ARTICLE

INDUSTRY 4.0 TECHNOLOGIES IN SMEs AND DIFFERENCES ACCORDING TO COMPANY SIZE AND SECTOR: THE CASE OF CZECHIA

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Abstract

The article focuses on adoption of Industry 4.0 technologies in Czechia's small and medium-sized enterprises (SMEs). It examines how enterprise size and sector affect the level of implementation of these technologies. The main objective is to observe the differences in the use of modern technologies in SMEs based on enterprise size and the sector in which they operate and to identify the main barriers to their implementation. The research was conducted online between October 2023 and January 2024, involving 240 respondents from various sectors. The statistical analysis included a non-parametric multivariate analysis of variance (PERMANOVA), the Kruskal-Wallis test, ordinal logistic regression and the Dunn test. The results show that larger enterprises tend to implement modern technologies more frequently than smaller ones, the main barrier being a lack of financial resources. It was also found that the sector in which a company operates does not have a statistically significant impact on the level of implementation of Industry 4.0, but it is a specific predictor of implementing specific technologies in some cases. These findings highlight the need for targeted support to smaller enterprises in education, skill development and securing financial resources for technology investments.

Implications for Central European audience: The theoretical contribution of the article lies in expanding knowledge about the factors influencing adoption of Industry 4.0 technologies in small and medium-sized enterprises. The practical application focuses on identifying barriers that hinder implementation of these technologies and providing recommendations for improving support to small and medium-sized enterprises in adopting modern technologies, mainly through education and financial support.

Keywords: Industry 4.0; SMEs; technology; innovation

JEL Classification: M10, O30, O33

Introduction

Modern technologies and the advent of the new industrial revolution, known as Industry 4.0, affect various sectors and influence businesses across all economic sectors (Khan et al., 2024). This shift introduces an entirely new concept of competitiveness and business models for organisations and to a large extent, new technologies help shape new relationships and networks (Bilbao-Ubillos et al., 2024). However, the issue of implementing new technologies is not limited to large enterprises; on the contrary, it is crucial to address this matter in the context of small and medium-sized enterprises (SMEs). These organisations form the backbone of national economies. Within the European Union, SMEs constitute 99% of all organisations and employ 65% of the workforce (Häring et al., 2023). The situation in Central European countries is practically identical. Based on 2022 data, only 0.1% of companies in Czechia, Slovakia and Poland are large enterprises, while Austria registers 0.2% and Germany 0.5% of all organisations as large enterprises. In terms of the number of employed persons, the situation is more varied: in Czechia, 68.4% of the workforce is employed in SMEs, while these figures are 72.9% in Slovakia, 66.3% in Austria, 67.5% in Poland and 57.8% in Germany (Eurostat, 2022).

Eurostat (2023) also characterises the digital transformation of businesses based on the Digital Intensity Index (DII), which categorises enterprises into four levels (ranging from very low to very high). According to this index, 69.3% of SMEs in the European Union have reached at least a basic level (levels 0 and 1). Czechia is above the EU average in this respect, with 71.1% of its SMEs achieving the minimum required level. Cloud computing is a trending technology, with 40% of SMEs in the EU using this service (43.8% in Czechia). Artificial Intelligence is also gaining traction, with 7% of SMEs in the EU incorporating it into their operations (only 4.5% in Czechia).

It is essential to address the implementation of modern technologies in SMEs on a broader scale than is currently the case. Otherwise, their competitiveness and the national competitiveness of the entire economy would be lost. The main objective is to observe the differences in the use of modern technologies in SMEs based on the enterprise size and sector and to identify the main barriers to their implementation. Furthermore, the article addresses the issue of specific technologies and their application within organisations. Lastly, it discusses companies' problems and obstacles when adopting modern technologies. For this research, two research questions were defined. The first research question (RQ1) is: "What is the influence of the business sector and size on the level of Industry 4.0 implementation in SMEs?" The second research question (RQ2) is: "What barriers affect the implementation of Industry 4.0 in SMEs?"

The paper is structured as follows: after the introduction, there is a literature review that defines the key concepts associated with Industry 4.0, describes selected technologies and addresses the current research issues related to the topic, including formulation of hypotheses. This is followed by a section on the methodology and objectives of the study, detailing the data and selected statistical methods used. The next part focuses on the results and evaluation of the hypotheses. Finally, the paper concludes with a discussion, conclusions and limitations of the research and recommendations for future studies.

1 Literature Overview

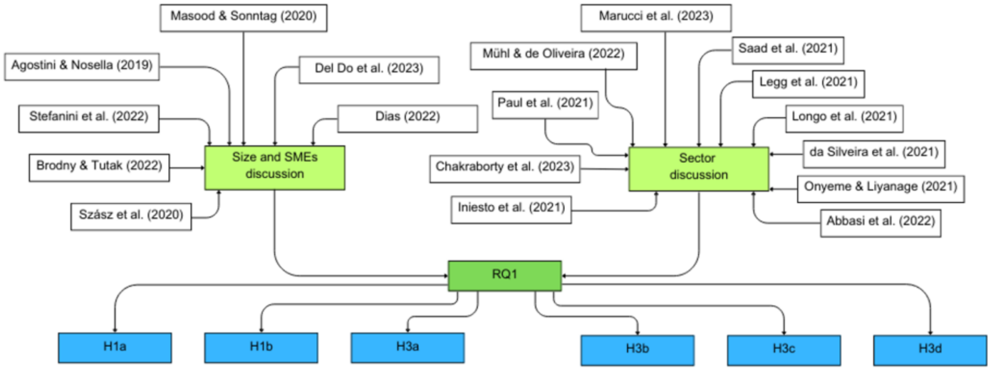
The Fourth Industrial Revolution originated in Hanover, Germany, in 2011, initially as a strategic initiative to elevate the local industry to a higher level. The term "Industry 4.0" was already used at that time. However, no-one realised then that it would become a global phenomenon influencing the daily operations of not only businesses but also society as a whole (Machado et al., 2022).

