



Publisher

<http://jssidoi.org/esc/home>

CURRENT TRENDS IN THE ADOPTION OF AI TECHNOLOGIES IN SMALL AND MEDIUM-SIZED ENTERPRISES IN THE EUROPEAN UNION*

Chenqing Zhang ¹, Edmunds Čižo ², Zhongdong Yang ³, Alina Danileviča ⁴, Ieva Boļakova ⁵,
Vera Komarova ⁶, Jiangang Qi ^{7*}

¹ Trinity College Dublin, College Green, Dublin 2, Ireland

^{2,4,5,6} Daugavpils University, 13 Vienības Street, Daugavpils, Latvia

³ Web3 Capital Pte. Ltd., 17/F, 12 Marina Boulevard, Singapore

⁴ EKA University of Applied Sciences, 62 Pervānas Street, Riga, Latvia

^{7*} Research Center of Intellectual Property, Zhongnan University of Economics and Law, Wuhan, Hubei, China

E-mails: ¹zcq_law_research@vip.163.com; ²edmunds.cizo@du.lv; ³stephen@web3.capital;

⁴alina.danilevica@du.lv; ⁵ieva.bolakova@du.lv; ⁶vera.komarova@du.lv;

^{7*}qijiangang@zuel.edu.cn (Corresponding author)

Received 11 January 2026; accepted 24 March.2026; published 30 June 2026

Abstract. This study analyses the rapid expansion of artificial intelligence (AI) adoption among small and medium-sized enterprises (SMEs) in the EU-27 during 2021–2025 and examines whether this diffusion leads to convergence or persistent disparities across countries. Using harmonised Eurostat indicators on enterprises employing at least one AI technology by size class (10–49 and 50–249 employees), the study combines descriptive analysis with σ -convergence (coefficient of variation) and β -convergence regressions linking average log growth to initial adoption levels. Club convergence analysis is additionally applied to identify heterogeneous dynamics across groups of countries. The results show rapid growth in SME AI adoption: the share of small enterprises using AI increased from 6.1% to 17.0%, while among medium-sized enterprises it rose from 12.6% to 30.4%. Relative dispersion declined (CV: 0.69→0.52 for small firms; 0.62→0.45 for medium-sized firms), indicating σ -convergence, while β -convergence is statistically significant in both segments ($\beta = -0.0815$, $p < 0.01$; $\beta = -0.0872$, $p < 0.001$). However, club convergence analysis shows that convergence is concentrated among high-adoption economies, whereas low-adoption countries display increasing internal divergence. These findings suggest that accelerated AI diffusion alone does not ensure balanced digital transformation, highlighting the importance of targeted SME capability-building in lagging ecosystems.

Keywords: artificial intelligence (AI) technologies; small and medium-sized enterprises (SMEs); AI adoption; adoption gap; convergence; divergence; European Union (EU)

Reference to this paper should be made as follows: Zhang, Ch., Čižo, E., Yang Zh., Danileviča, A., Boļakova, I., Komarova, V., Qi, J. (2026). Current trends in the adoption of AI technologies in small and medium-sized enterprises in the European Union. *Entrepreneurship and Sustainability Issues*, 13(4), 152-169. <http://doi.org/10.9770/k2928634357>

JEL Classifications: O33, L26, C23, O52

Additional disciplines: Innovation economics; SME studies; Digital transformation; Regional development; Econometrics

* The article has been developed and funded within the Daugavpils University's (Latvia) research project No 14-95/2026/17 "AI-Based Enterprise Transformation and Its Impact on Managerial Decision Quality".

1. Introduction

Recent statistical evidence indicates a rapid acceleration in the adoption of artificial intelligence (AI) technologies among small and medium-sized enterprises (SMEs) in the EU-27, forming an important empirical background for the present study. According to Eurostat data, the share of small enterprises (10–49 employees) using at least one AI technology increased from 6.1% in 2021 to 17.0% in 2025. Among medium-sized enterprises (50–249 employees), adoption levels were consistently higher, rising from 12.6% in 2021 to 30.4% in 2025 (Eurostat, 2025). These figures reflect a several-fold increase within a short time horizon and suggest that AI diffusion in the SME sector has entered an accelerated expansion phase (Shi & Shen, 2025; Calvino et al., 2026). At the same time, a persistent size-related adoption gap remains visible across the EU-27 (Eurostat, 2025).

International analytical assessments interpret this dynamic as part of a broader structural wave of digital transformation rather than a temporary fluctuation (OECD, 2025; Innovation, Science and Economic Development Canada, 2025; G7 Industry, Digital and Technology Ministers, 2025; Calvino et al., 2026). OECD analyses emphasise that the diffusion of cloud-based AI services and generative AI tools has reduced entry barriers for SMEs and expanded the scope of feasible business applications, particularly in process automation, customer interaction, and data analytics (OECD, 2025). However, adoption remains uneven across firms and countries due to persistent constraints related to skills shortages, limited data availability, implementation costs, regulatory uncertainty, and differences in national innovation ecosystems (Menshikov et al., 2025; Calvino et al., 2026).

Importantly, rapid growth in adoption rates does not automatically imply inclusive or balanced digital transformation. Empirical studies demonstrate that accelerated digitalisation may simultaneously strengthen technologically advanced firms while widening structural disparities within the SME sector (Čižo et al., 2024; Ruža et al., 2024; Muhammad et al., 2025). Analysing AI adoption during the COVID-19 crisis, Muhammad et al. (2025) show that technological factors (digital inertia, digital literacy), organisational characteristics (entrepreneurial mindset, innovation attitudes, resource constraints), and environmental pressures jointly determine whether AI adoption enhances resilience or contributes to a digital divide.

This perspective is particularly relevant in the EU context (UNDP, 2019; Grafström & Alm, 2025; Cimino et al., 2025). Although aggregate indicators point to dynamic growth (Eurostat, 2025), the qualitative and structural dimensions of adoption remain differentiated across countries and enterprise size groups. It is therefore not self-evident that faster AI diffusion automatically translates into sustainable productivity gains or long-term competitiveness, despite optimistic claims in parts of the literature (e.g., Papić, 2025; Cimino et al., 2025; Le Dinh et al., 2025). From a structural standpoint, the critical issue may lie not in the speed of adoption per se, but in its distribution. If AI technologies diffuse unevenly across Member States and enterprise size categories, structurally lagging firms and national ecosystems risk losing competitive positions within the Single Market and becoming marginalised in emerging digital value chains.

The question of convergence in AI adoption is thus not merely empirical but also strategically significant in the context of the European Union's digital cohesion agenda. The EU's Digital Decade Policy Programme 2030 explicitly aims to strengthen technological sovereignty, reduce digital disparities between Member States, and ensure that digital transformation contributes to balanced economic development across the Union (European Commission, 2021). SMEs are central to this objective, accounting for over 99% of all enterprises in the EU and a substantial share of employment and value added (European Commission & Joint Research Centre, 2023). Persistent divergence in AI adoption among SMEs may therefore undermine broader goals of economic, social and territorial cohesion enshrined in EU policy frameworks.

Theoretical approaches to regional development and cohesion suggest that technological change may act both as a convergence mechanism and as a source of divergence (Fagerberg, 1995; Hollanders et al., 1999; Sadik, 2007; Scuotto et al., 2023; Grafström & Alm, 2025). Lower entry barriers and scalable digital tools can facilitate catch-up processes. Conversely, knowledge intensity, complementary capabilities, institutional quality, and path dependency may reinforce first-mover advantages and cumulative inequalities. In the case of AI adoption

among SMEs, these mechanisms may operate simultaneously, producing differentiated trajectories across Member States.

Against this background, the research problem of this article can be formulated as follows: does the accelerated diffusion of AI technologies among SMEs in the EU lead to structural convergence in adoption levels across countries and enterprise size categories, or does it reproduce and potentially intensify existing digital disparities? The aim of this article is to analyse current trends in the adoption of AI technologies among small and medium-sized enterprises in the European Union, with particular attention to structural differentiation and convergence dynamics across EU countries and enterprise size groups in the period 2021–2025.

To investigate these dynamics, the study applies a convergence-oriented analytical framework. Convergence analysis, widely used in regional and socio-economic research, examines whether heterogeneous units become more similar or more divergent over space and time with respect to selected indicators (Marques & Soukiazis, 1998). This approach has been successfully applied in studies of regional development and digital inequality, where dispersion measures and longitudinal comparisons help identify processes of catch-up or persistent stratification (Clark et al., 2003; Boronenko et al., 2014; Čižo et al., 2024; Ruža et al., 2024). Applying this framework to AI adoption enables assessment not only of cross-sectional differences between countries and enterprise size categories, but also of their temporal evolution. The empirical analysis is based on harmonised Eurostat data covering all EU countries for the period 2021–2025 (Eurostat, 2025). The dataset includes the percentage of enterprises using at least one AI technology, disaggregated by size class (10–49 and 50–249 employees). This cross-country and longitudinal structure allows for simultaneous examination of growth dynamics and structural dispersion within the EU SME ecosystem.

