



Environmental, organizational, and individual determinants of AI adoption: A multilevel knowledge and analysis

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ABSTRACT

This study examined the determinants of artificial intelligence (AI) adoption in small- and medium-sized enterprises (SMEs) through a comprehensive dual-methodology approach. Drawing on the Country-Human resources-Adoption/technological-Individual AI adoption (CHAIN-AI) framework, we integrated different theoretical currents, namely, the Technology-Organization-Environment (TOE) framework, the Technology Acceptance Model (TAM), and Regret Theory (RT), to analyze adoption patterns across multiple levels. Our research methodology encompassed two distinct phases. First, we conducted a macro-level analysis using Eurobarometer (2023) survey data to examine AI adoption trends across European SMEs. Second, we administered an online survey to 186 digital marketing professionals to investigate micro-level adoption behaviors and attitudes. Study 1 revealed significant correlations between AI adoption rates and organizational characteristics, including firm size, sector, and geographic location. Larger and service-oriented firms demonstrated higher adoption propensities. Macroeconomic indicators such as gross domestic product (GDP) and innovation capacity were positively correlated with adoption rates, whereas cultural dimensions, particularly long-term orientation (LTO), exhibited negative correlations. Study 2 illustrated the psychological and organizational mechanisms underlying AI adoption, with perceived usefulness (PU) emerging as the primary predictor of behavioral intention. In contrast, perceived ease of use (PEOU) showed non-significant effects on adoption outcomes. Post-adoption regret (R) negatively influenced both attitudes and behavioral intentions toward AI implementation. This study contributes to the literature on technology adoption by providing an empirically grounded framework for understanding the dynamics of AI adoption in SMEs. This model offers evidence-based recommendations for policy development and organizational implementation strategies.

Introduction

Firms' adoption of artificial intelligence (AI) has evolved significantly, transitioning from basic digital integration to a transformative force reshaping industries and societies (Heredia et al., 2022; Peng & Tao, 2022). AI offers potential productivity gains and innovation opportunities for small and medium-sized enterprises (SMEs). However, deploying AI is challenging because its success depends not only on the availability of technology (Lada et al., 2023) but also on organizational readiness and human acceptance of AI (Li et al., 2023; Peng & Tao, 2022). Employees' willingness, capabilities, and confidence in using AI systems are therefore crucial to unlocking AI's value; human factors frequently determine whether AI applications are used effectively in the

workplace (Kim & Kim, 2024).

Thus, the entire understanding of the AI adoption process is shaped by a complex interplay of technological, organizational, and environmental factors, which collectively influence its success and scalability. Technological factors, including system compatibility, algorithm transparency, and infrastructure readiness, determine the ease of integration and reliability of AI solutions (Heredia et al., 2022; Saeedikiya et al., 2025). Organizational factors, including leadership support, employee readiness, and cultural openness to innovation, play a crucial role in fostering or hindering the adoption of AI (Huang et al., 2025; Li et al., 2023). Resistance to change, skill gaps, and ethical concerns about fairness and accountability amplify these challenges, particularly in workforce-centric implementations (Peng & Tao, 2022). External

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environmental factors, such as competitive pressure, regulatory frameworks, and market dynamics, further complicate the adoption landscape (Saeedikiya et al., 2025). Prior research on technology adoption has broadly examined specific dimensions in isolation without fully capturing the multilevel interplay of factors (Heredia et al., 2022). In the SME environment, particularly given the scarcity of resources and the need for agility, a comprehensive understanding of adoption drivers is essential. SME businesses typically lack large organizational structures and specialized staff—skilled personnel found in larger multinational companies (Giotopoulos et al., 2017; Pandya & Kumar, 2023; Sharma et al., 2024). However, to remain competitive and drive broader economic innovation, they must be able to adopt AI (Oldemeyer et al., 2024).

This has left a clear theoretical gap since current models do not adequately explain how individual, organizational, and environmental determinants collectively influence AI adoption decisions. To bridge this gap, we propose an integrated multilevel framework for AI adoption, Country-Human resources-Adoption/technological-INdividual AI (CHAIN-AI). It combines the technology-organization-environment (TOE) Model (Tornatzky & Fleischer, 1990), technology acceptance model (TAM) (Davis, 1989), and regret theory (RT) (Loomes & Sugden, 1982) to capture individual-level perceptions, organizational characteristics, and external environmental factors influencing the adoption of AI in SMEs. We employed a dual-study research design that leverages both macro-level and micro-level analyses. In Study 1, data from Flash Eurobarometer, European Commission (2023), were used to investigate how firm characteristics and country-level contexts influence AI adoption among over 13,000 enterprises (primarily SMEs) across 27 countries in the European Union (EU). In Study 2, an online survey was conducted among 186 digital marketing professionals in SMEs that have adopted AI tools, analyzing both firm-internal and individual drivers with a focus on user perceptions, attitudes, and experiences. This two-study approach allowed us to connect broader trends with in-depth behavioral insights, providing a nuanced, multiperspective understanding of AI adoption. By combining the findings from a large-scale dataset with a targeted field survey, we validated the results cross-sectionally. We examined how macro-level conditions relate to micro-level behavior, thereby supporting theoretical claims. This study provides actionable recommendations for policymakers, technology providers, and SME leaders to facilitate AI adoption in various sectors. It considers not only firms' internal conditions but also country and resource market conditions while mitigating potential regrets. The dual-model approach provides a comprehensive understanding of the adoption journey, underscoring the importance of aligning technological solutions with organizational needs and user expectations.