As mentioned earlier, this is the Fourth Industrial Revolution. The First Industrial Revolution occurred in the 18th century, beginning in Britain, a technological powerhouse. Its main characteristics included using steam and water power and transitioning from manual production, or manufacturing, to earliest machine-based production. There is no fixed perspective on the exact time frame of this revolution, but it is generally considered to have occurred between 1760 and 1840 (Groumpos, 2021). Later on, around 1860, another technological upheaval began, lasting until the start of World War I in 1914. This period is known as the Second Industrial Revolution, marked by electrification and the advancement of machine production (Zhang & Yang, 2020). Many technologies were invented during this revolution. This was followed by the Third Industrial Revolution, closely associated with the invention and use of computers and the Internet. Its beginnings can be dated to around 1970 and it ended only recently, at the start of the 21st century, just before the advent of the current concept of Industry 4.0 (Taalbi, 2018).

Since 2011, we have discussed the Fourth Industrial Revolution, which is associated with digitalisation, robotics, artificial intelligence and augmented reality. It was expected to increase labour productivity, reduce environmental pollution and promote sustainable production (Galizia et al., 2023). Even though many businesses struggle to implement Industry 4.0 successfully (Zhou et al., 2024; Frecassetti et al., 2024), this concept has evolved and there is now talk of Industry 5.0. This new phase focuses on technologies and practices to prevent further climate change, reduce the wasting of non-renewable resources, minimize environmental pollution and balance inequalities (Pereira & dos Santos, 2023).

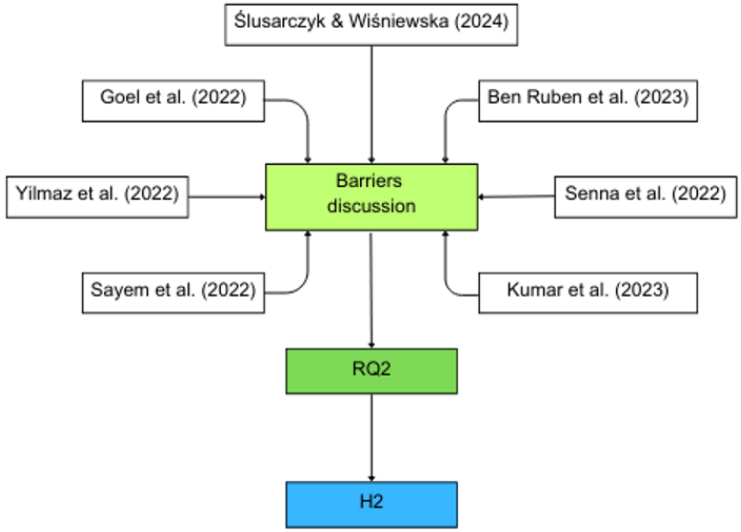
Figures 1 and 2 below present a systematic literature review in the form of mind maps created to gather and synthesize relevant sources for formulating research questions (see Introduction) and hypotheses (see later). Mind maps provide a clear visual representation of key concepts and their relationships, offering a logical framework for the research. These figures illustrate how the selected literature sources connect to critical topics of Industry 4.0 in the context of small and medium-sized enterprises (SMEs). Figure 1 focuses on the influence of the business sector and company size on the level of Industry 4.0 implementation, showing what role these factors play in the adoption process. Figure 2 depicts the main barriers affecting Industry 4.0 implementation, highlighting SMEs' challenges. This approach makes the literature review structure easier to understand, showing how the sources are linked to the research questions and lead to the formulation of hypotheses, which will be tested in the empirical part of the study. By utilising mind maps, the analysis becomes more intuitive and accessible, allowing a more transparent comprehension of the literature review logic and structure. This approach helps illustrate how various sources have informed the research questions and how these questions, in turn, have guided the formulation of specific hypotheses. These hypotheses are rigorously tested in the empirical section of this study, contributing to a comprehensive understanding of Industry 4.0 adoption in SMEs.

Figure 1 | Mind map for research question 1



Source: Authors

Figure 2 | Mind map for research question 2



Source: Authors

1.1 Industry 4.0

In connection with the term Industry 4.0, a wide range of possible technologies can be discussed. Among the most well-known are big data, smart sensors, digital twins, cloud computing, augmented reality, 3D printing and additive manufacturing and the internet of things (IoT) (Amrani & Vallespir, 2021). However, it is also essential to consider virtual reality and robotics (Enrique et al., 2021). Additionally, technologies related to digitalisation, cyber-physical systems and machine learning must be mentioned (Pech & Vaněček, 2022). At the core of Industry 4.0 is the horizontal and vertical integration of production systems through real-time data exchange. Critical technologies for this core integration include the internet of things (IoT), artificial intelligence (AI), robotics and cyber-physical systems. These innovations enable the existence of the so-called "smart factory", where machines and devices autonomously communicate and make decisions to optimise production efficiency and flexibility (Piccarozzi et al., 2018).

A smart factory is one of the possible practical applications of Industry 4.0. These factories use sensors and cyber-physical systems to monitor and control real-time production processes. This approach allows greater flexibility, efficiency and adaptability to changing market conditions (Mazzei & Ramjattan, 2022). Another example of a practical application is predictive maintenance, which uses data obtained from IoT devices and advanced analytical tools to predict machine failures and malfunctions. This approach allows maintenance to be performed based on the actual condition of the equipment, minimising unplanned downtime and reducing maintenance costs (Tiddens et al., 2023). Another significant practical application is intelligent control systems and digital twins. Digital twins enable the simulation and optimisation of physical processes in real time, increasing efficiency and preventing potential problems before they occur (Tikwayo & Mathaba, 2023).

One of the main trends in Industry 4.0 is the shift towards mass customisation and improved operational performance (Arnarson et al., 2024). Implementing Industry 4.0 technologies enhances various performance metrics, including costs, quality and delivery times (Frank et al., 2019). Integrating AI and data analytics enables predictive maintenance, increasing the lifespan and reliability of equipment. Additionally, Industry 4.0 contributes to the circular economy by allowing sustainable practices and reducing waste through efficient resource management (Ghobakhloo, 2020).

Industry 4.0 offers numerous benefits that significantly affect various sectors and business areas. One of the main advantages is increased flexibility and productivity achieved through the automation and digitalisation of production processes (Bonello et al., 2024). These technologies enable companies to respond more quickly to changes in demand and adapt production to customers' specific needs, resulting in the making of customized products with high quality and lower costs (Zhang et al., 2021). Another significant advantage is the ability to transform business models through digital transformation. Digital technologies such as artificial intelligence, machine learning and the internet of things allow companies to integrate products and services across different functional, organisational and geographical boundaries, accelerating the pace of change and leading to significant transformations in production processes and operational models (Vaska et al., 2021). Industry 4.0 also fosters collaboration and innovation between companies and their customers. Modern technologies enable greater customer involvement in developing new products, reducing the risk of product failure and improving market acceptance. This allows companies to better respond to customer needs while increasing customer satisfaction (Kitsios & Kamariotou, 2021).