Although the observed period is relatively short, it is analytically appropriate given the rapidly evolving nature of AI adoption. In such contexts, even a five-year window may capture meaningful divergence or convergence dynamics, particularly when the objective is to analyse relative positioning and dispersion across countries rather than long-run steady-state equilibria. For fast-growing digital indicators, short- to medium-term convergence analysis therefore provides valuable insight into the early formation of structural asymmetries within the European digital economy.

2. Literature review

The growing body of research on AI adoption in SMEs reflects both the accelerating diffusion of advanced digital technologies and the persistence of structural inequalities associated with their use. Existing literature spans multiple analytical levels, from firm-level determinants and organisational capabilities to macro-level processes of technological convergence and divergence. While these strands differ in focus, they converge on a common insight: the diffusion of AI is inherently uneven, shaped by heterogeneous capabilities, resources, and institutional environments, and therefore cannot be assumed to lead automatically to balanced or inclusive development.

Foundational contributions in the economics of technological change emphasise that diffusion processes are neither uniform nor self-equilibrating. Early work by Fagerberg (1995) demonstrates that convergence in technological development depends critically on countries' "social capability," including human capital, innovation systems, and institutional quality. Similarly, Hollanders et al. (1999) show that convergence is not a stable outcome but a contingent process that may shift toward divergence when new technological paradigms emerge and are unevenly adopted. This perspective is reinforced by Clark and Feenstra (2003), who argue that differences in productivity performance are driven less by access to technology than by the efficiency with which it is used. Sadik (2007) extends this reasoning by introducing a threshold model of technological adoption, where only economies below certain cost barriers are able to adopt new technologies, leading to convergence among adopters but persistent divergence between adopters and non-adopters. More recent empirical evidence suggests that, although some convergence in technological capabilities is observable, it is typically slow, partial, and conditioned by structural factors. Grafström and Alm (2025) identify gradual convergence in innovation indicators across EU Member States but emphasise the persistence of substantial gaps in technological capacity, while global analyses indicate that advanced technologies such as AI may

reinforce divergence even as basic digital access converges (UNDP, 2019). Taken together, this literature establishes that technological diffusion—particularly in the case of complex, knowledge-intensive technologies—is path-dependent and conditional, with a strong potential to generate divergence alongside, or even instead of, convergence.

At the firm level, a substantial body of research highlights the central role of organisational capabilities in shaping AI adoption. Early empirical studies indicate that SMEs tend to adopt AI incrementally, focusing initially on operational efficiency applications such as automation and data analytics before progressing to more advanced, strategic uses (Papić, 2025). This staged adoption pattern suggests that diffusion is not only uneven across firms but also differentiated in terms of depth and sophistication. Building on this insight, Cimino et al. (2025) demonstrate that dynamic capabilities—specifically the ability to sense, seize, and transform opportunities—are key determinants of both AI adoption intensity and its performance outcomes. Similarly, Scuotto et al. (2023) introduce a “crossvergence” perspective, arguing that digital transformation processes may simultaneously produce convergence through shared technologies and divergence through heterogeneous firm-level capabilities and strategic responses. More recent studies further highlight the functional heterogeneity of AI adoption within firms. Le Dinh et al. (2025) show that SMEs concentrate AI use in operational and analytical functions, while more advanced applications remain limited, reflecting differences in perceived usefulness and organisational readiness. Kopka and Fornahl (2024) provide additional evidence of heterogeneous outcomes, demonstrating that AI adoption affects firms differently depending on their size and position relative to the productivity frontier. Collectively, these findings indicate that AI adoption is not simply a matter of access to technology but a capability-driven process, where firms differ significantly in their ability to integrate, scale, and capitalise on AI.

A complementary stream of research focuses on structural inequalities in AI adoption, often framed through the lens of the digital divide and resource-based perspectives. Empirical studies consistently show that digital transformation may simultaneously enhance the performance of leading firms while widening gaps within the SME sector (Čižo et al., 2024; Ruža et al., 2024; Muhammad et al., 2025). At the firm level, adoption is constrained by a complex set of interrelated factors, including skills shortages, limited data availability, financial constraints, and organisational readiness (Ayinaddis, 2025; Sánchez et al., 2025). Qualitative evidence reinforces this view, identifying barriers such as insufficient data infrastructure, lack of specialised talent, and dependence on external expertise (Roa Baez & Igbekele, 2021). Recent research also highlights the importance of strategic alignment and leadership in shaping adoption outcomes. Ul Haq et al. (2025) show that AI contributes to firm performance primarily when supported by technological readiness and managerial vision, while Amanollahnejad et al. (2026) conceptualise AI adoption as a recursive socio-technical process shaped by continuous interactions between organisational, technological, and environmental factors. These studies collectively suggest that AI diffusion is structurally uneven because firms differ in their resource endowments, organisational capabilities, and institutional contexts. As a result, equal access to AI technologies does not translate into equal outcomes, reinforcing the distinction between input and output digital inequality.

At the macro level, a growing body of literature highlights the importance of national innovation systems and ecosystem conditions in shaping AI adoption. Cross-country analyses show that AI diffusion remains limited to a minority of firms and is strongly associated with complementary assets such as digital infrastructure, human capital, and prior digitalisation (Calvino et al., 2026). These findings are consistent with broader evidence on the role of national ecosystems in determining digital transformation trajectories (Menshikov et al., 2025) and with policy-oriented analyses emphasising structural barriers related to skills, data, and regulatory environments (OECD, 2025). Importantly, these factors vary significantly across EU Member States, contributing to persistent differences in adoption patterns. At the same time, the literature suggests that AI diffusion is embedded in broader processes of technological convergence and divergence. While some degree of convergence may occur through the diffusion of widely accessible technologies, advanced technologies such as AI are more likely to amplify existing inequalities due to their reliance on complementary capabilities and institutional support. This dual dynamic—simultaneous convergence in access and divergence in capability—has been identified as a defining feature of contemporary digital transformation (UNDP, 2019).

Despite the richness of existing research, several important gaps remain. First, much of the literature focuses either on micro-level determinants of AI adoption or on macro-level patterns of technological convergence, with limited integration between these perspectives. As a result, the link between firm-level capabilities and cross-country convergence dynamics remains insufficiently explored. Second, while the uneven nature of AI diffusion is widely acknowledged, there is a lack of systematic empirical analysis of whether these disparities are increasing or decreasing over time within the EU SME sector. Existing studies tend to provide static snapshots of adoption levels or determinants, rather than examining the dynamic evolution of differences across countries and firm categories. Third, the literature pays limited attention to the role of enterprise size in shaping convergence processes, despite consistent evidence of a size-related adoption gap. In particular, there is a need to analyse whether smaller and medium-sized enterprises follow similar or divergent trajectories in AI adoption across different national contexts.

Against this background, the key research gap lies in the absence of a comprehensive empirical analysis that examines how differences in AI adoption among SMEs across EU Member States evolve over time, taking into account both cross-country variation and differences between small and medium-sized enterprises. Existing studies rarely assess whether countries with initially lower levels of AI adoption are catching up with more advanced ones, or whether the persistent adoption gap between small (10–49 employees) and medium-sized (50–249 employees) enterprises is narrowing or widening. Moreover, the dynamic aspect of these differences remains insufficiently explored, as most research focuses on static comparisons rather than changes over time. The present study addresses this gap by applying convergence approaches to harmonised Eurostat data for the period 2021–2025.

3. Conceptual framework of the study

The conceptual framework of the present study is based on the integration of several theoretical approaches that make it possible to explain both the mechanisms of AI adoption at the firm level and the structural differentiation and dynamics of disparities across EU countries. In particular, the framework combines the Technology Acceptance Model (TAM), Digital Divide Theory, the resource–asset–capital approach, and the convergence paradigm, complemented by an analysis of club convergence. Such a synthesis provides a multi-level explanation of AI diffusion processes among SMEs and makes it possible to link micro- and macroeconomic aspects of digital transformation.

At the micro-level, the conceptual foundation is provided by the Technology Acceptance Model (Davis, 1989), which explains technology adoption through perceived usefulness and perceived ease of use. In the context of SMEs, these perceptions are manifested at the organisational level through managerial decision-making and strategic orientation. Firms that perceive AI technologies as beneficial for performance enhancement and manageable in terms of implementation complexity are more likely to adopt them (Papić, 2025; Cimino et al., 2025). Conversely, perceived risks, lack of expertise, and organisational inertia may limit adoption. Thus, TAM explains the motivational and cognitive mechanisms underlying AI diffusion, particularly at the early stages of adoption.