Literature review and theoretical framework

Integrated framework (CHAIN-AI) for AI adoption

Existing research suggests that successful AI adoption in organizations is not determined solely by technology, but by a confluence of factors across different levels (Polisetty et al., 2024). This study drew on several theoretical perspectives to structure these determinants. Specifically, the TOE framework by Tornatzky and Fleischer (1990), which highlights how technological readiness, organizational context, and external environmental pressure collectively affect innovation adoption, was adopted (Faiz et al., 2024; Sharma et al., 2024). The TAM, which focuses on individual users' perceptions of usefulness and ease of use as primary drivers of technology acceptance, was adopted. RT was also incorporated to consider how anticipated or experienced regret from prior decisions might influence ongoing technology usage decisions (Loomes & Sugden, 1982). Subsequently, the CHAIN-AI framework was developed, integrating the determinants at the environmental, human resource, organizational, and personal levels, as presented in Fig. 1.

Environmental factors

The TOE framework, initially developed by Tornatzky and Fleischer (1990), serves as a comprehensive analytical model for examining the various factors influencing the adoption and implementation of technological innovations. This is because it asserts that the successful adoption of technology is influenced not only by the intrinsic characteristics of the technology itself but also by organizational dynamics and the broader environmental context.

Cultural differences are a significant aspect of the environmental context in the TOE framework (Lee et al., 2013). Culture shapes attitudes toward technology and technological risks, as seen in Hofstede's research. In cultures with high uncertainty avoidance, resistance to adopting new technologies may exist because of perceived risks (Jan et al., 2024). Conversely, cultures that foster innovation and openness to change are more likely to embrace new technologies, such as AI. This led us to hypothesize the following:

H1a. Cultural differences influence AI adoption.

Gross domestic product (GDP) is another key factor in the environmental context (Avelar et al., 2024; Cubric, 2020). Higher GDP is often correlated with greater availability of resources for investing in technological advancements, including AI. This reflects a country's economic health and capacity to fund large-scale technology initiatives, supporting innovation and adoption. Wealthier nations with higher GDP can allocate more resources toward building necessary infrastructure, conducting research, and providing education and training, all of which contribute to an environment conducive to AI adoption. Thus, we hypothesized the following:

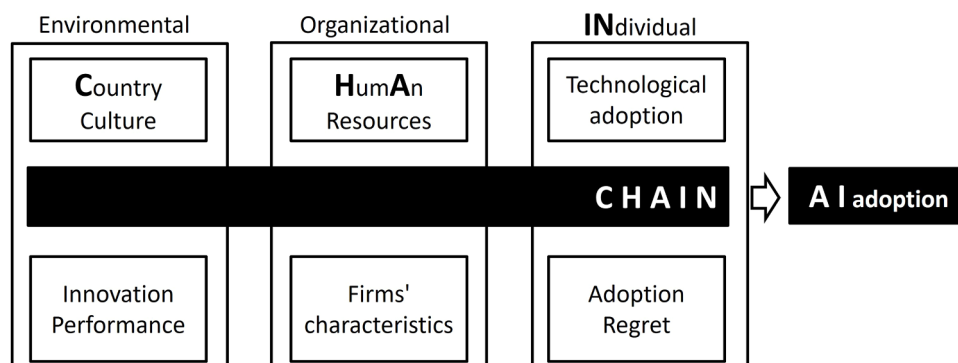


Fig. 1. Conceptual framework CHAIN-AI.

H1b. The GDP level of a country influences AI adoption.

National innovation capacity, encompassing government policies, research and development (R&D) investments, and the presence of academic and research institutions, plays a crucial role in the adoption of AI. Countries with high innovation capacity provide supportive environments for the development and deployment of technology (Watkins et al., 2015). These nations can have robust policies that incentivize AI research and implementation, as well as academic and industry collaborations that accelerate AI adoption (Yu et al., 2021). Based on these findings, we hypothesized the following:

H1c. National innovation capacity affects AI adoption.

Similarly, the state of digital infrastructure is a fundamental environmental factor in the TOE framework that influences technology adoption (Skare & Ribeiro Soriano, 2021). Advanced digital infrastructures, including high-speed Internet, cloud computing capabilities, and reliable data centers, are crucial for the deployment and operation of AI technologies. Regions with well-developed digital infrastructure enable seamless integration of AI tools, facilitate experimentation, and support the scalability of AI solutions across various sectors. Based on this, the following was hypothesized:

H1d. Digital infrastructure influences AI adoption.

Organizational factors

From the TOE perspective, the first element to consider is the technological dimension and the adoption of AI technologies, which can be robustly analyzed through the lens of diffusion innovation theory (DIT), formulated by Everett Rogers (Lund, 2025; Rogers, 1995). This theory offers a comprehensive framework for understanding how, why, and at what rate new ideas and technologies spread within cultures. It identifies several key elements directly related to the hypotheses presented, from which insights into AI adoption can be drawn. In the context of DIT, firm size is a critical factor because larger firms have the increased capability to absorb the costs and risks associated with innovation adoption. Moreover, organizational attributes can significantly affect an SME's propensity to adopt AI (Faiz et al., 2024; Schwaeke et al., 2024). As mentioned by McElheran et al. (2024), larger firms tend to explore the potential of AI more extensively. Unlike larger corporations, SMEs often operate with limited financial and human capital, which heightens the perceived risk associated with investing in emerging technologies such as AI (Schwaeke et al., 2024). These constraints can hinder their capacity to absorb implementation costs or sustain the trial-and-error processes typically required for successful integration. Moreover, larger organizations also tend to have dedicated R&D capabilities and more formalized processes for integrating innovations (Oldemeyer et al., 2024), which can facilitate the adoption of AI (Ayinaddis, 2025). Accordingly, we hypothesized the following:

H2a. Firm size positively influences AI adoption (larger firms are more likely to adopt AI).