When considering implementation of Industry 4.0, it is most commonly associated with manufacturing enterprises (Marrucci et al., 2023; Saad et al., 2021), but it also extends to healthcare (Paul et al., 2021; da Silveira et al., 2021), the oil industry (Longo et al., 2021;

Onyeme & Liyanage, 2021), the wood industry (Legg et al., 2021), agriculture (Abbasi et al., 2022; Mühl & de Oliveira, 2022) and education (Chakraborty et al., 2023; Iniesto et al., 2021). The concept also affects almost every functional area of businesses, such as project management (Kanski & Pizon, 2023), supply chain (Asrol, 2024), marketing (Rosário & Dias, 2022), human resource management (HRM) (Pató et al., 2022), process management (Monti et al., 2024), leadership (Gatell & Avella, 2024) and accounting (Onyshchenko et al., 2022). From this information, it can be inferred that the adoption of Industry 4.0 in businesses is not influenced by the industry sector in which the company operates because according to available literary sources, Industry 4.0 affects all sectors. However, different technologies are typical of each sector, so it can be assumed that their usage will vary across sectors. These statements are reflected in hypotheses H1a and H1b.

H1a: The sector in which a given SME operates does not affect the level of Industry 4.0 implementation.

H1b: The sector in which a company operates affects the level of use of specific technologies in the majority of cases.

Industry 4.0, as a significant change and investment in the life of an organisation, naturally brings specific barriers to implementation. These include a great need for financial resources (Senna et al., 2022; Ben Ruben et al., 2023), a lack of qualified workers (Ślusarczyk & Wiśniewska, 2024), insufficient technological infrastructure (Goel et al., 2022), inadequate interest and support from the organisation's management (Yilmaz et al., 2022), employee resistance to change (Sayem et al., 2022) and concerns about misalignment with sustainable development (Kumar et al., 2023). In the case of Czechia, based on a survey by the Association of Small and Medium-Sized Enterprises and Crafts of the Czech Republic (2024), it is possible to state that the most significant barrier faced by small and medium-sized enterprises (SMEs) in implementing modern technologies is the lack of financial resources, both internal and external. The aim of hypothesis H2 is to confirm this assertion.

H2: The lack of financial resources is the most significant barrier for SMEs in implementing Industry 4.0.

1.2 Small and medium-sized enterprises

To introduce this chapter, it is necessary to define the term small and medium-sized enterprises (SMEs). According to the European Union's definition, SMEs are considered to be those enterprises that employ a maximum of 249 employees, have an annual turnover not exceeding 50 million EUR and have a balance sheet total of no more than 43 million EUR. Table 1 illustrates a more specific breakdown.

Table 1 | SME definition according to EU

Enterprise category	Headcount	Annual turnover	Annual balance sheet
Medium-sized	< 250	≤ EUR 50 million	≤ EUR 43 million
Small	< 50	≤ EUR 10 million	≤ EUR 10 million
Micro	< 10	≤ EUR 2 million	≤ EUR 2 million

Source: European Commission (2020)

Small and medium-sized enterprises (SMEs) play a crucial role in the economies of many countries and their ability to adopt and implement Industry 4.0 technologies is crucial to their competitiveness and innovation (Dias, 2022). Implementing Industry 4.0 technologies, such as automation, IoT or big data, can significantly enhance the efficiency and productivity of SMEs. Agostini & Nosella (2019) argued that SMEs investing in advanced manufacturing technologies and developing strong internal and external relationships are more likely to adopt Industry 4.0 technologies successfully. The study also indicated that management support and absorptive capacity, facilitated through internal relationships within the enterprise, contribute to the adoption of technologies.

Businesses categorized as micro and small enterprises play a pivotal role. The barriers to adopting modern technologies mentioned above are particularly evident in these businesses. The primary challenge for this category of enterprises is generally the need for more resources to implement technologies. Unfortunately, this barrier is compounded by several other factors, such as the current low level of technological infrastructure or inadequate perception of external pressures placed on these businesses (Del Do et al., 2023). Beyond financial constraints, another significant challenge for this category is increasing knowledge about this issue (Masood & Sonntag, 2020). In general, it has been observed that the larger the enterprise, the more likely it is to invest in modern technologies (Szász et al., 2020). When examining the adoption of specific technologies by enterprise size, it is evident that even within the SME category, the same principle applies: the larger the enterprise, the more likely it is to implement Industry 4.0 and adopt specific technologies (Stefanini et al., 2022).

The fact that larger enterprises tend to adopt modern technologies more frequently is observed in only some countries. As Brodny & Tutak (2022) noted, for example, Slovakia has the best digital index in the small enterprise category, while the medium-sized enterprise category shows the worst results. In Czechia, however, the expected trend is observed. It is equally important to monitor the situation of micro-enterprises and, in general, to observe the differences between SMEs regarding specific technologies. Based on the above, the following hypotheses, labelled H3a–H3d, have been formulated to determine whether enterprise size influences the adoption of Industry 4.0 in general and specifically whether medium-sized enterprises, compared to smaller ones, are more likely to implement specific technologies.

H3a: The larger the size of the organisation, the higher the level of Industry 4.0 implementation.

H3b: There are differences between medium-sized and small enterprises in the use of specific technologies in the majority of cases.

H3c: There are differences between medium-sized and micro-enterprises in the use of specific technologies in the majority of cases.

H3d: There are differences between medium-sized enterprises and businesses without employees in the use of specific technologies in the majority of cases.

2 Objectives and Methodology

The main objective is to observe the differences in the use of modern technologies in SMEs based on the enterprise size and sector and to identify the main barriers to their implementation. Data collection necessary for evaluating these objectives was conducted through an online survey. This survey was carried out between October 2023 and January 2024, resulting in 240 responses. The respondents were SMEs in various industries. The relevance of the questionnaire was ensured through a pilot survey, after which specific questions were adjusted and the answer options modified. The pilot survey involved 20 representatives of SMEs, who provided an informed perspective from practice and highlighted the need to change the wording of three questions and modify the answer options of another five questions.