However, individual or organisational acceptance alone does not explain the observed structural disparities in AI adoption. To address this limitation, the framework incorporates Digital Divide Theory (van Dijk, 2017), which conceptualises inequality in access to and use of digital technologies. The theory distinguishes between motivational, material, skills, and usage access, all of which are relevant in the SME context. Applied to AI adoption, these dimensions correspond to firms' willingness to adopt AI, availability of technological infrastructure, digital competencies, and the extent to which AI is effectively integrated into business processes. Importantly, this approach allows distinguishing between input inequality (differences in access to resources and capabilities) and output inequality (differences in the ability to generate value from AI adoption). Empirical studies confirm that even when access to digital technologies improves, disparities in outcomes persist due to differences in organisational capabilities and resource endowments (Čižo et al., 2024; Ruža et al., 2024; Muhammad et al., 2025).

To further explain these differences, the framework draws on the resource–asset–capital approach (Meņšikovs, 2009; Komarova et al., 2022), which conceptualises development as a process of transforming resources into assets and, subsequently, into capital. Within this framework, technological resources—such as digital infrastructure, data availability, and AI-related competencies—play an increasingly important role. However, firms and national ecosystems differ not only in the availability of these resources but also in their ability to activate and capitalise on them. This implies that AI adoption is not merely a function of resource availability but of the efficiency with which these resources are transformed into productive and innovative outcomes (Calvino et al., 2026; ul Haq et al., 2025). As a result, structural differences in resource portfolios across countries and enterprise size groups may lead to differentiated trajectories of AI adoption. At the macro level, the framework is grounded in the convergence paradigm, which allows assessing whether differences in AI adoption across countries and enterprise size categories are decreasing or increasing over time. Following the classical approach (Barro & Sala-i-Martin, 1992, 1997), two main types of convergence are distinguished. β -convergence refers to a process in which units with lower initial levels of an indicator exhibit higher growth rates, implying a catching-up effect. In the context of this study, β -convergence would indicate that countries with initially low levels of AI adoption among SMEs are adopting AI more rapidly than more advanced countries. σ -convergence, in turn, refers to a reduction in dispersion of an indicator across units and is typically measured using the coefficient of variation (Marques & Soukiazis, 1998). A decline in dispersion indicates convergence, while an increase signals divergence.

At the same time, recent research suggests that convergence processes in the EU are often not uniform but occur within groups of countries with similar structural characteristics. This has led to the concept of club convergence, according to which economies form clusters (or “clubs”) that converge internally but diverge from other groups (Barrios & Flores, 2019; Glawe, 2025). In the EU context, such clustering often reflects differences between more advanced and less developed economies, as well as variations in innovation capacity, institutional quality, and digital readiness. Applying this concept to AI adoption among SMEs implies that convergence may occur within groups of countries with similar levels of technological development, while divergence persists between these groups. This perspective is particularly relevant given empirical evidence that advanced digital technologies tend to reinforce existing inequalities due to their dependence on complementary capabilities (Sadik, 2007; UNDP, 2019).

The integration of these theoretical approaches provides a coherent analytical framework for the present study. TAM explains the motivational and organisational determinants of AI adoption; Digital Divide Theory highlights structural inequalities in access and use; the resource–asset–capital approach explains differences in the ability to transform technological resources into economic outcomes; and convergence analysis evaluates whether these differences are narrowing or widening over time. The addition of club convergence further allows capturing the possibility that AI adoption dynamics may differ systematically across groups of EU countries. Taken together, this framework allows analysing AI adoption not only as a process of technological diffusion but also as a structurally differentiated and potentially stratifying phenomenon. It enables a multi-level assessment of whether the rapid expansion of AI adoption among SMEs in the European Union leads to more similar adoption patterns across countries and between small and medium-sized enterprises, or whether it reinforces existing disparities and creates distinct clusters of technological development within the EU.

4. Research methodology

The empirical strategy of the present study is grounded in the convergence framework widely used in regional and socio-economic analysis to examine whether differences in key indicators across heterogeneous units decrease or increase over time. In contrast to approaches that focus solely on static comparisons of adoption levels, convergence analysis enables the assessment of the dynamic evolution of disparities across countries and enterprise size categories, making it particularly suitable for analysing the diffusion of rapidly evolving technologies such as AI (Marques & Soukiazis, 1998). In line with the research objective, the methodology is designed to capture both cross-country variation and differences between small and medium-sized enterprises, as well as their changes over time.

The empirical analysis is based on harmonised Eurostat data covering all EU Member States for the period 2021–2025 (Eurostat, 2025). The dataset includes the percentage of enterprises using at least one AI technology, disaggregated by size class: small enterprises (10–49 employees) and medium-sized enterprises (50–249 employees). This structure allows for consistent cross-country comparison and for analysing differences between enterprise size groups. The longitudinal dimension of the dataset makes it possible to examine both growth dynamics and structural dispersion. Although the observed period is relatively short, it is analytically appropriate given the high growth rates and rapid structural changes characteristic of emerging digital technologies.

The analysis proceeds in several stages. First, descriptive statistical analysis is conducted to identify initial differences in AI adoption across countries and between small and medium-sized enterprises, as well as overall growth patterns during the period under study. This step provides the empirical foundation for subsequent convergence analysis.

Second, σ -convergence is assessed to evaluate changes in dispersion of AI adoption across countries. σ -convergence is measured using the coefficient of variation (CV), defined as:

$$CV = \sigma_t / x \quad (1)$$

where σ_t is the standard deviation of AI adoption levels across countries in year t , x is the corresponding mean value (Marques & Soukiazis, 1998). A decrease in CV over time indicates σ -convergence (a reduction in dispersion), while an increase indicates σ -divergence. In this study, the coefficient of variation is calculated separately for small and medium-sized enterprises, allowing for comparison of dispersion dynamics between these groups. Following conventional interpretation, values below 10% indicate low dispersion, 10–30% moderate dispersion, 30–60% high dispersion, and above 60% very high dispersion. Third, β -convergence analysis is applied to examine whether countries with lower initial levels of AI adoption exhibit higher subsequent growth rates. The standard regression specification is:

$$1 / T \ln ((y_{i,t} + T) / y_{i,t}) = \sigma_t + \beta \ln (y_{i,t}) + \varepsilon_i \quad (2)$$

where $y_{i,t}$ represents the level of AI adoption in country i in year t , and T is the time interval (Barro & Sala-i-Martin, 1992, 1997). A negative and statistically significant coefficient β indicates β -convergence, implying that countries with lower initial adoption levels grow faster (catch-up effect). A positive or insignificant coefficient suggests divergence or persistence of differences. The regression is estimated separately for small and medium-sized enterprises, allowing for identification of size-specific convergence patterns.

In addition to absolute β -convergence, the analysis conceptually allows for conditional convergence, where differences in structural characteristics—such as digital infrastructure, human capital, and institutional quality—may affect convergence dynamics. Although these factors are not explicitly modelled econometrically in the present study, their influence is considered in the interpretation of results (Calvino et al., 2026; OECD, 2025). Finally, the study incorporates elements of club convergence analysis to account for the possibility that convergence processes may occur within groups of countries rather than across the entire EU. The concept of club convergence suggests that economies with similar structural characteristics converge toward similar steady states, while divergence persists between groups (Fagerberg, 1995; Hollanders et al., 1999). Formally, this implies that:

$$\lim_{t \rightarrow \infty} |y_{i,t} - y_{j,t}| = 0 \text{ for } i, j \in C_k \quad (3)$$

where C_k denotes a specific convergence club (Alexiadis, 2012). In the context of this study, such clubs may correspond to groups of EU countries with similar levels of economic development, innovation capacity, or digital readiness. Empirically, club convergence is explored through comparative analysis of country groupings and the identification of patterns in adoption levels and growth rates that suggest clustering of trajectories. This

approach allows capturing heterogeneous convergence dynamics that may not be observable through aggregate σ - and β -convergence measures.

Overall, the methodological framework combines descriptive analysis with σ -convergence, β -convergence, and elements of club convergence analysis, providing a comprehensive approach to examining AI adoption among SMEs in the European Union. This integrated methodology makes it possible to assess not only whether AI adoption is increasing, but also whether differences across countries and between small and medium-sized enterprises are narrowing, persisting, or widening over time, thereby offering a robust empirical basis for analysing the evolving structure of AI diffusion in the EU SME sector.

