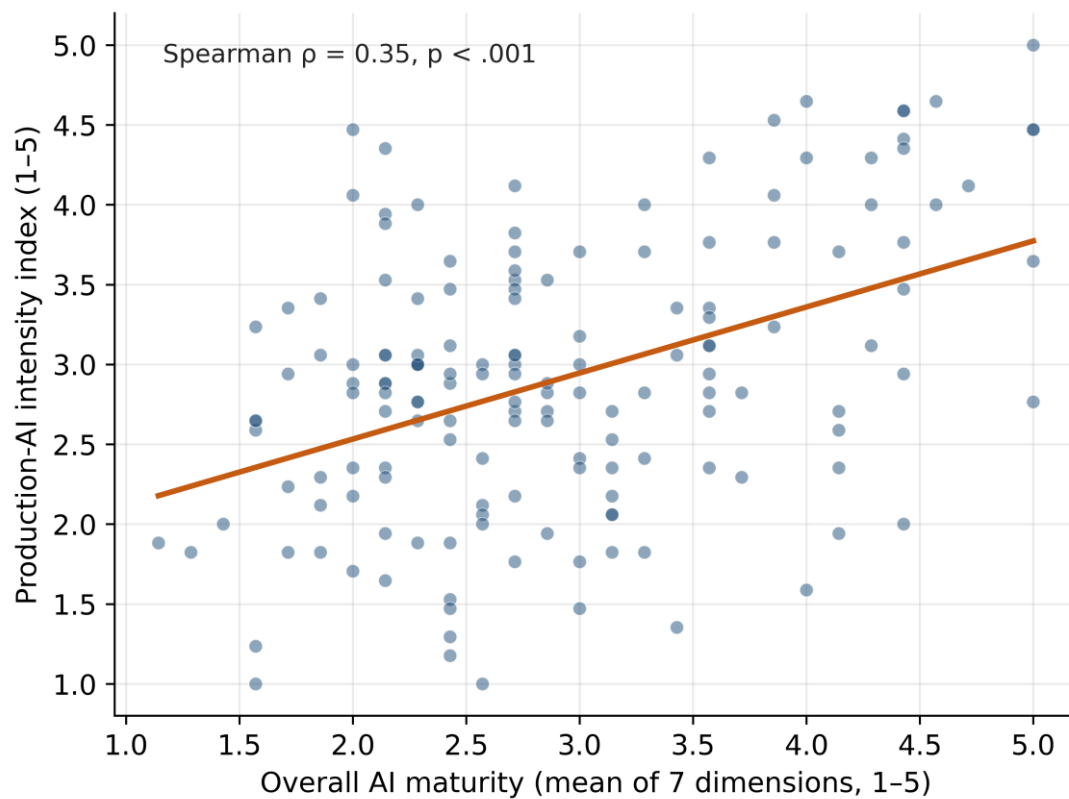


Figure 12. Production-AI intensity as a function of overall AI maturity, with fitted regression line (Spearman $\rho = 0.35, p < .001$).

Corporate sentiment shows a weaker positive association with intensity ($\rho = 0.25, p = .001$) and breadth ($\rho = 0.29, p < .001$). Perceived benefit is the strongest bivariate correlate of intensity of all ($\rho = 0.50, p < .001$), but its causal status is ambiguous: deployment experience plausibly shapes benefit perceptions as much as the reverse (Chapter 7 returns to this). For that reason benefit is treated as a likely consequence or reciprocal of deployment rather than a driver, and is kept out of the explanatory model below; including it would raise the fit but blur cause and consequence.

To weigh the remaining factors jointly, intensity was regressed on firm size, AI maturity, positive sentiment, goods-producing-sector membership and barrier severity.

Table 8. OLS regression of Production-AI Intensity Index ($R^2 = 0.219$; $F = 8.49, p < .001$; $n = 157$).

Predictor	b	SE	p
(Intercept)	1.315*	0.543	0.017
Firm size (band)	-0.089	0.085	0.298
AI maturity	0.367***	0.078	0.000
Positive sentiment	0.237	0.120	0.051
Manufacturing sector	0.169	0.137	0.220
Barrier severity	-0.007	0.086	0.937

The model accounts for a modest share of the variance ($R^2 = 0.219$, adjusted $R^2 = 0.194$; $F = 8.49, p < .001$)—meaning roughly four-fifths of the variation in intensity is left unexplained. Within it, AI maturity is the only conventionally significant predictor ($b = 0.37, p < .001$): a one-point increase in

composite maturity is associated with a 0.37-point increase in intensity, other factors held constant. Positive sentiment is marginal ($b = 0.24$, $p = .051$) and, given the modest reliability of that scale, is read cautiously. Firm size, goods-producing sector and barrier severity are non-significant once maturity is included. Maturity is thus the strongest of the measured correlates of intensity, even though it explains only part of it.

6.4 Two margins, two sets of correlates

The findings point to a separation that runs through the monograph. Whether a firm extends AI into production at all is associated with structural position—goods-producing sector and firm size (Chapter 4; confirmed multivariately in Chapter 11). How broadly and deeply it deploys, among those that have begun, is associated instead with AI maturity, the kind of accumulated strategy, data, technology and governance capability that the readiness and absorptive-capacity literatures treat as the basis for turning access into use (Cohen & Levinthal, 1990; Jöhnk et al., 2021; Mikalef & Gupta, 2021). Hypothesis 3 is supported: maturity is positively associated with intensity and breadth and is a stronger correlate of intensity than firm size, which shows no independent association with intensity at all.

Two cautions attach to this. The two margins are estimated on different (nested) samples (the adoption margin on all 562 adopters, the intensification margin on the 157 focal firms) so part of the contrast may reflect that difference rather than two distinct processes. And the data are cross-sectional, so "associated with" should not be read as "drives." With those caveats, the practical reading is that widening production AI (getting more firms to begin) and deepening it (getting adopters to scale) appear to track different things (structural position the former, organisational readiness the latter) so a single undifferentiated "AI adoption" target would speak to neither cleanly.

In short, variation in how intensively adopters deploy production AI is associated mainly with organisational AI maturity, not with the structural factors tied to adoption itself; size, sales and perceived barriers show no association with intensity. The result supports Hypothesis 3 and motivates both the benefit–risk analysis of Chapter 7 and the readiness typology of Chapter 9.

7. The benefit–risk calculus

Why do firms deploy production AI, and how do they weigh its promise against its hazards? This chapter (Research Question 5) analyses the seven perceived positive impacts and nine perceived negative impacts the deep-dive module measured. Adopters rate positive impacts as more significant than negative ones; both sets of perceptions are largely unidimensional; and perceived benefit is strongly correlated with how intensively firms deploy. Each of these points carries a methodological qualification, set out as it arises.

7.1 Perceived benefits

Firms rate the positive impacts of production AI as moderately to fairly significant across the board, with all seven items between 3.39 and 3.69 on the 1–5 scale and majorities calling each significant or very significant.

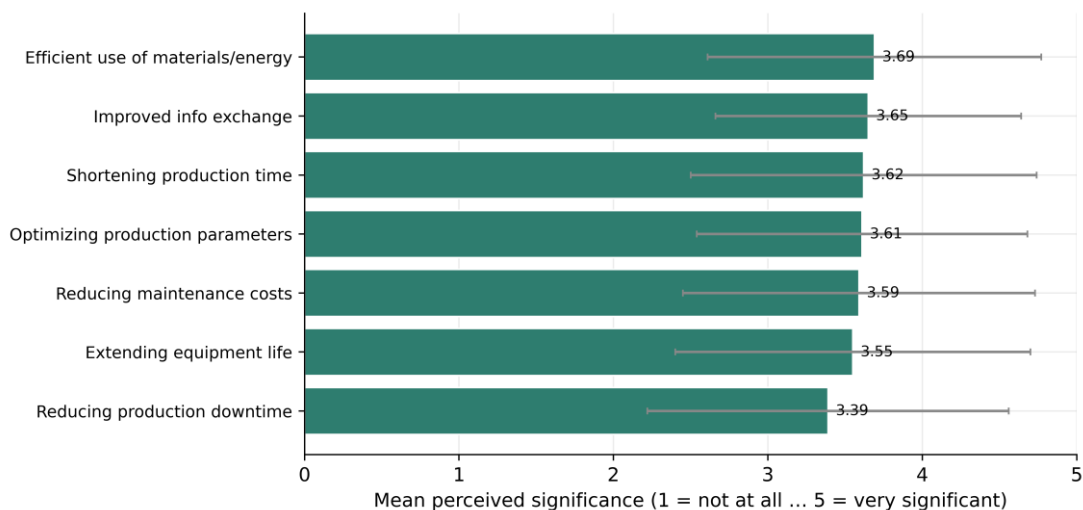


Figure 13. Perceived positive impacts of production-AI, mean significance ratings with standard deviations (n = 157).