The questionnaire consisted of 18 questions, of which four were identification questions (business ID, size, age and sector) and the remaining 14 focused on the use of modern technologies and perceived barriers. Ten of these questions were closed-ended and four were open-ended. The critical questions for evaluating the hypotheses were: (a) The level of Industry 4.0 implementation in the enterprise, which could be answered on a Likert scale from 0 to 5. (b) The level of use of selected technologies could also be answered on the same scale from 0 to 5. (c) The barriers observed by the enterprise concerning the adoption of Industry 4.0, where respondents could evaluate the offered barriers with a yes/no response. See Table 2 for details. The critical question for determining the size of the enterprise was the number of employees, respecting the EU classification into categories of micro, small and medium-sized enterprises. Additionally, a separate category was created for enterprises without any employees. As Rauch et al. (2020) indicated, many studies on Industry 4.0 use the selected six-point Likert scale from 0 to 5. Marrucci et al. (2023) provided examples of its specific use in practice.

Table 2 | Likert scale

Question	0	1	2	3	4	5
Barriers to implementation	No	Yes	---	---	---	---
Level of Industry 4.0 implementation	None	Maximum 25% of activities	Maximum 50% of activities	Maximum 75% of activities	Maximum 90% of activities	More than 90% of activities
Usage of specific technologies	None	Very low	Low	Moderate	High	Expert

Source: Authors

For barriers to implementation, the scale simply identifies whether the business perceives the existence of any obstacles. A score of 0 indicates no perceived barriers, while 1

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acknowledges their presence. This straightforward binary choice allows quick identification of challenges without needing in-depth analysis.

The Likert scale used in the table was designed to provide a more precise and detailed measurement of various aspects related to the implementation of technologies in businesses. The six-point scale from 0 to 5 allows a broader range of responses, offering more granular insights into the level of barriers, the degree of implementation and the usage of specific technologies. Including a score of 0, which indicates a complete absence of activity or barriers, and a score of 5, representing maximum implementation or expert-level usage, ensures that the entire spectrum from extremely low to extremely high values is covered. This approach is well-suited for evaluating businesses with different levels of digital maturity.

This scale expresses the level of Industry 4.0 implementation as the percentage of tasks within the company that are already supported or performed by Industry 4.0 technologies. Each point on the scale from 0 to 5 corresponds to a specific range, from 0% of activities (score of 0) to more than 90% (score of 5). This scale was chosen for its effectiveness in categorising businesses based on their degree of implementing Industry 4.0, enabling clear comparisons across different organisations.

The usage of specific technologies is described using the descriptors "none", "very low", "low", "moderate", "high" and "expert". This descriptive structure makes it easier to interpret the level of technology usage and allows respondents to identify their level without the need for complex technical analysis.

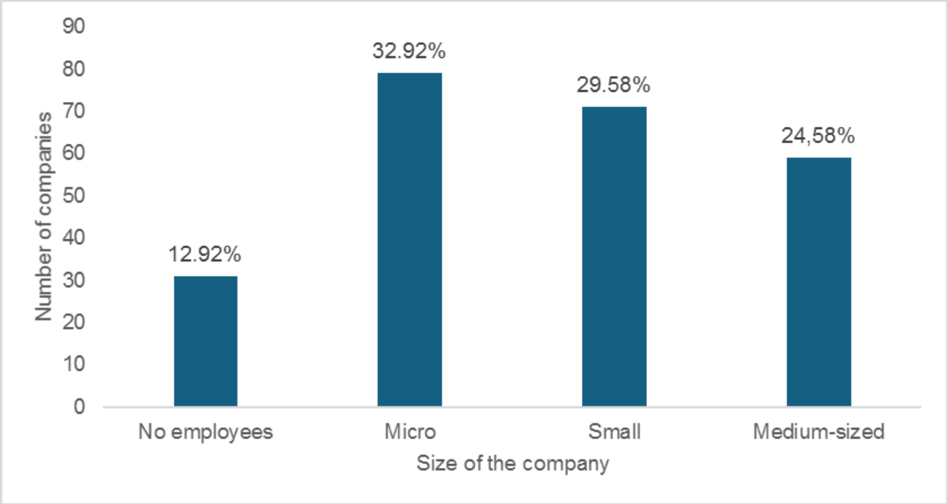
The technologies included in the survey were selected based on a literature review (Amrani & Vallespir, 2021; Enrique et al., 2021; Pech & Vaněček, 2022; Piccarozzi et al., 2018) and are as follows: big data, machine learning, the internet of things, artificial intelligence, smart sensors, 3D printing, cloud computing, robotics, digitalisation, virtual and augmented reality, cybersecurity and cyber-physical systems. Similarly, the identification and selection of critical barriers were approached (Senna et al., 2022; Ben Ruben et al., 2023; Ślusarczyk & Wiśniewska, 2024; Goel et al., 2022; Yilmaz et al., 2022; Sayem et al., 2022; Kumar et al., 2023), with the following barriers chosen: lack of financial resources, uncertain benefits of technology implementation, insufficient employee qualifications, employee resistance to change, inadequate or insufficient technical infrastructure, lack of trust in modern technologies and changes and concerns about sustainability.

The statistical software R was used to evaluate the formulated hypotheses. Initially, data normality was assessed using the Shapiro-Wilk test and a histogram, which rejected the normality assumption. Afterwards, the Kolmogorov-Smirnov test was performed and Cronbach's alpha was calculated. Another four analyses were applied: a non-parametric multivariate analysis of variance (PERMANOVA), the Kruskal-Wallis test, ordinal logistic regression and the Dunn test. All the analyses were conducted with a confidence level of $\alpha = 0.05$. The results were rounded to three decimal places, except values that could not be rounded to this number of decimal places.

The structure of the sample in terms of organisational size (determined by the number of employees) is shown in Figure 3. For the sample segmentation by sector, the CZ-NACE classification was used. Table 3 presents the sectors included in the observed sample along with their descriptions. Figure 4 shows the share of individual sectors in the sample.

The sample illustrates the structure by sectors classified according to CZ-NACE, indicating that it is representative of small and medium-sized enterprises (SMEs) in Czechia. Key sectors such as C (Manufacturing), which accounts for the largest share (32.08%) and G (Wholesale and Retail Trade; Repair and Maintenance of Motor Vehicles) with 15%, align with the distribution of SMEs in Czechia, where manufacturing and trade businesses play a significant role. Sector F (Construction), with a share of 9.58%, is also well represented, reflecting the important role of the construction industry among SMEs. Other represented sectors, such as H (Transportation and Storage) and J (Information Technologies and Communication Activities), highlight the crucial support of services and technological innovations in the SME economy. Smaller sectors such as P (Education) and Q (Health and Social Care) have lower shares, which corresponds to the fact that these areas are not typically dominated by SMEs but rather by larger or state-owned entities.