5. Research results

The results of the empirical analysis are presented in this section in order to identify key patterns in the adoption of AI technologies among SMEs across EU Member States and to assess whether these patterns indicate convergence or divergence over time. Building on the convergence-oriented methodological framework, the analysis focuses on three interrelated dimensions: overall growth dynamics, cross-country dispersion, and differences between small and medium-sized enterprises. Particular attention is given to whether countries with initially lower levels of AI adoption are catching up with more advanced economies, and whether the adoption gap between enterprise size groups is narrowing or persisting. The results are interpreted in light of the theoretical assumptions outlined earlier, including the role of organisational capabilities, resource constraints, and structural differences between national innovation systems, which may lead to heterogeneous adoption trajectories and the potential formation of convergence clubs within the EU.

The empirical analysis begins with a descriptive statistical examination of AI adoption across EU Member States in order to identify general trends, initial differences, and growth patterns over the period 2021–2025. This stage provides the empirical foundation for subsequent convergence analysis by revealing the scale and dynamics of adoption, as well as structural differences between countries and enterprise size groups. Particular attention is paid to the distribution of adoption levels across small (10–49 employees) and medium-sized (50–249 employees) enterprises, allowing for an initial assessment of whether observed growth is accompanied by persistent disparities or signs of alignment across countries (Eurostat, 2025).

Table 1. Enterprises using at least one of the AI technologies, % of small enterprises (10–49 employees), EU countries, 2021–2025

Country	2021	2023	2024	2025
Austria	7.14	8.94	17.83	26.18
Belgium	8.00	10.61	20.70	28.82
Bulgaria	2.60	2.96	5.45	7.17
Croatia	8.06	6.98	10.51	12.77
Cyprus	1.95	3.74	6.30	7.72
Czechia	2.75	4.00	8.72	13.38
Denmark	19.74	12.37	23.52	37.45
Estonia	1.80	4.12	12.14	20.74
Finland	12.37	11.48	20.02	33.51
France	5.03	4.72	8.51	15.04
Germany	8.90	9.68	16.92	23.06
Greece	1.97	3.54	8.20	7.33
Hungary	2.53	2.98	6.50	8.70
Ireland	6.05	5.27	11.75	16.75
Italy	5.35	4.36	6.89	14.23
Latvia	2.79	3.47	7.24	9.77
Lithuania	3.18	3.40	6.51	18.06
Luxembourg	11.53	12.26	21.12	30.48
Malta	8.34	10.75	14.31	17.89
Netherlands	10.10	11.75	19.96	28.76
Poland	1.88	2.25	3.93	5.79
Portugal	5.29	5.77	6.66	9.43
Romania	1.06	1.07	2.57	4.13
Slovakia	4.11	5.95	8.78	15.59
Slovenia	9.42	8.88	19.26	18.29
Spain	6.07	6.39	8.56	17.17
Sweden	7.63	8.69	22.05	30.74

Source: Eurostat, 2025

The data presented in Table 1 demonstrate a rapid increase in the share of small enterprises using AI technologies across the EU during the period under study. Despite the overall upward trend, the distribution of adoption levels remains highly uneven across countries. For instance, countries such as Germany, Denmark, and the Netherlands exhibit relatively high and steadily growing adoption rates, while countries including Bulgaria, Romania, and Greece remain at significantly lower levels throughout the period. At the same time, the data indicate that countries with initially low adoption levels—such as Croatia, Slovakia, and Portugal—tend to experience faster relative growth, suggesting the presence of a catching-up process. However, the persistence of substantial differences between leading and lagging countries indicates that convergence remains partial and uneven. These patterns are consistent with the literature emphasising the capability-driven and non-uniform nature of digital technology diffusion (Calvino et al., 2026; Grafström & Alm, 2025).

Table 2. Enterprises using at least one of the AI technologies, % of medium-sized enterprises (50–249 employees), EU countries, 2021–2025

Country	2021	2023	2024	2025
Austria	14.57	16.91	29.10	44.56
Belgium	16.89	22.99	35.71	54.49
Bulgaria	5.19	5.53	9.99	13.30
Croatia	9.85	11.17	16.49	25.50
Cyprus	5.32	9.43	14.27	15.31
Czechia	7.63	9.79	16.91	28.79
Denmark	37.25	22.56	40.92	58.27
Estonia	5.32	8.06	19.34	33.10
Finland	26.66	26.40	37.67	51.35
France	13.07	10.16	14.52	30.81
Germany	14.80	16.21	28.22	35.56
Greece	7.53	5.68	15.91	15.18
Hungary	3.73	5.54	10.07	15.34
Ireland	13.19	17.79	24.85	28.02
Italy	10.02	7.30	14.71	27.62
Latvia	6.75	8.27	13.65	19.78
Lithuania	7.71	8.78	15.11	30.36
Luxembourg	14.88	19.65	31.86	43.68
Malta	17.82	21.01	25.58	30.69
Netherlands	21.44	19.75	31.19	46.62
Poland	4.96	6.49	10.41	14.77
Portugal	13.40	16.43	15.35	18.21
Romania	1.90	2.38	3.88	7.79
Slovakia	7.01	8.57	15.73	23.05
Slovenia	19.84	16.85	22.66	30.62
Spain	13.36	19.57	20.54	30.10
Sweden	18.09	13.51	34.53	49.60

Source: Eurostat, 2025.

The data for medium-sized enterprises presented in Table 2 reveal a similar but more pronounced pattern of AI adoption. Overall adoption levels are consistently higher than those observed among small enterprises, confirming the existence of a size-related adoption gap (Eurostat, 2025). Countries such as Germany, Finland, and Sweden demonstrate the highest levels of AI adoption among medium-sized enterprises, while Bulgaria, Romania, and Latvia remain among the lowest throughout the observed period. At the same time, countries including Poland, Hungary, and Spain show relatively strong growth dynamics, indicating a degree of catching-up. Compared to small enterprises, the dispersion of adoption levels appears somewhat lower, suggesting a higher degree of alignment among medium-sized firms. Nevertheless, persistent differences across countries indicate that adoption trajectories continue to be shaped by structural factors such as national innovation capacity, digital infrastructure, and organisational readiness. Overall, the descriptive analysis confirms that AI adoption is expanding rapidly across the EU, but remains unevenly distributed both across countries and between enterprise size groups, thereby justifying further convergence analysis.

To further assess whether the observed differences in AI adoption across EU countries are narrowing or widening over time, σ -convergence analysis is applied. This approach focuses on changes in the dispersion of adoption levels and allows evaluating whether countries are becoming more similar in terms of AI use among SMEs. The coefficient of variation (CV), calculated on the basis of country-level adoption data, is used as the main indicator of dispersion. By examining the evolution of this measure separately for small and medium-sized enterprises, it becomes possible to identify whether convergence dynamics differ across enterprise size

groups and whether the rapid growth in AI adoption is accompanied by increasing alignment or persistent heterogeneity across the EU.

Table 3. σ -convergence parameters for SMEs in the EU countries using at least one of the AI technologies, 2021–2025

Parameters	2021	2023	2024	2025
Small enterprises (10–49 employees)				
Standard deviation of AI adoption levels across countries, %	4.22	3.46	6.40	9.31
Mean value, %	6.13	6.53	12.03	17.74
Coefficient of variation (CV), score from 0 to 1	0.69	0.53	0.53	0.52
Medium-sized enterprises (50–249 employees)				
Standard deviation of AI adoption levels across countries, %	7.83	6.54	9.69	13.77
Mean value, %	12.53	13.21	21.08	30.46
Coefficient of variation (CV), score from 0 to 1	0.62	0.50	0.46	0.45

Source: calculated by the authors based on the data from Tables 1–2 and using Formula 1.

The results presented in Table 3 indicate a gradual decline in the coefficient of variation for both small and medium-sized enterprises over the period 2021–2025, suggesting the presence of σ -convergence in AI adoption across EU countries. For small enterprises, the coefficient of variation decreases from 0.69 in 2021 to 0.52 in 2025, while for medium-sized enterprises it declines from 0.62 to 0.45 over the same period. This trend implies that, despite increasing absolute differences in adoption levels—as reflected in the rising standard deviation—the relative dispersion across countries is decreasing due to the rapid growth in average adoption rates. In other words, countries are becoming more similar in proportional terms, even though the gap in absolute values remains significant. At the same time, the lower and more steadily declining coefficient of variation for medium-sized enterprises indicates a higher degree of alignment within this group compared to small enterprises. This suggests that medium-sized firms follow more homogeneous adoption trajectories, while small enterprises remain more sensitive to country-specific conditions. Overall, the results point to partial convergence in AI adoption across the EU, but also highlight the persistence of structural differences, which may be further explored through β -convergence and club convergence analysis.

