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DETERMINANTS OF AI ADOPTION INTENTION IN SMES. ROMANIAN CASE STUDY

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Abstract. The paper investigates the drivers and barriers that encourage or hinder the adoption of artificial intelligence (AI) technologies within Romanian SMEs. By using the Technology-Organisation-Environment (TOE) framework, we examined the role of several factors from each TOE dimension in predicting the AI adoption behaviour. The factors were constructed through factor analysis followed by the estimation of a linear regression model. Partial least squares structural equation modelling was then used in order to further explore the relationships and to check the robustness of the linear regression model. Our findings highlight the significant role played by leadership, organizational readiness, as well as the "push-and-pull" effect of competitors and customers in encouraging SMEs to adopt AI technologies. However, in the case of Romania, specific challenges related to a lack of digital skills among employees, a limited understanding of the relative advantage that digitalisation can offer, as well as a lack of marketing efforts from the side of vendors make it difficult for SMEs to consider the implementation of AI technologies. This exploratory study seeks to understand the underlying trends of the phenomenon and serves as a stepping stone for vendors, managers, as well as researchers to better understand the market for AI tools and solutions among Romanian SMEs.

Keywords: artificial intelligence, small and medium sized enterprises, TOE framework, AI adoption behaviour, Romania, structural equation modelling.

JEL Classification: O33, M10, L20.

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1. Introduction

Nowadays, sustaining growth and ensuring success in the increasingly competitive business environment, companies have to be flexible and adapt to the latest (IT) technologies, including Artificial Intelligence (AI). If leveraged properly, AI technologies can empower companies to achieve superior performance and, in turn, can be a powerful booster for the society's overall economic development. The COVID-19 crisis acted as a significant catalyst for companies to accelerate investments in digitalization as a response to the challenges it presented. In addition, the Fourth Industrial Revolution pushed even more companies into the digitalization race (Maroufkhani et al., 2023). Hence, proper embracing of the AI phenomena by Small and Medium-sized Enterprises (SMEs) can result in huge benefits from productivity enhancements to cost reductions to employee experience improvements (Chaudhuri et al., 2022), among many other benefits that we shall see later on.

The latest results of the 2022 European Investment Bank Survey report that, in the EU, 53% of firms report taking action to become more digital (European Investment Bank [EIB], 2023c). However, significant differences persist across countries and firm sizes (Jaumotte et al., 2023).

This occurs because some barriers exist with regard to AI advancements in all three stages of a business venture: innovation/research, development and adoption. It seems that, despite the vast potential of AI, the adoption of a disruptive technology is generally missing among SMEs (as some figures will reveal later on in the manuscript).

Our attention is focused on SMEs, the backbone of Europe's economy, which comprises 99% of all businesses in the EU (European Commission [EC], 2024). In Romania, SMEs play a central role in the economy, accounting for 99.7% of the roughly 521,000 active companies (EIB, 2023b). Despite these strengths, SMEs often limited by scarce resources, such as inadequate investment in up-to-date technologies. Nonetheless, SMEs share the mutual need to plan and use their scarce resources efficiently and effectively (Wong et al., 2020). Therefore, the topic of AI adoption in SMEs is more than ardent, garnering significant attention from practitioners, researchers, and policymakers alike.

In this context, our aim is to shed some light onto the challenges of AI adoption in the Romanian business environment, by focusing on SMEs from four strategic industries. The focus is on Romania because it is a representative country for Eastern Europe. In addition, we adopt an industrial perspective focusing on four key strategic sectors of Romania: Agri-food, Healthcare, Tourism and the Wood industry. These are also included in the European Union's Smart Specialization Strategy, among others, throughout the development regions of Romania.

Methodologically, the paper is grounded in the Technology-Organization-Environment (TOE) model and builds on the data from 145 SME respondents from the four key sectors of Romania. The relevance of TOE lies in its capacity to offer valuable insights into the motivating factors and challenges that enterprises encounter in the process of adopting technology. The framework provides a structured approach to analyzing the factors that shape AI adoption in SMEs by grouping the them into three main categories: technological readiness, organizational capabilities, and environmental influences (El-Haddadeh, 2020). The usefulness of this particular model (beyond popular user-centric models which will be explored in great detail in the next section) and its strongpoints are brought forward, in detail, in the following section.

This particular model, recognized as a strong framework for understanding the factors driving AI adoption in SMEs, is considered superior to other models (as detailed in the earlier section). It emphasizes the unique context of the adoption process and aids in evaluating the key factors that influence AI adoption.

RQ1: What are the main factors that drive the intention of Romanian SMEs to adopt Artificial Intelligence technologies within their internal structure?

RQ2: What is the strength / importance of such factors in regard to AI adoption intent?

The study mostly confirms the results of previous research on the topic, but its most important contributions (or, in other words, the novelty of the paper) are related to the practical implications that it has on understanding AI technology adoption among SMEs in Romania and, through possible extension, other countries in Eastern Europe. We also find evidence on the existence of a "push-and-pull effect" that "perceived competitive pressure" and "perceived customer pressure" can have on AI adoption in businesses.

Beyond the current introduction, the paper is structured in five sections. A review of existing scientific literature is presented in Section 2. Section 3 presents the theoretical framework and the hypothesis development. Section 4 presents the methodology of the research. Section 5 presents and discusses the implications of the results. Finally, the conclusion summarizes the entire work, focusing on policy recommendations, limitations and future research.

