Artificial Intelligence in Small and Medium-Sized Companies – Comparative Analysis of V4 Region

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Abstract: The main aim of this paper is to examine the application of artificial intelligence in small and medium-sized enterprises and to investigate whether the adoption of AI in enterprises across the V4 countries varies not only by country but also by enterprise size. The analysis is based on the latest available Eurostat data and combines descriptive statistics with chi-square tests: (i) a goodness-of-fit test to assess whether AI adoption rates differ across countries, and (ii) an independence test to verify the relationship between company size and AI adoption. The results show statistically significant differences across V4 countries and size categories: larger enterprises show higher adoption than SMEs, and there are significant disparities between countries, with some lagging behind. The findings confirm that structural factors (company size, national context) play a key role in AI deployment. The study provides practical recommendations for policymakers and SME managers: to develop competencies and infrastructure in a targeted manner, to focus support on overcoming identified barriers to adoption, and to monitor the effect of company size on the return on AI implementation.

Keywords: Artificial intelligence, Industry 4.0, small and medium-sized enterprises, V4
JEL Classification: M10, M15, O30.

1 Introduction

The issue of continuous development in the technological environment is one of the most important for businesses. Development is constantly accelerating, and new opportunities continually emerge for organizations. In general, these changes can be called Industry 4.0 – a concept encompassing a range of technologies that seek to connect production with people, processes, and services in real time (Nayernia et al., 2022). These technologies include artificial intelligence (AI), the Internet of Things (IoT), big data, cyber-physical systems, cloud computing, robotics, and one of the most talked-about applications of Industry 4.0: digital twins (Reaidy et al., 2024; Yao et al., 2023). A digital twin enables a digital representation of production operations, communication flows, and material movement (Javaid et al., 2023). Modern technologies bring several advantages, the most important of which include increased product quality and safety, reduced operating and maintenance costs, shorter production downtime, and enhanced sustainability of the production process (Stefanini et al., 2022). However, companies still grapple with how to successfully implement these technologies. Research shows there is no internationally recognized readiness model and that many proposed models do not receive positive feedback from companies (Ünlü et al., 2023). The literature shows that the scientific debate on Industry 4.0 is continually expanding, which is why this topic remains relevant 14 years after the term was first used (Rad et al., 2022).

Artificial intelligence – a term describing systems or software that simulates human intelligence – is not a new concept, having been coined in 1956 (Mishra, 2024; Xu et al., 2021). AI is often compared to transformative technologies like the internet or the steam engine, given its broad industry impact (Lei & Kim, 2024). Various AI models process vast amounts of data for downstream applications (Schneider et al., 2024). The best-known are generative language models (Chang et al., 2024). These generative models, most notably ChatGPT, are significantly transforming the world today and substantially affecting employee productivity (Noy & Zhang, 2023). AI is changing industry and manufacturing as well as science, enabling new research opportunities (Karpatne et al., 2025). Additionally, discussion is growing around linking AI

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with IoT to create the Artificial Intelligence of Things (AIoT), enhancing human-machine interaction and improving operational efficiency (Siam et al., 2025).

Small and medium-sized enterprises (SMEs) are a crucial component of global economies, representing roughly 90% of all businesses and employing about 50% of the global workforce. Thus, their performance during digital transformation is highly significant (Costa Melo et al., 2023). Current literature suggests SMEs should pursue digital transformation through incremental changes and innovations, while investing in education and continuous learning oriented toward Industry 4.0 (Sagala & Őri, 2024). It is especially important to implement these changes in ways that align with sustainability, one of central goals of Industry 4.0 (Philbin et al., 2023). Nonetheless, several barriers hinder SMEs from adopting these innovations more rapidly, including limited financial resources, shortages of skilled personnel, high IT requirements, and lack of knowledge (Kumar et al., 2023; Restrepo-Morales et al., 2024). These observations underscore the need for research on implementing modern technologies in SMEs, both generally and for specific technologies.