Table 9. Perceived positive impacts, ranked (n=157).

Impact item	Mean	SD	Significant (4-5)
Efficient use of materials/energy	3.69	1.08	61.1%
Improved info exchange	3.65	0.99	60.5%
Shortening production time	3.62	1.12	60.5%
Optimizing production parameters	3.61	1.07	59.9%
Reducing maintenance costs	3.59	1.14	63.1%
Extending equipment life	3.55	1.15	57.3%
Reducing production downtime	3.39	1.17	50.3%

The highest-rated benefits are more efficient use of materials and energy (3.69; 61.1% significant or very significant), better information exchange in production (3.65), shorter process times (3.62) and

optimised production parameters (3.61). The asset-and-maintenance benefits (lower maintenance cost (3.59), longer equipment life (3.55) and reduced downtime (3.39)) rate slightly lower. That resource-efficiency and coordination benefits lead while the classic maintenance-and-downtime benefits trail echoes the application pattern of Chapter 5: the benefits firms emphasise are those of the accessible applications they actually use, not those of the predictive-maintenance case they mostly do not. The prominence of materials-and-energy efficiency also fits the sustainability emphasis of the Industry 5.0 framing (Breque et al., 2021) and firm-level evidence that AI can raise manufacturing energy efficiency (Liu et al., 2022).

7.2 Perceived risks

Risks are rated lower than benefits and, like them, are tightly clustered, with all nine items between 3.08 and 3.39.

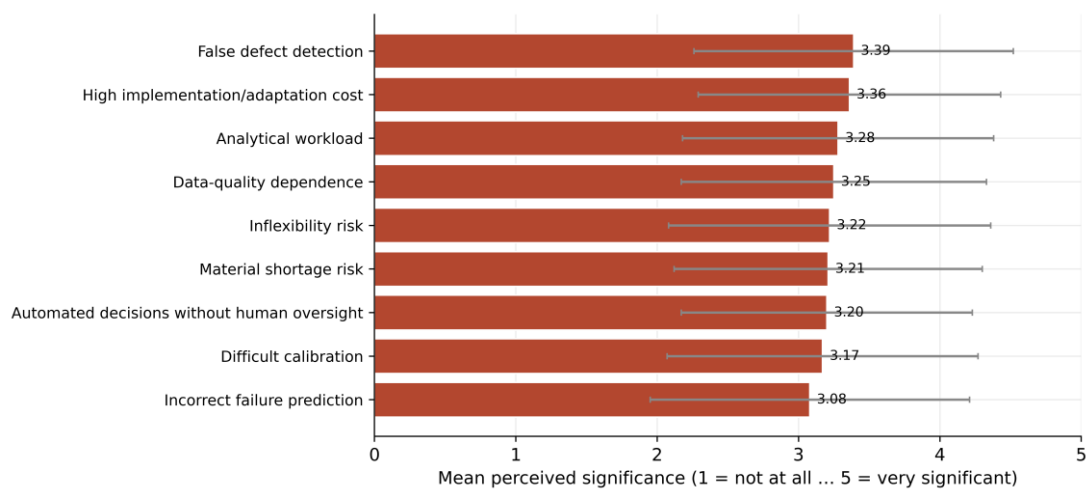


Figure 14. Perceived negative impacts of production-AI, mean significance ratings with standard deviations (n = 157).

Table 10. Perceived negative impacts, ranked (n=157).

Impact item	Mean	SD	Significant (4-5)
False defect detection	3.39	1.13	52.2%
High implementation/adaptation cost	3.36	1.07	48.4%
Analytical workload	3.28	1.10	46.5%
Data-quality dependence	3.25	1.08	43.3%
Inflexibility risk	3.22	1.14	44.6%
Material shortage risk	3.21	1.09	42.7%
Automated decisions without human oversight	3.20	1.03	40.8%
Difficult calibration	3.17	1.10	43.9%
Incorrect failure prediction	3.08	1.13	36.9%

The most salient risks are false detections of faulty products (3.39), the cost of implementation and adaptation (3.36), the analytical workload of interpreting AI outputs (3.28) and dependence on production-line data quality (3.25). The least salient is incorrect failure prediction causing unplanned

downtime (3.08)—again a predictive-maintenance-specific risk that ranks low partly because predictive maintenance is little used. Firms' concerns centre on the near-term operational and economic hazards of the applications they actually run rather than on more speculative ones (automated decisions without human oversight rank seventh of nine), which suggests a pragmatic, experience-anchored risk perception.

7.3 Benefits exceed risks—a baseline, and a robustness check

Hypothesis 4 predicted that adopters perceive benefits as exceeding risks. They do: the composite benefit mean (3.59) exceeds the risk mean (3.24) by 0.35 points, and a Wilcoxon signed-rank test makes the difference clear ($W = 2469.5$, $p < .001$, $r = 0.40$), with a positive net-benefit score for most firms.

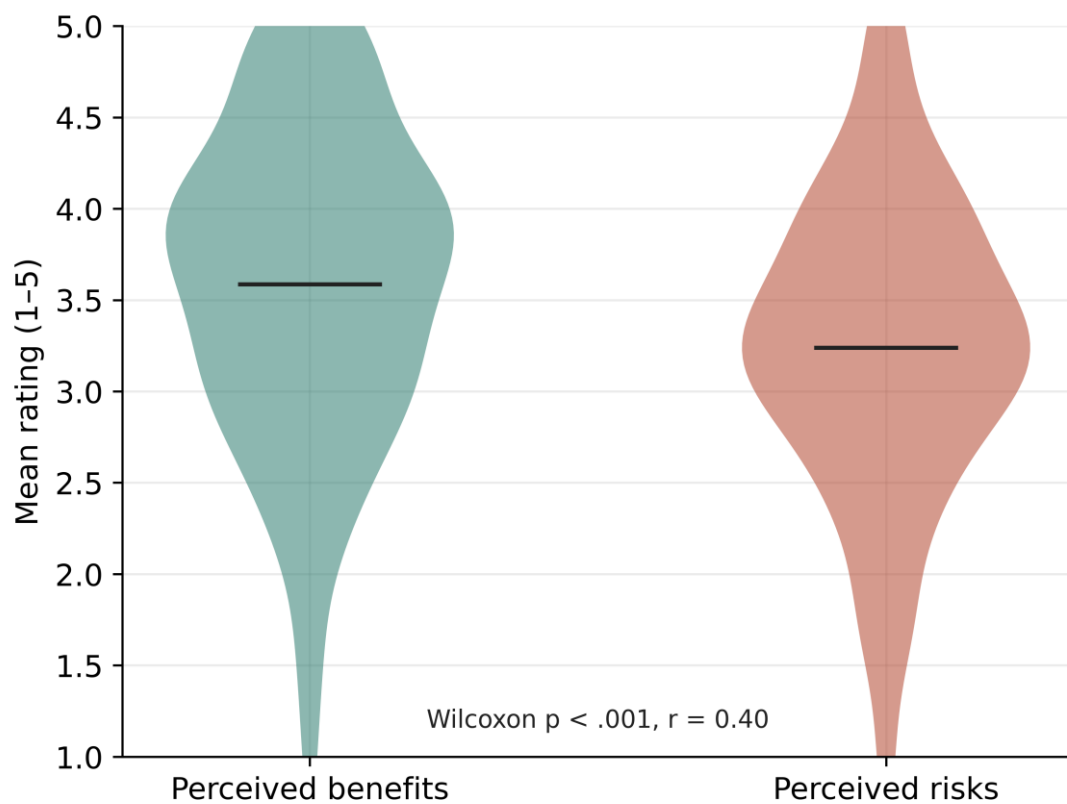


Figure 15. Distribution of composite benefit and risk perceptions among production-AI firms, with means indicated (Wilcoxon $p < .001$, $r = 0.40$).