2. Review of the scientific literature

A straightforward and useful definition of the main concept is provided by Joiner (2018): Artificial Intelligence (AI) refers to "the field of computer science that focuses on creating intelligent machines capable of performing tasks that typically require human intelligence". According to AlSheibani et al. (2018) AI is defined as "a collection of tools and technology capable of augmenting and enhancing organizational performance". Basically, the term AI is commonly used to illustrate machines that impersonate cognitive capabilities (Ingalagi et al., 2021) to exert a change in the labor relations model and in employment itself (Morikawa, 2016). According to Eurostat (2023) AI refers to "systems that use technologies such as text mining, computer vision, speech recognition, natural language generation, machine learning or deep learning". These modern definitions have advanced significantly since the term was initially coined by computer scientist John McCarthy more than 60 years ago. Given its' technical features, AI can be leveraged in various applications in various domains such as agriculture, healthcare, tourism, hospitality, finance, transportation, gaming, etc.

AI adoption in particular refers to the integration of AI products or services within the internal production processes or service delivery of companies (Hoffmann & Nurski, 2021). However, there is currently no empirical measure of AI acceptance. Hu et al. (2021) noticed that AI is gaining momentum, and companies are experiencing significant advantages from the broadening range of human cognitive and functional capabilities enhanced by this technology. And, as Chen et al. (2023) recently suggested, the adoption of AI and its performance within SMEs have attracted increasing attention from various parties. However, the literature on AI adoption in SMEs, while abundant, often lacks coherence and comprehensiveness (Schwaeke et al., 2024; Treiblmaier, 2018). But the focus of this paper is not on establishing the most suitable definition of AI, nor on grasping the full extent of the process of AI adoption in businesses. As for the state-of-the-art research of AI in business, this was already investigated (Ruiz-Real et al., 2021). In addition, a more recent study, provides a structured overview of AI research within the SME sector (106 peer-reviewed articles), identifying challenges, facilitators, opportunities, and implementation domains (Schwaeke et al., 2024). Our focus is rather on identifying specific determinants (eithers barriers or boosters) of AI adoption in Enterprises, and more specifically, in small and medium-sized enterprises.

Enterprises may be motivated to adopt AI within their internal architecture for various reasons, including: the chance to streamline internal processes, make correct or better decisions, boost productivity, improve marketing strategies, gain a competitive advantage or retain employees (Chen et al., 2023), enhance growth and maintain competitiveness despite limited resources (Rawashdeh et al., 2023), enhance operations and the strategic decision-making process and optimize overall business performance (Lada et al., 2023) or simply maximize operational efficiency and transparency (Ingalagi et al., 2021). While some argue that AI technology is not a comprehensive solution for businesses (Wang & Pan, 2022), it nonetheless has the potential to transform the business and global economic landscape by bringing forward advantages such as enhancing productivity, minimizing human error, enabling companies to make timely and accurate decisions, predicting customer preferences, and maximizing sales (Soni et al., 2020). Aside from the studies that bring forward the positive effects of AI adoption on organizational performance, there is also another strand of the literature that pays attention to the negative aspects of AI adoption on business performance. As Chen et al. (2023) suggest, there are studies which highlight the negative impact on organizational performance of AI attributes, such as: AI opacity and unfairness, robotics awareness and perceived risk (Khaliq et al., 2022). These attributes have also been found to increase employee turnover while decreasing employee happiness and efficiency (Khaliq et al., 2022; Wu et al., 2022).

Concerning the barriers in adopting AI in SMEs, Lada et al. (2023) identified three main challenges that such companies face in the process of adopting AI technologies: lack of thought leadership and commitment from leadership toward investment in AI, shortage of skills and resources despite ongoing learning efforts, and insufficient development of analytics, infrastructure, and tools needed to produce actionable insights. In addition, Ingalagi et al. (2021) point out that the barriers in adopting AI in SMEs are more of an internal nature: a lack of fundamental understanding of AI capabilities and benefits as well as insufficient resources for AI adaption and integration.

According to Hoffmann and Nurski (2021), AI adoption in European businesses is rather low and most probably lagging behind other regions of the globe. The authors call for a comprehensive understanding of the existing adoption barriers so that AI adoption within European firms might take place. Also, as EIB (2023a) suggests that the European business environment it is poorly positioned in terms of digital innovation and faces the risk of becoming dependent on several critical technologies. In particular, micro and small firms are lagging behind medium-sized and large firms when it comes to investing in digitalization. In the EU, only 30% of microenterprises reported taking steps to enhance digitalization in 2022, whereas 62% of large firms made similar efforts (EIB, 2023a). Eurostat (2023) presents the most recent statistical data on the use of AI technologies by EU enterprises. With regard to the US, the situation is similar. A report ptovided by MIT Sloan Management Review in partnership with The Boston Consulting Group revealed that 85% of surveyed CEOs believe AI provides a competitive edge for their companies. However, its adoption has been gradual, with only 20% of businesses having fully integrated this technology (Ransbotham et al., 2017). A recent Deloitte report reveals a divergence: while 94% of business leaders agree that AI will be essential for success within the next five years, they anticipate that its implementation will yield delayed results. As a result, the willingness to invest in AI dropped from 85% in 2021 to 76% among the surveyed group (Mittal et al., 2022).

Most of the studies conducted on SMEs and AI have primarily focused on the more developed countries (Khanzode et al., 2021; Sharma et al., 2024), neglecting developing economies. Leveraging the case of Romania, this research sheds light on potential trends in AI adoption across all of Eastern Europe, given the region's shared characteristics. While the historic, cultural and socio-demographic background of the Eastern European countries is different from the wealthier North and West part of Europe, it is, at the same time, quite homogeneous within the group. The shared socio-economic background of the region includes the use of the socialist central planning system, followed by a synchronous transition towards market economies, albeit at differing speeds (Apostoaie & Bilan, 2020).