In contrast, a firm's age might influence its openness to change (Leyva-de la Hiz & Bolívar-Ramos, 2022) and its proclivity to adopt new technologies (Rogers, 1995). Older firms may resist change due to deeply ingrained processes and paradigms, often described as organizational inertia. However, such firms may also adopt AI to rejuvenate and maintain their competitive edge against younger, more agile competitors. The history and accumulated expertise in older firms can be barriers or catalysts to innovation adoption, depending on the leadership's strategic vision. Therefore, we hypothesized the following:

H2b. Firm age influences AI adoption.

Industry type is fundamentally connected to the concept of compatibility within Rogers' theory, which refers to the extent to which an innovation is perceived as consistent with potential adopters' existing

values, needs, and past experiences. Thus, the industry context of a firm determines the compatibility and perceived relevance of AI technology. Firms in high-tech or knowledge-intensive sectors usually find AI solutions more aligned with their existing processes and competitive environment, leading to faster adoption. In contrast, those in more traditional sectors may perceive AI as less immediately applicable and thus adopt it more slowly. Hence, we theorized the following:

H2c. Industry type moderates AI adoption.

Moreover, firms located in regions renowned for innovation benefit from a robust ecosystem that supports the adoption of technology. This ecosystem is characterized by a strong network of innovators, proximity to research institutions, and the availability of venture capital, making these firms more likely to adopt AI (Avelar et al., 2024; Christensen & Drejer, 2005). These factors foster a culture of innovation, leading to the faster adoption of AI technologies. Conversely, firms in less tech-centric areas may face challenges, such as limited access to skilled labor and weak innovation networks, which can slow the diffusion of AI technologies. Based on this, we posited the following:

H2d. Location influences AI adoption.

For SMEs, challenging traditional practices. It challenges them to rethink business models and streamline processes, ultimately leading to a potential increase in competitiveness in a saturated market (Lada et al., 2023). However, the impetus for implementing AI is often driven by technological advancements and environmental pressures, highlighting the need for a robust change management strategy to harness AI's potential for value proposition innovation effectively (Lada et al., 2023; Oldemeyer et al., 2024). Although prior research has examined technological and organizational enablers of AI adoption, the influence of human resource factors remains insufficiently theorized (Malik et al., 2023; Pereira et al., 2023). Drawing on the TAM and human capital theory, empirical evidence emphasizes the strategic value of employee skills in fostering innovation and sustaining competitiveness (Gerhart & Feng, 2021). Firms that prioritize workforce development not only enhance absorptive capacity (Pereira et al., 2023) but also strengthen their ability to integrate and refine AI systems (Avelar et al., 2024; Cubric, 2020). Accordingly, we hypothesized the following:

H3a. Information technology (IT) human resources positively influence AI adoption.

A shortage of skilled workers presents a significant barrier to AI adoption (Shang et al., 2023). Firms struggle to implement AI technologies effectively without the necessary expertise, resulting in suboptimal outcomes or project failures (Raj et al., 2020). Skill shortages can drive up costs, as companies may need to invest in training their existing employees or hiring specialized consultants. This skill gap can slow down the implementation process and make it more challenging for the company to remain competitive when utilizing AI for strategic benefits. Based on this, we hypothesized the following:

H3b. Skills shortage negatively affects AI adoption.

Effective recruitment capabilities are crucial for assembling a workforce that supports the adoption of AI (Chowdhury et al., 2023; Pillai et al., 2024a; Pillai & Sivathanu, 2020b). Companies with solid recruitment strategies can attract the best AI professionals, which helps them stay ahead of technological advancements, spearhead AI projects, and foster a culture of innovation. Recruitment agility plays a central role in staying ahead of the AI adoption curve, which could mean the following:

H3c. Recruitment capabilities influence AI adoption.

Younger workers usually have an easier time adapting to AI because they are more familiar with modern skills and digital tools (Pillai et al., 2024). Contrarily, older employees may take longer to adapt to fast-paced technological changes. By finding a balance between the two

age groups and providing reskilling opportunities, we can tackle these challenges and encourage a diverse range of viewpoints that enhance AI integration. Therefore, we posited the following:

H3d. The age demographics of human resources influence AI adoption.

Individual factors

The TAM (Davis, 1989) provides a framework for explaining AI adoption via perceived usefulness (PU) and perceived ease of use (PEOU). Empirical studies have confirmed that PU and PEOU strongly predict AI acceptance in diverse contexts (Lim & Zhang, 2022; Pillai & Sivathanu, 2020a). Related factors, such as user trust, have also been identified as influencing adoption (Pillai & Sivathanu, 2020a). Likewise, users' AI literacy promotes both PU and PEOU, thereby also promoting adoption, although societal concerns about AI can temper this effect (Schiavo et al., 2024). Within SMEs, studies on the TAM have revealed PU and PEOU as primary drivers of technology adoption, although organizational and environmental factors (e.g., strategic orientation, social influence) play significant roles (Nazir & Khan, 2024; Nugraha et al., 2022; Pandya & Kumar, 2023). Recognizing this, researchers have proposed extending the TAM with SME-specific considerations, such as organizational readiness, managerial attitude, and external pressures, to provide a more comprehensive view of AI adoption (Mogaji et al., 2024).

PU is widely recognized as a key driver of technology adoption (Lim & Zhang, 2022; Pillai & Sivathanu, 2020a; Venkatesh & Davis, 2000). In this context, it represents the degree to which an individual believes that using AI will enhance performance or productivity. When users perceive an AI tool as useful, they are more likely to view it favorably and integrate it into their work. Empirical studies on technology acceptance have confirmed an association between higher PU and more favorable attitudes toward technology use (Lim & Zhang, 2022; Pillai et al., 2024; Pillai & Sivathanu, 2020a). In the context of AI, when individuals perceive clear benefits and value in AI technology, their overall receptiveness increases. Accordingly, we hypothesized the following:

H4. Perceived usefulness of AI positively influences users' attitude toward using technology.