This is better seen as a baseline than as a discovery. These are firms that chose to proceed with production AI, so a net-positive perception is close to what their behaviour implies; the test confirms the expected direction and shows the gap is measured rather than overwhelming. What is informative is less the sign than the magnitude: both benefits and risks are rated in the moderate range, so these firms read as pragmatic adopters who judge the operational gains to outweigh the hazards by a modest margin, not as enthusiasts dismissing risk. The result also survives the obvious robustness check—restricting to the 85 goods-producing focal firms, for whom the impact items are squarely relevant, leaves benefits clearly above risks (3.72 versus 3.30, Wilcoxon $p < .001$)—so it is not an artefact of non-manufacturing firms rating manufacturing-specific impacts as moot.

7.4 The structure of perceptions

Do benefit and risk perceptions break into interpretable sub-dimensions, or are they global? Exploratory factor analysis on each battery, with the number of factors set by parallel analysis, points to a single dominant factor in both cases. For the seven benefit items the first eigenvalue (4.39) far exceeds the second (0.74) and its parallel-analysis threshold, with high internal consistency ($\alpha = .90$); the nine risk items behave the same way (first eigenvalue 5.13 versus 0.69; $\alpha = .91$).

Table 11. Dimensionality and reliability of perceived benefits and risks ($n = 157$).

Battery	KMO	Bartlett p	Eigen 1 / 2	Factors retained	Cronbach α
Benefits (7 items)	0.90	6e-112	4.39 / 0.74	1 (parallel analysis)	0.90
Risks (9 items)	0.92	3e-120	5.13 / 0.69	1 (parallel analysis)	0.91

There are two readings of this, and the data do not cleanly separate them. Substantively, firms may evaluate benefits, and separately risks, as global judgments rather than itemised appraisals—an overall orientation toward production AI that colours each item. Methodologically, single-factor structure with very high alpha in single-respondent Likert data is also the signature of a halo or acquiescence response style, a form of common-method bias. Harman's test across all the perceptual batteries (Chapter 3) is mildly reassuring on cross-construct bias—the largest component explains only 26.7% of the variance, so benefits, risks, barriers and maturity are empirically distinct constructs—but it does not rule out a within-battery response-style component. The honest position is that the unidimensionality is consistent with both a genuine general-evaluation construct and a response-style artefact; either way, the high reliabilities justify using the simple composite means as summaries.

7.5 Benefit perception and deployment intensity

The strongest bivariate correlate of intensity in Chapter 6 was perceived benefit ($\rho = 0.50$, $p < .001$): firms perceiving greater benefits deploy more intensively. The cross-sectional data cannot say which way this runs. Benefit perceptions may motivate deeper deployment, as the technology-acceptance tradition would predict; or deeper deployment may generate more first-hand evidence of gains and so raise benefit ratings; reciprocal influence is plausible but untested. Notably, perceived risk also rises with intensity ($\rho = 0.36$, $p < .001$), which the experiential reading explains, firms deploying more widely meet more of the real hazards, and the net-benefit score is uncorrelated with intensity ($\rho = 0.11$, $p = .19$). As firms deepen deployment, in other words, their sense of both benefits and risks sharpens together, leaving the balance roughly unchanged. Deployment goes with a fuller perception of production AI's consequences on both sides, not with naive enthusiasm.

In sum, adopters perceive the benefits of production AI as moderately significant and as exceeding its risks (Wilcoxon $p < .001$, $r = 0.40$, robust to a goods-producing-only check), with both sets of perceptions largely unidimensional—plausibly a general evaluation, though a response-style component cannot be excluded. The benefits and risks firms emphasise are those of the accessible applications they run, reinforcing Chapter 5, and the strong, symmetric association of both with intensity points to perceptions deepening as firms scale. Chapter 8 turns to the constraints that bound that scaling.

8. Barriers to production AI

If benefits are perceived to exceed risks and maturity tracks intensity, what holds production AI back? This chapter (Research Question 6) uses the twenty-item barrier battery, which all firms answered. It ranks the barriers production-AI firms feel most acutely, compares them with other adopters, and asks whether barriers form distinct dimensions or one general factor. Three things emerge: production-AI firms and other adopters perceive barriers almost identically; the barriers felt most are integration complexity, skills, and a gap in state support; and the items load on a single factor—though, as with the impact batteries, that single factor admits both a substantive and a method-bias reading.

8.1 The barrier profile

Across the twenty items, firms rate barriers as moderate, with most means around the scale midpoint (3.0–3.2 on the 1–5 scale) and no single barrier dominating—an early sign of the unidimensionality discussed below.

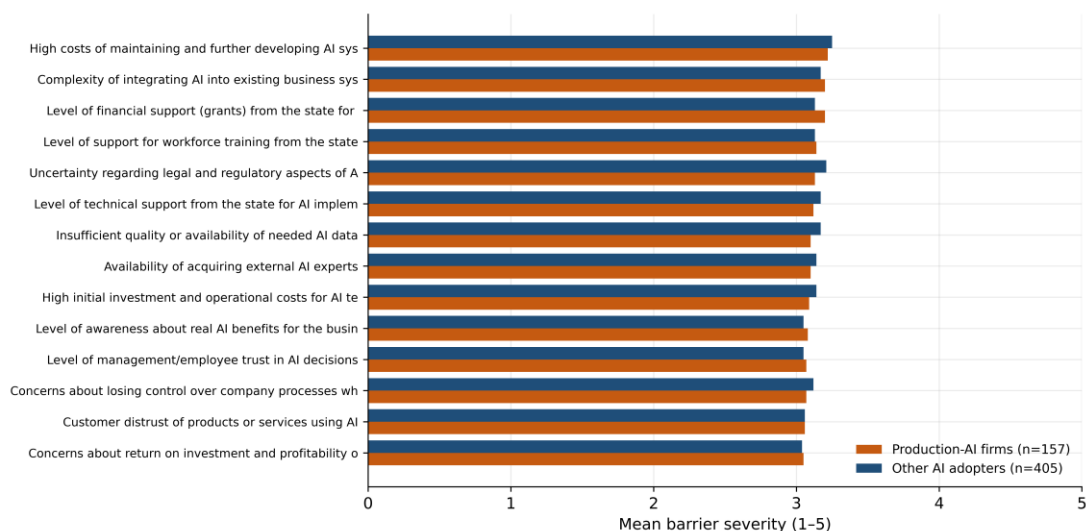


Figure 16. Perceived severity of the leading barriers to AI, production-AI firms versus other AI adopters.

Table 12. Leading perceived barriers among production-AI firms vs other adopters (top 12 by focal mean).

Barrier	Focal mean	Focal (4-5)	Other adopters mean
High costs of maintaining and further developing AI systems	3.22	40.1%	3.25
Level of financial support (grants) from the state	3.20	37.6%	3.13
Complexity of integrating AI into existing business systems	3.20	42.0%	3.17
Level of support for workforce training from the state	3.14	38.2%	3.13
Uncertainty regarding legal and regulatory aspects of AI	3.13	35.0%	3.21
Level of technical support from the state for AI implementation	3.12	36.3%	3.17
Insufficient quality or availability of needed AI data	3.10	36.3%	3.17
Availability of acquiring external AI experts	3.10	36.9%	3.14

High initial investment and operational costs for AI te	3.09	40.8%	3.14
Level of awareness about real AI benefits for the busin	3.08	35.7%	3.05
Concerns about losing control over company processes wh	3.07	37.6%	3.12
Level of management/employee trust in AI decisions	3.07	36.9%	3.05

The barriers rated most severe are the high costs of maintaining and developing AI systems, the level of state financial support (grants), the complexity of integrating AI into existing systems, the level of state support for workforce training, and uncertainty over legal and regulatory aspects. The prominence of integration complexity fits the pattern in Chapter 5, where the most integration-intensive applications had the highest non-engagement; the prominence of skills matches the adoption-barriers literature, in which the AI-skills shortage is among the most persistent constraints (OECD, 2025a; Mikalef et al., 2019; Horváth & Szabó, 2019).

8.2 Production-AI firms perceive barriers like other adopters

One might expect firms that have pushed AI into the demanding domain of production to face distinctively higher (or, having cleared them, distinctively lower) barriers than other adopters. Neither holds. Item-by-item Mann–Whitney comparisons between the 157 focal firms and the 405 other adopters show no significant differences on any of the twenty barriers after Holm correction; the two profiles nearly coincide. The barriers measured here are thus general obstacles to organisational AI rather than production-specific ones: the difficulty of integrating AI, finding skills, securing trust and obtaining public support is felt across the board.

