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The Role of Artificial Intelligence in Improving Resource Utilization, Business Productivity and Competitive Positioning Among Small and Medium-Sized Enterprises

Arjun Mehta[1], Elena Popescu[1], Mateusz Kowalski[1], Daniel Mitchell[1]

[1] Faculty of Economics and Business Administration, Babeș-Bolyai University, Teodor Mihali Street 58–60, 400591 Cluj-Napoca, Romania
Corresponding author: Arjun Mehta, Faculty of Economics and Business Administration, Babeș-Bolyai University, Cluj-Napoca, Romania

ABSTRACT :

Purpose: Small and medium-sized enterprises (SMEs) represent 99.8% of enterprises and 65.2% of employment in the European Union's non-financial business economy, yet they remain systematically behind large firms in adopting artificial intelligence (AI). This study examines how AI improves resource utilization, business productivity and competitive positioning in SMEs, and why the benefits are unevenly distributed across firm sizes and national contexts, with particular attention to Central and Eastern Europe (CEE).

Design/methodology/approach: The study combines an integrative literature review grounded in the resource-based view, dynamic capabilities theory and the technology–organisation–environment (TOE) framework with a secondary quantitative analysis of harmonised Eurostat enterprise survey data for 2021–2025 and a structured synthesis of experimental and quasi-experimental evidence on AI-induced productivity gains. A conceptual model with six testable propositions is developed, and illustrative resource-utilization scenarios are derived using a task-based (Hulten-type) approximation.

Findings: AI use among EU enterprises rose from 7.7% in 2021 to 20.0% in 2025. Small firms recorded the fastest relative growth (+51.8% between 2024 and 2025, from 11.2% to 17.0%), narrowing the large-to-small adoption ratio from 3.67 to 3.24; however, the absolute gap widened from 29.9 to 38.0 percentage points, because large firms reached 55.0%. Geographic divergence is sharper still: Romania (5.2%), Poland (8.4%) and Bulgaria (8.6%) remained at less than half the EU average in 2025, and the Denmark–Romania gap widened from 24.5 to 36.8 points. Among firms that had considered AI, 70.3% cited a lack of relevant expertise, 53.6% unclear legal consequences and 52.7% data-protection concerns. Controlled studies report task-level gains of 12–56% in speed or output, with the largest benefits for less experienced workers—an effect especially valuable to SMEs with thin managerial and technical layers. Illustrative scenarios suggest firm-level labour productivity gains of roughly 1.4–12% depending on task exposure and fit.

Originality/value: The paper connects micro-level productivity evidence with macro-level diffusion data and frames AI adoption mode (build, buy or subscribe) as a strategic resource-allocation decision for constrained firms. It distinguishes relative from absolute convergence in AI diffusion, a distinction largely overlooked in existing SME literature, and offers managerial and policy recommendations tailored to lagging CEE economies.

Keywords: *artificial intelligence; small and medium-sized enterprises; resource utilization; productivity; competitive advantage; digital transformation; generative AI; Central and Eastern Europe*

JEL classification: D24; L25; L26; M15; O33

1. Introduction

Small and medium-sized enterprises (SMEs) are the structural backbone of the European economy. In 2023 they accounted for 99.8% of all enterprises in the EU-27 non-financial business sector, employed 88.7 million people—65.2% of total employment—and generated just over half of the sector's value added (European Commission, 2024). Their productivity performance therefore shapes aggregate growth, regional cohesion and employment resilience to a degree that no group of large firms can match. Yet SMEs have historically trailed larger enterprises in the adoption of frontier technologies, and this lag has been a persistent explanation for the dispersion of productivity across firms within the same industries.

Artificial intelligence (AI) presents both an unusual opportunity and a familiar risk for this population of firms. The opportunity arises because recent advances, particularly in generative AI and large language models, have dramatically reduced the fixed costs of accessing sophisticated analytical and cognitive capabilities. Services that a decade ago required in-house data-science teams can now be subscribed to on a monthly basis, embedded in

standard productivity software, or accessed through application programming interfaces. In principle, this democratisation lowers the scale threshold for profitable adoption and could allow SMEs to substitute AI-enabled processes for the specialised functions—marketing analytics, demand forecasting, legal drafting, customer service—that they cannot afford to staff internally. The risk is that, as with earlier waves of digitalisation, the complementary investments required to convert access into productivity (skills, data infrastructure, process redesign and managerial attention) remain scale-dependent, so that AI widens rather than narrows the gap between leading and lagging firms (Brynjolfsson et al., 2021; Calvino & Fontanelli, 2023).

Recent evidence demonstrates that both forces are at work. On the one hand, controlled studies report substantial task-level gains from AI assistance: a 14% increase in issues resolved per hour among 5,179 customer-support agents, rising to 34% for novice workers (Brynjolfsson et al., 2025); a 40% reduction in completion time for professional writing tasks (Noy & Zhang, 2023); and gains of more than 12% in tasks completed and 25% in speed among management consultants (Dell'Acqua et al., 2023). On the other hand, diffusion data reveal stark heterogeneity. In 2025, 55.0% of large EU enterprises used AI, compared with 17.0% of small enterprises; and the share of enterprises using AI ranged from 42.0% in Denmark to 5.2% in Romania (Eurostat, 2025b).

This heterogeneity is especially consequential in Central and Eastern Europe (CEE). Romania, Poland and Bulgaria, alongside neighbouring non-EU economies such as Moldova and Ukraine, combine a large SME sector, a comparatively low baseline of digital intensity and a regulatory environment in transition. In 2023, 72.1% of Romanian enterprises had a "very low" digital intensity index—the highest share in the EU (Eurostat, 2024). Recent regional scholarship has begun to examine how such firms choose between developing AI capabilities in-house, commissioning bespoke solutions or subscribing to off-the-shelf services under resource and regulatory constraints (Сидорук, 2023), and has applied value-yield optimisation reasoning to compare SME market structures in the border economies of Poland, Romania, Moldova and Ukraine (Євсюкова, 2024) and in mature North American markets (Євсюкова, 2025). These contributions suggest that the question confronting CEE SMEs is not simply *whether* to adopt AI, but *how* to allocate scarce resources across adoption modes so as to maximise the yield of value per unit of investment.

Against this background, the present study addresses three research questions:

- **RQ1.** Through which mechanisms does AI improve resource utilization and business productivity in SMEs, and what is the magnitude of the gains documented in the empirical literature?
- **RQ2.** How has AI diffusion evolved across firm-size classes and national contexts in Europe, and is the SME–large firm gap converging or diverging?
- **RQ3.** Under what organisational, technological and environmental conditions do AI-driven productivity gains translate into durable competitive positioning for SMEs, particularly in lagging CEE economies?