As mentioned earlier, the focus of the paper is on SMEs. In Europe, they represent the backbone of the economy, representing around 99% of all businesses (EC, 2024), while in Romania, they sum up to 99.7% of approximately 521,000 active companies (EIB, 2023b). SMEs are crucial to the global economy, and in response, the EU is focused on boosting their business activities and ensuring they stay aligned with emerging technologies. This is because the international competitiveness of SMEs has a direct impact on economic stability (Hansen & Bøgh, 2021). A particular feature of this kind of companies regard the financial constraints which are found to exert a first-order impact on business growth, especially on the ability of smaller businesses to grow. Beck et al. (2005) evaluated the impact of financial constraints on firms' performance and found that financing constraints exert a first-order impact on business growth, especially on the ability of smaller businesses to grow. Although there are also other features that distinguish SMEs from larger companies (such as size, flexibility and hierarchy as Dong and Yang (2020) inclines), resource and budget limitations are the main barriers to value creation from AI adoption (Mangla et al., 2021).

The most well-known model that academics employ when analyzing the impact of technology, in general, on business development is the TOE framework (e.g., Chen et al., 2023; Lada et al., 2023; Maroufkhani et al., 2023; Phuoc, 2022; Wong et al., 2020). In summary, the TOE model analyzes how Technological, Organizational, and Environmental factors impact AI adoption performance (Chen et al., 2023). Being a theoretical model, it explains how organizations adopt technology, highlighting the influence of technological, organizational, and environmental contexts on the process of adopting and implementing technological innovations in companies (Rawashdeh et al., 2023). This framework is notable for its comprehensive approach to technology adoption, incorporating both human and non-human factors, and extending beyond the popular user-centric models (Wong et al., 2020). An alternative, not as viable as TOE, would have been the Theory of Reasoned Action (TRA). This theory, proposed by Fishbein and Ajzen in the 1960s, suggests that a particular behavior can be anticipated based on the intentions to engage in it (Fishbein & Ajzen, 2010). AlSheibani et al. (2018) offer valuable insights into individuals' technological adoption behaviors by referring to TRA, which explains how attitudes and social norms shape and guide a person's actions. Building on the existing TRA, Ajzen (2012) proposed the Theory of Planned Behavior (TPB) which posits that an individual's intentions and actions are shaped by their attitude toward the behavior, the impact of subjective norms, and their perceived control over the behavior. As a response to the limitations of a theoretical framework and measurement scales for assessing technology acceptance, Davis (1985) introduced the Technology Acceptance Model (TAM), grounded in TRA. The core idea behind TAM was that, in the context of technology use, behavioral intention was influenced not by a general attitude toward behaviour but by specific beliefs regarding the use of technology (Marikyan & Papagiannidis, 2023). Tornatzky et al. (1990) introduced the TOE model to outline how technological, organizational, and environmental factors influence a company's decisions regarding the adoption of technological innovations. Acknowledging its usefulness and versatility, we embrace this framework and address the existing gap in the literature by providing a country case analysis on Romania.

3. Theoretical framework and hypotheses development

The study applies the TOE framework, which considers technological, organizational and environmental factors that impact the adoption and implementation of technological innovation. Tornatzky et al. (1990) introduced the model, and subsequent research indicates its effectiveness in identifying the occurrences across diverse technical, industrial, and national/cultural settings. According to Maroufkhani et al. (2020) the TOE factors are dynamic based on the specific type of technology and characteristics of the organization. This particular model serves as a reliable framework for analyzing the factors influencing AI adoption in SMEs, is superior to other models (its specific features being described in the earlier section). It highlights the specific context of the adoption process and helps evaluate the factors influencing AI adoption. Consequently, this study adopts the TOE framework as its theoretical basis. In addition, we follow Oliveira and Martins (2011) and Phuoc (2022) to employ the TOE framework within the Diffusion of Innovation Theory to evaluate IT adoption.

3.1. The technological dimension of the TOE framework

We believe that any of the technological factors can play a critical role in determining the success of AI adoption in a SMEs, providing these businesses a relative advantage from the very beginning. Notably, internal technological capabilities contribute to a deeper understanding of business processes, empowering organizations to leverage AI effectively as Maroufkhani et al. (2023) suggest. Furthermore, continuous technological innovation serves as a fundamental driver of sustainable competitive advantage. Also, as Wang and Pan (2022) suggest, the implementation of an effective system can lead to significant improvements in business processes, ultimately enhancing profitability and fostering an organization's competitive edge. Collectively, these aspects underscore the potential of AI to equip SMEs with a range of distinct relative advantages (Sharma et al., 2024).

In addition, one must not neglect the size of a company. The existing research on AI adoption primarily focuses on large companies. However, prior studies have extensively documented that SMEs differ significantly from large corporations in terms of critical factors like resource availability, size, organizational flexibility, and hierarchical structures. For instance, resource constraints and budgetary limitations are frequently cited as key obstacles hindering SMEs' ability to extract value from AI adoption. In particular, SMEs often view AI adoption as a process that is costly, challenging, uncertain and complex (Dong & Yang, 2020; Mangla et al., 2021; Maroufkhani et al., 2020). Maroufkhani et al. (2023) bring into the spotlight various studies that reveal a negative effect of the perceived complexity of a technology on the adoption of such technologies such as intelligent agent technology, cloud computing, blockchain and big data. Sharma et al. (2024) also highlight that perceived implementation complexity can negatively impact the adoption of new technologies, as users are less likely to embrace solutions they find challenging or complicated to implement (and brings forward some studies which have shown that a new technology's ease of use significantly affects its acceptance).

Given all the above, our research hypotheses related to the technological dimension are:

H1: The perceived relative advantage of AI based technologies positively influences a company's intention to adopt AI technologies.

H2: The perceived complexity of AI based technologies negatively influences a company's intention to adopt AI technologies.

H3: The perceived high costs related to technological readiness when it comes to AI based technologies negatively influences a company's intention to adopt AI technologies.