To further assess whether countries with lower initial levels of AI adoption are catching up with more advanced ones, β -convergence analysis is applied. Unlike σ -convergence, which captures changes in dispersion, β -convergence focuses on the relationship between the initial level of an indicator and its subsequent growth rate. In the context of this study, it allows evaluating whether countries with lower initial shares of enterprises using AI technologies demonstrate higher growth rates over the period 2021–2025. The analysis is conducted separately for small and medium-sized enterprises in order to identify potential differences in convergence dynamics across enterprise size groups. Table 4 presents the intermediate calculations used for estimating β -convergence for small enterprises, including initial levels of AI adoption, growth rates, and their logarithmic transformations.

Table 4. Intermediate calculations for β -convergence, small enterprises (10–49 employees) using at least one of the AI technologies, EU countries, 2021–2025

Country	y_2021	y_2025	Growth (p.p.)	Growth (log)	ln(y_2021)
Austria	7.14	26.18	19.04	0.325	1.966
Belgium	8.00	28.82	20.82	0.320	2.079
Bulgaria	2.60	7.17	4.57	0.254	0.956
Croatia	8.06	12.77	4.71	0.115	2.087
Cyprus	1.95	7.72	5.77	0.344	0.668
Czechia	2.75	13.38	10.63	0.396	1.012
Denmark	19.74	37.45	17.71	0.160	2.983
Estonia	1.80	20.74	18.94	0.611	0.588
Finland	12.37	33.51	21.14	0.249	2.515
France	5.03	15.04	10.01	0.274	1.615
Germany	8.90	23.06	14.16	0.238	2.186
Greece	1.97	7.33	5.36	0.329	0.678
Hungary	2.53	8.70	6.17	0.309	0.928

Ireland	6.05	16.75	10.70	0.255	1.800
Italy	5.35	14.23	8.88	0.245	1.677
Latvia	2.79	9.77	6.98	0.313	1.026
Lithuania	3.18	18.06	14.88	0.434	1.157
Luxembourg	11.53	30.48	18.95	0.243	2.445
Malta	8.34	17.89	9.55	0.191	2.121
Netherlands	10.10	28.76	18.66	0.262	2.313
Poland	1.88	5.79	3.91	0.281	0.631
Portugal	5.29	9.43	4.14	0.145	1.666
Romania	1.06	4.13	3.07	0.340	0.058
Slovakia	4.11	15.59	11.48	0.333	1.413
Slovenia	9.42	18.29	8.87	0.166	2.243
Spain	6.07	17.17	11.10	0.260	1.803
Sweden	7.63	30.74	23.11	0.348	2.032

Note: Growth (log) is calculated as the average annual growth rate $g_i = (1/4) \ln(y_{2025} / y_{2021})$; $\ln(y_{2021})$ denotes the natural logarithm of the initial level of AI adoption.

Source: calculated by the authors based on the data from Table 1 and using Formula 2.

The data presented in Table 4 indicate substantial variation in both initial levels of AI adoption and subsequent growth rates across EU countries. Countries such as Romania, Estonia, Cyprus, and Czechia, characterised by relatively low initial adoption levels, exhibit notably high growth rates over the observed period. In contrast, countries with higher initial levels, including Denmark, Finland, and Luxembourg, tend to demonstrate more moderate growth dynamics. This pattern is consistent with the hypothesis of a catching-up process. To visualise the relationship between initial conditions and growth rates, Figure 1 presents a scatter plot with a fitted regression line, illustrating the direction and strength of the relationship underlying β -convergence.

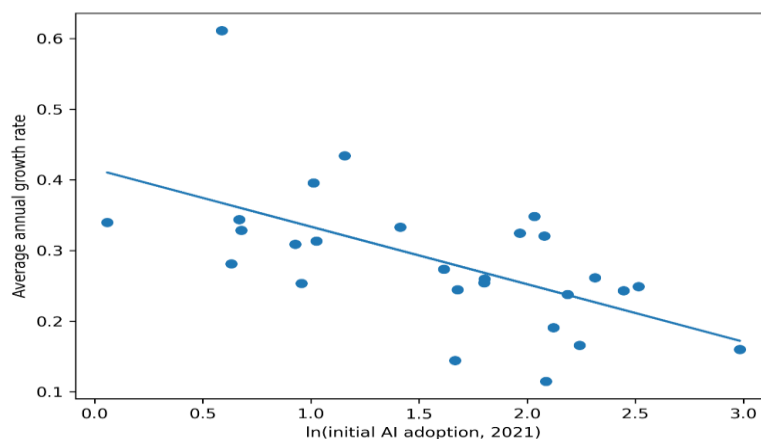


Figure 1. β -convergence in AI adoption among small enterprises in the EU countries, 2021–2025

Source: elaborated by the authors based on the data from Table 4 and using the software IBM SPSS Statistics.

As shown in Figure 1, a clear negative relationship can be observed between the logarithm of the initial level of AI adoption and the subsequent growth rate among small enterprises. Countries with lower starting levels are concentrated in the upper-left part of the graph, indicating higher growth rates, while countries with higher initial adoption are located in the lower-right part, reflecting slower growth. This visual pattern supports the presence of β -convergence, suggesting that countries with initially lower levels of AI adoption are catching up with more advanced economies. At the same time, the dispersion of points around the regression line indicates that convergence is not uniform and may be influenced by country-specific factors such as innovation capacity, digital infrastructure, and organisational readiness (Calvino et al., 2026; OECD, 2025).

This visual pattern is confirmed by the regression results. The estimated β coefficient is negative and statistically significant ($\beta = -0.0815$, $p < 0.01$) (calculated by the authors using the software IBM SPSS Statistics), indicating the presence of β -convergence among EU countries in AI adoption by small enterprises. The explanatory power of the model ($R^2 = 0.354$) suggests that initial conditions account for a substantial share of the variation in growth rates, although country-specific factors remain important.

To examine whether similar dynamics are observed among medium-sized enterprises, the β -convergence analysis is extended to this group. Table 5 presents the corresponding intermediate calculations.

Table 5. Intermediate calculations for β -convergence, medium-sized enterprises (50–249 employees) using at least one of the AI technologies, EU countries, 2021–2025

Country	y_2021	y_2025	Growth (p.p.)	Growth (log)	ln(y_2021)
Austria	14.57	44.56	29.99	0.279	2.679
Belgium	16.89	54.49	37.6	0.293	2.827
Bulgaria	5.19	13.3	8.11	0.235	1.647
Croatia	9.85	25.5	15.65	0.238	2.287
Cyprus	5.32	15.31	9.99	0.264	1.671
Czechia	7.63	28.79	21.16	0.332	2.032
Denmark	37.25	58.27	21.02	0.112	3.618
Estonia	5.32	33.1	27.78	0.457	1.671
Finland	26.66	51.35	24.69	0.164	3.283
France	13.07	30.81	17.74	0.214	2.57
Germany	14.8	35.56	20.76	0.219	2.695
Greece	7.53	15.18	7.65	0.175	2.019
Hungary	3.73	15.34	11.61	0.354	1.316
Ireland	13.19	28.02	14.83	0.188	2.579
Italy	10.02	27.62	17.6	0.253	2.305
Latvia	6.75	19.78	13.03	0.269	1.91
Lithuania	7.71	30.36	22.65	0.343	2.043
Luxembourg	14.88	43.68	28.8	0.269	2.7
Malta	17.82	30.69	12.87	0.136	2.88
Netherlands	21.44	46.62	25.18	0.194	3.065
Poland	4.96	14.77	9.81	0.273	1.601
Portugal	13.4	18.21	4.81	0.077	2.595
Romania	1.9	7.79	5.89	0.353	0.642
Slovakia	7.01	23.05	16.04	0.298	1.947
Slovenia	19.84	30.62	10.78	0.108	2.988
Spain	13.36	30.1	16.74	0.203	2.592
Sweden	18.09	49.6	31.51	0.252	2.895

Note: Growth (log) is calculated as the average annual growth rate $gi = (1/4) \ln(y_{2025} / y_{2021})$; $\ln(y_{2021})$ denotes the natural logarithm of the initial level of AI adoption.

Source: calculated by the authors based on the data from Table 2 and using Formula 2.

The results presented in Table 5 reveal a pattern broadly similar to that observed for small enterprises, but with some notable differences. Countries such as Romania, Hungary, Estonia, and Lithuania, which had relatively low initial levels of AI adoption, demonstrate comparatively high growth rates, indicating strong catch-up dynamics. At the same time, countries including Denmark, Finland, the Netherlands, and Sweden, characterised by higher initial adoption levels, show more moderate growth rates. Compared to small enterprises, the distribution of growth rates among medium-sized enterprises appears more consistent, suggesting a higher degree of alignment across countries. To further illustrate these relationships, Figure 2 presents the corresponding scatter plot with a regression line.