PEOU is another fundamental construct influencing technology adoption (Davis, 1985; Giotopoulos et al., 2017; Venkatesh & Davis, 2000). It refers to the degree to which an individual believes that using an AI system will be effortless. An intuitive, user-friendly AI tool lowers the barrier to experimentation, builds user confidence, and thereby encourages adoption (Myin & Watchravesringkan, 2024). Based on prior research, when users find a technology easy to use, they tend to develop more favorable attitudes toward it (Schiavo et al., 2024). This is because a lack of complexity allows users to focus on the benefits, making the experience more pleasant and less frustrating. Thus, a higher PEOU should foster a more positive disposition toward AI. Based on this reasoning, we hypothesized the following:

H5. Perceived ease of use of AI positively influences users' attitudes toward using technology.

Beyond directly shaping attitudes, the ease of use also enhances the technology's perceived utility (Venkatesh & Davis, 2000). A system that is easy to operate can amplify a user's perception of its usefulness. If an AI tool is easy to learn and interact with, users can readily unlock its capabilities, which in turn heightens their sense of its value (Lim & Zhang, 2022; Schiavo et al., 2024). Indeed, PEOU is a causal antecedent to PU in classic technology adoption models. In other words, the less effort a user expects to spend, the more useful AI appears in accomplishing tasks. Hence, we hypothesized the following:

H6. Perceived ease of use of AI positively influences its perceived usefulness to the user.

Attitude toward technology (AT) reflects an individual's overall evaluation of AI, i.e., whether they deem it favorable or unfavorable (Pillai et al., 2024; Schiavo et al., 2024). This attitudinal disposition is a pivotal predictor of adoption decisions. According to the TAM, a user's attitude toward innovation significantly influences their intention to use innovative technologies (Pillai et al., 2024; Schiavo et al., 2024). In practice, individuals with a positive attitude toward AI tools are more likely to adopt and continue using them (Venkatesh & Davis, 2000). Numerous studies have documented this attitudinal impact on behavioral intentions in various technological contexts (Ayinaddis, 2025). Therefore, we expected that a favorable attitude toward AI would translate into a stronger resolve to use it, hypothesizing the following:

H7. Attitude toward using AI positively influences the behavioral intention to adopt the technology.

Regret (R), particularly the anticipation of regrettable outcomes stemming from past experiences, can also play a significant role in the adoption of AI. Loomes and Sugden's RT proposes that individuals evaluate past decisions based on anticipated or experienced regret, which then influences their future behaviors. In the context of technology adoption (Ha, 2018), especially AI adoption, professionals may experience regret due to unmet expectations, ethical concerns, or challenges in integrating AI into their workflows (Zimmermann et al., 2023). Consistent with this reasoning, we hypothesized the following:

H8. Regret associated with past AI use negatively influences users' behavioral intention to adopt the technology.

In this study, we proposed a CHAIN-AI framework designed to explore the multidimensional factors influencing AI adoption within organizations by integrating individual, organizational, and environmental perspectives. This framework builds upon existing theories, such as the TOE framework, TAM, and RT, offering a holistic approach to understanding the dynamics of AI adoption.

Methods and approaches

Overview

To investigate the above hypotheses and the CHAIN-AI framework, we conducted two complementary studies with distinct but connected methodologies. In Study 1, secondary data analysis was conducted to examine organizational and environmental factors in a broad sense. In Study 2, a survey was conducted to investigate individual and internal organizational factors in depth. Both studies focused on SMEs (firms with fewer than 250 employees), reflecting our interest in this firm type and ensuring consistency in scope. This section details the data collection timeline, sampling approach, measures, and analytical methods for each study.

Study #1

The "Flash Eurobarometer 537 - SMEs and skills shortages" survey database was utilized to support Study 1. Fieldwork was conducted in September–October 2023, focusing on SMEs (fewer than 250 employees) and a select number of larger firms across NACE subsectors in manufacturing, retail, industry, and services. The data collection spanned 27 EU and 8 non-EU countries, although the analysis was restricted to EU27 to ensure consistency. A probability-based, representative sampling strategy yielded 13,253 interviews, with country-level samples ranging from 250 to 600 observations.

This study examined how country-level variables (socioeconomic, technological, and cultural) influence firms' willingness to adopt AI. Analysis of variance results showed significant differences across countries, with firms in less developed EU economies demonstrating lower support for AI. To further explore these disparities, an ordered logit regression model was employed to assess the influence of national-

level factors typically associated with adoption dynamics. Firms were categorized by their AI adoption stage and expectations, ranging from no adoption to advanced plans and perceived benefits. The outcome variable was treated as ordinal, reflecting progression from low to high adoption and expectations. Ordered logit regression, appropriate for Likert-type scales, was used to model this structure. This approach assumes a meaningful order among response categories but not necessarily equal intervals among them.

This study considered both internal and external explanatory variables. Internal factors were used to capture firm-level characteristics, particularly IT-related resources, as measured by items from the “Barometer” survey. Sectoral affiliation is proposed to shape a firm’s IT strategy both directly and indirectly, influencing customer and competitor pressure, market orientation, technological standards, the intensity of rivalry, and perceived short-term benefits of AI. Accordingly, we examined four broad sectors: manufacturing, industry, services, and retail. Firm size, categorized from micro (1–4 employees) to large (250–500+), is a core determinant, as larger firms typically have broader access to human, financial, and technical resources, facilitating the adoption of complex technologies. Similarly, firm age, classified into cohorts post-January 1, 2022, affects innovation dynamics. Younger firms are often key drivers of employment and are more agile in adopting new models and technological systems. Location also matters. Firms headquartered in urban agglomerations (with a population of 500,000 or more) benefit from deeper labor markets and innovative ecosystems, while rural firms face greater difficulty in attracting skilled talent. We assessed location using two dummy variables: rural and large urban. The average age of personnel was categorized into 10-year bands (up to 50), based on evidence that older employees are generally less inclined toward tech adoption. Access to IT talent is another key factor. The variable “Difficulties [in hiring IT resources]” served to capture recruitment challenges and was expected to influence AI uptake negatively. Conversely, “skilled resources” reflects the internal availability of specialized roles and was hypothesized to promote adoption. Labor shortages were assessed via the “skills shortages” variable. At the country level, we examined variables reflecting innovation capacity, digital maturity, cultural traits, and economic development. Innovation was measured using the Summary Innovation Index (SII), and digitalization was measured using the Digital Economy and Society Index (DESI), both compiled by the European Commission. The cultural context was captured through Hofstede’s (1980) long-term orientation (LTO) dimension, while GDP per capita served as a proxy for economic development. All indicators refer to 2023, except THE DESI.