3.2. The organizational dimension of the TOE framework

A company's performance on the market relies not only on its adoption of AI technologies, but also on the leadership, support, and investment provided by the company's top management. Top management support is "the degree to which managers comprehend and embrace the technological capabilities of a new technology system" (Maroufkhani et al., 2020). Abundant literature highlights the influence of top management support on the adoption of technologies such as cloud computing, CRM systems, and big data (Maroufkhani et al., 2023). Hence, the presence of top management support is crucial for fostering an environment conducive to AI adoption, as it ensures the allocation of sufficient resources to facilitate technology implementation, and, in the end accelerates business transformation and facilitates AI adoption (Chen et al., 2015; Wang & Pan, 2022). This support is a critical factor in the success of IT projects (Chen et al., 2023), either in the implementation phase, or in the acceptance stage (Phuoc, 2022).

Organizational readiness denotes the degree to which an organization possesses the necessary resources, encompassing financial, technological, and skilled human capital, to successfully adopt and utilize a new technology (Maroufkhani et al., 2020). Lada et al. (2023) highlight leadership, workforce capabilities, cultural alignment, and infrastructure as dimensions of organizational readiness. Lee and Tajudeen (2020) also reveal that, in addition to organizational readiness, compatibility, efficiency improvement, and time savings are key factors that directly and indirectly affect AI adoption through accounting automation. These resources are deemed essential for SMEs to fully exploit the potential of AI technologies. Within this component we also account for the innovativeness of a firm which can be characterized as an organization's capacity to continuously acquire and effectively integrate new technological knowledge. This capability enables organizations to recognize the value of external knowledge, synergize it with their existing knowledge base, and ultimately translate it into commercially viable outputs.

We also investigated a firm's perceived employee capability as a determinant factor of AI adoption. The presence of qualified employees plays a critical role in facilitating the successful adoption of information and communication technology (ICT) within any business. We consider this factor to be particularly relevant for Romanian SMEs (Popa et al., 2024). Limited access to qualified human resources, a disadvantage commonly faced by SMEs compared to larger businesses, can hinder their innovative capabilities according to Sharma et al. (2024). And this is even more important when little is known on the intricacy of AI's impact on employees' professional and personal life. Consequently, SMEs often hire external consultants to bridge the skills gap. Baker (2012) also acknowledges the importance of employee capability in adopting new technology, such as artificial intelligence.

Accordingly, the following hypotheses were proposed:

H4: The top management support positively influences a company's intention to adopt AI technologies.

H5: A company's organizational readiness positively influences its intention to adopt AI technologies.

H6: A company's perceived employee capability positively influences its intention to adopt AI technologies.

3.3. The environmental dimension of the TOE framework

One important pressure that SMEs have to deal with (especially given their size when compared to the bigger corporations) comes from the competitors. The amount of pressure an entrepreneur faces from the competitors in the same industry is termed "competitive pressure" (Sun et al., 2020). This encompasses both internal and external forces that drive firms to adopt innovative technologies (Wong et al., 2020). Internally, the desire to gain a competitive advantage motivates technology adoption. Externally, firms face pressure from various stakeholders within the supply chain, including upstream and downstream players. Additionally, the pressure to adapt to evolving business models and industry standards acts as a further impetus for technological innovation. The relationship between the perceived competitive pressure and technology adoption (AI specifically) has already received some scholarly attention. Studies have consistently identified a positive association, suggesting that businesses perceiving greater competition are more inclined to adopt AI technologies (Phuoc, 2022; Sharma et al., 2024; Sun et al., 2020; Xu et al., 2017) or other innovative technologies (Wong et al., 2020). External competitive pressure compels organizations to leverage AI technologies, in order to further enhance customer service and achieve a competitive advantage, and ultimately leading to an improved organizational performance (Chen et al., 2023).

In their desire to satisfy customers' demand and expectation, and thus increase engagement, companies are leveraging technological advancements, including AI technologies. Empirical studies indicate a positive relationship between customer pressure and a firm's willingness to adopt innovative technologies. In this regard, Sharma et al. (2024) successfully bring forward a pool of existing research on the topic. Last but not least, we believe that there is also a positive effect that can be exerted on SMEs by various partners that the business interacts with, including from vendors. When a vendor provides a business with support and training in innovative technologies, it more likely for that business to also innovate and adapt various technological advancements, whether these are in the hospitality industry, IT industry, health sector or any another industry – as Sharma et al. (2024) extensively documents on.

Accordingly, the following hypotheses were proposed:

H7: A company's perceived competitive pressure positively influences its intention to adopt AI technologies.

H8: A company's perceived customer pressure positively influences its intention to adopt AI technologies.

H9: A company's perceived availability of vender support positively influences its intention to adopt AI technologies.

Building on the nine hypotheses derived from the TOE framework, this study presents a conceptual model, which is verified through a linear regression analysis, as seen in Table 4, followed by structural equation modelling, as seen in Figure 1, which depicts and tests the hypothesized relationships.

4. Research methodology

The TOE framework has been applied to delineate the adoption of inter-organizational systems and has demonstrated efficacy in European, American, and Asian contexts, as well as in both developed and developing countries (Sharma et al., 2024). Researches prefer this framework because it distinguishes between technology non-adopters and adopters (Sun et al., 2020). From a theoretical standpoint, this framework has been applied across various technological contexts, including but not limited to: customer facing in-store technologies, big data, semantic Web, e-business, software as a service and information and communication technologies – for the specific references please check Chen et al. (2023) – or customer relationship management, cloud computing, blockchain, social commerce, social media marketing, internet of things, and BDA – for the specific references please check Maroufkhani et al. (2023). Drawing on Baker's work (2012), the TOE framework demonstrates adaptability across diverse contexts. This adaptability stems from its focus on the interplay between the composing and independent factors. As different innovations possess unique adoption drivers, and cultures and contexts vary, the specific factor combinations influencing adoption will also differ. Consequently, the TOE framework's versatility lies in its ability to accommodate these nuanced dynamics.