Figure 3 | Sample structure according to company size



Source: Authors

Table 3 | Sample CZ-NACE classification

Sector description	Code
Agriculture, Forestry and Fishing	A
Manufacturing	C
Electricity, Gas, Steam and Air Conditioning Supply	D
Construction	F
Wholesale and Retail Trade; Repair and Maintenance of Motor Vehicles	G

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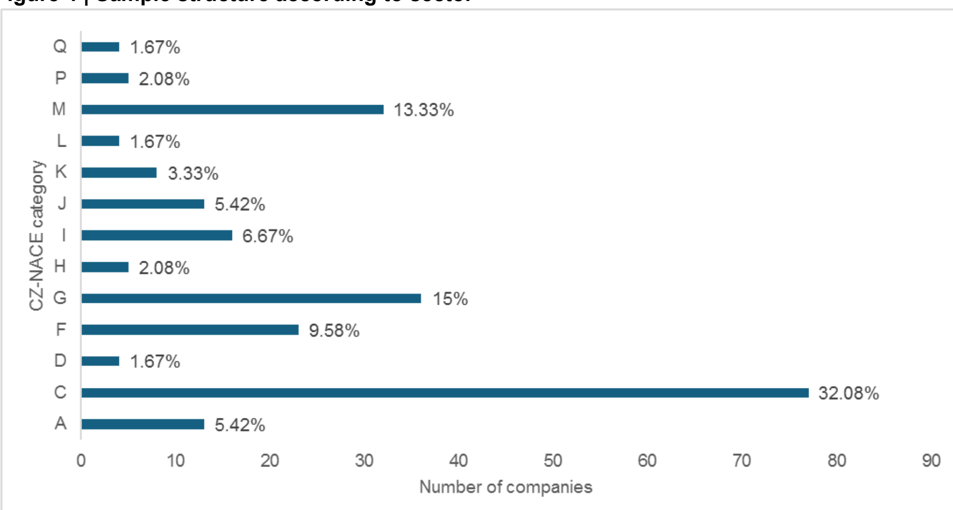
Transportation and Storage	H
Accommodation, Food Services and Hospitality	I
Information technologies and Communication Activities	J
Financial and Insurance Activities	K
Real Estate Activities	L
Professional, Scientific and Technical Activities	M
Education	P
Health and Social Care	Q

Source: Authors

Figure 4 | Sample structure according to sector



Source: Authors

3 Results

The first step was the statistical verification of the sample representativeness. For this verification, the sample was compared with data from the Czech Statistical Office (a; n.d.) for sector representativeness and Czech Statistical Office (b; n.d.) for size representativeness. The Kolmogorov-Smirnov test was used for analysis. The resulting p-value of 0.729 for the sector indicates that the sample is representative and its distribution corresponds to that in the population. The p-value for size analysis is 0.229, again higher than 0.05, and it can be stated that the sample is representative from the size point of view. The p-value in both cases is higher than the 0.05 significance level, which means that the hypothesis about the data distribution in the sample is not statistically different from the data distribution in the reference population; thus, the hypothesis is not rejected.

Another important analysis was a reliability analysis, conducted using the calculation of Cronbach's alpha. The resulting value of 0.72 suggests that the data have good internal consistency. Generally, a value above 0.7 is recommended, which this test met. The alpha could be increased by removing the variable "sector", but this was not considered due to the importance of further observations related to this variable. Other variables lowered the value of Cronbach's alpha.

The first step involved conducting an ordinal logistic regression. A classical logistic regression was not performed because the dependent variable could be ordered from the smallest to the largest. This method aimed to determine which of the two factors (sector and size) statistically affect the level of Industry 4.0 adoption in enterprises and to identify the barriers to Industry 4.0 adoption perceived by the enterprises. The results of this analysis are presented in Tables 4 and 5, respectively.

Table 4 | Ordinal logistic regression – variables

Variable	Coefficient value	Standard error	t-value	p-value
Sector	0.031	0.029	1.052	0.292
Size	0.465	0.124	3.766	0.0001

Source: Authors

The coefficient for the variable "sector" is minimal (0.031) and its p-value (0.292) is high, indicating that the sector is not a statistically significant predictor of the level of Industry 4.0 adoption in enterprises. The coefficient for enterprise size is 0.465, with a p-value of 0.0001, which is a meagre value and suggests that enterprise size is a statistically significant predictor of the level of adoption of modern technologies. Therefore, a higher number of employees is positively associated with a higher level of Industry 4.0.

Table 5 | Ordinal logistic regression – barriers

Barrier	Coefficient value	Standard error	t-value	p-value
Lack of financial resources	0.582	0.265	2.201	0.028
Uncertain benefit	-0.080	0.304	-0.263	0.793
Lack of skilled employees	0.168	0.265	0.634	0.526
Insufficient infrastructure	-0.245	0.263	-0.933	0.351
Resistance to change	0.304	0.294	1.034	0.301
Sustainability	0.177	0.495	0.359	0.720
Missing trust	0.354	0.282	1.256	0.210

Source: Authors

As shown in Table 5, all barriers, except the lack of financial resources, are statistically insignificant. In contrast, the lack of financial resources is the only significant barrier to adopting Industry 4.0.

Based on the above, hypothesis H1a can be confirmed, as it was demonstrated that the sector does not significantly affect the level of Industry 4.0 adoption. Furthermore, hypothesis H2 is confirmed, as the lack of financial resources was found to be the most significant barrier to adoption. Finally, hypothesis H3a is also confirmed since it was found that enterprise size influences the level of Industry 4.0 adoption within the company.

To determine whether the sector or enterprise size is related to the use of specific technologies, a non-parametric multivariate analysis of variance (PERMANOVA) was used. The Kruskal-Wallis test was applied to examine particular technologies separately for both variables, utilising the Bonferroni correction. The analysis was conducted with 11 selected technologies. The results can be found in Tables 6 and 7.