The paper makes four contributions. First, it integrates micro-level experimental evidence on AI productivity effects with macro-level harmonised diffusion statistics, linking two literatures that have largely developed in parallel. Second, it introduces an explicit distinction between *relative* and *absolute* convergence in AI adoption, showing that the two can move in opposite directions and that policy conclusions differ accordingly. Third, it develops a conceptual model connecting AI adoption mode, resource utilization, productivity and competitive positioning, moderated by organisational, technological and environmental contingencies, and articulates six testable propositions. Fourth, it derives practical recommendations for SME managers and for policymakers in lagging economies, including Romania.

The remainder of the paper is organised as follows. Section 2 reviews the theoretical and empirical literature. Section 3 presents the conceptual framework and propositions. Section 4 describes the methodology. Section 5 reports the results of the diffusion analysis, barrier analysis and evidence synthesis. Section 6 discusses implications for theory, management and policy, together with limitations. Section 7 concludes.

2. Theoretical Background and Literature Review

2.1 SMEs, resource constraints and technology adoption

SMEs differ from large enterprises not merely in scale but in the structure of the constraints they face. Their financial resources are thinner and more expensive, their management teams are smaller and more generalist, and their access to specialised technical skills is limited by both cost and labour-market competition with larger employers. They typically have shorter planning horizons and less slack to absorb the transitional productivity losses that accompany the introduction of new technology. These characteristics explain why the adoption of general-purpose technologies—from enterprise resource planning to cloud computing—has consistently followed a size gradient, with SMEs adopting later and less intensively than large firms.

At the same time, SMEs possess characteristics that can favour rapid adoption once barriers are overcome: flatter hierarchies, shorter decision chains, closer proximity between owners and operations, and fewer legacy systems that need to be integrated or replaced. The net effect of these opposing

forces is technology-specific. Technologies that require large upfront fixed investment and extensive integration favour large firms; technologies offered as modular, low-cost services with low switching costs can, in principle, favour agile smaller firms. Contemporary AI—especially generative AI accessed through subscription platforms—sits closer to the second category than any previous wave of analytical technology, which is why its diffusion trajectory in the SME population warrants close attention.

2.2 The resource-based view and dynamic capabilities

The resource-based view (RBV) holds that sustained competitive advantage derives from resources that are valuable, rare, imperfectly imitable and non-substitutable (Barney, 1991). From an RBV perspective, AI raises an immediate puzzle: if AI tools are widely available on subscription, they are neither rare nor difficult to imitate, and therefore cannot in themselves be sources of sustained advantage. The resolution lies in distinguishing between the AI *tool* and the AI-enabled *capability*. The latter combines the tool with firm-specific data, process knowledge, customer relationships and organisational routines, a bundle that is considerably harder to replicate.

Dynamic capabilities theory extends this reasoning by emphasising the firm's capacity to integrate, build and reconfigure internal and external competences in response to rapidly changing environments (Teece et al., 1997). For SMEs, AI can be understood both as an object of dynamic capability (the firm must sense, seize and reconfigure around AI opportunities) and as an enabler of dynamic capability (AI improves the firm's ability to sense market signals, test alternatives quickly and reconfigure operations). This dual role implies that the competitive returns to AI depend heavily on complementary organisational capacities that vary considerably across SMEs.

2.3 The technology–organisation–environment framework

The technology–organisation–environment (TOE) framework (Tornatzky & Fleischer, 1990) provides a parsimonious structure for explaining firm-level adoption decisions. Technological factors include the perceived relative advantage, compatibility and complexity of the innovation; organisational factors include firm size, managerial support, slack resources and human capital; environmental factors include competitive pressure, industry characteristics, regulation and the availability of external support. The framework has been widely applied to SME digitalisation and is well suited to AI, where adoption depends simultaneously on technical fit with specific tasks, internal skills and data readiness, and an external environment shaped by regulation such as the General Data Protection Regulation and the EU Artificial Intelligence Act (Regulation (EU) 2024/1689).

2.4 Micro-level evidence on AI and productivity

A rapidly expanding body of experimental and quasi-experimental research has quantified the productivity effects of AI at the level of tasks and workers. Brynjolfsson et al. (2025) studied the staggered introduction of a generative AI conversational assistant to 5,179 customer-support agents and found that access increased issues resolved per hour by 14% on average and by 34% for novice and low-skilled workers, with minimal impact on the most experienced agents. The assistant also improved customer sentiment and employee retention, suggesting that AI diffused the tacit practices of high performers to the rest of the workforce.

Noy and Zhang (2023), in a preregistered online experiment with 453 college-educated professionals performing occupation-specific writing tasks, found that access to ChatGPT reduced average completion time by 40% and increased output quality by 18%, while also compressing inequality between workers. Dell'Acqua et al. (2023) conducted a field experiment with 758 consultants at Boston Consulting Group. For tasks within the capability frontier of AI, consultants with access to GPT-4 completed 12.2% more tasks, worked 25.1% faster and produced output rated more than 40% higher in quality. For a task deliberately chosen to lie outside that frontier, however, consultants using AI were 19 percentage points less likely to produce correct solutions—a finding the authors summarised as a "jagged technological frontier". In software development, Peng et al. (2023) found that developers with access to GitHub Copilot completed a standardised programming task 55.8% faster than a control group.

Firm-level evidence is more limited but broadly consistent. Using survey data on German firms and instrumental-variable estimators to address the endogeneity of adoption, Czarnitzki et al. (2023) found positive and significant associations between AI use and firm productivity, whether AI was measured as a binary adoption indicator or as the intensity of use across business processes. Related work on German firm-level data links AI use to product and process innovation (Rammer et al., 2022). Cross-country analysis of AI adopters indicates that adopting firms tend to be larger, younger and more digitally intensive, and that productivity premia are concentrated among firms that combine AI with complementary digital assets and skills (Calvino & Fontanelli, 2023).

2.5 Macro-level caution: the J-curve and modest aggregate effects

Strong task-level effects do not translate automatically into commensurate aggregate gains. Brynjolfsson et al. (2021) argue that general-purpose

technologies generate a "productivity J-curve": during early adoption, firms invest heavily in unmeasured intangible complements—training, reorganisation, data—which depresses measured productivity before the gains materialise. Acemoglu (2025), applying a task-based framework built on Hulten's theorem, estimates that AI will raise total factor productivity by no more than 0.66% over ten years, and by less than 0.53% once one accounts for the fact that early evidence comes disproportionately from easy-to-learn tasks. These estimates are not incompatible with large firm-level gains; rather, they reflect the limited share of economy-wide tasks that are currently exposed to AI and the modest average cost savings on those tasks. For SMEs, the implication is that gains are likely to be concentrated in firms whose task portfolios are highly exposed to AI and that make the complementary investments necessary to capture them.