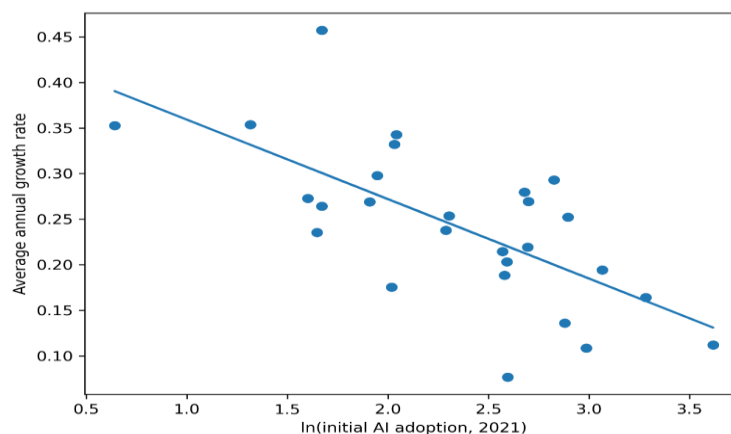


Figure 2. β -convergence in AI adoption among medium-sized enterprises in the EU countries, 2021–2025

Source: elaborated by the authors based on the data from Table 5 and using the software IBM SPSS Statistics.

Figure 2 confirms the presence of a negative relationship between the initial level of AI adoption and subsequent growth rates among medium-sized enterprises, indicating β -convergence across EU countries. Countries with lower starting levels of AI adoption—such as Romania, Bulgaria, Hungary, and Estonia—are located in the upper-

left part of the graph, reflecting higher growth rates, while countries with higher initial adoption levels, including Denmark, Finland, the Netherlands, and Sweden, are concentrated in the lower-right part, indicating more moderate growth dynamics. This visual pattern is supported by the regression results, which reveal a negative and highly statistically significant β coefficient ($\beta = -0.0872$, $p < 0.001$) (calculated by the authors using the software IBM SPSS Statistics). The explanatory power of the model ($R^2 = 0.453$) suggests a relatively strong relationship between initial conditions and subsequent growth rates.

Compared to small enterprises, the more pronounced slope of the regression line, together with the larger absolute value of the β coefficient and higher R^2 , indicates that convergence dynamics are stronger and more consistent among medium-sized firms. This suggests that medium-sized enterprises are better positioned to benefit from catch-up processes, likely due to greater resource availability, more developed organisational structures, and higher levels of digital readiness.

At the same time, the dispersion of observations around the regression line indicates that convergence remains incomplete and heterogeneous across countries. Differences in national innovation systems, digital infrastructure, and organisational capabilities continue to shape adoption trajectories, preventing full alignment. This implies that convergence may not occur uniformly across all EU Member States, but rather within groups of countries sharing similar structural characteristics. Such a pattern points to the potential existence of convergence clubs, which justifies the application of club convergence analysis in the next stage of the study. To identify potential convergence clubs, EU countries were grouped into three categories based on their initial levels of AI adoption in 2021 using a distribution-based (tercile) approach (Alexiadis, 2012). The results reveal a largely consistent structure across small and medium-sized enterprises, with a clear distinction between low-adoption, intermediate, and high-adoption groups.

The low-adoption cluster includes countries such as Romania, Poland, Estonia, Cyprus, Greece, Hungary, Bulgaria, and Latvia, which are consistently characterised by low initial levels of AI use across both enterprise size groups. Similarly, the high-adoption cluster—comprising Denmark, Finland, the Netherlands, Luxembourg, Belgium, Germany, Slovenia, and Malta—remains highly stable across both groups, indicating a structurally advanced set of economies with strong digital capabilities.

At the same time, the intermediate group exhibits greater variability, with several countries—including Czechia, Slovakia, Croatia, and Sweden—shifting between clusters depending on enterprise size. This suggests that convergence dynamics are not fully uniform across firm categories and that some countries occupy transitional positions within the EU digital landscape.

To further examine whether convergence dynamics differ across groups of countries, σ -convergence was assessed within the previously identified convergence clubs. The results reveal a highly uneven pattern of convergence across clusters.

For small enterprises, divergence is observed within both the low- and medium-adoption groups. In the low-adoption cluster, the coefficient of variation increases from 0.264 in 2021 to 0.528 in 2025, indicating a substantial widening of differences among initially lagging countries. A similar pattern is observed in the medium group, where dispersion increases from 0.251 to 0.356. In contrast, the high-adoption group demonstrates a slight decrease in dispersion (from 0.346 to 0.317) (calculated by the authors based on the data from Table 1 and using Formula 1), suggesting weak convergence among leading countries.

A comparable but more pronounced pattern is observed for medium-sized enterprises. While the low-adoption group continues to exhibit divergence (CV increases from 0.328 to 0.411), and the medium group remains largely stable (0.232 to 0.235), the high-adoption group shows clear convergence, with the coefficient of variation decreasing significantly from 0.343 to 0.229 (calculated by the authors based on the data from Table 2 and using Formula 1).

These results indicate that convergence in AI adoption among EU SMEs is not uniform across countries but is largely confined to a group of already advanced economies. At the same time, countries with initially low levels of adoption do not converge among themselves but instead exhibit increasing internal differentiation. This suggests that AI diffusion may reinforce structural stratification within the EU, leading to the emergence of distinct convergence clubs rather than a single, unified convergence process. This pattern suggests that AI diffusion in the EU follows a “dual-speed” trajectory, where convergence occurs among technologically advanced economies, while lagging countries become increasingly heterogeneous.

6. Discussion of results

The empirical results of this study provide robust evidence that the diffusion of AI technologies among SMEs in the EU follows a non-linear and structurally differentiated pattern. While β -convergence is observed for both small and medium-sized enterprises, indicating a general catching-up process, the σ -convergence and club convergence analyses reveal that this process is far from uniform. Instead of a single convergence trajectory, the results point to the emergence of distinct convergence clubs, within which dynamics differ substantially. The finding that convergence is primarily concentrated among countries with initially high levels of AI adoption, while low-adoption countries exhibit increasing internal divergence, aligns with the predictions of endogenous growth theory and the technology-gap approach. According to these frameworks, technological diffusion depends not only on access to innovation but also on absorptive capacity, human capital, and institutional conditions (Fagerberg, 1995; Sadik, 2007). In this context, the observed divergence within the low-adoption group suggests that the mere availability of AI technologies does not guarantee convergence; rather, countries differ significantly in their ability to integrate and scale these technologies. This is consistent with recent empirical studies highlighting the role of organisational capabilities, digital skills, and resource constraints in shaping AI adoption outcomes among SMEs (Calvino et al., 2026; OECD, 2025; Muhammad et al., 2025).

At the same time, the stronger and more consistent convergence observed among medium-sized enterprises suggests that firm size plays a critical role in shaping digital transformation trajectories. Medium-sized firms appear better positioned to benefit from AI adoption due to greater resource endowments, more developed organisational structures, and higher levels of digital maturity. This finding reinforces the argument that digital transformation is not neutral with respect to firm characteristics and may reproduce or even amplify structural inequalities within the SME sector.

The club convergence patterns identified in this study closely resonate with findings from the literature on innovation dynamics in Europe. In particular, the results are consistent with the evidence presented by Barrios et al. (2019), who identify multiple convergence clubs in innovation activity across European regions. Their study demonstrates that regions with similar initial levels of innovation capacity tend to converge towards distinct equilibria rather than a common steady state. Similarly, our findings suggest that EU countries form groups of AI adopters with different trajectories, reflecting underlying differences in technological capabilities and structural conditions. The presence of stable “high-adoption” and “low-adoption” clusters in both studies supports the hypothesis that technological development in Europe follows a centre–periphery pattern, where advanced regions maintain their leadership while lagging regions face persistent challenges in catching up.

However, an important difference emerges in the dynamics observed in this study. While Barrios et al. (2019) report some degree of convergence between clubs over time, our results indicate that, in the case of AI adoption among SMEs, divergence within lagging groups may be intensifying. This suggests that AI technologies, particularly in their current phase of rapid development, may act as a divergence force as much as a convergence mechanism. The dual nature of technological change—simultaneously enabling catch-up and reinforcing disparities—has been widely discussed in the literature (Roa Baez & Igbekele, 2021; Glawe, 2025), and our findings provide empirical support for this perspective in the context of AI diffusion.