The V4 group includes Hungary, Slovakia, Poland, and the Czech Republic, and its goal is close cooperation between these countries and mutual assistance within the framework of European integration (Kovacs & Domonkos, 2024). Unfortunately, research shows that the V4 countries are poorly prepared for the implementation of Industry 4.0, with no significant progress evident, although the Czech Republic performs best among the four (Molendowski et al., 2024). Studies indicate that the Czech Republic's preparedness is very good, particularly in AI – the strongest among the V4 countries – yet there are few cases of excellence (Filipec, 2022). Across the EU, the share of companies with more than 10 employees using at least one AI-related technology is small – just 13% (Ionașcu, 2025). Given these facts, research on AI in SMEs in the V4 region remains relevant and requires updating and new contributions to the scientific debate. Therefore, the research question (RQ) is: "Are there differences in the field of AI between the individual countries of the V4 region?"

This study contributes to the existing literature on the adoption of artificial intelligence in businesses in two main ways. First, it provides a focused comparative analysis of AI adoption in the Visegrad Four (V4) countries, a region that has so far received limited empirical attention in the context of AI adoption, despite its distinctive economic, institutional, and technological characteristics. By explicitly examining differences within this specific regional grouping, the study enhances understanding of how national context shapes the uptake of artificial intelligence in enterprises. Second, the study combines harmonized Eurostat data with comparative statistical testing, which allows not only for the identification of differences in AI adoption across countries and enterprise size categories, but also for a more systematic assessment of the structural nature of these differences. In doing so, the results extend existing knowledge on the role of enterprise size and national context as key determinants of AI implementation in businesses. The findings provide empirically grounded insights that are relevant for academic research, policymakers, and managers of small and medium-sized enterprises, particularly in relation to addressing and reducing adoption gaps within the V4 region.

2 Methods

The main aim of this paper is to examine the application of artificial intelligence in small and medium-sized enterprises and to investigate whether the adoption of AI in enterprises across the V4 countries varies not only by country but also by enterprise size. The fact that different countries use AI to varying degrees is supported by the professional literature (Filipec, 2022; Ionașcu, 2025; Kovacs & Domonkos, 2024; Molendowski et al., 2024). This study is a comparative secondary analysis. To achieve the set aim, secondary data from the Eurostat database (2025a; 2025b) was used. The year 2023 was selected for analysis, as it is the last year with complete data in the database.

As mentioned above, the V4 geographical area (Czechia, Slovakia, Poland, Hungary) is the standard area for analyzing individual differences. The data were extracted on September 12, 2025, from the Eurostat database (2025a) to determine the number of companies reporting the use of AI, as well as the number of companies in each size category in the individual countries (Eurostat, 2025b). These are structural and cross-sectional statistics that the database provides as part of gathering information on the digital economy and society. The data are offered in percentage form, so it is important to also determine the total number of enterprises in the regions to calculate the actual number of enterprises using AI. For size categories, the standard European Union approach was used, i.e., dividing enterprises by number of employees, with up to 10 employees are micro-enterprises, 10–49 employees are small enterprises, and 50–249 employees are medium-sized enterprises (Child et al., 2022). The research uses with two of these categories (small and medium-sized), as the database does not contain information on micro-enterprises. The dependent variable is the use of artificial intelligence, with individual countries and size categories used as predictors.

Several methods and procedures were used to achieve the aim. First, descriptive statistics were computed (Ali & Bhaskar, 2016). Subsequently, a chi-square test of goodness-of-fit was used to determine whether differences between countries were random or statistically significant (Pfeifer, 2008), along with a chi-square test of independence to examine differences between size categories within the observed countries (Ranganathan, 2021). Two-proportion tests were used to compare pairs of countries (Kim, 2016). A standard significance level of 0.05 (Miller & Ulrich, 2019) was applied for all statistical tests, which is the value commonly recommended for interpretation in most scientific disciplines. All calculations and graphical processing were performed using RStudio and Microsoft Excel.