Main findings for study 1

The basic descriptive statistics indicated that the average percentage of firms “using AI or having concrete plans to do so” and “expecting a significant impact on the company’s skill needs” varied by country, ranging from 6 % (France) to 23 % (Malta), as shown in Table 1.

The minimum and maximum levels for country-related variables were much more concentrated and less dispersed, except for GDP. More importantly, the degree of correlation between the level of economic development (GDP), digital development (DESI), and a pro-innovation attitude (SII) was relatively high. The impact of cultural differences (proxied by the LTO dimension) was relatively minor or not statistically significant.

Regarding the goodness-of-fit of the ordered logit model, the p-values for the HL, PR, and Lipsitz tests suggested that while the PR test indicated a lack of fit, the HL and Lipsitz tests did not. The goodness-of-fit for the logit model was reasonable, as indicated by the Pearson χ^2 goodness-of-fit test (Table 2).

This study confirmed that both firm- and country-level factors significantly influence AI adoption, providing strong empirical evidence for several sub-hypotheses derived from the CHAIN-AI framework. Regarding the environmental dimension (H1 sub-hypotheses), the data

Table 1
Country-specific statistics.

	Country	AI-4	GDP	SII	DESI	LTO
fr	France	6 %	61,473,3	114	53,3	63
be	Belgium	12 %	72,070,8	136	50,3	82
nl	Netherlands	16 %	80,760,6	138	67,4	67
de	Germany	17 %	71,438,3	123	52,9	83
it	Italy	13 %	59,719,8	98,6	49,3	61
lu	Luxembourg	14 %	143,809,5	123	58,9	64
dk	Denmark	19 %	77,236,8	149	69,3	35
ie	Ireland	15 %	127,873,2	125	62,7	24
gr	Greece	15 %	41,922,6	85,3	38,9	45
es	Spain	10 %	54,123,1	98,9	60,8	48
pt	Portugal	17 %	48,859,1	91,8	50,8	28
fi	Finland	13 %	64,055,9	141	69,6	38
se	Sweden	11 %	69,223,5	146	65,2	53
at	Austria	17 %	73,134,8	128	54,7	60
cy	Cyprus	16 %	60,144,6	117	48,4	45
cz	Czech Republic	8 %	55,875,1	98,7	49,1	70
ee	Estonia	7 %	49,500,7	115	56,5	82
hu	Hungary	9 %	45,931,1	77,6	43,8	58
lv	Latvia	8 %	41,251,8	59	49,7	69
lt	Lithuania	12 %	53,184,8	92	52,7	38
mt	Malta	23 %	66,589,0	96,8	60,9	47
pl	Poland	7 %	49,338,3	72,5	40,5	38
sk	Slovakia	7 %	55,710,4	71,6	43,4	77
si	Slovenia	12 %	55,710,4	100	53,4	49
bg	Bulgaria	11 %	38,904,9	50,6	37,7	69
ro	Romania	11 %	47,864,0	37,4	30,6	52
hr	Croatia	7 %	46,777,5	76,6	47,5	58
	Mean	0,1	63,425,3	102,3	52,5	55,7
	St. Dev	0,04	22,963,1	28,7	9,5	15,8

yielded mixed findings. Cultural differences (H1a), operationalized through LTO, were negatively associated with the adoption of AI. This suggests that in cultures with high LTO, which often favor stability and long-term planning, the preference for established technologies may be stronger, aligning with findings from northern European contexts. Economic development (H1b), proxied by GDP per capita, showed a positive and significant effect, indicating that resource-rich environments facilitate AI investment. National innovation capacity (H1c), as captured by the innovation index, also positively influenced AI adoption, consistent with the literature that emphasizes the role of R&D and supportive policies. However, H1d could not be fully corroborated: while the digital infrastructure index showed a positive coefficient, it lacked statistical significance, potentially due to collinearity with other national-level variables.

Regarding organizational factors (H2), firm size (H2a) emerged as a significant predictor: larger firms were more likely to adopt AI, possibly due to greater access to financial and human capital, as well as formalized innovation processes. Similarly, firm age (H2b) showed a significant effect, with younger firms being more likely to adopt AI, consistent with the notion that newer ventures are more agile and open to integrating emerging technologies. Location (H2d) also proved to be essential. Firms headquartered in large urban centers exhibited higher adoption rates, possibly benefiting from richer innovation ecosystems and better access to specialized labor. In contrast, rural location had a negative impact, corroborating findings on geographic disparities in innovation diffusion. Sectoral variation (H2c) was partially validated: firms in manufacturing, services, and retail showed higher adoption, while the coefficient for the industry sector was not statistically significant.

Turning to human resource variables (H3), the results confirmed that internal capabilities and constraints play a critical role in shaping AI adoption. Firms with a higher number of skilled roles staffed internally were found to be significantly more likely to adopt AI (H3a), reinforcing the strategic value of human capital. Conversely, difficulties in hiring IT personnel and broader skill shortages were found to negatively affect adoption, validating H3b and H3c. Additionally, the demographic profile of the workforce was found to influence adoption: firms with

Table 2
Ordered logit model.