8.3 The structure of barriers

The barriers literature usually sorts obstacles into neat dimensions—technological, organisational, environmental; cost, capability, data, trust, regulation. These data resist that. The battery is highly factorable (KMO = 0.92; Bartlett's test highly significant) and internally consistent to an unusual degree ($\alpha = .94$), and parallel analysis points to a single dominant factor: the first eigenvalue (9.71) dwarfs the second (1.58), and nearly half the total variance loads on one factor on which all twenty items load positively.



Figure 17. Loadings of the twenty barrier items on a four-factor exploratory solution, presented as a descriptive item grouping; parallel analysis nonetheless supports a single general factor.

Table 13. Dimensionality and reliability of the twenty-item barrier battery ($n = 157$).

Battery	KMO	Bartlett p	Eigen 1 / 2	Factors	α	Variance (forced 4-factor)
Barriers (20 items)	0.92	4e-282	9.71 / 1.58	1 (parallel analysis)	0.94	57.8% (4-factor descriptive)

A forced multi-factor rotation, shown in Figure 17 for descriptive interest, does arrange the items into recognisable groups—internal capability and integration (cost, skills, external experts, IT infrastructure, integration, data); state support (workforce-training support, bank-loan frameworks, technical and financial state support); trust and legitimacy (loss of control, customer distrust, ethics); and awareness and readiness. These correspond to the categories of the literature and are useful for description. But statistically they are facets of one factor, not independent dimensions. Two interpretations again coexist: firms that perceive any barrier as severe perceive most as severe, which could reflect a genuine general sense of how hard AI is for the firm, or an acquiescence or halo response style of the kind common in single-respondent batteries—a Cronbach's alpha of .94 across twenty items is as much a marker of item redundancy and response set as of a substantive construct. The case-to-item ratio here (about 8:1) is also below the usual guideline, so the one-factor result is offered as indicative rather than settled. What is clear is the practical implication: the barriers do not separate cleanly into independently targetable dimensions in these data.

8.4 The state-support component

One group within the battery deserves note for policy. Four items concern public support—state grants, technical support, support for workforce training, and a bank-loan framework for SMEs—and they form the most coherent secondary grouping in the factor solution and are among the more severely rated barriers. Their prominence matters in the CEE setting, where state support has been found to condition AI adoption and where national and EU strategy explicitly aims to raise enterprise digital intensity (Sánchez et al., 2025; Ministry of Investments, Regional Development and Informatization of the Slovak Republic, 2019; European Commission, 2022). That production-AI firms (the relative vanguard of operational AI here) rate state financial, technical and training support among their more pressing constraints points to a gap between policy ambition and firm experience that Chapter 13 takes up.

8.5 Barriers do not predict intensity

Hypothesis 5 predicted that perceived barrier severity would be negatively associated with deployment intensity. It is not: the Spearman correlation of composite barrier severity with intensity is essentially zero ($\rho = -0.01$, $p = .87$), and barrier severity was non-significant in the Chapter 6 model. Hypothesis 5 is therefore not supported. Among firms that have begun production AI, those perceiving high barriers deploy no less intensively than those perceiving low ones.

It is tempting to infer that barriers must instead operate on the decision to begin. The data here do not support even that: barrier severity is also non-significant in the Chapter 11 logistic model of who adopts. So in this sample perceived barriers neither distinguish production adopters from other adopters nor track how intensively adopters deploy. The most defensible reading is narrow: among firms already engaged with AI, a general sense of difficulty does not differentiate how far they take production AI. Whether barriers deter firms that never engage with AI at all is a question this sample of adopters cannot answer, since non-adopters were not asked the production items.

To conclude, production-AI firms perceive barriers as moderate, undifferentiated, and much like those perceived by other AI adopters, led by integration complexity, skills, trust and a gap in state support. The twenty items load on a single factor ($\alpha = .94$), which is consistent with a general-severity disposition but also with response-style bias and rests on an under-powered factor analysis. Barriers show no association with deployment intensity, and the state-support component, though statistically part of the general factor, stands out for its policy relevance. The chapter now gives way to a firm-level synthesis: a typology of adopters.

9. A readiness-based typology of adopters

The previous chapters analysed production AI variable by variable. This chapter looks at the firm as a whole and asks whether adopters fall into recognisable types. A cluster analysis on the maturity profile separates the 157 firms into two groups whose dividing line is organisational readiness and which differ, predictably, on deployment, perception, sentiment and workforce outcomes. The typology is best understood as a useful way of summarising the maturity gradient of Chapter 6 rather than as evidence of sharply distinct kinds of firm.

9.1 Deriving the typology

To avoid building the result into its own inputs, the clustering uses only the seven AI-maturity dimensions; intensity, breadth and perceived benefit are then examined as external variables to see whether the maturity-based grouping also separates firms on deployment. A two-cluster k-means solution was chosen by the silhouette criterion (0.394, against lower values for three to five clusters)—modest-to-moderate separation, not a sharp natural division. It splits the firms into 107 and 50.

Table 14. Profile of the two production-AI adopter segments.

Measure	Mature Integrators	Operational Experimenters
Firms (n)	50	107
AI maturity (1-5)	4.04	2.39
Intensity (1-5)	3.43	2.66
Breadth (active apps)	9.0	4.0
Benefit (1-5)	3.85	3.46
Barrier (1-5)	3.01	3.11
Sentiment (1-5)	3.66	3.11
Manufacturing share	32%	45%
New-job share	24%	17%
Layoff share	10%	12%

The groups differ above all on maturity, by construction: the smaller group averages about 4.0 across the seven dimensions, the larger about 2.4. The smaller, higher-readiness group is labelled Mature Integrators (n = 50) and the larger, lower-readiness group Operational Experimenters (n = 107).

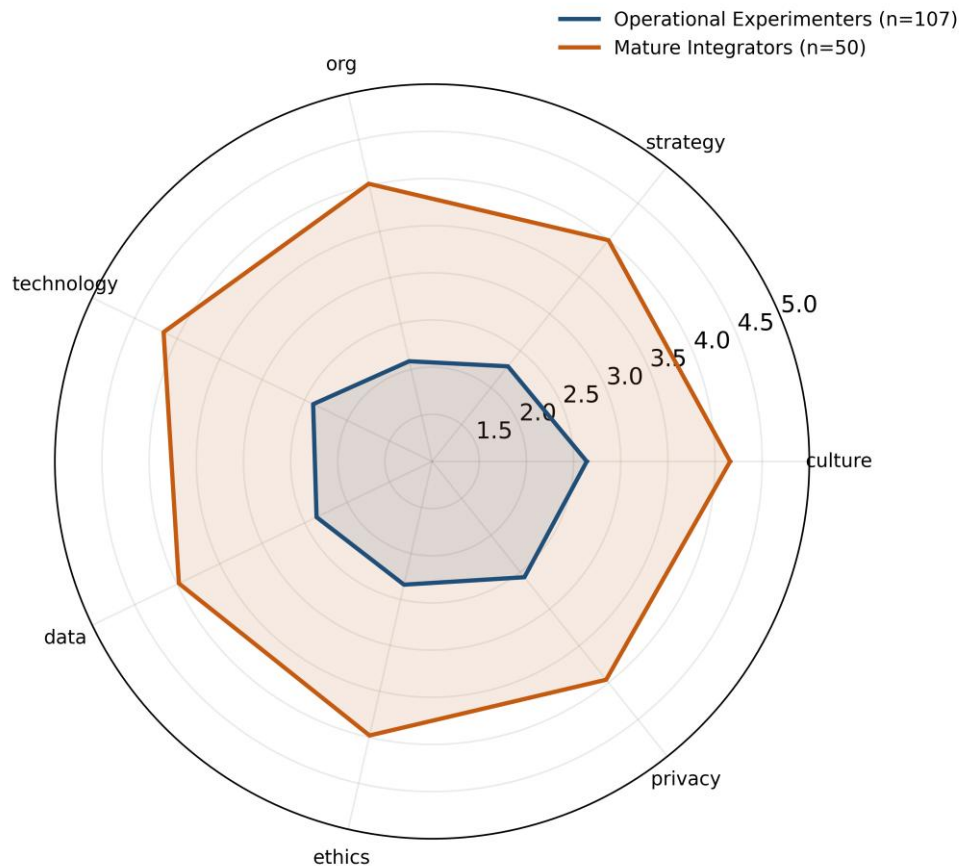


Figure 18. AI-maturity profiles of the two adopter segments across the seven maturity dimensions.

9.2 What the maturity split also separates

Because deployment was not used to form the clusters, the differences below are genuine external validation of the maturity grouping rather than restatements of it.