The TOE framework's unique strength lies in its comprehensive approach, integrating both human and non-human factors into a single framework. This holistic perspective distinguishes it from traditional models like TRA, TBM, TAM, Diffusion of Innovation, and UTAUT (discussed earlier in detail), which tend to focus primarily on either technological or user-centric aspects of adoption (Wong et al., 2020). Another important strength lies in its consideration of both internal and external factors at a single model (Xu et al., 2017).

After consulting several studies which use the TOE framework, we adapted a series of scales in order to construct 9 predictors (grouped along the three TOE dimensions) and one dependent variable. The responses were provided on a five-point scale from "1 – completely disagree", to "5 – completely agree". We present the constructs and the sources from which their scales were adapted in Table 1. A detailed list of the items contained in each scale is provided in the online supplementary material.

Table 1. Definition of variables

TOE	Var.	Description	# items	Adapted from
T	REA	perceived relative advantage	7 items	Maroufkhani et al. (2023)
	CPX	perceived complexity	5 items	Eurostat (2023)
	CST	perceived high costs	6 items	Wong et al. (2020), Sharma et al. (2024)
O	TMS	top management support	4 items	Chen et al. (2023), Sharma et al. (2024)
	ORG	organizational readiness	4 items	Chen et al. (2023), Maroufkhani et al. (2023)
	EMP	perceived employee capability	4 items	Sharma et al. (2024)
E	COM	perceived competitive pressure	4 items	Chen et al. (2023)
	CUS	perceived customer pressure	4 items	Wong et al. (2020), Sharma et al. (2024)
	VEN	perceived vendor support	3 items	Sharma et al. (2024), Maroufkhani et al. (2023)
-	AI	AI adoption intention (dependent)	4 items	Wang and Pan (2022)

We focused on these four key industries in Romania for multiple reasons. On one hand, we wanted to narrow our research by focusing on a specific number of industries, thus channeling our resources and attention more efficiently. On the other hand, these particular industries were selected given their overall coverage in the list of smart specialization domains in Romania (Indaco, 2017), their high potential of generating gross added value and an expected high incidence among the existing Romanian SMEs. In addition, we believe these sectors to be the among the most conservative ones in terms of AI adoption in business.

The data collection methods were CAPI and CAWI, with Sawtooth Software 6.4 being used as the collection tool. We used quota sampling in order to ensure a balanced representation of the four industries and a representation of company sizes that matches the SME population structure across Romania, with microenterprises representing a staggering 89.6% of all active SMEs from the roughly 521,000 active companies. This means these small businesses with fewer than ten employees and €2 million in turnover play an outsized role in the Romanian economy (EIB, 2023b). Respondents were randomly selected from a database that compiles the publicly available contact information of private enterprises in Romania. Over 4000 companies were contacted and 145 valid responses were collected (see Table 2).

After collection, the item scales were combined into the 10 constructs mentioned above using factor analysis. The results were first estimated using a linear regression model, which is more familiar and easily explained and presented to potential stakeholders. Both these analyses were performed in STATA MP 16.

Since not all hypotheses were confirmed, the second phase of the analysis involved using partial least squares structural equation modeling (PLS-SEM) to assess the robustness of the results and further examine the relationships between the variables. The one advantage that PLS-SEM could have over the linear regression analysis used initially is that it does not require the preliminary step of performing factor analysis on the measurement items. Thus, all of the information from the initial dataset is utilized to form the latent variables which are then used in the model, instead of generating constructs which only capture some of the variance of the observations. This can lead to more robust results, as suggested by Chen et al. (2023). However, the fact that we were able to successfully generate these factors in the first stage of the analysis, confirms that the combination of the items in each scale into the latent variables used in the second stage is a valid approach.

PLS-SEM was used instead of covariance-based SEM because it allowed us to create formative relationships between the measurement items and the latent variables (similar to the factor analysis of the initial model) and it also tends to have greater statistical power on smaller sample sizes (Chen et al., 2023). This analysis was conducted using WarpPLS 7.0.

5. Results and discussion

The respondents represent a wide variety of micro, small and medium sized enterprises spread across all eight development regions of Romania. The sample has a balanced representation of the four target industries and tends to include smaller businesses that have been in existence for several years (Table 2).

Table 2. Descriptive statistics of respondent entities

Variable	Category	Frequency	Percent
Industry	Agri-food	34	23.4%
	Wood/Lumber	39	26.9%
	Health	35	24.1%
	Tourism	37	25.5%
Company size	Micro (under 10 employees)	96	66.2%
	Small (10–49 employees)	38	26.2%
	Medium (50–249 employees)	11	7.6%
Founding date	Last 5 years	35	24.1%
	5–10 years ago	28	19.3%
	Over 10 years ago	82	56.6%

In order to confirm the internal consistency of the scales used to estimate the ten construct variables through factor analysis, we calculated Cronbach's Alpha and the Composite Reliability (CR) for each set of scales. The Cronbach alpha values ranged from 0.79–0.93, while the CR values ranged between 0.76–0.94 – well above the 0.7 (Sharma et al., 2024), confirming a good level of internal consistency.

The average standardized factor loading (SFL) is between 0.73–0.91 for each scale. A single item from the CPX scale was considered for elimination due to a relatively low SFL (0.59). The Average Extracted Variance (AVE) values are all above 0.5 (ranging from 0.57 to 0.83), suggesting that the constructs used in the analysis have adequate convergent validity and reliability (Wang & Pan, 2022). The results of the factor analysis run on each of the ten scales resulted in relatively high eigenvalues (2.3–3.5) for the first components, with the second components having eigenvalues between 0.38–0.84. This suggests that the results are in line with previous studies and that extracting a single component from each scale is adequate.

Table 3 shows the correlations among the constructs. The results, although in many cases statistically significant, do not suggest a risk of multicollinearity in the regression analysis. This can be further supported by the theoretical background of the model, as well as the successful use of similar constructs in previous referenced studies. In addition, the square root of the average variance extracted for each factor is typically much higher than the correlation between that construct and the other constructs in the model, demonstrating adequate discriminant validity of the variables (Wang & Pan, 2022).