	Coefficient	Std. err.	z	P > z	[95 % conf. interval]
AI-A					
Firm size	.0329056	.0167668	1.96	0.050	.0000433 .065768
Manufacture	.2707519	.0622556	4.35	0.000	.1487331 .3927707
Industry	.0592666	.1138686	0.52	0.603	-0.1639118 .282445
Retail	.2746333	.0589888	4.66	0.000	.1590173 .3902493
Services	.6562903	.0575614	11.40	0.000	.5434719 .7691086
Firms age	.043327	.026017	1.67	0.096	-0.0076655 .0943194
Rural location	-0.0861623	.0483372	-1.78	0.075	-0.1809016 .0085769
Urban location	.2135491	.0468526	4.56	0.000	.1217197 .3053786
IT employees	.1535271	.0114159	13.45	0.000	.1311522 .1759019
Employees age	-0.1459612	.0231677	-6.30	0.000	-0.1913691 -0.1005533
Hiring difficulties	-0.0305659	.0178227	-1.72	0.086	-0.0654976 .0043659
HR shortage	.1220388	.0194429	6.28	0.000	.0839315 .1601461
Cultural differences	-0.0048144	.0006355	-7.58	0.000	-0.00606 -0.0035687
GDP	2.73e-06	1.10e-06	2.47	0.013	5.67e-07 4.89e-06
Innovation index	.0008383	.0009237	0.91	0.364	-0.0009722 .0026488
Digital index (proxy)	.0080953	.003871	2.09	0.037	.0005083 .0156824

younger employee cohorts showed greater compatibility with AI investments, lending support to H3d.

Study 2

Considering the differences observed in Study 1, which showed that firms in the services sector present a higher level of AI adoption, this study examined the practices of firms in digital marketing that are already adopting AI tools. The data for this study were collected in October 2024 and June 2025 through an online survey targeting marketing professionals to explore their perceptions and adoption of AI in digital marketing. A non-probability sampling approach, combining convenience and snowball sampling, was employed to recruit participants through professional networks, such as LinkedIn, and marketing-focused online communities. A total of 186 responses were obtained from Germany (53.2 %), Spain (22.5 %), Italy (15 %), and Portugal (9.3 %), ensuring diversity in country, age, gender, education, and years of professional experience in marketing. The questionnaire was structured to assess core constructs of the TAM and an additional regret measurement (RM) construct to evaluate potential regret associated with AI adoption (Table 3). The participants provided informed consent before completing the survey, ensuring compliance with ethical standards related to confidentiality and voluntary participation.

In terms of gender, 58.3 % of respondents identified as women. Most participants (51 %) were aged 25–34 years, followed by those aged 35–44 (29.8 %). In terms of education, the participants were highly qualified, with 47 % holding a master’s degree, 40.4 % having a bachelor’s degree, and 12.6 % possessing a doctorate or other advanced credentials. Professional experience in digital marketing varied: 23.8 % had 7–10 years of work experience, 23.2 % had 1–3 years, and 20.5 % had 4–6 years of experience.

The analysis was conducted using partial least squares structural equation modeling (PLS-SEM) via SmartPLS 4.1.1.4, following a two-stage approach. First, the measurement model was assessed to confirm the reliability and validity of the reflective constructs. All item loadings exceeded the recommended threshold of 0.70, except for PEOU3 (0.550), which was retained due to theoretical justification and minimal impact on construct reliability, and BI3 (-0.106), which was removed. Composite reliability values ranged from 0.863 to 0.964, and Cronbach’s α values were above 0.76 for all constructs, indicating strong internal consistency. Average variance extracted values exceeded 0.50 across the board, confirming convergent validity. Discriminant validity was examined through the Fornell–Larcker criterion and Heterotrait–Monotrait ratios (HTMT). Although the Fornell–Larcker criterion was met, HTMT values for PU–AT and BI–AT slightly exceeded conservative thresholds, indicating possible conceptual overlap in user

evaluations.

Second, the structural model was estimated to evaluate the hypothesized relationships among constructs. Collinearity was within acceptable bounds ($VIF < 5$), and the model demonstrated strong explanatory power, with R^2 values of 0.829 for BI, 0.796 for AT, and 0.540 for PU. The path analysis revealed that PEU exerts a strong positive effect on PU ($\beta = 0.735$), indicating that users who find AI tools easier to operate are more likely to perceive them as beneficial. In turn, PU was found to have a positive influence on AT ($\beta = 0.570$), confirming TAM assumptions that usefulness drives attitudinal favorability. Additionally, PEOU was found to directly contribute to AT ($\beta = 0.469$), indicating that ease of use not only improves perceptions of utility but also shapes emotional readiness toward AI adoption.

AT had the most substantial direct impact on BI ($\beta = 0.681$), highlighting the central mediating role of affective evaluations in shaping user commitment to future use. PU also had a direct effect on BI ($\beta = 0.458$), although this was less pronounced. Notably, R had significant negative paths to both AT ($\beta = -0.340$) and BI ($\beta = -0.432$), confirming that users with prior negative experiences or regret are less inclined to adopt or continue using AI systems. These results provide empirical support for Hypotheses 4 through 8. Table 4 summarizes all the results from both studies.

Discussion

The findings from both studies conducted within the CHAIN-AI framework model provide a comprehensive understanding of AI adoption dynamics in SMEs.

The results from Study 1, based on the dataset, confirm the relevance of country-level factors in shaping AI adoption. Higher GDP per capita and greater innovation capacity, as measured by the SII, were positively associated with adoption levels (supporting H1b and H1c). These results suggest that economically advanced and innovation-driven environments create conditions that are conducive to the adoption of AI. In contrast, digital infrastructure, measured by the DESI, showed no significant effect, suggesting that barriers beyond technological readiness, such as regulatory complexity or institutional inertia, may be at play. Additionally, the cultural context emerged as a meaningful constraint. Countries with higher scores on Hofstede’s LTO dimension reported lower AI adoption rates (supporting H1a), implying that a cultural preference for gradual, stable change may discourage firms from engaging with emerging technologies. This highlights the need to consider national and organizational culture when formulating AI integration strategies.