2.6 SMEs and AI in Central and Eastern Europe

CEE economies present a distinctive context for SME AI adoption. Enterprise digital intensity in the region remains low: in 2023, 72.1% of Romanian enterprises and 70.6% of Bulgarian enterprises had a very low digital intensity index, compared with an EU-wide figure of 58% of SMEs reaching at least a basic level (Eurostat, 2024). The EU's Digital Decade programme sets targets of 90% of SMEs reaching at least basic digital intensity and 75% of enterprises using cloud, big data or AI by 2030—targets that appear particularly distant for lagging member states.

Regional scholarship has begun to address these specific constraints. Сидорук (2023) frames AI adoption by SMEs in Poland, Romania and Moldova as a choice among three modes—creating AI solutions in-house, commissioning them from external developers, or subscribing to ready-made services—and examines how that choice is shaped by resource and regulatory constraints. This framing is important because it shifts analytical attention from the binary adoption decision captured in official statistics to the strategic question of how constrained firms should configure their AI investments. Євсюкова (2024) applies the Value-Yield Optimization (VYO) methodology to a comparative analysis of SME markets in the border countries of Poland, Romania, Moldova and Ukraine over 2019–2024, while Євсюкова (2025) extends the same methodology to the digital optimisation of SMEs in the more mature markets of the United States and Canada over 2024–2025, highlighting the "invisible constraints" that persist even where digital infrastructure is well developed. Read together, these studies suggest that the binding constraints on SME value creation differ systematically between emerging and mature markets, and that digital-optimisation strategies—including AI adoption—should be calibrated to the yield of value they generate relative to the resources they consume.

2.7 Research gap

The literature reviewed above reveals three gaps. First, the experimental literature quantifies task-level productivity effects but rarely relates them to the resource-allocation realities of SMEs, where managerial time, skills and cash are the binding constraints. Second, diffusion studies typically report adoption rates by size class and country but seldom distinguish between relative and absolute convergence, leaving ambiguous whether SMEs are catching up. Third, theoretical work on AI and competitive advantage has largely focused on large firms with proprietary data and in-house capabilities, with less attention to how SMEs relying on commoditised AI services can nonetheless build defensible positions. This study addresses these gaps by combining an evidence synthesis with a structured diffusion analysis and a contingency-based conceptual model.

3. Conceptual Framework and Propositions

Building on the RBV, dynamic capabilities theory and the TOE framework, we propose a conceptual model in which AI adoption affects SME competitive positioning through a sequential mediation chain: AI adoption improves *resource utilization*, which raises *business productivity*, which in turn strengthens *competitive positioning*. The strength of each link is moderated by organisational, technological and environmental contingencies, and productivity gains feed back into further AI investment (Figure 1).

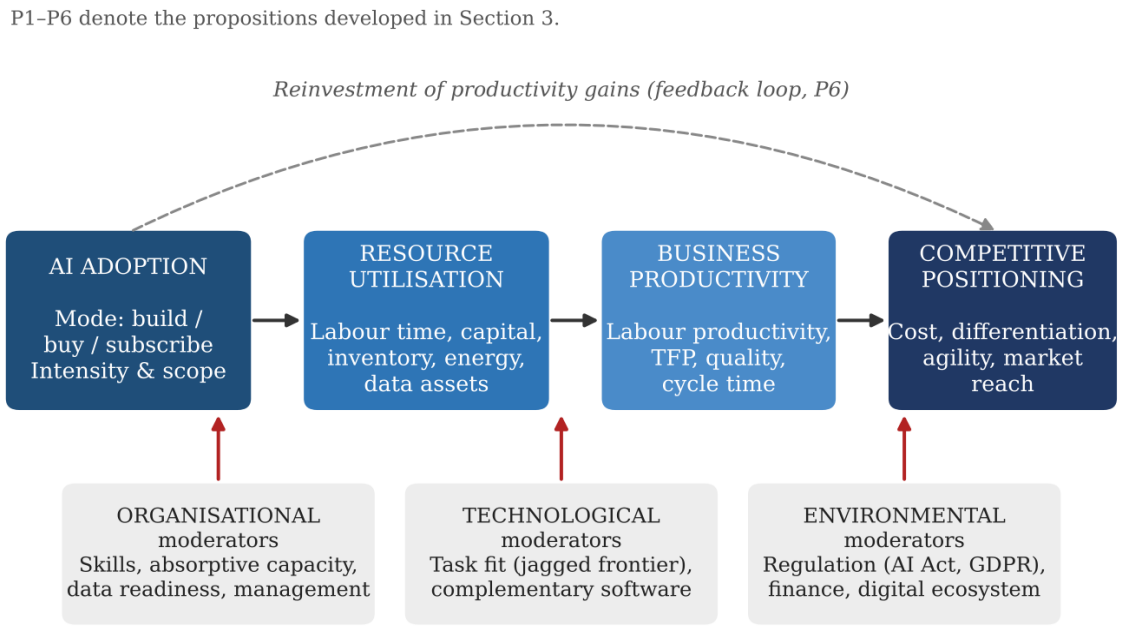


Figure 1. Conceptual model linking AI adoption, resource utilization, business productivity and competitive positioning in SMEs, with organisational, technological and environmental moderators. *Source:* Authors' elaboration.

3.1 AI adoption and resource utilization

We define resource utilization as the efficiency with which a firm converts its scarce inputs—labour time, working capital, physical capital, energy, materials and data—into outputs. AI improves resource utilization through four principal mechanisms. First, *labour reallocation*: by automating or accelerating routine cognitive tasks (drafting correspondence, summarising documents, categorising transactions, answering standard customer queries), AI frees employee time for higher-value activities. For SMEs, in which owner-managers frequently perform administrative tasks themselves, the reallocation of managerial attention may be the most valuable effect of all. Second, *capital and inventory optimisation*: machine-learning-based forecasting reduces stock-outs and excess inventory, tying up less working capital. Third, *asset utilisation*: predictive maintenance and scheduling algorithms increase the effective availability of equipment. Fourth, *data monetisation*: AI allows SMEs to extract value from transactional and customer data that would otherwise remain unused.

> **Proposition 1 (P1).** *The intensity of AI use in an SME is positively associated with the efficiency of its resource utilization, and this association is strongest for labour-time reallocation in knowledge-intensive tasks.*

3.2 Resource utilization and business productivity

Improved resource utilization raises productivity directly, through more output per unit of input, and indirectly, through the redeployment of freed resources to growth-generating activities such as product development or market expansion. The experimental evidence suggests that the largest gains accrue to less experienced workers (Brynjolfsson et al., 2025; Noy & Zhang, 2023). This *skill-levelling* effect has particular significance for SMEs, which typically lack deep benches of experienced specialists and face difficulty recruiting them. AI may therefore act as a partial substitute for the scarce specialised human capital that large firms acquire through scale.