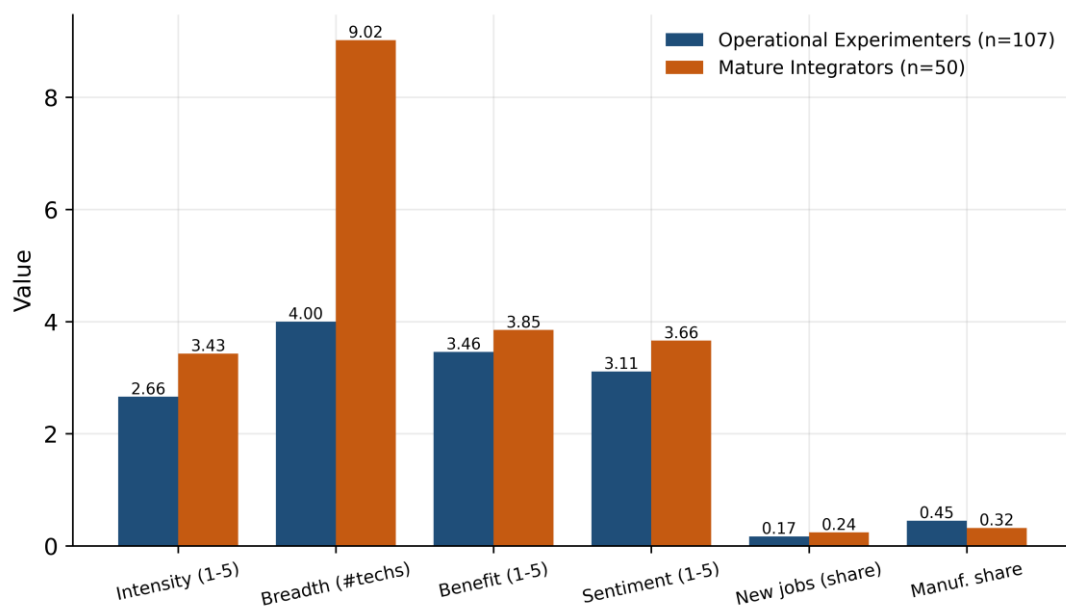


Figure 19. Comparison of the two adopter segments across deployment, perception, sentiment and workforce measures.

Mature Integrators (n = 50) deploy more broadly and a little more deeply: 9.0 applications in active use on average, against 4.0 for the other group, and a higher intensity index (3.43 versus 2.66; the difference in intensity between the groups is significant at $p < .001$). They perceive somewhat greater benefits (3.85 versus 3.46), hold more positive AI sentiment (3.66 versus 3.11), and perceive marginally lower barriers (3.01 versus 3.11). They are the firms that have turned the broad-but-shallow portfolio of Chapter 5 into broad active use.

Operational Experimenters (n = 107) combine lower readiness with narrower, earlier-stage deployment—4.0 applications in active use on average, intensity below the scale midpoint, more guarded sentiment. This larger group includes the intenders of Chapter 6: firms that have declared production-AI activity but not yet put individual applications into use. The label is not pejorative. Experimentation is the appropriate posture one or two years into an AI effort, which, given the 2024–2025 surge, most of them are.

9.3 What the split does not reflect: size, sector and vintage

The instructive part is what does not separate the groups. They are statistically alike in firm size and sales, and in the year they began their first AI project. Manufacturing-sector membership is, if anything, a little lower among the Mature Integrators (32%) than among the Operational Experimenters (45%). The divide is not one of scale, vintage or industry: a large, long-established manufacturer can be an Operational Experimenter, and a mid-sized service firm a Mature Integrator. What sorts firms into broad and narrow deployment is organisational readiness, not the structural attributes tied to adoption.

This reinforces the two-margin reading of Chapter 6 at the firm level. The structural factors of Chapter 4 sort firms onto the adoption margin, which firms appear in the focal group at all, but within that group they fall quiet; what then separates broad from narrow deployers is maturity. The typology is the firm-level face of the intensification margin. It should be read as a heuristic discretisation of a continuous maturity gradient rather than as proof of two naturally distinct populations: the silhouette is modest, and the two "types" largely re-describe a high/low split on a maturity composite already analysed dimensionally in Chapter 6. Its value is presentational—a compact way to carry the gradient into the discussion—not a claim that firms come in two kinds.

9.4 The typology and workforce outcomes

The groups also differ in a way that anticipates Chapter 10. Mature Integrators are somewhat more likely to have created or planned new AI-related jobs (24%) than Operational Experimenters (17%), while the two are alike in their low incidence of layoffs (10% versus 12%). The job-creation tilt is thus a little stronger among the higher-readiness, broader-deploying firms—those that have integrated production AI most fully are marginally more likely to be adding roles around it than shedding them. This fits firm-level automation evidence in which more advanced adopters expand their own employment (Acemoglu, Lelarge, & Restrepo, 2020), though the segment difference is modest and, like the rest of this chapter, descriptive.

In short, the adopters separate into a larger lower-readiness group and a smaller higher-readiness group whose dividing line is organisational maturity rather than size, vintage or sector. Validated

against deployment measures it did not use, the maturity grouping also separates firms on intensity, breadth, benefit perception and sentiment, and on job creation. The typology makes the intensification margin concrete, and points to the workforce question Chapter 10 takes up.

10. The workforce dimension: augmentation or displacement?

Few questions about AI in production carry more weight than its effect on jobs. This chapter (Research Question 7) uses the survey's two workforce items, which asked whether AI implementation has led to, or is planned to lead to, layoffs and the creation of new positions. Among these Slovak adopters the firm-level signal leans towards job creation rather than destruction: more firms report or plan new roles than report or plan layoffs, the difference is statistically significant, and the tilt is a little stronger among the more integrated firms. Several qualifications, set out below, keep this from being read as more than it is.

10.1 The displacement–augmentation debate

The task-based account of automation (Chapter 2) holds that AI and automation displace labour from routine tasks while complementing it in non-routine ones, and also reinstate labour by creating new tasks and roles (Acemoglu & Autor, 2011; Acemoglu & Restrepo, 2018, 2019). The net effect is therefore an empirical matter. Local-labour-market studies document real displacement from robots (Acemoglu & Restrepo, 2020), while firm-level studies repeatedly find that adopting firms expand their own employment even as they pressure competitors (Acemoglu, Lelarge, & Restrepo, 2020; Dauth et al., 2021), and recent AI-specific evidence leans toward augmentation (Brynjolfsson & Mitchell, 2017; Brynjolfsson, Li, & Raymond, 2025; Agrawal, Gans, & Goldfarb, 2019). The firm-level question this survey can speak to is the narrow one: at the adopting firm itself, does production AI go with adding roles or shedding them? The measure is coarse—binary incidence, not headcounts, and it cannot test the task-level reallocation the theory describes—so the chapter speaks only to the direction of firm-level headcount change, not to its magnitude or to aggregate employment.

10.2 More firms add jobs than cut them

Among the 157 focal firms, 19.1% report that AI has led to, or is planned to lead to, new job positions, while 11.5% report that it has led to, or is planned to lead to, layoffs.

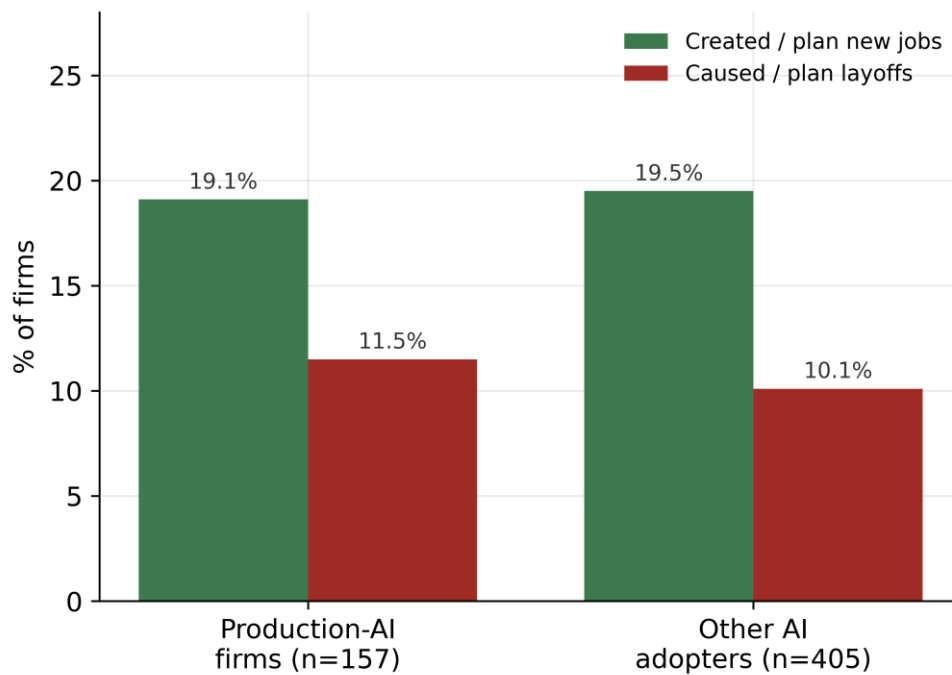


Figure 20. Incidence of AI-related new job creation versus layoffs, production-AI firms compared with other AI adopters.