Table 6 | PERMANOVA results

Variable	Mean sum of squares	F-value	p-value
Sector	202.008	8.457	0.001
Size	226.458	9.151	0.001

Source: Authors

The results of the PERMANOVA indicate that the variable "sector" has a statistically significant effect on the use of specific technologies in general, as the p-value is 0.001, which is lower than the commonly used significance level of 0.05. However, as shown in Table 7, a closer examination reveals these differences. The variable "size" significantly affects the use of these technologies, with a p-value of 0.001, which is considerably lower than 0.05. The conclusion from this analysis is that both sector and enterprise size influence the use of the studied technologies.

Table 7 | Kruskal-Wallis test

Technology	p-value (sector)	p-value (size)
Big data	0.413	0.004
Machine learning	1.000	0.113
Internet of things	0.025	1.000
Artificial intelligence	0.0004	1.000
Smarts sensors	0.221	0.002
3D printing	0.065	0.354
Cloud	0.001	1.000
Robots	0.129	0.00007
Digitalisation	0.00002	0.276
Cybersecurity and cyber-physical systems	0.017	0.0002
Virtual and augmented reality	0.421	1.000

Source: Authors

The following conclusions can be drawn regarding the use of different technologies across various industries. Statistically significant differences in the use of technologies based on the sector are observed for internet of things, artificial intelligence, cloud computing, digitalisation and cyber-physical systems. Non-significant differences based on sector are noted for big data, machine learning, smart sensors, 3D printing, robots and virtual and augmented reality. Thus, the conclusion is that the sector in which a business operates does not influence the use of specific technologies in the majority of cases. Some of these findings (e.g., big data) are expected as particular industries utilise certain technologies. On the other hand, the lack of statistically significant differences for six out of the 11 technologies may indicate a generally low level of modern technology implementation across businesses. Based on this test, hypothesis H1b is rejected, as it was not proven that the sector in which a company operates affects the level of use of specific technologies in the majority of cases.

The following conclusions can be drawn when examining using specific technologies based on enterprise size. Significant differences by size were found for big data, smart sensors, robots and cyber-physical systems. In contrast, statistically insignificant differences were observed for technologies such as machine learning, IoT, artificial intelligence, 3D printing, cloud computing, digitalisation and virtual and augmented reality. The observed differences in the use of certain technologies suggest that they are primarily utilised by enterprises with greater capital strength and larger size, as they tend to be more expensive and are heavily oriented towards the engineering sector, where such organisations typically operate. On the other hand, technologies that do not show differences based on size generally do not require substantial investments and can be adopted even by smaller enterprises or those with less access to capital.

The Dunn test was conducted to observe the differences in the use of specific technologies among enterprises of different sizes; the results are shown in Table 8. All the categories of enterprises were compared: medium-sized (labelled as 3), small (labelled as 2), micro (labelled as 1) and enterprises without employees (labelled as 0). The corresponding p-values are presented in each field of the table. Technologies that showed a value of 1.000 in the previous table, indicating no observed differences in their use based on enterprise size, were excluded from this test. Specifically, these were the internet of things, artificial intelligence, cloud computing and virtual and augmented reality. Generally, these technologies are now used across all size categories, so this finding is unsurprising. Other statistically insignificant technologies from the previous test were included in this testing.

Table 8 | Dunn-test

Technology	1-0	2-0	3-0	2-1	3-1	3-2
Big data	0.069	0.098	0.0001	1.000	0.033	0.027
Machine learning	0.032	0.071	0.003	1.000	0.743	0.453
Smarts sensors	0.935	0.017	0.0009	0.059	0.002	0.716
3D print	1.000	0.171	0.063	0.233	0.069	1.000
Robots	0.111	0.238	0.0001	1.000	0.001	0.0004
Digitalisation	1.000	1.000	0.063	1.000	0.020	0.065
Cybersecurity and cyber-physical systems	0.426	0.640	0.0001	1.000	0.0007	0.0004

Source: Authors

For the first observed technology, big data, medium-sized enterprises show a statistically significant difference in usage compared to all other categories of enterprises. In contrast, no significant differences are found between different categories for this technology. For machine learning, there are significant differences between micro-enterprises and enterprises without employees and between medium-sized enterprises and those without employees. The use of smart sensors differs between enterprises without employees and small or medium-sized ones. It also varies between micro-enterprises and medium-sized enterprises. 3D printing technology does not show any statistically significant differences between the different enterprise size groups. Robotics-related technologies show apparent differences between medium-sized enterprises and all other categories. There is a statistically significant difference between micro-enterprises and medium-sized enterprises in terms of digitalisation. Cyber-physical and protective systems also differ between medium-sized enterprises and all other groups.

Generally, if there are differences in the use of specific technologies based on the organisation's size, these differences typically exist between medium-sized enterprises and other size categories. The most frequently observed differences are between medium-sized enterprises and those without employees (5 times) and between medium-sized enterprises and micro-enterprises (also a total of 5 times). Such differences are less apparent between medium-sized and small enterprises (significant differences observed only 3 times in total).

There are practically no statistically significant differences between all other categories of enterprises. In conclusion, out of the 11 observed technologies, seven were selected for closer examination based on the Kruskal-Wallis test. Medium-sized enterprises show the most significant differences compared to other groups. Still, these differences are not observed in the majority of cases (compared to enterprises without employees in five out of 11 technologies, similarly compared to micro-enterprises and compared to small enterprises in only three out of 11 cases).

Based on the results of this test, hypotheses H3b—H3d can be evaluated. All these hypotheses are rejected, as no differences in the use of technologies between medium-sized enterprises and other size categories are observed in the majority of cases. Table 9 provides a comprehensive summary and evaluation of all the hypotheses.