> **Proposition 2 (P2).** *The productivity returns to AI are larger, in relative terms, for SMEs whose workforce has lower average task-specific experience, because AI disproportionately raises the performance of less experienced workers.*

3.3 Business productivity and competitive positioning

Productivity improvements strengthen competitive positioning through three channels identified in classical strategy: *cost leadership* (lower unit costs), *differentiation* (higher quality, personalisation and responsiveness) and *agility* (faster adaptation to changing demand). Because AI tools are widely accessible, however, productivity gains derived purely from generic tools are likely to be competed away as rivals adopt the same tools. Durable advantage requires combining AI with resources that are firm-specific and difficult to imitate, such as proprietary data, deep customer relationships and process

know-how (Barney, 1991).

> **Proposition 3 (P3).** *AI-driven productivity gains translate into durable competitive advantage only when AI is combined with firm-specific complementary resources; gains from generic, widely available AI tools converge towards competitive parity over time.*

3.4 Adoption mode as a strategic resource-allocation decision

Following Сидорук (2023), we distinguish three AI adoption modes: *build* (in-house development), *buy* (commissioning bespoke solutions from external providers) and *subscribe* (using standardised software-as-a-service AI tools). The modes differ in upfront cost, time-to-value, control over data, degree of customisation and the potential to generate inimitable capabilities. For resource-constrained SMEs, subscription minimises entry costs and risk but offers limited differentiation; building offers maximum differentiation but is feasible only for firms with substantial technical capabilities. The optimal mode therefore depends on the fit between the firm's resources and the strategic importance of the targeted process.

> **Proposition 4 (P4).** *Resource-constrained SMEs maximise the value yield of AI investment by subscribing for generic support functions and reserving buy or build modes for core, differentiating processes in which proprietary data or know-how can be embedded.*

3.5 Moderating conditions

The TOE framework identifies the contingencies under which the mediation chain operates. Organisational moderators include digital skills, absorptive capacity, data readiness and managerial commitment. Technological moderators centre on *task fit*: the jagged frontier documented by Dell'Acqua et al. (2023) implies that AI can degrade performance on tasks outside its capabilities, so firms that correctly match AI to suitable tasks will capture gains while those that misapply it may incur losses. Environmental moderators include regulatory clarity, access to finance and the density of the local digital ecosystem, including the availability of advisory services and skilled labour.

> **Proposition 5 (P5).** *The positive effect of AI adoption on SME productivity is amplified by digital skills, data readiness and regulatory clarity, and attenuated where AI is applied to tasks outside its capability frontier.*
>
> **Proposition 6 (P6).** *Productivity gains from initial AI adoption increase the probability and intensity of subsequent AI investment, creating a cumulative dynamic that tends to widen the absolute gap between early and late adopters.*

4. Methodology

4.1 Research design

The study adopts a multi-method design comprising three complementary components: (i) an integrative literature review, used to construct the theoretical framework and propositions; (ii) a secondary quantitative analysis of harmonised official statistics on enterprise AI use, used to address RQ2; and (iii) a structured evidence synthesis of experimental and quasi-experimental studies on AI and productivity, used to address RQ1 and to calibrate illustrative resource-utilization scenarios. This design is appropriate given the early stage of the field, the absence of longitudinal firm-level panel data on AI use among CEE SMEs, and the need to integrate evidence across levels of analysis.

4.2 Data sources

Diffusion data are drawn from the Eurostat community survey on ICT usage and e-commerce in enterprises, which covers enterprises with ten or more persons employed in the non-financial business economy across EU member states (Eurostat, 2025a, 2025b). Enterprises are classified by size into small (10–49 persons employed), medium-sized (50–249) and large (250 or more). An enterprise is considered to use AI if it uses at least one of the AI technologies listed in the survey. Indicators extracted include the share of enterprises using AI by size class and country for 2024 and 2025, the EU aggregate for 2021, 2023, 2024 and 2025, and the reported barriers to AI use among enterprises that had considered adopting it. Digital intensity data for 2023 are drawn from Eurostat (2024), and SME structural statistics from the Annual Report on European SMEs (European Commission, 2024).

Two methodological caveats apply. First, the 2025 survey widened the definition of AI from seven to eight technologies, explicitly adding the generation of images, video or audio; part of the increase between 2024 and 2025 therefore reflects the broader definition rather than new adoption alone. Second, enterprises with fewer than ten employees—micro-enterprises, which make up the large majority of EU SMEs by number—are not covered, so the results relate to small and medium-sized firms in the narrower sense.

4.3 Literature search and evidence synthesis

The literature review drew on Scopus, Web of Science, EconLit, SSRN, NBER and Google Scholar, supplemented by regional databases for CEE scholarship, for publications from 1990 to 2026. Search strings combined terms for artificial intelligence ("artificial intelligence", "machine learning", "generative AI", "large language model") with terms for the unit of analysis ("SME", "small business", "firm") and outcomes ("productivity", "efficiency", "resource utilization", "competitive advantage", "adoption"). For the productivity synthesis, inclusion was limited to studies with a credible causal identification strategy (randomised experiments, staggered rollouts or instrumental-variable designs), a quantified effect on output, speed or quality, and publication in a peer-reviewed outlet or a recognised working-paper series.

4.4 Analytical procedures

For the diffusion analysis, we computed absolute changes (percentage points), relative changes (percentage growth), and two gap measures for each pair of groups: the *absolute gap* (difference in adoption rates) and the *relative gap* (ratio of adoption rates). We define relative convergence as a declining ratio between leader and laggard and absolute convergence as a declining difference. Because S-shaped diffusion curves imply that laggards may grow faster in relative terms while leaders add more percentage points, the two measures can diverge, and both are reported.

For the illustrative resource-utilization scenarios, we apply the task-based approximation used by Acemoglu (2025), under which the first-order effect of a technology on productivity equals the share of tasks affected multiplied by the average cost saving on those tasks. Task-level savings are calibrated on the experimental literature described in Section 2.4. These scenarios are illustrative rather than predictive, and are intended to bound the plausible magnitude of firm-level effects rather than to estimate them for any specific firm.

5. Results

5.1 The diffusion trajectory of AI in European enterprises

AI use among EU enterprises remained almost flat for several years before accelerating sharply. The share of enterprises using at least one AI technology rose from 7.7% in 2021 to 8.0% in 2023, then to 13.5% in 2024 and to 20.0% in 2025 (Table 1). The increase of 12.0 percentage points between 2023 and 2025 exceeds the cumulative increase of the preceding years by an order of magnitude and coincides with the commercial availability of generative AI services. The composition of use confirms this interpretation: in 2025, the most common AI applications were the analysis of written language (11.8% of enterprises, up 4.9 percentage points in a single year), the creation of images, video or audio (9.5%), the generation of written or spoken language (8.8%, up 3.4 points) and speech-to-text conversion (7.2%). These are precisely the applications that generative AI platforms have made cheap and accessible.