From a policy perspective, these results have important implications for the European Union’s digital cohesion agenda. The existence of convergence clubs implies that a uniform policy approach may be insufficient to address disparities in AI adoption. Instead, differentiated strategies tailored to the specific needs and capabilities

of different groups of countries may be required. For instance, while advanced economies may benefit from policies that support frontier innovation and scaling, lagging countries may require targeted investments in digital infrastructure, skills development, and institutional capacity to enhance their absorptive potential.

Overall, the findings of this study suggest that the current wave of AI diffusion in the EU SME sector follows a “multi-speed” pattern. While some countries and firms are rapidly advancing and converging towards higher levels of adoption, others remain on divergent trajectories. This highlights the importance of considering not only the pace but also the distribution of technological adoption when assessing the progress of digital transformation in the EU.

7. Conclusions

This study examined whether the rapid growth of AI adoption among EU SMEs in 2021–2025 is accompanied by convergence in adoption levels across Member States and size classes. Using harmonised Eurostat data and a convergence-oriented analytical framework, we find strong diffusion dynamics in both segments: the share of small enterprises (10–49 employees) using at least one AI technology increased from 6.1% in 2021 to 17.0% in 2025, while medium-sized enterprises (50–249 employees) increased from 12.6% to 30.4%. Although a persistent size-related adoption gap remains, the overall dispersion of adoption levels decreases in relative terms, indicating partial σ -convergence (CV: 0.69→0.52 for small firms; 0.62→0.45 for medium-sized firms).

β -convergence analysis further supports a catch-up process: countries with lower initial adoption levels tend to grow faster, with statistically significant negative β coefficients for both small ($\beta = -0.0815$, $p < 0.01$; $R^2 = 0.354$) and medium-sized enterprises ($\beta = -0.0872$, $p < 0.001$; $R^2 = 0.453$). Convergence is stronger and more consistent among medium-sized firms, suggesting that larger resource bases and organisational readiness facilitate faster diffusion. However, a club-convergence perspective reveals that EU-wide convergence is not uniform: while the high-adoption cluster shows convergence, the low-adoption cluster exhibits growing internal dispersion, implying that accelerated diffusion may coexist with increasing stratification among lagging ecosystems.

From a policy and managerial perspective, these results indicate that aggregate EU progress in AI uptake does not automatically translate into balanced digital cohesion. Targeted measures remain necessary to support SMEs in low-adoption environments, with an emphasis on capability-building (skills, data infrastructure, implementation support, and access to trustworthy AI services) rather than solely on access to technology. The study also has clear limitations: the observation window is short; the Eurostat indicator captures the use of at least one AI technology rather than adoption intensity or value creation; and the convergence framework does not establish causal mechanisms. Future research should extend the analysis by incorporating sectoral structure, complementary digitalisation measures, and institutional controls, and by linking country-level adoption dynamics to micro-level evidence on capabilities, deployment depth, and performance outcomes.

References

- Alexiadis, S. (2012). Club convergence. In *Convergence Clubs and Spatial Externalities* (61–88). Springer. https://doi.org/10.1007/978-3-642-31626-5_4
- Amanollahnejad, A., Fosso-Wamba, S., Shabbir, M. S., & Pakseresht, A. (2026). Aligning socio-technical systems: Rethinking AI adoption and digital transformation in SMEs. *Information Systems Management*, 1–15. <https://doi.org/10.1080/10580530.2025.2612175>
- Ayinaddis, S. G. (2025). Artificial intelligence adoption dynamics and knowledge in SMEs and large firms: A systematic review and bibliometric analysis. *Journal of Innovation & Knowledge*, 10(3), 100682. <https://doi.org/10.1016/j.jik.2025.100682>
- Barrios, C., & Flores, E. (2019). Club convergence in innovation activity across European regions. *MPRA Papers*, 123486. University Library of Munich. <https://ideas.repec.org/p/pramprapa/123486.html>
- Barro, R., & Sala-i-Martin, X. (1992). Convergence. *Journal of Political Economy*, 100(2), 223–251. Retrieved from <https://www.columbia.edu/~xs23/papers/pdfs/converg.pdf>

- Barro, R., & Sala-i-Martin, X. (1997). Technological diffusion, convergence, and growth. *Journal of Economic Growth*, 2(1), 1–26. <https://doi.org/10.1023/A:1009746629269>
- Boronenko, V., Mensikovs, V., & Lavrinenko, O. (2014). The impact of EU accession on the economic performance of the countries' internal (NUTS 3) regions. *Journal of Economics and Business (Proceedings of Rijeka Faculty of Economics)*, 32(2), 313–341. <https://ideas.repec.org/a/rfe/zbefri/v32y2014i2p313-341.html>
- Calvino, F., Costa, H., & Haerle, D. (2026). Digital technology diffusion in the age of AI: Cross-country evidence from microdata. *OECD Science, Technology and Industry Working Papers*, 1. OECD Publishing. <https://doi.org/10.1787/ebc2debe-en>
- Cimino, A., Corvello, V., Troise, C., Thomas, A., & Tani, M. (2025). Artificial intelligence adoption for sustainable growth in SMEs: An extended dynamic capability framework. *Corporate Social Responsibility and Environmental Management*, 32(5), 6120–6138. <https://doi.org/10.1002/csr.70019>
- Čižo, E., Bogdanova, N., Mietule, I., Kokarēviča, A., & Kudiņš, J. (2024). Inequality among residents and enterprises in the Latvian online market of digital marketing. *Baltic Region*, 16(3), 136–162. <https://doi.org/10.5922/2079-8555-2024-3-7>
- Clark, G., & Feenstra, R. C. (2003). Technology in the great divergence. In M. D. Bordo, A. M. Taylor & J. G. Williamson (Eds.), *Globalization in Historical Perspective* (277–323). National Bureau of Economic Research, University of Chicago Press. Retrieved from <https://ideas.repec.org/h/nbr/nberch/9591.html>
- Davis, F. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly*, 13(3), 319–340. <https://doi.org/10.2307/249008>
- van Dijk, J. (2017). Digital divide: Impact of access. In P. Rössler, C. Hoffner & L. van Zoonen (Eds.), *The International Encyclopedia of Media Effects*. John Wiley & Sons. <https://doi.org/10.1002/9781118783764.wbieme0043>
- European Commission. (2021). *2030 Digital Compass: The European Way for the Digital Decade*. COM(2021) 118 final. Retrieved from <https://eufordigital.eu/library/2030-digital-compass-the-european-way-for-the-digital-decade/>
- European Commission & Joint Research Centre. (2023). *Annual Report on European SMEs 2022/2023*. Publications Office of the European Union. Retrieved from <https://publications.jrc.ec.europa.eu/repository/handle/JRC134336>
- Eurostat. (2025). *Artificial Intelligence by Size Class of Enterprise (Isoc_eb_ai) [Data Set]*. Retrieved from https://ec.europa.eu/eurostat/databrowser/view/isoc_eb_ai/default/table?lang=en
- Fagerberg, J. (1995). Convergence or divergence? The impact of technology on “why growth rates differ”. *Journal of Evolutionary Economics*, 5(3), 269–284. <https://doi.org/10.1007/BF01198307>
- G7 Industry, Digital and Technology Ministers. (2025). *G7 Industry, Digital and Technology Ministerial Statement on the SME AI Adoption Blueprint*. Montréal, Canada, 8–9 December. Retrieved from <https://www.g7.utoronto.ca/ict/2025-sme-ai-adoption.html>
- Glawe, L. (2025). Club convergence in innovation activity – evidence from the us. *Papers in Regional Science*, 104(6), 100127. <https://doi.org/10.1016/j.pirs.2025.100127>
- Grafström, J., & Alm, C. (2025). Diverging or converging technology capabilities in the European Union? *The Journal of Technology Transfer*, 50(2), 728–751. <https://doi.org/10.1007/s10961-024-10070-0>
- ul Haq, F., Suki, N. M., Zaigham, H., Masood, A., & Rajput, A. (2025). Exploring AI adoption and SME performance in resource-constrained environments: A TOE–RBV perspective with mediation and moderation effects. *Journal of Digital Economy*, journal pre-proof. <https://doi.org/10.1016/j.jdec.2025.07.002>
- Hollanders, H., Soete, L., & Weel, B. (1999). *Trends in Growth Convergence and Divergence and Changes in Technological Access and Capabilities*. Maastricht Economic Research Institute on Innovation and Technology (MERIT). Retrieved from <https://files01.core.ac.uk/download/pdf/6936987.pdf>
- Innovation, Science and Economic Development Canada. (2025). *SME AI Adoption Blueprint*. Government of Canada. Retrieved from <https://ised-isde.canada.ca/site/ised/en/sme-ai-adoption-blueprint>
- Komarova, V., Mietule, I., Arbidane, I., Tumulavičius, V., & Kokarēviča, A. (2022). Resources and capital of different social classes in modern Latvia. *Journal of Eastern European and Central Asian Research*, 9(3), 500–512. <https://doi.org/10.15549/jecar.v9i3.861>
- Kopka, A., & Fornahl, D. (2024). Artificial intelligence and firm growth – catch-up processes of SMEs through integrating AI into their knowledge bases. *Small Bus Econ*, 62, 63–85. <https://doi.org/10.1007/s11187-023-00754-6>