Table 15. AI-related workforce outcomes (% of firms). McNemar (focal, new-job vs layoff) $p = .036$.

Outcome	Production-AI (n=157)	Other adopters (n=405)
New job creation	19.1%	19.5%
Layoffs	11.5%	10.1%

Because both items are measured on the same firms, the appropriate test is McNemar's on the discordant firms—those that differ on the two items. Among the 157, the cross-tabulation gives 119 firms reporting neither, 10 reporting both, 20 that create (or plan) jobs without layoffs, and 8 that lay off without creating jobs. The test compares those two discordant cells, 20 against 8; the exact McNemar test is significant ($p = .036$; continuity-corrected $\chi^2(1) = 4.32$, $p = .038$). The headline 19.1% and 11.5% are the marginal totals, 30 and 18 firms, of which these 20 and 8 are the discordant parts. So among firms whose workforce response to AI went one way and not the other, job creation outnumbers layoffs by a significant margin, and Hypothesis 6 is supported.

This does not make production AI costless for workers: eight firms (about 5% of the focal group, or 11.5% counting those that also create roles) do associate it with layoffs, and the survey cannot weigh the number or quality of jobs created against those lost. But the direction of the firm-level signal favours creation over destruction, which runs against the common presumption that AI in production is primarily a job-shedding technology. In this sample of early adopters the more common accompaniment of production AI is new roles—presumably the technical, analytical and oversight positions needed to run and govern AI systems—rather than the removal of existing ones.

10.3 Production-AI firms resemble other adopters

The new-job rate among production-AI firms (19.1%) is statistically identical to that among other AI adopters (19.5%), and the layoff rate is similar (11.5% versus 10.1%); neither difference approaches significance. The job-creation tilt is thus a feature of AI adoption generally among these firms, not something specific to its production variant. That makes the finding more robust to over-attribution: it is a consistent pattern across AI adopters rather than a peculiarity of the production domain.

10.4 Where the jobs are: the maturity connection

As Chapter 9 showed, the higher-readiness Mature Integrators create or plan new roles at a somewhat higher rate (24%) than the Operational Experimenters (17%), while the two lay off at the same low rate. The descriptive difference is consistent with the augmentation literature: firms that integrate production AI most fully have more occasion to add the roles needed to build, run and oversee it. A logistic model of new-job creation on intensity, size and maturity points the same way but is built on only about thirty job-creation events and is not reported in detail; the claim rests on the descriptive 24%-versus-17% contrast, not on a fragile regression. The constructive reading—that deeper integration tends to go with more job creation, and that capability-building which raises maturity might therefore be indirectly job-supporting—is offered as a hypothesis consistent with the data, not as an established effect.

10.5 Qualifications

Three qualifications bound these conclusions. The items conflate realised with planned actions ("has led to, or do you plan to"), so some reported creation and some reported layoffs are prospective. They capture incidence, not magnitude: a firm adding two analysts and one adding twenty count alike, so the finding concerns how many firms add versus cut roles, not net employment. And the cross-sectional design cannot exclude a common driver such as firm growth: growing firms both adopt AI and hire. The precise claim is therefore narrow—among Slovak firms that have begun production AI, adding roles is a significantly more common reported accompaniment than layoffs, a little more so among the most integrated—and it matches the firm-level augmentation evidence rather than overturning it.

To summarise, the firm-level workforce signal points to creation rather than destruction: 19.1% of focal firms report or plan new roles against 11.5% reporting or planning layoffs, a significant difference on the discordant firms (McNemar $p = .036$) that supports Hypothesis 6. The pattern matches other AI adopters and is a little stronger among higher-maturity firms. Subject to the coarse, partly prospective measure and the cross-sectional design, production AI in this sample looks more complementary than substitutive for labour. Chapter 11 consolidates the structural correlates of adoption in one model.

11. Correlates of production-AI adoption: a multivariate model

Chapter 4 showed sector and size to be associated with production-AI adoption, but bivariate associations cannot separate correlated predictors—larger and goods-producing firms partly overlap, and both might stand in for maturity or sentiment. This chapter (Research Question 3) uses binary logistic regression to ask what independently distinguishes the firms that extend AI into production from the other AI adopters that do not, and tests Hypotheses 1 and 2 in multivariate form. Within the limits of a model that discriminates only modestly, the structural reading of the adoption margin holds up: goods-producing sector and, more weakly, firm size are the predictors that survive, while maturity, sentiment and barriers add nothing once structure is included.

11.1 Model specification

The estimation sample is the 562 AI adopters—the only firms eligible for the focal group, since the focal item was shown only to AI users and pilots. The outcome is 1 for the 157 production-AI firms and 0 for the 405 others. The predictors operationalise the competing accounts of Chapter 2: a goods-producing-sector indicator and firm size for the structural account; composite AI maturity and positive sentiment for the readiness and attitudinal accounts; and composite barrier severity for the constraint account.

Table 16. Logistic regression predicting production-AI adoption among adopters ($n = 562$; $AUC = 0.68$; $pseudo-R^2 = 0.08$).

Predictor	Odds ratio	95% CI	p
(Intercept)	0.04***	—	0.000
Goods-producing sector	3.67***	[2.46, 5.46]	0.000
Firm size (band)	1.30*	[1.01, 1.66]	0.041
AI maturity	1.03	[0.81, 1.32]	0.811
Positive sentiment	1.38	[0.90, 2.11]	0.139
Barrier severity	0.94	[0.72, 1.22]	0.630

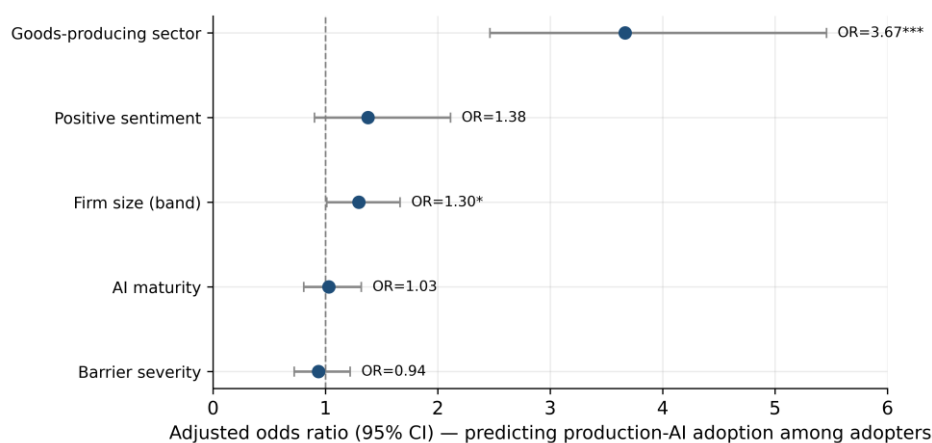


Figure 21. Adjusted odds ratios (95% CI) for predictors of production-AI adoption among AI adopters.

11.2 Results

The model is significant overall (likelihood-ratio $p < .001$) but its fit is limited: the area under the ROC curve is 0.68 and McFadden's pseudo- R^2 is 0.08, so it identifies predictors without discriminating adopters from non-adopters at all sharply. Its content sits in two of them.

Goods-producing sector is the largest predictor. Firms in goods-producing sectors have about 3.7 times the odds of extending AI into production as service firms, holding size, maturity, sentiment and barriers constant (OR = 3.67, 95% CI [2.46, 5.46], $p < .001$). The effect is robust to the attitudinal and constraint predictors, which is what one would expect if it reflects something structural about goods-producing activity—having physical production and operations for AI to act on—rather than a correlation with maturity or enthusiasm. Hypothesis 2 is supported, with sector the strongest of the measured structural correlates.