Table 1. Share of EU-27 enterprises using artificial intelligence, 2021–2025

Year	Enterprises using AI (%)	Change vs previous observation (pp)	Relative change (%)	Notes
2021	7.7	—	—	Baseline year
2023	8.0	+0.3	+3.9	Two-year interval
2024	13.5	+5.5	+68.8	Generative AI enters mainstream use
2025	20.0	+6.5	+47.8	Definition widened from 7 to 8 technologies

Source: Authors' calculations based on Eurostat (2025a, 2025b). Enterprises with 10 or more persons employed; financial sector excluded. pp = percentage points.

5.2 The firm-size gap: relative convergence, absolute divergence

Table 2 and Figure 2 report AI adoption by size class. In 2025, 17.0% of small enterprises, 30.4% of medium-sized enterprises and 55.0% of large enterprises used AI. Between 2024 and 2025 small enterprises recorded the fastest relative growth (+51.8%), followed by medium-sized (+45.3%) and large enterprises (+33.9%). As a result, the ratio of large-firm to small-firm adoption fell from 3.67 to 3.24—evidence of relative convergence. Yet because large firms added 13.9 percentage points against 5.8 for small firms, the absolute gap widened from 29.9 to 38.0 percentage points.

Table 2. AI adoption by enterprise size class in the EU-27, 2024–2025

Size class (persons employed)	2024 (%)	2025 (%)	Change (pp)	Relative growth (%)	Ratio to small firms (2024 → 2025)
Small (10–49)	11.2	17.0	+5.8	+51.8	1.00 → 1.00
Medium-sized (50–249)	20.9	30.4	+9.5	+45.3	1.87 → 1.79
Large (250+)	41.1	55.0	+13.9	+33.9	3.67 → 3.24
All enterprises	13.5	20.0	+6.5	+47.8	—
Large–small absolute gap	29.9 pp	38.0 pp	+8.1	—	—

Source: Authors' calculations based on Eurostat (2025a, 2025b). Ratios computed as adoption rate of size class divided by adoption rate of small enterprises.

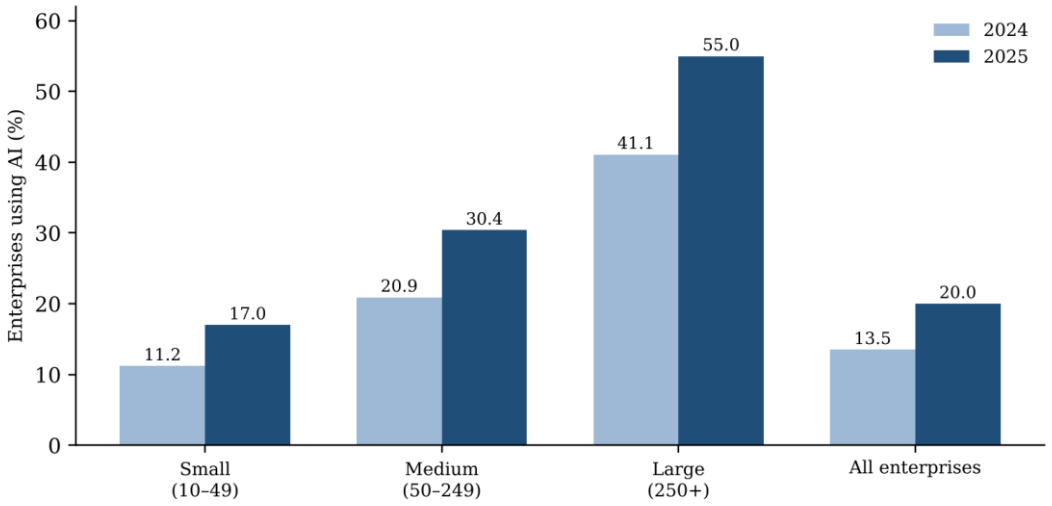


Figure 2. Share of EU-27 enterprises using AI by size class, 2024 and 2025. *Source:* Authors' elaboration based on Eurostat (2025a, 2025b).

This pattern is consistent with an S-shaped diffusion process in which small firms, starting from a lower base, grow faster proportionally while large firms, positioned on the steep middle portion of the curve, add more adopters in absolute terms. Its practical significance is that headline claims of SMEs "catching up" depend on the metric chosen. In terms of the share of firms that have *not yet* adopted AI, the picture is stark: 83.0% of small enterprises remained non-users in 2025 compared with 45.0% of large enterprises.

5.3 The geographic gap: Central and Eastern Europe

Cross-country differences are larger than size differences (Table 3, Figure 3). In 2025, AI adoption ranged from 42.0% in Denmark, 37.8% in Finland and 35.0% in Sweden to 8.6% in Bulgaria, 8.4% in Poland and 5.2% in Romania—the lowest in the EU. Romania recorded the highest relative growth among the countries examined (+68.1%), raising its ratio to the EU average from 0.23 to 0.26. Nevertheless, its absolute gap with the EU average widened from 10.4 to 14.7 percentage points, and its gap with Denmark from 24.5 to 36.8 points. Poland's position deteriorated on both measures, with its ratio to the EU average falling from 0.44 to 0.42.

Table 3. AI adoption in selected EU member states, 2024–2025

Country	2024 (%)	2025 (%)	Change (pp)	Relative growth (%)	Ratio to EU average (2024 → 2025)	Gap to EU average, pp (2024 → 2025)
Denmark	27.6	42.0	+14.4	+52.3	2.04 → 2.11	+14.1 → +22.1
Sweden	25.1	35.0	+9.9	+39.6	1.86 → 1.76	+11.6 → +15.1
EU-27	13.5	20.0	+6.5	+47.8	1.00 → 1.00	—
Bulgaria	6.5	8.6	+2.1	+31.5	0.48 → 0.43	−7.0 → −11.4
Poland	5.9	8.4	+2.5	+41.7	0.44 → 0.42	−7.6 → −11.6
Romania	3.1	5.2	+2.1	+68.1	0.23 → 0.26	−10.4 → −14.7

Source: Authors' calculations based on Eurostat (2025b) and Eurostat data for 2024 reported by the Polish Investment and Trade Agency (2025). Relative growth and ratios calculated from unrounded 2025 values (EU 19.95%; Denmark 42.03%; Sweden 35.04%; Bulgaria 8.55%; Poland 8.36%; Romania 5.21%).