3 Research results

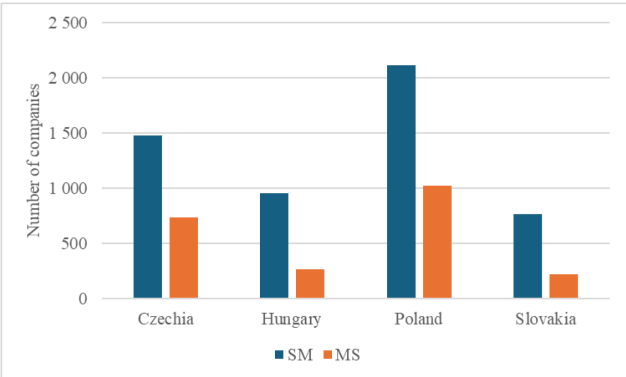
The first step provides a descriptive overview of AI adoption in businesses. Table 1 presents the use of AI across individual firm-size categories in V4 countries, expressed both as percentages (original data) and as absolute values, which were subsequently calculated. Figure 1 offers a graphical representation of the number of companies using AI in the V4 region in absolute terms. Both Table 1 and Figure 1 employ abbreviations for firm-size categories, where SM denotes small enterprises and MS denotes medium-sized enterprises. The Summary column reports aggregated values for these two categories only.

Table 1 Intensity of AI adoption in V4 countries (SM – small enterprises, MS – medium-sized enterprises)

Country	SM (%)	SM (absolute)	MS (%)	MS (absolute)	Summary (%)	Summary (absolute)
Czechia	4.00	1,479	9.79	736	4.99	2,215
Hungary	2.98	953	5.54	269	3.31	1,221
Poland	2.25	2,110	6.49	1,020	2.91	3,129
Slovakia	5.95	764	8.57	223	6.42	986

Source: Own processing according to Eurostat (2025a; 2025b)

Figure 1 Graphical visualization of AI adoption intensity in V4 countries (SM – small enterprises, MS – medium-sized enterprises)



Source: Own processing according to Eurostat (2025a; 2025b)

As shown in Table 1, the adoption of AI varies across both regions and firm-size categories. Among small enterprises, Slovakia records the highest share in relative terms, followed by the Czech Republic. In absolute terms, however, Poland leads this category, with the Czech Republic in second place. In the category of medium-sized enterprises, the Czech Republic performs best in relative terms, followed by Slovakia, while Poland again records the highest values in absolute terms. When considering the aggregated results for these two size categories, Slovakia ranks first in relative terms, followed by the Czech Republic, Hungary, and Poland in last place. In contrast, the absolute terms place Poland in the leading position, followed by the Czech Republic, Hungary, and Slovakia. From an interpretative perspective, relative indicators of AI adoption are particularly important, as they highlight the strong position of Slovakia in the small enterprise category and of the Czech Republic, especially among medium-sized enterprises. Overall, Poland (with less than 3%) and Hungary (just over 3%) appear to have the lowest shares of enterprises using AI.

Subsequently, a chi-square goodness-of-fit test was applied to examine whether statistically significant differences exist between countries in the overall distribution. The null hypothesis H_0, stating that “The proportion of companies using AI is the same in all countries” was tested against the alternative hypothesis H_A, which assumes “The proportion of companies using AI differs in at least one country”. The results of the test are presented in Table 2.

Table 2 Chi-square goodness-of-fit test

Test characteristics	Value
χ^2	730.58
Degrees of freedom	3
p-value	<0.001

Source: Own processing

The resulting p-value is significantly lower than the selected significance level of 0.05; therefore, the null hypothesis is rejected. The results indicate that the proportion of companies using AI differs statistically significantly in at least one country, suggesting that the observed differences between countries are not random. As part of the same analysis, a pairwise comparison were subsequently conducted to identify between which countries these differences occur. For all pairwise comparisons, the p-values were also below 0.05, indicating that the differences between all countries are statistically significant. From a practical perspective, this finding indicates that AI adoption in the V4 region is strongly influenced by country-specific conditions, suggesting that a uniform EU-level policy approach may be insufficient and that national-level measures are necessary.