Firm size is a weaker, marginally significant predictor: each step up the four-band size ladder multiplies the odds by about 1.3 (OR = 1.30, 95% CI [1.01, 1.66], $p = .041$), supporting Hypothesis 1 multivariately. The size effect is much smaller than the sector effect and barely clears significance, consistent with the Chapter 4 observation that part of the bivariate size association runs through the correlation between size and goods-producing membership.

The remaining predictors are non-significant: AI maturity, positive sentiment and barrier severity. The maturity result is the one to interpret with most care. Maturity is the strongest correlate of how intensively firms deploy (Chapter 6) yet shows no association with whether they begin, once sector and size are accounted for. Part of this may be range restriction: the focal item was shown only to AI users and pilots, so the model compares adopters with adopters (a population already selected on a maturity-correlated gateway) which would attenuate any residual maturity effect on the adoption margin. With that caveat, the contrast is still striking: the factors associated with the two margins are largely different.

11.3 Reading the structural result

The prominence of sector and size on the adoption margin has a straightforward reading. Whether a firm extends AI into production and operations depends first on whether it has substantial production and operations of the kind AI can address, a feature of goods-producing activity, and second on whether it has the scale of resources, data and personnel that production AI tends to require—a feature of larger firms. These are preconditions; readiness, attitude and perceived obstacles bear instead on what a firm does once they are met, as Chapters 6 and 9 suggested. The model is the multivariate counterpart of that separation, with the usual caveat that cross-sectional associations are not mechanisms and the two margins are estimated on different (nested) samples.

11.4 The sectoral paradox, quantified

The model also puts numbers on the sectoral paradox of Chapter 4. The goods-producing odds ratio (3.67) captures the propensity gradient: goods-producing adopters are far more likely, firm for firm, to pursue production AI. Yet the estimation sample holds 379 service-sector adopters against 183 goods-producing ones, so the 19.0% service rate still yields most production-AI firms in absolute

count—the paradox the descriptives surfaced. The model does not dissolve it but explains it, by separating propensity (high in goods-producing sectors) from incidence (spread across the many service firms). A specification replacing the goods-producing indicator with a manufacturing-only indicator gives the same qualitative pattern with a smaller odds ratio, which is why the broader goods-producing construct, not narrow manufacturing, is treated as the operative category.

In sum, among AI adopters, production-AI adoption is associated with structural factors (goods-producing sector above all (OR = 3.67), firm size secondarily (OR = 1.30)) while maturity, sentiment and barriers have no independent association with whether a firm begins, though the model's discrimination is limited (AUC = 0.68) and the maturity null is partly subject to range restriction. Hypotheses 1 and 2 are supported multivariately. Set beside maturity's association with intensity in Chapter 6, the result is the clearest evidence for the two-margin pattern that organises the monograph. Chapter 12 draws the findings together.

12. Discussion

This chapter draws the eight lenses together. It states the integrated picture, relates it to the literatures of Chapter 2, sets out what the study does and does not contribute, and places the results in the Slovak and CEE context—keeping, throughout, to the associational and sample-bound language the design requires.

12.1 An integrated picture

Across Chapters 4–11 a consistent account emerges. AI in production and operational processes, in the Slovak enterprise sample of 2025, is recent, broadly based and structurally patterned. Most adopting firms began their AI work in 2024–2025, and their deployment looks early-stage: wide engagement across many applications, low average intensity, and large planning shares. It is broadly based in that production is the second most common application area in the sample, behind only marketing and sales, and the firms doing it span the sectoral range, with most outside manufacturing as conventionally classified. And it is structurally patterned in that the firms involved are disproportionately in goods-producing sectors and larger, while how far they deploy, among those that have begun, tracks organisational maturity instead.

The deployment itself is a wide set of applications rather than a spearhead. Firms spread moderate, fairly even levels of active use across all seventeen applications—led by accessible process-optimisation, quality-control and energy-monitoring uses and, against the grain of the technical literature, lagging on predictive maintenance, whose data and integration prerequisites exceed what most of these firms yet have; that pattern holds among goods-producing firms alone, so it is not a measurement artefact of the mixed sample. Genuinely routine use of any single application is, however, uncommon, so "portfolio" describes breadth more than depth. Firms perceive this deployment as beneficial on balance—benefits exceed risks by a measured margin—and they evaluate benefits, risks and barriers each largely as global judgments, a pattern consistent with a general orientation toward the technology but also with response-style bias. The barriers felt most are integration complexity, skills, trust and a gap in state support; barriers neither separate production adopters from other adopters nor track deployment intensity. The adopters fall into a larger lower-readiness group and a smaller higher-readiness group, distinguished by maturity rather than scale or sector, and the firm-level workforce signal across both leans toward job creation over destruction, a little more so among the more integrated firms.

12.2 The two-margin pattern and the adoption literature

The study's clearest analytical thread is the separation, visible bivariately and in the multivariate models, between the correlates of beginning production AI and the correlates of scaling it. Whether a firm begins is associated with structural position (goods-producing sector (adjusted OR = 3.67) and, weakly, size) with maturity showing no independent association once structure is controlled. How far an adopter deploys is associated with maturity, the strongest of the measured correlates of intensity, though one that still leaves most of the variance unexplained. The two sets of correlates are largely different. This should be read as a pattern in cross-sectional data rather than as two proven

mechanisms, and with the caveat that the two margins are estimated on different (nested) samples and the maturity null on the adoption margin is partly a range-restriction effect.

Even so framed, the pattern speaks to two strands of the adoption literature usually pursued apart. The structural-determinants strand, organised around TOE and diffusion theory, stresses size, sector and resources as correlates of adoption (Khanfar et al., 2024; OECD, 2025b; Katz & Jung, 2025); the capability strand, organised around AI maturity, readiness and absorptive capacity, stresses strategy, data and culture as the basis for realising value (Jöhnk et al., 2021; Mikalef & Gupta, 2021; Cohen & Levinthal, 1990). The present results are consistent with these being complementary rather than rival: structure relating to the binary fact of adoption, capability to its degree. A binary adoption indicator alone cannot show this; the value of the production-AI lens, with its intensity battery, is that it lets the two margins be measured on the same firms—though the maturity construct measured here is better described as AI readiness than as absorptive capacity in the strict sense, so the theoretical link is suggestive rather than exact.

12.3 Production AI beyond manufacturing

A second thread concerns reach. Only 40.8% of the focal firms are classified in manufacturing, and the activity is most common not there but in construction, with substantial presence in ICT, finance, transport and other operationally intensive services; in the multivariate model it is membership of the broad goods-producing category, not the narrow manufacturing class, that predicts adoption. Production AI, in this sample, is better understood as AI applied to the operational core of organisations wherever that core involves transforming inputs into outputs and coordinating the activity around it.

This is less a new idea than a firm-level confirmation, in a CEE setting, of a point the operations-management literature already makes—that AI is an operations technology diffusing across goods and services alike (Mithas et al., 2022; Toorajipour et al., 2021). Its value is empirical and practical rather than conceptual. Empirically, it cautions that a study sampling only "manufacturing" firms would miss most of the production-AI population. Practically, it widens the relevant audience from manufacturers to the larger set of operationally intensive firms. The point rests on a single self-classification item whose breadth the methods flag as a limitation, so it is offered as a well-supported description of this sample rather than as a settled generalisation. The most common companion to production AI in the data is logistics, the other half of the operational core, which fits the operational reading.

12.4 The shape of deployment

A third thread concerns what real-world production AI looks like. The technical literature is organised around flagship applications, predictive maintenance foremost (Çınar et al., 2020; Achouch et al., 2022). These firms deploy not a flagship but a wide, shallow set: active use is fairly even across all seventeen applications and predictive maintenance sits near the bottom, a ranking that survives restricting to goods-producing firms. The reading is measured, rank order among closely spaced applications should not be over-interpreted, but the broad lesson holds: a literature calibrated to advanced discrete and process manufacturing is an imperfect guide to production AI in a typical national economy, where accessible, low-threshold applications come first and the data- and

integration-hungry ones lag. That points back to readiness: the constraint on portfolios maturing is the data infrastructure and integration capability the maturity battery measures and the barrier analysis flagged.