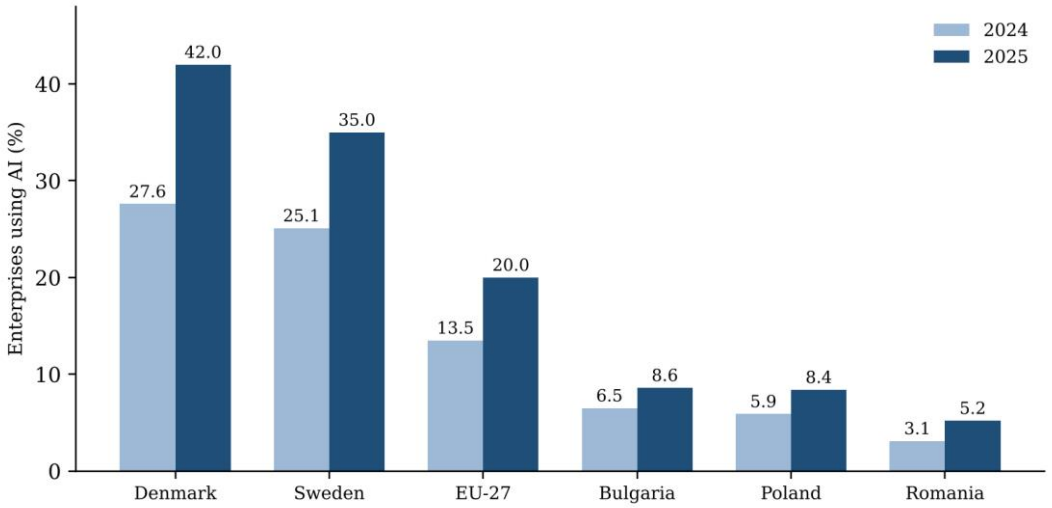


Figure 3. Share of enterprises using AI in selected EU member states, 2024 and 2025. *Source:* Authors' elaboration based on Eurostat data.

These figures sit on top of a low baseline of general digitalisation. In 2023, 72.1% of Romanian enterprises had a very low digital intensity index, and only 1.3% a very high one, compared with 5% at the EU level (Eurostat, 2024). Because AI adoption is cumulative on prior digital investments—cloud services, structured data, digital customer channels—the CEE gap in AI is in part an inherited gap in digital foundations. This is consistent with the observation of Євсюкова (2024) that SME markets in the Polish, Romanian, Moldovan and Ukrainian border region exhibit structural characteristics that condition the value yield attainable from digital optimisation, and with the argument of Сидорук (2023) that resource and regulatory constraints shape not only whether, but how, firms in Poland, Romania and Moldova adopt AI.

5.4 Barriers to adoption

Among EU enterprises that had considered using AI but had not adopted it, the most frequently cited barrier in 2025 was a lack of relevant expertise (70.3%), followed by unclear legal consequences (53.6%) and data-protection and privacy concerns (52.7%). Only 17.8% stated that AI was not useful for the enterprise (Table 4). The structure of barriers therefore points primarily to capability and institutional constraints rather than to a lack of perceived value. Comparable patterns are observed in lagging economies: in Bulgaria, for example, the corresponding shares were 72.7%, 50.3% and 47.7%.

Table 4. Reported barriers to AI use among enterprises that considered adopting AI, 2025 (% of such enterprises)

Barrier	EU-27	Bulgaria	TOE dimension	Interpretation for SMEs
Lack of relevant expertise	70.3	72.7	Organisational	Skills scarcity is the dominant constraint; scale disadvantages in recruiting specialists
Unclear legal consequences	53.6	50.3	Environmental	Regulatory uncertainty imposes a fixed compliance-learning cost
Data protection and privacy concerns	52.7	47.7	Environmental / technological	GDPR exposure; limited in-house legal and data-governance capacity
AI not useful for the enterprise	17.8	16.3	Technological	A minority perceive no relevant use case

Source: Eurostat (2025b), as compiled by the Bulgarian Chamber of Commerce and Industry (2025); TOE classification by the authors. Shares refer only to enterprises that had ever considered using AI (11.1% of EU enterprises).

Each of the three leading barriers has a strong fixed-cost component that weighs more heavily on small firms. Acquiring expertise, interpreting regulation and establishing data-governance procedures require broadly similar effort whether the firm employs 20 people or 2,000. These barriers therefore provide a direct explanation for the size gradient documented in Section 5.2, and suggest that interventions which socialise these fixed costs—shared advisory services, standardised compliance guidance, sector-specific templates—are likely to be more effective for SMEs than generic subsidies.

5.5 Evidence synthesis: the magnitude of productivity gains

Table 5 and Figure 4 summarise the causal evidence on productivity effects. Across studies, reported gains range from 12% to 56% on the measured outcome. Three regularities emerge. First, gains are largest for well-defined, text- or code-based tasks that lie within the capabilities of current models. Second, gains are systematically larger for less experienced workers, with the effect for novice customer-support agents (34%) more than double the average effect (14%). Third, gains are conditional on task fit: outside the capability frontier, AI assistance can reduce accuracy.

Table 5. Causal evidence on the productivity effects of AI assistance

Study	Setting and sample	Design	Principal result	Relevance to SMEs
Brynjolfsson et al. (2025)	Customer support; 5,179 agents	Staggered rollout	+14% issues resolved per hour; +34% for novices; minimal effect for experts	Skill levelling; diffusion of best practice without senior staff
Noy & Zhang (2023)	Professional writing; 453 professionals	Randomised experiment	−40% completion time; +18% quality	Administrative and communication tasks prevalent in SMEs
Dell'Acqua et al. (2023)	Management consulting; 758 consultants	Field experiment	+12.2% tasks; +25.1% speed; >40% quality within frontier; −19 pp correctness outside frontier	Importance of task selection (jagged frontier)
Peng et al. (2023)	Software development; professional programmers	Randomised experiment	55.8% faster task completion	Small IT and digital-service firms
Czarnitzki et al. (2023)	German firms; innovation survey	Panel and IV estimation	Positive, significant association between AI use (and intensity) and firm productivity	Firm-level confirmation beyond task level
Acemoglu (2025)	US economy; task-based model	Macroeconomic calibration	≤0.66% TFP gain over 10 years (≤0.53% adjusted)	Aggregate gains modest; concentration in exposed firms

Source: Authors' compilation. pp = percentage points; IV = instrumental variables; TFP = total factor productivity.