The findings indicate that AI adoption is significantly shaped by firm size, sector, and geographic context. Larger firms reported higher

Table 3
Scales used and sources.

Section	Question	Question Type	Source
AI-Marketing Experience	Are you currently working, or have you recently worked, in the field of marketing?	Y/N	-
Perceived Usefulness	PU1 "Using AI would improve my job performance." PU2 "Using AI would increase my productivity." PU3 "Using AI would enhance my effectiveness at work." PU4 "I would find AI useful in my job." PU5 "Using AI would make it easier to do my job."	Likert scale (1–5)	Davis (1989) Gupta et al. (2021)
Perceived Ease of Use	PEOU1 "Learning to operate AI would be easy for me." PEOU2 "I would find it easy to get AI to do what I want it to do." PEOU3 "My interaction with AI would be clear and understandable." PEOU4 "I would find AI easy to use." PEOU5 "It would be easy for me to become skillful at using AI."		Davis (1989)
Attitude Toward AI	AT1 "Using AI is a good idea." AT2 "I have a positive attitude toward using AI." AT3 "Using AI is pleasant." AT4 "I like the idea of using AI in my work." AT5 "Overall, I think using AI would be beneficial."		Venkateswaran et al. (2024)
Behavioral Intention	BI1 "I intend to use AI in the future." BI2 "I will make every effort to use AI whenever it is appropriate." BI3 "I plan to use AI regularly in my work." BI4 "Assuming I have access, I predict that I would use AI." BI5 "I expect to increase my use of AI over time."		Koneti et al. (2023)
Regret	R1 "Looking back, I sometimes wish I had not used AI." R2 "Using AI now feels like it may have been a mistake." R3 "If I could decide again, I would avoid using AI." R4 "I feel disappointed with the outcomes of using AI." R5 "I regret the time and effort I invested in AI."		Zimmermann et al. (2023)
Demographics	Age, gender, education, experience	Multiple choice	-

adoption levels, likely due to their superior financial and human capital resources, which facilitate investment in emerging technologies. This supports H2, reinforcing the view that larger organizations are better equipped to manage the costs and risks associated with AI implementation. Service-oriented sectors demonstrated the highest adoption rates, aligning with prior research that suggests these industries derive substantial value from AI-enabled process efficiencies and personalized

Table 4
Summary of hypothesis testing.

Hypothesis	Study 1 (EU SMEs)	Study 2 (Marketing SMEs)	Result
H1a	Cultural context →AI-A	Not explored	Supported
H1b	GDP →AI-A		
H1c	Innovation capacity →AI-A		
H1d	Digital infrastructure →AI-A		
H2a	Size →AI-A	PU →AT PEOU →AT PEOU →PU AT →R R → BI	Not fully supported Supported
H2b	Age →AI-A		
H2c	Sector →AI-A		
H2d	Location →AI-A		
H3a	IT HR →AI-A		
H3b	Skill shortages →AI-A		
H3c	Recruitment capability →AI-A		
H3d	Workforce →AI-A		
H4	Not explored		
H5			
H6			
H7			
H8			

services. Conversely, firms located in rural areas reported lower adoption levels than their urban counterparts, underscoring the role of infrastructure and talent availability in enabling technological uptake.

Study 2, based on a survey of marketing professionals in SMEs, sheds light on individual-level drivers of AI adoption. The findings obtained reaffirm key principles of the TAM, confirming that PU and PEOU strongly influence user acceptance. Notably, the inclusion of post-experience regret introduces an essential emotional dimension: negative experiences can weaken both attitudes and intentions, indicating that cognitive assessments alone do not fully explain adoption behavior.

Theoretical and practical implications

Theoretical contributions

While early adoption focused on basic digital tools, the rise of Industry 4.0 and subsequent technological breakthroughs propelled AI into mainstream applications (Heredia et al., 2022; Peng & Tao, 2022). However, the adoption of these tools does not occur similarly in all organizations, reflecting a dynamic interplay of technological advancements, economic drivers, and organizational adaptation (Cubric, 2020; Nazir & Khan, 2024; Raj et al., 2020), highly conditioned by individual acceptance of these technological tools (Pandya & Kumar, 2023).

This study contributes to the literature by adopting a multilevel approach to AI adoption through the CHAIN-AI framework, which simultaneously considers country-level factors, human resources within organizations, and individual behavior. This framework presents a more holistic theoretical approach, illustrating how individual-level acceptance of AI (shaped by perceptions such as usefulness and regret) is embedded within an organizational and environmental context. This multilevel approach answers recent calls in the literature for more integrated technology adoption models that capture cross-level interactions.

The findings revealed that country-level conditions, including GDP and national innovation capacity, significantly influence AI uptake, supporting the argument that external environmental factors create enabling conditions for adoption (Avelar et al., 2024; Mogaji et al., 2024). This study also highlights the impact of country-cultural dimensions on AI adoption, specifically the negative relationship between Hofstede's LTO and AI adoption rates. Previous studies have indicated that LTO cultures prioritize strategic planning and incremental innovation (Lumpkin et al., 2010). Nevertheless, our findings suggest that such cultures may be reluctant to adopt disruptive technologies such as

AI due to their inherent uncertainty and perceived risks. This challenges conventional assumptions and highlights the need for culturally sensitive AI adoption strategies, particularly in regions where long-term planning is a dominant factor in corporate decision-making processes.