12.5 Perceptions as global judgments

The unidimensionality of benefit, risk and barrier perceptions is a consistent pattern, and one to interpret carefully. It is consistent with firms holding overall orientations toward production AI rather than itemised appraisals—a reasonable reading at an early adoption stage. It is equally consistent, in single-respondent Likert data, with halo or acquiescence response styles, and the very high reliabilities (α around .90-.94) are as much a sign of item redundancy as of a strong construct. Harman's test offers some reassurance that the four constructs are empirically distinct from one another, but it cannot settle the within-battery question. The cautious conclusion is that perceptions of production AI in these data are best summarised at the construct level, and that interventions aimed at shifting them likely operate on overall orientation (demonstrated value, visible exemplars, trusted information) more than on itemised argument.

12.6 The workforce signal

The workforce result adds firm-level evidence to the augmentation side of the automation debate. That more firms report adding roles than cutting them, and that the tilt is a little stronger among the more integrated adopters, is consistent with firm-level work in which advanced adopters expand their own employment (Acemoglu, Lelarge, & Restrepo, 2020) and with AI-specific augmentation evidence (Brynjolfsson & Mitchell, 2017; Agrawal et al., 2019). The measure is coarse (binary incidence, partly prospective) so the claim is about the direction of firm-level headcount change, not net employment, and confounding by firm growth cannot be excluded. The constructive inference—that the workforce upside of production AI is realised through deeper integration, which tracks maturity—is a hypothesis the data are consistent with, not a demonstrated effect, and it reframes the labour question from "will AI in production destroy jobs" toward "what helps firms integrate it well enough to realise complementary labour demand."

12.7 The Slovak and CEE context

The results sit against a familiar regional backdrop: a manufacturing- and automotive-intensive economy in a CEE region that trails the EU digital frontier (Eurostat, 2025; European Commission, 2022; Kádárová et al., 2026), with robotisation historically driven by foreign-owned automotive value chains rather than indigenous capability (Cséfalvay, 2020; Vakulenko et al., 2020). A few results bear that imprint. The (non-significant) tendency for focal firms to be foreign-owned is in the direction the dependence literature would suggest. The prominence of the state-support gap among perceived barriers chimes with a distance between the digital-transformation ambitions of national and EU strategy and firm experience. And the early-stage, broad-but-shallow character of deployment is what one might expect of a region still in the catching-up phase of AI diffusion. Whether these patterns extend to other CEE economies is a question this single-country, non-random sample cannot answer; the Slovak case is offered as a substantively important one that invites comparative

replication, not as a template for the region. Its informativeness lies in the detail it provides on one economy, not in a claim to speak for the European periphery.

13. Implications, limitations, and conclusion

13.1 Implications for managers

A few practical lessons follow for managers in firms weighing or pursuing AI in production and operational processes. The first is that beginning and scaling appear to be different problems. For a goods-producing or operationally intensive firm of some size, crossing into production AI is largely a matter of starting; but realising value is about deepening, and in these data depth tracks organisational maturity (strategy, data infrastructure, technology and governance) more than further tool purchases. Firms that treat production AI as a procurement problem may stay broad and shallow; those that treat it as a capability-building problem are the ones, in this sample, that deploy widely and actively and that are somewhat more likely to add jobs around their AI.

The second concerns application strategy. The fashionable advice to "find your killer application" sits awkwardly with the reality of broad, even experimentation, but so does undisciplined breadth. The most widely used applications are the more accessible, lower-barrier ones (process optimisation, quality control, and energy monitoring). Firms may therefore do well to consolidate their routine use of these applications before moving to more data- and integration-intensive applications, such as predictive maintenance and digital twins, for which most firms have yet to develop the necessary capabilities.

The third concerns the internal case for production AI. In these firms it rests on operational gains (materials and energy efficiency, coordination, throughput) more than on the maintenance-and-downtime benefits that dominate external discourse, and the risks that most concern adopters are near-term operational ones: false detections, implementation cost, interpretive burden, data dependence. Managers building support may do better to foreground operational efficiency and to address data quality and interpretive capacity directly than to lead with the predictive-maintenance narrative.

13.2 Implications for policy

For policymakers in Slovakia and the wider region, the two-margin pattern suggests that widening adoption and deepening it call for different instruments. Widening the base—bringing more goods-producing and smaller firms across the threshold—points to the structural and informational obstacles to starting: cost, integration complexity, and the demonstration of operational value. Deepening incumbents' deployment, and with it any workforce upside, points to organisational capability: data infrastructure, AI skills, and the practices the maturity battery measures. A single undifferentiated "AI adoption" target risks serving neither well.

The state-support gap identified in Chapter 8 is worth policy attention in its own right. That production-AI firms (the relative vanguard of operational AI in this sample) rate state financial, technical and training support among their more pressing barriers suggests a distance between the ambitions of national and EU strategy and their reach at firm level. Because skills recur as a constraint—prominent among barriers, central to the maturity that tracks intensification, and the dimension along which the augmentation literature locates AI's complementary labour demand—workforce-development policy is well placed to address depth of adoption and any job dividend

together. The recency and momentum of the wave suggest that timely, targeted support could matter for a transition already under way, though that, too, is a conjecture this snapshot cannot test.

13.3 Implications for research

The clearest research priority is longitudinal evidence. The two-margin pattern, the maturity–intensity association and the workforce signal are all associations in cross-sectional data; tracking firms over time would show whether maturity precedes intensification, whether deployment shapes benefit perceptions, and whether job creation follows AI integration or merely accompanies it. The recency of the wave makes the coming years an unusually good window for such panel work. Comparative work across CEE economies, and across the manufacturing/services boundary, would test whether the goods-producing gradient and the two-margin pattern generalise. The unidimensional perceptions raise a measurement question worth pursuing—whether the global-evaluation structure is an early-stage feature that differentiates as firms mature, or largely a response-style artefact, which only longitudinal or method-controlled designs could separate. And the workforce question warrants measures of the magnitude and composition of job change, which the present incidence items cannot supply. Methodologically, the study illustrates the value of skip-logic-routed deep-dive modules for measuring intensity, not just adoption—an ordinary design choice that other firm-level AI surveys could adopt.

13.4 Limitations

The constraints set out in Chapter 3 bound everything above. The data are cross-sectional and cannot establish causation, which is why the language throughout is associational. All measures are self-reported by one respondent per firm, exposing the analysis to common-method variance (mitigated, on Harman's test, but not removed), social-desirability bias and key-informant error; the workforce items conflate realised with planned action and incidence with magnitude. The focal measure is a binary self-classification whose breadth, useful as it is, introduces interpretive heterogeneity, and the deep-dive battery it triggers is labelled "manufacturing" though administered to all sectors. The focal sample of 157, adequate for the analyses performed, is modest for fine subgroup work and underpowered for weak associations, so several nulls are better read as undetected than as demonstrated absences. The achieved sample is non-random and, like most voluntary enterprise surveys, over-represents AI-engaged firms and effectively omits micro-enterprises, so the prevalence figures describe the sample rather than the national population. The barrier factor analysis sits below the usual case-to-item ratio, and the clustering shows only modest separation. These are reasons to read the monograph as a careful, multi-angle account of associations within an achieved sample of Slovak enterprises in 2025, not as causal estimates for a defined population.

13.5 Conclusion

This monograph set out to describe, from several angles and with some rigour, AI in production and operational processes among Slovak enterprises. Working from one survey item that routed 157 firms into a dedicated module, it has assembled a reasonably full firm-level picture of production AI in a setting where such evidence is scarce.

The picture is coherent. Production AI in this sample is recent and still maturing; it reaches well beyond the manufacturing sector even as it is most common in goods-producing activity; it takes the form of broad, mostly shallow engagement across many applications rather than concentration on one, with the literature's flagship, predictive maintenance, near the rear; adopters perceive it as beneficial on balance, evaluating benefits, risks and barriers each largely as global judgments; the barriers felt most are integration, skills, trust and a gap in state support; the firms separate into lower- and higher-readiness groups along a maturity gradient rather than by size or sector; and the firm-level workforce signal leans toward job creation, a little more so among the most integrated.

Running through these is one analytical thread, supported in the multivariate models but offered as a pattern rather than a mechanism: the factors associated with whether a firm begins production AI differ from those associated with how far it goes. Beginning tracks structural position—sector and size; deepening tracks organisational maturity. The structural factors that open the door say little about what happens inside; the organisational factors that go with depth say little about who enters. Recognising that separation—in the data, in the reach of production AI beyond manufacturing, and in the different levers it implies for widening versus deepening—is the study's main takeaway. For a manufacturing-intensive economy at the start of an adoption wave whose appetite outruns its current footprint, knowing not only how much AI has entered production but along which margins it widens and deepens is a useful basis for thinking about how to shape its course.

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