Table 9 | Hypotheses

Number	Wording of hypothesis	Result
H1a	The sector in which a given SME operates does not affect the level of Industry 4.0 implementation.	Supported
H1b	The sector in which a company operates affects the level of use of specific technologies in the majority of cases.	Rejected
H2	The lack of financial resources is the most significant barrier for SMEs in implementing Industry 4.0.	Supported
H3a	The larger the size of the organisation, the higher the level of Industry 4.0 implementation.	Supported
H3b	There are differences between medium-sized and small enterprises in the use of specific technologies in the majority of cases.	Rejected
H3c	There are differences between medium-sized and micro-enterprises in the use of specific technologies in the majority of cases.	Rejected
H3d	There are differences between medium-sized enterprises and businesses without employees in the use of specific technologies in the majority of cases.	Rejected

Source: Authors

Hypothesis H1a was accepted based on the ordinal logistic regression, which did not show the parameter "sector" to be statistically significant. Hypothesis H1b is rejected, as the Kruskal-Wallis test (Table 7) revealed differences in fewer than the majority of specific technologies. Thus, while the sector plays a role to some extent, it is still not a key variable in examining the adoption of Industry 4.0. The ordinal logistic regression also supported the evaluation of hypothesis H2, where a lack of financial resources was observed as the only (and thus the most significant) barrier to implementation. Hypothesis H3a was also confirmed by the ordinal logistic regression, which clearly showed that the "size" parameter is significant when assessing the level of Industry 4.0 adoption. Hypotheses H3b-H3d cannot be accepted, as it was not demonstrated that medium-sized enterprises, compared to other categories, show differences in the majority of cases. The maximum number of differences between the categories was five, which is not a majority of the 11 technologies.

Based on further analysis, it was found that big data is most widely used in the Information Technologies and Communication Activities sector, as well as machine learning, artificial intelligence, cloud, digitalisation, cybersecurity and cyber-physical systems. The differences observed in this sector are also statistically significant. The internet of things technology is most commonly used in the Electricity, Gas, Steam and Air Conditioning Supply sector, similar to smart sensors. However, cybersecurity and cyber-physical systems are also frequently utilised, although statistical significance did not support the observed differences. The Manufacturing sector shows the highest 3D printing and robot usage, with strong statistical significance. Significant use of digitalisation was observed in the Financial and Insurance Activities sector. Virtual and augmented reality technologies are predominantly used in the Real Estate Activities sector and in Education, where statistical significance was observed. The remaining sectors do not play a significant role in terms of the extent of usage of specific technologies. However, the most widely used technologies across all sectors are artificial intelligence, cloud computing and digitalisation and the highest statistical significance is clearly observed for the sectors Manufacturing and Information Technologies and Communication Activities.

In terms of company size, medium-sized enterprises use almost all the technologies the most, except the internet of things, artificial intelligence and virtual and augmented reality. However, as shown in Table 7, not all of the observed differences are statistically significant. Regarding the highest usage levels, the internet of things and virtual and augmented reality technologies are most commonly used by small enterprises. In contrast, companies with no employees predominantly use artificial intelligence. However, these conclusions are not supported by statistical significance.

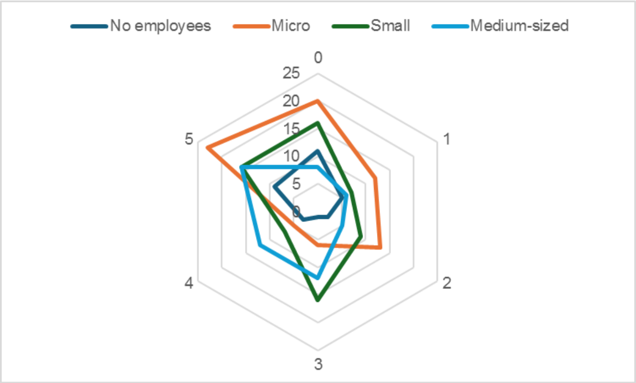
Furthermore, Figures 5 to 7 below provide a visual overview of the current use of selected technologies among SMEs in Czechia. These figures illustrate the differences in technology usage according to enterprise size and demonstrate how enterprises of different sizes approach the implementation of technologies.

Although no statistically significant differences were found for all the technologies, visual representations of technology usage by company size still hold value for several reasons. Firstly, the images help illustrate potential trends and patterns that might not be strong enough to reach statistical significance but could still indicate exciting tendencies. For example, slight variations in the adoption of certain technologies by SMEs suggest potential areas for further research.

Secondly, including these images provides a complete and transparent overview of how technologies are utilised across different company sizes, giving readers a better understanding of the context and variation within the data. Even if the differences are not statistically significant, they provide a comprehensive picture of technology adoption.

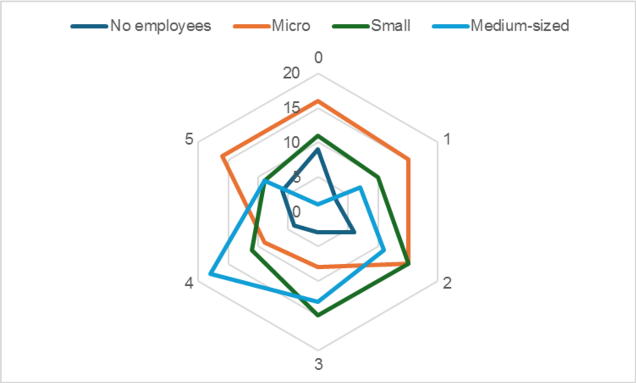
Finally, visualisations can have practical implications for decision making, especially for managers and policymakers who may find it helpful to see how different types of companies employ various technologies. While the observed differences may not be statistically confirmed, the visual insights can still inform strategies and help tailor technology support programmes for SMEs.