However, the findings also revealed that firm-level factors are critical for successful AI adoption, corroborating evidence found in prior studies (Pillai et al., 2024). By paying attention to AI adoption by and within SMEs, our findings align with sectoral studies that emphasize the unique challenges SMEs face in hiring, retaining, and motivating human resources to adopt technologies that enhance agility (Avelar et al., 2024; Ghobakhloo & Ching, 2019; Mogaji et al., 2024; Nazir & Khan, 2024).

Another key contribution of this study is the extension of the TAM with RT, offering a novel perspective on the emotional and cognitive aspects of AI adoption. Traditional TAM approaches emphasize PU and PEOU as primary determinants of technology acceptance (Venkatesh & Davis, 2000); however, our findings demonstrate that regret, an often-overlooked factor, plays a critical role in shaping both attitudes and behavioral intentions. The results indicate that negative post-adoption experiences or unfulfilled expectations can create significant resistance to further AI adoption, reinforcing the need for organizations to manage expectations and provide adequate post-implementation support. This extension bridges a critical gap in existing adoption models by acknowledging that psychological factors influence long-term technology integration.

Practical implications

The findings of this study offer several practical implications for business leaders, policymakers, and technology providers aiming to enhance AI adoption in SMEs. Specifically, this study observed that the adoption of AI technologies in SMEs is affected by several macro, micro-environmental, and organizational dimensions. Thus, organizations should first focus on aligning AI implementation with their business strategy, ensuring that AI solutions address specific operational challenges and deliver measurable value in terms of efficiency and competitive advantage. To achieve this, firms can prioritize investments in organizational readiness and workforce capability development, as these factors significantly impact the successful integration of AI. Second, the study highlights the critical role of managing employee attitudes toward AI, indicating that fostering innovation and openness is essential to overcoming resistance. Granting comprehensive training and ongoing support can build employee confidence and alleviate concerns regarding job displacement and operational complexity. Third, firms must carefully consider cultural influences in their AI adoption strategies, as LTO has been found to negatively impact adoption rates. Tailoring adoption strategies to cultural preferences and promoting gradual, structured implementation can help mitigate resistance and facilitate smoother integration. By addressing these considerations, SMEs can better navigate the complexities of AI adoption and position themselves for sustainable success in an increasingly dynamic technological landscape.

Fourth, from a policy perspective, governments should introduce targeted incentives and support programs, focusing on SMEs in rural and underserved areas where infrastructure and access to skilled talent may be limited. Policies that promote public-private partnerships and knowledge-sharing initiatives can further encourage the diffusion of AI across diverse sectors. Finally, AI technology providers should strike a balance between functionality and user experience, offering solutions that meet business needs while ensuring accessibility and ease of use, thereby lowering the barriers to entry for SMEs. These practical insights provide actionable guidance for accelerating AI adoption while addressing key organizational and environmental challenges.

Conclusions

This study investigated the multilevel determinants that influence AI

adoption within SMEs, utilizing a dual-method approach that supports the CHAIN-AI framework. Integrating the TOE framework, TAM, and RT, the study examined how countries, human resources in organizations, and individuals' behaviors impact AI adoption. The research was conducted in two phases. Study 1 drew data from the survey to offer a macro-level analysis of AI adoption among European SMEs. This phase focused on structural determinants, including firm size, industry sector, and geographic context. Study 2 complemented this with a micro-level perspective, based on an online survey of 186 digital marketing professionals that examined individual attitudes and behavioral drivers.

The findings from Study 1 revealed that macroeconomic factors such as GDP and innovation capacity enhance adoption, whereas cultural aspects, notably LTO, hinder AI uptake. Firm size, sector, and location were also found to have a significant influence on AI adoption, with larger firms and those in service-oriented industries reporting higher adoption rates. Study 2 examined the psychological and organizational drivers of AI adoption, identifying AT as the strongest predictor of BI. Additionally, regret was found to influence attitudes and intentions negatively, highlighting the need to manage expectations and provide users with sufficient support.

Limitations

One of the primary limitations of this study is its reliance on the samples used. The secondary data used in Study 1 did not permit the inclusion of other factors that may influence AI adoption or alter the classification of AI as either traditional or generative. In Study 2, using a non-probabilistic sample that focused on marketing professionals from SMEs may have introduced selection bias, as the respondents could have had a predisposed interest in AI technologies. This potentially skews the results toward more favorable adoption attitudes. The present research employed a cross-sectional research design, capturing AI adoption factors at a single point in time. Given the evolving nature of AI technologies and organizational strategies, future studies should adopt a longitudinal approach to track adoption trends, barriers, and enablers over an extended period.

Although the study provides valuable insights into the marketing sector, AI adoption varies significantly across industries with distinct regulatory, technological, and operational challenges. The generalizability of the findings is, therefore, limited. Future research should conduct comparative studies across various sectors, including healthcare, manufacturing, and finance, to gain a deeper understanding of industry-specific drivers of adoption and the barriers they present.

Future research

As the AI field continues to advance, future research and practical applications in the context of SMEs must address several critical areas to facilitate the broader adoption of AI. Interdisciplinary studies integrating the TOE framework with a more comprehensive analysis of human resource capabilities could yield valuable insights into the interactions that enable or constrain AI integration. Additionally, addressing the specific challenges faced by SMEs, such as resource limitations and skill shortages, necessitates the development of customized AI solutions aligned with their strategic goals. Expanding the scope to different industries and geographic regions will further enhance the understanding of the process and generalizability of the findings.

Multiple country-level and organizational factors influence the adoption of AI in SMEs. Thus, the successful integration of AI technologies ultimately depends on managing user expectations, providing adequate support systems, and creating a positive adoption experience that minimizes post-implementation regret.

CRediT authorship contribution statement

Flávio Tiago: Writing – original draft, Resources, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Conceptualization. **António Almeida:** Methodology, Data curation.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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