The question then arises as to whether statistically significant differences exist between firm-size categories within individual countries. In the first step, individual countries were not considered; instead, differences between small and medium-sized enterprises across regions were examined. The null hypothesis H_0 was formulated as "Both categories show the same level of AI use," while the alternative hypothesis H_A stated that "There is a difference in the level of AI use between the two categories under review." The results of this test are presented in Table 3.

Table 3 Chi-square test of independence

Test characteristics	Value
χ^2	1,370.60
Degrees of freedom	1
p-value	<0.001

Source: Own processing

The test results indicate statistically significant differences between the two size categories under consideration, as the p-value is below 0.05; therefore, the null hypothesis is rejected. The findings reveal that the level of AI adoption differs between the two categories. Medium-sized enterprises exhibit a higher level of AI adoption compared to small enterprises, while small enterprises display a higher incidence of non-adoption of this technology. In practical terms, the results suggest that medium-sized enterprises possess organizational and resource advantages that enable more frequent AI adoption, while small enterprises remain structurally disadvantaged.

Subsequently, partial comparisons of firm-size categories within individual countries were conducted using the chi-square test. In this step, several pairwise comparisons were found to be statistically insignificant. An overview of all statistically insignificant pairwise comparisons is provided in Table 4.

Table 4 Pairs of statistically insignificant size categories in countries (SM – small enterprises, MS – medium-sized enterprises)

First comparison group	Second comparison group	P-value
Hungary MS	Poland MS	0.068
Slovakia SM	Poland MS	0.182
Czechia MS	Slovakia MS	0.182
Slovakia SM	Hungary MS	0.299

Source: Own processing

Most pairwise comparisons still indicate statistically significant relationships; however, medium-sized enterprises in Hungary and Poland exhibit twice as many statistically insignificant relationships as medium-sized enterprises in Slovakia.

Specifically, no statistically significant differences were identified between Hungarian and Polish medium-sized enterprises. Similarly, the differences between Hungarian medium-sized enterprises and Slovak small enterprises, as well as between Polish medium-sized enterprises and Slovak small enterprises, were found to be statistically insignificant. These results suggest that medium-sized enterprises in Poland and Hungary, together with small enterprises in Slovakia, stand out from the overall pattern observed in the analysis, as these categories display the lowest levels of statistical differentiation.

The statistical significance of the differences observed between individual countries indicates not only variations in AI adoption levels, but also the systematic influence of the national context on the extent to which artificial intelligence is used in businesses. From a practical perspective, this implies that differences in AI adoption cannot be regarded as random; rather, they reflect long-term economic, institutional, and structural factors. Similarly, the differences identified between company size categories suggest that firm size is a key determinant of the capacity to implement and effectively use artificial intelligence. Medium-sized enterprises exhibit higher absorptive capacity, which is reflected in their significantly higher level of AI adoption compared to small enterprises.

4 Conclusions

The main aim of this paper is to examine the application of artificial intelligence in small and medium-sized enterprises and to investigate whether the adoption of AI in enterprises across the V4 countries varies not only by country but also by enterprise size. This aim has been achieved, as the study identifies clear differences in AI adoption across the V4 countries as well as between enterprise size categories. Statistically significant differences in AI adoption among countries were confirmed, and the results further indicate that medium-sized enterprises adopt and work with AI more frequently than small enterprises. In relative terms, Slovakia performs best among small enterprises, while the Czech Republic shows the strongest performance among medium-sized enterprises. In absolute terms, Poland records the highest number of enterprises using AI; however, this outcome primarily reflects its larger business base compared to the other countries. Overall, the findings demonstrate that factors such as firm size and country-specific conditions play a significant role in shaping AI adoption in enterprises.