The regression analysis results are illustrated in Table 4. The assumptions of linearity, independence of errors, homoscedasticity and normal distribution of errors have been met. The VIF values ranging from 1.54 to 4.50, as well as the Tolerance values, between 0.22 and 0.65, suggest that there is no problematic multicollinearity among the predictors. The Durbin-Watson statistic of 2.24 indicates that there is no significant autocorrelation in the residuals. The R-squared value shows that the model explains approximately 75.5% of the variance of adoption intent, indicating a relatively strong fit to the data, although not all of the variables have proven to be good predictors of the intention of adopting AI technologies. Only two of the three Environment, as well as two of the three Organization constructs have a statistically significant effect on adoption intent. Our results do not reveal a significant link between any of the Technology constructs on the companies' intention of adopting AI technologies.

Table 3. Correlations and discriminant validity among the constructs

	REA	CPX	CST	TMS	ORG	EMP	VEN	COM	CUS	AI
REA	0.79									
CPX	.178*	0.74								
CST	.097	.551**	0.76							
TMS	.521**	.082	0	0.83						
ORG	.352**	.065	–.119	.504**	0.80					
EMP	.377**	.079	–.084	.440**	.477**	0.91				
VEN	.456**	.199*	.102	.517**	.519**	.545**	0.87			
COM	.494**	.115	.085	.631**	.422**	.465**	.477**	0.86		
CUS	.575**	.079	.081	.593**	.458**	.501**	.532**	.853**	0.83	
AI	.559**	.155	.084	.691**	.582**	.533**	.573**	.781**	.786**	0.81

Note: see Table 1 for explanation of variables; * p < 0.01; ** p < 0.05; values in bold represent the square root of the AVE of each component.

Table 4. Regression model summary and coefficients

Hyp.	Var.	Standardized β	Std. er.	t values	p values	95,0% Confidence Interval for β		Collinearity Statistics	
						Lower Bound	Upper Bound	Tolerance	VIF
H1	REA	0.058	0.055	1.045	0.298	–0.052	0.168	0.590	1.696
H2	CPX	0.031	0.053	0.582	0.562	–0.074	0.135	0.650	1.538
H3	CST	0.039	0.053	0.735	0.464	–0.066	0.145	0.637	1.569
H4	TMS	0.189	0.062	3.070	0.003***	0.067	0.310	0.479	2.088
H5	ORG	0.183	0.055	3.326	0.001***	0.074	0.292	0.597	1.675
H6	EMP	0.060	0.055	1.083	0.281	–0.050	0.169	0.592	1.690
H7	COM	0.279	0.086	3.224	0.002***	0.108	0.449	0.243	4.121
H8	CUS	0.263	0.090	2.911	0.004***	0.084	0.441	0.222	4.501
H9	VEN	0.038	0.059	0.642	0.522	–0.079	0.155	0.518	1.932
-	Const.		0.042	0.000	1.000	–0.084	0.084		

Note: Dependent variable: AI; R^2 = 0.755 (F (9.135) = 46.317, p = 0.000); Durbin-Wattson = 2.238; *** p < 0.01.

The influence of REA, CPX and CST on AI adoption was shown to be statistically insignificant, with no support or rejection of Hypotheses H1, H2 and H3, thus not being able to acknowledge the influence of the technological dimension. Regarding the coefficient "perceived relative advantage" (REA), its value is not statistically significant, and this might be due to several reasons. It is likely that the perceived advantages of adopting AI that we measured (in terms of easing the work of HR, positioning on the market) might not be the primary factors influencing these firms' decisions to adopt AI. There could be other, unmeasured relative advantages that play a stronger role. Also, it is possible that the benefits of AI are not clearly understood or appreciated by businesses in the analyzed sectors (especially given the heterogeneity of the sectors involved). This presumption is also backed-up by a report delivered by the European Investment Bank which brought forward a list of gaps preventing Romanian SMEs from unleashing the full potential of digital transformation. Interviews have constantly pointed out that one of the main, if not the main, causes of low digitalization among Romanian SMEs is a lack of understanding of the process of digitalization among citizens. Therefore, this leads to a lack of confidence in adopting digital solutions, as many SMEs either fail to recognize the potential benefits or, more often, are unsure of how to implement and capitalize on them. The result is that many consider the challenges of digitalization to be much greater than they actually are (EIB, 2023b). When examining the factors influencing the adoption of AI in Jordanian SMEs, Almashawreh et al. (2024) included within the technological dimension, the "technology strategy". Upon investigating the 5 items that the authors considered for this variable (e.g., … accelerates new product and service launches, …takes advantage of data, information and knowledge), one can view these items as the technological advantage that AI brings to the company. When running their model, the authors were also not able to validate their hypothesis (the relationship between technology and attitude being insignificant).

Regarding the lack of statistical significance for the coefficients of the other two factors composing the technological dimensions ("perceived-complexity" and "perceived-costs"), this is likely a result of the mixed views that exist on the topics. While some might consider that AI adoption has a certain degree of complexity or costs, others might find ways to overcome these issues or that they prioritize other factors in their adoption decisions. This might imply that businesses are finding workarounds or alternatives to address data limitations without relying heavily on AI technologies. Moreover, given that the market for AI technologies in Romania is in its infancy, with limited availability of suitable AI solutions tailored to the needs of businesses in the analysed industries, one might not have a clear idea with regard to the complexity or overall costs of AI adoption. Wong et al. (2020) also were not able to confirm their hypothesis related to the impact of costs on BOSCM adoption while Chen et al. (2023) could not confirm the impact of AI system quality (as part of the technological dimension) on BDA adoption.