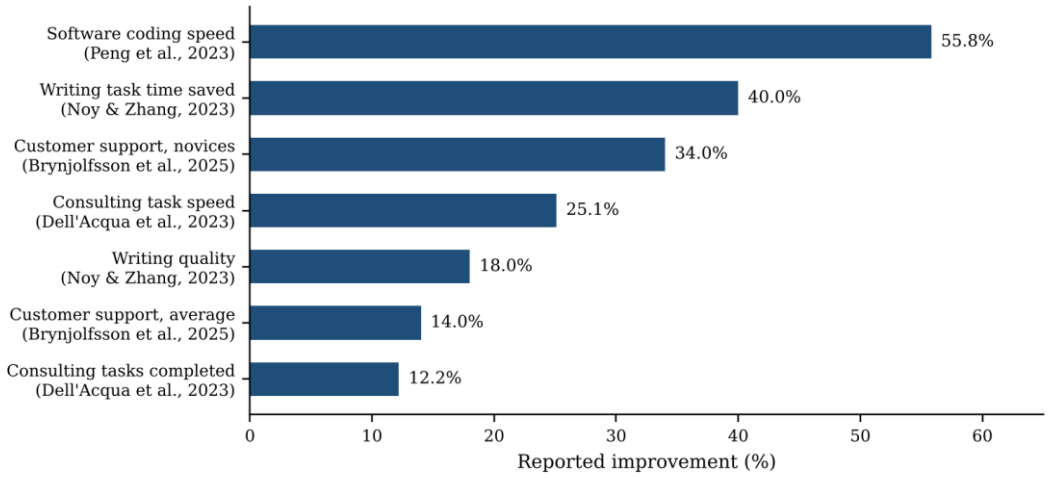


Figure 4. Task-level productivity improvements reported in experimental and quasi-experimental studies of AI assistance. *Source:* Authors' elaboration based on the studies listed in Table 5. Measures differ across studies (speed, output or quality) and are not directly comparable.

5.6 Illustrative resource-utilization scenarios for SMEs

To translate task-level evidence into firm-level magnitudes, Table 6 applies the task-based approximation in which the productivity effect equals the share of the firm's labour tasks affected by AI multiplied by the average cost saving on those tasks. Three scenarios are constructed for a stylised SME. The *conservative* scenario assumes that 10% of tasks are affected with an average saving of 14%, matching the average customer-support effect. The *moderate* scenario assumes 20% of tasks and a 25% saving, matching the speed gain within the frontier among consultants. The *high-exposure*

scenario, relevant to knowledge-intensive service firms, assumes 30% of tasks and a 40% saving, matching the time reduction in professional writing.

Table 6. Illustrative first-order labour productivity effects of AI for a stylised SME

Scenario	Share of tasks affected (s)	Average cost saving on affected tasks (c)	First-order productivity effect (s × c)	Equivalent hours freed per 10 full-time employees per year*	Typical SME profile
Conservative	10%	14%	1.4%	≈ 250	Manufacturing or retail SME using AI for administration only
Moderate	20%	25%	5.0%	≈ 900	Service SME using AI for customer communication, marketing and documentation
High exposure	30%	40%	12.0%	≈ 2,160	Knowledge-intensive SME (consulting, IT, design, professional services)

Source: Authors' calculations following the task-based approximation in Acemoglu (2025), with savings calibrated on Brynjolfsson et al. (2025), Dell'Acqua et al. (2023) and Noy and Zhang (2023). *Assuming 1,800 working hours per full-time employee per year. Figures are illustrative upper bounds on first-order effects before adjustment costs, and are not forecasts for any specific firm.

Even the conservative scenario implies a non-trivial reallocation of resources: around 250 working hours per year for a firm with ten employees, equivalent to roughly 14% of one full-time position. In the high-exposure scenario, the freed capacity approaches 1.2 full-time positions. Whether these freed resources raise measured productivity depends on whether they are redeployed to value-creating activities or simply absorbed as slack—a managerial rather than a technological question. Moreover, these figures exclude the transition costs emphasised in the productivity J-curve literature (Brynjolfsson et al., 2021), which may be proportionally larger for SMEs.

6. Discussion

6.1 AI as a resource-utilization technology for constrained firms

The findings support the view that, for SMEs, AI is first and foremost a resource-utilization technology. Its most immediate effect is to relax the binding constraint on the scarcest input in small firms: skilled labour time, and particularly managerial and specialist time. The skill-levelling effect documented in the experimental literature is especially relevant. Large firms typically address skill shortages by hiring specialists; SMEs frequently cannot. If AI raises the performance of less experienced workers towards that of experts, it partly substitutes for the specialist roles that small firms are unable to fill, consistent with Proposition 2. This interpretation aligns with OECD survey evidence that generative AI was in use in 31% of SMEs across seven OECD countries in 2024 and that SMEs regard it as a means of offsetting skill gaps and labour shortages (OECD, 2025).

At the same time, the dominance of expertise shortages among adoption barriers (70.3%) reveals a paradox: the firms that could gain most from AI's skill-substituting properties are those least equipped to implement it. Resolving this paradox requires that the initial implementation capability be supplied externally—through vendors, intermediaries, peer networks or public support—so that the firm can then benefit from AI's internal capability-enhancing effects.

6.2 From productivity to competitive positioning

The translation of productivity gains into competitive positioning is neither automatic nor uniform. Because generative AI tools are broadly available on similar commercial terms, efficiency gains derived from generic use will tend to diffuse across competitors and be passed on to customers through prices. In this sense, early adoption confers a temporary rather than permanent advantage, and failure to adopt becomes a source of competitive *disadvantage* as rivals' costs fall. For SMEs, three routes to more durable positioning can be identified, in line with Proposition 3: embedding AI in processes that draw on proprietary data accumulated through customer relationships; using freed capacity to offer personalised, high-touch services that larger competitors find costly to replicate; and exploiting organisational agility to reconfigure business models faster than incumbents.

The jagged-frontier finding adds a further dimension. Competitive advantage may derive not from access to AI but from superior *judgement* about

where to apply it. Firms that develop routines for testing AI on specific tasks, verifying outputs and withdrawing AI from tasks where it underperforms will capture gains while avoiding the quality losses that indiscriminate use can produce. Such routines are a form of dynamic capability in the sense of Teece et al. (1997), and they are firm-specific and difficult to imitate.

6.3 Adoption mode as strategy: build, buy or subscribe

The build–buy–subscribe framing advanced by Сидорук (2023) offers a practical bridge between resource constraints and strategic intent. Table 7 summarises the trade-offs. Our analysis suggests that for most SMEs, and particularly for those in lagging CEE economies, a portfolio approach is optimal: subscribe for generic support functions where differentiation is neither possible nor necessary; commission targeted solutions for a small number of core processes where proprietary data can be leveraged; and build in-house only where AI is itself the product or the principal source of differentiation. This logic is consistent with value-yield reasoning of the kind applied by Євсюкова (2024, 2025), in which digital investments are evaluated by the value they yield relative to the resources they absorb, and with Proposition 4.