Figure 5 | Cloud use in SMEs



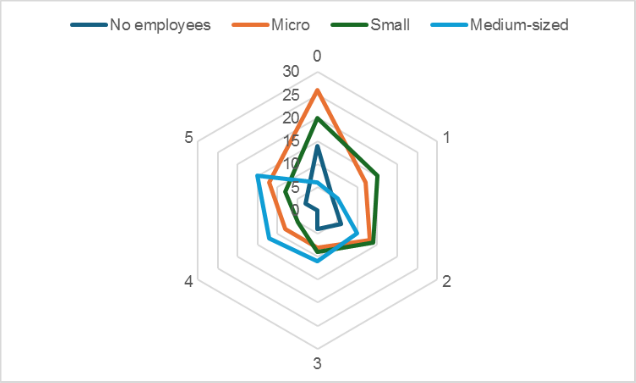
Source: Authors

Figure 6 | Use of digitalisation in SMEs



Source: Authors

Figure 7 | Use of cybersecurity and cyber-physical systems in SMEs



Source: Authors

4 Discussion

The results indicate that the size and sector of an organisation play a role in implementing modern technologies, with larger enterprises and those in specific sectors more frequently adopting modern technologies. Müller et al. (2018) evaluated the implementation of Industry 4.0 technologies in both large enterprises and SMEs, finding that larger enterprises have greater financial and better human resources, enabling them to implement modern technologies more effectively. The research also emphasised the significant role of leadership in supporting digital transformation. Agostini & Nosella (2019), focusing on SMEs in Italy, observed that smaller enterprises can also successfully implement various technologies if they can access external resources and support, such as government grants or partnership programmes with larger companies. This difference may be attributed to varying levels of government support and resource availability in different countries. Similarly, Marrucci et al. (2023) showed that enterprise size is an essential factor in decisions regarding the implementation of Industry 4.0 technologies, with larger enterprises having a greater chance of successful implementation due to better infrastructure and financial resources. All these findings align with the results of this research. Dvořáková et al. (2021) pointed out that micro and small enterprises most frequently work with technologies such as artificial intelligence, the internet of things or virtual reality, while medium-sized organisations are more likely to use 3D printing and additive manufacturing, robotics or drones, alongside the same technologies used by smaller enterprises. It was also found that the primary source of problems in implementation is a lack of financial resources. This lack can also be framed as insufficient support from leadership and top management, as Sony & Naik (2020) noted. This lack of support was not explicitly defined as a barrier but was considered one of the ten critical success factors for Industry 4.0 adoption. However, other findings indicate that, apart from financial constraints, inadequate infrastructure or low levels of technological awareness among employees are also perceived as barriers (Horváth & Szabó, 2019). Additionally, it has been observed that the barriers differ between SMEs and enterprises with international cooperation. Goel et al. (2022) provided a detailed examination of implementation barriers while mentioning the key barriers identified in this research.

Vaska et al. (2021) demonstrated that digital transformation significantly enhances the competitiveness of SMEs. Implementing AI and big data technologies enables companies to optimise production processes and better respond to changing market conditions. Similarly, Khan et al. (2024) suggested that industrial technologies improve operational efficiency and flexibility, leading to better competitiveness on the global market. Chakraborty et al. (2023) examined the implementation of Industry 4.0 technologies in the education sector and the results of their bibliometric analysis suggest that these technologies can significantly improve teaching efficiency and administrative processes. This finding broadens the perspective on implementing Industry 4.0 technologies beyond traditional manufacturing sectors. Another study focused outside the traditional manufacturing enterprises by da Silveira et al. (2021) looked at the healthcare sector and found that Industry 4.0 can significantly improve diagnostic processes and healthcare facility management. However, modern technologies are still most frequently mentioned in the literature concerning the manufacturing sector, where their use is also the most prevalent.

The present study identified the most commonly used technologies for several sectors, often without statistical significance, indicating that many industries do not stand out in using any specific technology. For example, in the Manufacturing sector, the most important and widely used technologies are 3D printing and robotics. However, as shown by Mofolasayo et al. (2022), even for manufacturing companies, it is crucial to adopt a broader range of technologies beyond these two to successfully enhance the level of Industry 4.0 implementation within the enterprise. Galizia et al. (2023) also highlighted that SMEs frequently utilise advanced manufacturing technologies; however, their success largely depends on adopting a comprehensive package of technologies rather than relying on just one. Ávila Bohórquez and Gil Herrera (2022) also emphasised the need for a holistic approach in utilising a wide range of technologies to achieve digital maturity within an organisation, regardless of the sector in which it operates.

A comparison of the research results on the implementation of Industry 4.0 technologies in Czech SMEs with other studies shows that many conclusions align with global trends. The main factors influencing successful implementation are enterprise size and availability of financial resources. To address the identified discrepancies, strengthening government support, investing in technological infrastructure and focusing on organisational and cultural factors are essential.

Conclusion

The answer to RQ1: "What is the influence of the business sector and size on the level of Industry 4.0 implementation in SMEs?" is that the business sector does not affect the overall level of Industry 4.0 implementation, but it does statistically influence the adoption of specific technologies. In contrast, company size is a significant predictor for the overall adoption of Industry 4.0 and implementing individual technologies. Regarding RQ2: "What barriers affect the implementation of Industry 4.0 in SMEs?", we can conclude that the only statistically significant barrier is the lack of financial resources. The main objective of this research, "To observe the differences in the use of modern technologies in SMEs based on enterprise size and the sector in which they operate and to identify the main barriers to their implementation", was therefore achieved as differences in the use of individual technologies were found across both sectors and company sizes. Additionally, the most critical barrier was successfully identified.

The data obtained identified key trends in implementing technologies in small and medium-sized enterprises (SMEs) in Czechia. The survey revealed that businesses across different sectors and sizes face various challenges when adopting new technologies. The most commonly cited barriers include a lack of financial resources, insufficient employee qualifications and resistance to change, with the lack of financial resources appearing as the most important and significant barrier. The results also revealed that larger enterprises, specifically medium-sized in this context, tend to implement modern technologies more frequently than smaller enterprises. This difference is particularly evident in the use of advanced analytical tools and automation. Medium-sized enterprises show a higher rate of technology adoption, likely due to better financial and human resources.

An interesting finding is that the sector in which a business operates does not have a statistically significant impact on the level of implementing Industry 4.0. However, there are examples of significant differences according to different technologies; for instance, businesses in the manufacturing sector are more likely to use technologies such as 3D printing and robotics, while service sector businesses such as IT focus more on digitalisation and cloud computing.

Examining statistically significant differences among groups of small and medium-sized enterprises (SMEs) in relation to technology implementation provides valuable insights for developing targeted strategies and informed decision making. Statistically significant differences indicate that the observed disparities are not due to random chance but reflect real market behaviour. This information can be valuable for policymakers, technology providers and other stakeholders in tailoring support programmes and tools that better meet the needs of SMEs and facilitate their transition towards digitalisation and Industry 4.0.

The main limitation of the research is the online survey, which could be influenced by respondents' subjective assessments and their limited awareness of technological options and barriers. There is also a geographical limitation to the territory of Czechia, preventing, for example, international comparisons. Methodologically, using only non-parametric statistical methods may also be limiting, as they may only partially capture some of the complex relationships between variables. However, given the rejection of the data normality assumption, their use was necessary.

These findings highlight the need for targeted support to smaller enterprises to help them better utilise available technologies and improve their competitiveness. It is essential to focus on employee education and skill development and ensure financial resources for investments in technology. For future research, expanding the sample to include more businesses from various regions and sectors would ensure better coverage of the diversity of SMEs. It is also recommended that in-depth interviews be conducted with key business stakeholders, which could provide deeper insights into practical challenges and barriers.

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