With regard to the organizational dimension, the results confirmed two of the three hypotheses, namely H4 and H5. In other words, top management support and a firm's organizational readiness play a significant role in influencing AI technology adoption within the businesses from the assessed industries. By providing evidence to support H4, our analysis reinforces the established connection between strong leadership support for AI and a company's successful integration of these technologies. This backing from the top management translates into critical resources for implementation and cultivates a company culture receptive to AI. The result highlights the leadership's role as a driving force in IT related projects and a key catalyst for business transformation through AI adoption. Such findings further solidify the positive impact of leadership on a firm's embrace of AI technologies. By confirming H5, our analysis strengthens the established belief that a company's organizational readiness (in terms of IT infrastructure and know-how, innovation capabilities and financial resources) directly impacts its ability to adopt innovative and disruptive technologies like AI. This readiness refers to having the necessary resources, financial backing, the right technology infrastructure, and a skilled workforce, to effectively implement and utilize the new system. These results are consistent with prior studies, including Almashawreh et al. (2024), Chen et al. (2023), Lada et al. (2023), Phuoc (2022), Schwaeke et al. (2024), Sharma et al. (2024).

The study was not able to confirm H6 with regard to the positive effect of employee capability on AI adoption behaviour. This may be due to the fact that companies have different opinions on the IT related capabilities of their own employees. While some might consider their employees capable to implement AI technologies in the firms, others might want to externalize this from the very beginning (to more capable specialists). According to EIB (2023b), while limited digitalization knowledge is a hurdle, the biggest barrier to Romanian SME digitalization is a widespread lack of digital skills. Interviews consistently revealed low digital literacy across both businesses and the general population. This deficiency is compounded by limited training opportunities and a lack of robust foundational digital education. Therefore, there is less need for training the personnel by experts. However, this is not in line with many existing studies that bring forward the importance of employees in the AI adoption process in SMEs. Almashawreh et al. (2024) was able to demonstrate the employees' IT proficiency on owners' and managers' attitudes towards AI application adoption. Owners and managers in Jordan's SMEs acknowledge the indispensability of proficient IT skills deeming them catalysts for innovation adoption.

Referring to the environmental dimension, the results confirmed two of the three hypotheses, namely H7 and H8. As expected, the pressure coming from competition and customers can be perceived as threats that SMEs need to address. While competitive pressure pushes SMEs to find ways to differentiate themselves and gain an edge (in the process AI can help them improve efficiency, personalize offerings, or develop innovative products), customer pressure, incentivizes SMEs to stay relevant and meet evolving customer expectations (therefore, AI can enhance customer service, provide targeted recommendations, or streamline the customer journey). These two kinds of pressure factors provide a sort of "push-and-pull effect" for AI adoption in businesses. In essence, both factors motivate Romanian SMEs to embrace AI as a tool for staying competitive and responsive to customer needs, highlighting, in the process, AI's potential as a key driver of innovation and growth for SMEs in a dynamic and highly competitive market. These results are consistent with the ones of Maroufkhani et al. (2023) and Wong et al. (2020). Nonetheless, we were not able to confirm H9. We speculate that either SMEs try to handle AI technologies themselves (user-friendly platforms, online resources, internal expertise) or, when they do seek tech solutions, SMEs face some difficulty in navigating the existing tech options on offer and finding those that are most appropriate for their needs, as also suggested by EIB (2023b). Another likely explanation could be that, while SMEs recognize the importance of vendor support, this assistance alone may not be enough for them to successfully implement AI technologies. Sharma et al. (2024) also were not able to confirm the impact of vendor support on SMEs' AI-based chatbot adoption intention.

In addition to the explanations explored above, the fact that some of the hypotheses have not been confirmed, could be partly explained by the scales used in constructing the variables not being adequate for our research problem and context. While the internal consistency of the scales was good and the theoretical background was solid, some of them were adapted from papers which looked at other types of technologies on different continents. In addition, to the best of our knowledge, the scale adapted from Eurostat (2023) was not itself used successfully in other academic studies. This potential issue could be addressed in future studies on the topic by conducting a qualitative study (e.g., in-depth interviews with company managers) in order to design and test scales specifically adapted to the local context.

As discussed in the Methodology section, following the regression analysis, we used PLS-SEM in order to further explore the relationships between the variables and to verify the robustness of the the regression results. The results of the PLS-SEM are presented in Figure 1. The latent variables that correspond to each of the constructs used in the regression model have an asterisk next to their label in order to distinguish the two sets of variables.

In terms of model fit and quality indices, the model presented in Figure 1 is well within the recommended parameters indicated by Kock (2021). It has an Average path coefficient (APC) of 0.121 (p = 0.03), a low Average block VIF (AVIF = 2.3) and a low Average full collinearity VIF (AFVIF = 2.57) – less than 3.3 is considered ideal – and a large Tenenhaus Goodness of Fit (GoF = 0.72 – values over 0.36 are considered large).

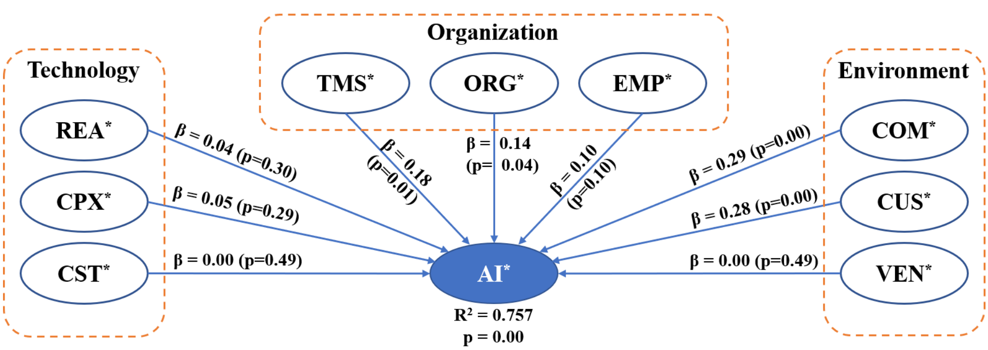

Figure 1. PLS-SEM estimation results and direct effects

The PLS-SEM confirms the same hypotheses as the regression model, namely H4, H5, H7 and H8. However, it also points us into the direction of confirming H6, although this would have to be done at a p-value of 0.1. Nonetheless, it is worth noting that the full diversity of the responses (excluding the effect of the factor analysis) does seem to suggest that the perceptions regarding employees' IT capabilities and the potential of increasing their productivity through AI technologies does have a measurable positive impact on the companies' intention of adopting such tools.