Le Dinh, T., Vu, M.-C., & Tran, G. T. C. (2025). Artificial intelligence in SMEs: Enhancing business functions through technologies and applications. *Information*, 16(5), 415. <https://doi.org/10.3390/info16050415>

Marques, A., & Soukiazis, E. (1998). *Per Capita Income Convergence Across Countries and Across Regions in the European Union. Some New Evidence*. Paper presented during the 2nd International meeting of European Economy organized by CEDIN(ISEG) in Lisbon. Retrieved from <https://www.studocu.vn/vn/document/truong-dai-hoc-cuu-long-tin-sinh-hoc/per-capita-income-convergence-in-the-eu-new-evidence-eco-101/148425091>

Menshikov, V., Ruza, O., Simakhova, A., & Bedianashvili, G. (2025). Common and unique features in the development of startup ecosystems in Latvia, Ukraine, and Georgia. *Comparative Economic Research. Central and Eastern Europe*, 28(4), 23–43. <https://doi.org/10.18778/1508-2008.2827>

Meņšikovs, V. (2009). Kopkapitāls un jaunatnes dzīves stratēģijas: sociālās zinātnes aspekts. *Sociālo Zinātņu Vēstnesis = Social Sciences Bulletin*, 9(2), 7–37. Retrieved from https://du.lv/wp-content/uploads/2022/11/SZV_2009_2.pdf (In Latvian)

Muhammad, S. S., Dey, B. L., Kamal, M. M., Samuel, L., & Alzeiby, E. A. (2025). Digital transformation or digital divide? SMEs' use of AI during global crisis. *Technological Forecasting and Social Change*, 217, 124184. <https://doi.org/10.1016/j.techfore.2025.124184>

OECD. (2025). *AI Adoption by Small and Medium-Sized Enterprises (OECD Report)*. Organisation for Economic Co-operation and Development. Retrieved from https://www.oecd.org/content/dam/oecd/en/publications/reports/2025/12/ai-adoption-by-small-and-medium-sized-enterprises_9c48eae6/426399c1-en.pdf

Papić, T. (2025). Artificial intelligence as a strategic tool for SME growth: From process automation to knowledge intelligence. *SCIENCE International Journal*, 4(4), 113–118. <https://doi.org/10.35120/scienceij0404113p>

Roa Baez, J., & Igbekele, R. (2021). *Challenges of AI Adoption in SMEs*. KTH Royal Institute of Technology. Retrieved from <https://www.diva-portal.org/smash/get/diva2:1591640/FULLTEXT01.pdf>

Ruža O., Kokarēviča A., Ostrovska I., & Zeng J. (2024). Growth of the internet market and its impact on digital divide in Latvia. *Sociālo Zinātņu Vēstnesis = Social Sciences Bulletin*, 39(2), 89–109. [https://doi.org/10.9770/szv.2024.2\(5\)](https://doi.org/10.9770/szv.2024.2(5))

Sadik, J. (2007). Technology adoption, convergence, and divergence. *European Economic Review*, 52(2), 338–355. <https://doi.org/10.1016/j.eurocorev.2007.02.005>

Sánchez, E., Calderón, R., & Herrera, F. (2025). Artificial intelligence adoption in SMEs: Survey based on TOE–framework, primary methodology and challenges. *Applied Sciences*, 15(12), 6465. <https://doi.org/10.3390/app15126465>

Scuotto, V., Crammond, R. J., Murray, A., & Del Giudice, M. (2023). Achieving global convergence? Integrating disruptive technologies within evolving SME business models: A micro-level lens. *Journal of International Management*, 29(6), 101095. <https://doi.org/10.1016/j.intman.2023.101095>

Shi, Q., & Shen, L. (2025). Advancing firm-level digital technology diffusion: A hybrid bibliometric and framework-based systematic literature review. *Systems*, 13(4), 262. <https://doi.org/10.3390/systems13040262>

UNDP. (2019). Technology's potential for divergence and convergence: Facing a century of structural transformation. In *Human Development Report 2019: Beyond Income, Beyond Averages, Beyond Today: Inequalities in Human Development in the 21st Century* (Chapter 6). UNDP. Retrieved from <https://hdr.undp.org/system/files/documents/hdr2019chapter6.pdf>

Funding. The article has been developed and funded within the Daugavpils University's (Latvia) research project No 14-95/2026/17 "AI-Based Enterprise Transformation and Its Impact on Managerial Decision Quality".

Author Contributions: Chenqing Zhang developed the initial research idea and the core conceptual and analytical framework; designed the convergence-based empirical strategy; drafted the Introduction, conceptual framework and methodology; and prepared the initial full manuscript draft. Alina Danileviča conducted and synthesised the relevant scientific literature, strengthening the theoretical background and clarifying key concepts and definitions. Ieva Boļakova assembled, cleaned and verified the Eurostat dataset (2021–2025); performed the σ - and β -convergence calculations and estimations; and prepared the tables and figures. Vera Komarova contributed to the interpretation of cross-country patterns and strengthened the applied and policy-relevant dimension of the discussion and conclusions, including territorial and SME-capability implications. Zhongdong Yang contributed to the interpretation of results and manuscript revision, with a focus on the robustness and clarity of the empirical argumentation. Edmunds Čižo supported the conceptual and methodological development of the study; ensured coherence between the title, abstract, results and conclusions; and

contributed to overall manuscript editing. Jiangang Qi coordinated the study as the corresponding author, supervised final integration of sections, and prepared the manuscript for submission. All authors have read and approved the final manuscript.

Chenqing ZHANG is a Master in International and European Business Law (LL.M.), graduated from Trinity College Dublin (Ireland). Research interests: comparative studies, conceptual framework of economic research, formal analytics, quantitative research methodology.

ORCID: <https://orcid.org/0009-0002-1017-6723>

Edmunds ČIŽO is a Science Doctor (Ph.D.) in Economics and Business, the Assistant professor at the Department of Law, Management and Economics of Faculty of Humanities and Social Sciences of Daugavpils University (Latvia). Research interests: regional economics, sustainable economic development, research design and methodology, quantitative research methods.

ORCID: <https://orcid.org/0000-0003-0654-2962>

Zhongdong YANG is a Master of Business Administration (MBA), the Manager at the Web3 Capital Pte. Ltd. (Singapore). Research interests: innovation economics, SME studies, digital transformation, regional development, econometrics.

ORCID: <https://orcid.org/0009-0004-7478-7763>

Alina DANILEVIČA is a Doctor in Economics (Dr.oec.), the Leading researcher at the Institute of Humanities and Social Sciences of Daugavpils University, the Visiting researcher at EKA University of Applied Sciences (Latvia). Research interests: regional economics, economic research methodology, convergence studies, statistical data analysis.

ORCID: <https://orcid.org/0000-0002-2749-2725>

Ieva BOĻAKOVA is a Master in Pedagogy (Mg.paed.), the Lecturer at the Department of Environment and Technologies of Faculty of Natural Sciences and Health Care of Daugavpils University (Latvia). Research interests: data analysis, mathematical logic, AI technologies.

ORCID: <https://orcid.org/0009-0009-4589-5390>

Vera KOMAROVA is a Doctor in Economics (Dr.oec.), the Leading researcher at the Institute of Humanities and Social Sciences of Daugavpils University (Latvia). Research interests: regional economics, sustainable development, economic research methodology, quantitative research methods.

ORCID: <https://orcid.org/0000-0002-9829-622X>

Jiangang QI is a Science Doctor (Ph.D.) in Constitutional and Administrative Law, the Researcher at the Research Center of Intellectual Property of Zhongnan University of Economics and Law (China). Research interests: innovation economics, SME studies, digital transformation, regional development, econometrics.

ORCID: <https://orcid.org/0009-0003-0570-2204>

Copyright © 2026 by author(s). Publishing rights by Entrepreneurship and Sustainability Center

This work is licensed under the Creative Commons Attribution International License (CC BY).

<http://creativecommons.org/licenses/by/4.0/>