Table 7. Strategic comparison of AI adoption modes for SMEs

Dimension	Subscribe (SaaS / platform)	Buy (commission bespoke)	Build (in-house)
Upfront investment	Very low	Moderate to high	High
Time to value	Days to weeks	Months	Months to years
Required internal expertise	Low (user-level)	Moderate (specification, vendor management)	High (data science, engineering)
Control over data and model	Limited	Moderate to high (contract-dependent)	Full
Differentiation potential	Low (available to competitors)	Moderate to high	High
Regulatory and compliance burden	Shared with provider	Shared; contractual allocation	Borne fully by the firm
Best suited for	Generic support functions (drafting, translation, scheduling, basic analytics)	Core processes using proprietary data (forecasting, pricing, quality control)	Firms whose product is AI-based or where AI is the core differentiator

Source: Authors' elaboration, building on the adoption-mode typology of Сидорук (2023).

6.4 Why the gap may widen: cumulative dynamics

The divergence between relative and absolute convergence documented in Sections 5.2 and 5.3 has important theoretical implications. If AI benefits are cumulative—because early adopters accumulate data, organisational learning and AI-ready processes that make subsequent adoption cheaper and more productive—then the absolute gap between leaders and laggards will tend to widen even as laggards grow rapidly in percentage terms, as stated in Proposition 6. This dynamic is visible both between large firms and SMEs and between Nordic and CEE economies. It suggests that policy interventions should be judged not by the growth rate of lagging groups but by whether they close the absolute distance to the frontier.

6.5 Implications for SME managers

Five managerial recommendations follow from the analysis:

- **Start with time audits, not technology.** Identify the recurring tasks that consume the most labour time and assess which lie within current AI capabilities; the largest early gains are typically in text-based administration, customer communication and documentation.
- **Prioritise task fit.** Pilot AI on a small number of well-specified tasks, establish verification procedures and measure outcomes before scaling, recognising that AI can degrade quality on tasks outside its frontier.
- **Adopt a portfolio of adoption modes.** Subscribe for generic functions; reserve investment in bespoke solutions for processes that use proprietary data and differentiate the firm.
- **Redeploy freed capacity deliberately.** Productivity gains materialise only when the time released is redirected to sales, product development, quality or customer relationships.
- **Invest in people alongside tools.** Because less experienced employees benefit most, structured training and clear usage policies can maximise returns while managing data-protection and intellectual-property risk.

6.6 Implications for policy, with reference to Romania and CEE

For lagging economies such as Romania, the analysis yields four policy priorities. First, because the binding constraints are expertise and regulatory uncertainty, public support should concentrate on socialising fixed costs: practical, sector-specific advisory services delivered through European Digital Innovation Hubs, chambers of commerce and universities, rather than generic grants for technology purchase. Second, regulatory clarity should be treated as an economic intervention. The EU Artificial Intelligence Act (Regulation (EU) 2024/1689) contains specific provisions to support SMEs, including priority access to regulatory sandboxes; national authorities can reduce the compliance-learning burden by publishing simplified guidance and templates tailored to typical SME use cases. Third, AI policy should be integrated with the broader digital-intensity agenda, since AI adoption builds on foundational digitalisation in which Romania remains furthest from the Digital Decade targets. Fourth, statistical monitoring should report absolute as well as relative gaps, and should be extended to micro-enterprises, which are currently outside the scope of the Eurostat survey but constitute the majority of SMEs.

Universities have a distinctive role in this agenda. By embedding applied AI skills in business and economics curricula, providing executive education for SME owner-managers, and acting as neutral intermediaries between firms and technology providers, institutions in regional centres such as Cluj-Napoca can help to build the absorptive capacity on which the returns to AI depend.

6.7 Limitations and directions for future research

This study has several limitations. First, the diffusion analysis relies on aggregate statistics, which do not allow the propositions to be tested at the firm level or causal relationships between adoption and outcomes to be identified. Second, the 2025 change in the definition of AI means that part of the measured 2024–2025 increase reflects the broader scope of the indicator. Third, the Eurostat survey excludes micro-enterprises, and its binary measure of use does not capture intensity, depth or adoption mode. Fourth, the experimental evidence on productivity derives largely from large organisations and from tasks in English-language, knowledge-intensive settings; its transferability to SMEs in CEE manufacturing, agriculture and traditional services requires direct verification. Fifth, the scenario analysis is illustrative and omits adjustment costs, second-order effects and general-equilibrium responses.

Future research should therefore prioritise (i) firm-level panel surveys of SMEs in CEE that record AI adoption mode, intensity and complementary investments alongside productivity outcomes; (ii) field experiments with SMEs that test the effect of advisory and training interventions on adoption and performance; (iii) studies of micro-enterprises; and (iv) empirical tests of Propositions 1–6, including the hypothesised cumulative dynamic and the role of adoption mode in moderating competitive outcomes.

7. Conclusion

Artificial intelligence offers SMEs a means of relieving the constraint that most limits their growth: scarce skilled labour time. Controlled studies show that AI assistance can raise task-level productivity by between roughly 12% and 56%, with the largest gains for less experienced workers—an effect well suited to the thin specialist layers of small firms. Translated to the firm level, plausible first-order gains range from around 1.4% for SMEs that use AI only for peripheral administrative tasks to around 12% for knowledge-intensive firms with high task exposure.

Yet the diffusion of AI remains strongly uneven. Between 2024 and 2025, small EU enterprises adopted AI faster in relative terms than large enterprises, but the absolute gap widened to 38.0 percentage points; Romania grew fastest among the countries examined, yet fell further behind the EU average in absolute terms. Barriers are dominated by expertise shortages and legal uncertainty, both of which bear disproportionately on small firms. The conversion of AI-driven productivity into durable competitive positioning depends on complementary, firm-specific resources, on judgement about where AI should and should not be applied, and on a deliberate choice of adoption mode suited to each process.

For SMEs, the strategic question is therefore no longer whether AI is relevant, but how to configure a portfolio of AI investments that maximises the value yield of scarce resources. For policymakers, particularly in CEE, it is how to reduce the fixed costs of expertise and regulatory compliance that currently prevent the firms with the most to gain from capturing those gains. Addressing both questions is essential if AI is to narrow, rather than widen, the productivity divide between small and large firms and between Europe's digital leaders and laggards.

Declarations

Author contributions: A.M.: conceptualisation, methodology and writing—original draft; E.P.: data curation, formal analysis and visualisation; M.K.: literature review and writing—review and editing; D.M.: validation, policy analysis and writing—review and editing. All authors have read and approved the final manuscript.

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Conflicts of interest: The authors declare no conflicts of interest.

Data availability statement: The data analysed in this study are publicly available from Eurostat (survey on ICT usage and e-commerce in enterprises) and from the publications cited in the reference list.

Ethical statement: This study uses only publicly available, aggregated secondary data and published research; no human participants were involved.

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