6. Conclusions

The current study aimed to assess the challenges and drivers of AI adoption in the Romanian business environment, by focusing on SMEs from four strategic industries. The assessment is built upon the Technology-Organization-Environment framework and includes survey data from 145 SMEs from all eight development regions of Romania. The predictors are estimated through a factor analysis and their effect on AI technology adoption is assessed through a linear regression model. The robustness of the results is afterwards verified through structural equation modelling.

Leveraging the case of Romania, this research sheds light on potential trends in AI adoption across all of Eastern Europe, given the region's shared characteristics. Although the historical, cultural, and socio-demographic backgrounds of Eastern European countries differ from those in the wealthier regions of Northern and Western Europe, they are relatively homogeneous within their own group. A common socio-economic characteristic of this region is the shared experience of a socialist central planning system, followed by a simultaneous shift toward market economies, though the pace of this transition varied between countries.

The research successfully reveals that, for the Romanian business environment (and hence, most probably, for Eastern European countries), the adoption of AI technologies is positively associated with "top management support", "organisational readiness", "competitive pressure" and "perceived customer pressure", confirming hypotheses H4, H5, H7, and H8. Hence, for Romanian businesses, internal factors, such as leadership, financial resources, infrastructure and openness to innovation play a crucial role when it comes to the adoption of AI technologies. In addition to that, some specific external factors also exhibit a catalyst like 'push-and-pull effect' on AI adoption, with customers expecting adoption and competitors forcing companies towards adoption in order to maintain market relevance.

Although some of the results are in line with existing literature, some specific traits of the Romanian business environment have likely resulted in some hypotheses not being confirmed. The lack of digital skills of people due to low incidence of such training in SMEs may have contributed to H6 not being confirmed in the regression analysis, although the PLS-SEM analysis suggests that "perceived employee capability" also has a marginal effect (partly confirming H6). Studies that have focused on digitalisation among Romanian SMEs have found that these businesses are not fully aware of either the benefits of such a process, nor of how to implement the process. Furthermore, AI is still in its infancy in Romania, thus making it difficult for companies to fully gauge the relative advantage that these technologies may have. However, those few companies that do have the resources and understanding of their need to digitalise and adopt some AI technologies find it challenging to identify appropriate solutions, partly due to limited marketing efforts directed toward Romanian SMEs by companies offering solutions. Although Romania dedicates impressive efforts to raise the level of digital skills, including through major reforms and significant investments, more than 72% of its population still lacks basic digital skills.

The fact that some of the hypotheses were not confirmed could be partly explained by the scales used to construct some of the independent variables (especially in the case of the technological dimension) were adapted from other studies and may not be directly relatable or relevant respondents for the current research problem and context. This issue could be addressed through a qualitative study that seeks to design and test scales specifically adapted to the local context.

The results of the study show that company leadership has a major role in increasing adoption. This could provide vendors or industry association leaders a basis for educating and encouraging top management representatives in SMEs on the benefits of AI adoption and the relative advantages that it can generate. In terms of policy implications, the 'push-and-pull' effect demonstrated by competitor and customer pressure can be leveraged by governmental authorities. By promoting the advantages of AI among consumers and promoting policies that encourage constructive competition, an increase in economic productivity and overall competitiveness could be achieved.

To address the challenges of adopting AI that the current investigation brings forward, effective public policies and government support should be provided in order to assist and incentivise companies to remain competitive and achieve sustainable growth in the global economy. Government policies could prove themselves to be crucial in shaping SMEs' digital transformation efforts, requiring supportive frameworks to help them overcome the financial barriers and knowledge gap associated with AI implementation. Such policies are likely to aid companies in leveraging the AI adoption determinant factors and foster a favorable environment for AI implementation within the SME sector. This is especially true when considering the significant role of the state in Eastern European economies.

When considering the findings of the study some limitations have to be considered. These are primarily related to the sample of respondents. Although quotas related to industry field and company size were employed in order to generate a sample that matches the overall structure of the Romanian SME population, quota sampling itself is not a probabilistic procedure. Thus, the realities that exist at the national level, may be somewhat different from those discussed in the current paper. In addition, for reasons discussed in the Research methodology section, we have chosen to focus for specific industries, meaning that the results cannot be confidently extrapolated at the level of the overall economy.

The current research represents a first exploratory step in identifying the drivers and barriers, as well as the impact that AI technology adoption can have on SMEs and the Romanian economy in general. Future expansions of the work should incorporate other industries and expand the number of respondents. In addition, we intend to expand the study by assessing the predictors in relation to two complementary dependents – actual AI adoption and intention of AI adoption. This would help expand the understanding of the various predictors, and also facilitate a comparative analysis of the two distinct states – observed behaviour versus stated intention (an approach not seen in the literature, to the best of our knowledge). Finally, a deeper dive into the various "technology" variables could be performed, in order to attempt an explanation of why none of the three constructs were proven to impact adoption intention.

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Author contributions

CMA and AM conceived the study and were responsible for the design and development of the data analysis. DTJ and AM were responsible for data collection and analysis. CMA and TR were responsible for data interpretation. CMA wrote the first draft of the article. TR and DTJ reviewed and edited the final version of the article.

Disclosure statement

The authors do not have any competing financial, professional, or personal interests from other parties.

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