The empirical findings can be interpreted in light of existing theoretical insights on AI adoption barriers in SMEs. Previous studies identify limited financial resources, lack of skilled personnel, insufficient digital infrastructure, and uncertainty about return on investment as key obstacles to AI adoption in smaller firms (Kumar et al., 2023; Restrepo-Morales et al., 2024). The observed lower AI adoption rates among small enterprises compared to medium-sized enterprises across the V4 countries are consistent with these theoretical expectations. Similarly, cross-country differences within the V4 region reflect differences in national innovation systems, digital readiness, and policy support, as highlighted in prior studies on Industry 4.0 preparedness in Central and Eastern Europe (Molendowski et al., 2024).

The results of this study have several practical implications. First, the findings indicate that support for artificial intelligence adoption should not be uniform but should reflect both enterprise size and national context. The consistently lower adoption rates observed among small enterprises suggest that these firms face structural constraints that limit their ability to implement AI solutions, even when the technology is increasingly accessible. As a result, measures aimed at promoting AI adoption should explicitly account for differences in absorptive capacity between small and medium-sized enterprises. Second, the identified cross-country differences within the V4 region imply that national institutional and economic conditions play an important role in shaping AI adoption outcomes. This suggests that policy interventions should be tailored to country-specific conditions rather than relying solely on generalized approaches at the regional or EU level. From a managerial perspective, the results highlight the importance of a gradual and strategic approach to AI adoption, particularly in smaller enterprises, where resource constraints are more pronounced. Overall, the study underscores the need for targeted and differentiated strategies to support effective AI adoption among SMEs in the V4 countries.

Several limitations and barriers of this study should be acknowledged. First, the analysis is based on secondary data from the Eurostat database for 2023, which represents the most recent complete dataset available. Second, the study does not provide a detailed perspective on micro-enterprises, as this category is not monitored by Eurostat with respect to AI adoption. The statistical methods and analytical approaches employed were appropriate for fulfilling the aim of the paper by identifying differences between countries and firm-size categories; however, they do not allow for an examination of the underlying causes of these differences or for the establishment of causal relationships. Moreover, the analysis does not account for sector-specific differences, the quality or maturity of AI implementation, or the economic performance of individual enterprises, which could otherwise serve as relevant control variables. As a result of these data-related limitations, the study is unable to assess the depth of AI adoption or to evaluate the actual effectiveness and success of the implemented AI solutions. With regard to directions for further research, several avenues may be pursued. First, the existing dataset could be extended by incorporating a representative sample of micro-enterprises in order to examine additional differences across firm-size categories. Furthermore, sectoral affiliation could be included as an additional explanatory variable to capture industry-specific patterns of AI adoption. Another promising direction involves complementing the quantitative analysis with qualitative research, which could enable the identification and subsequent compilation of best practices in AI adoption. In addition, future studies could focus on assessing the economic impacts of AI adoption in enterprises, particularly with respect to both costs and revenue effects, as well as identifying the key success factors associated with successful adoption. Finally, extending the analysis to a time-series perspective would allow for the examination of short-term fluctuations in relation to long-term trends. Collectively, these research directions could contribute to a deeper understanding of AI adoption in enterprises and support the development of more effective policy measures aimed at fostering AI adoption in the V4 region.

This study's recommendations can be summarized as follows. The findings indicate that effective support for artificial intelligence adoption among small and medium-sized enterprises should be differentiated according to enterprise size and national context. Smaller enterprises require more tailored approaches reflecting their more limited resources and absorptive capacity, while cross-country differences within the V4 region underline the importance of country-specific strategies. Overall, the results suggest that targeted and context-sensitive measures are more appropriate than uniform approaches when promoting AI adoption among SMEs.

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