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## Article

# Adoption of artificial intelligence in small and medium-sized enterprises in Spain: The role of competences and skills

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**ADOPTION OF ARTIFICIAL INTELLIGENCE IN SMALL AND MEDIUM-SIZED  
ENTERPRISES IN SPAIN: THE ROLE OF COMPETENCES AND SKILLS**

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**Abstract**

This article explores the determinants of the adoption of artificial intelligence (AI) in small and medium-sized enterprises (SMEs) with special attention to the impact of competencies and skills. The research was based on data from a representative sample of SMEs in Spain and used logistic regression econometric analysis. Additionally, the study applied an innovative AI technique, Generative Adversarial Networks (GANs), to balance the data set. The findings indicate that SMEs whose business owners / managers have university degrees or high levels of professional training, those with information technology (IT) experts among their staff, and those providing IT-related training for employees are all more likely to adopt AI. Furthermore, SMEs equipped with management skills in Enterprise Resource Planning (ERP) systems and marketing analytics tools, and SMEs engaged in collaboration with universities and research centres, demonstrate a greater propensity to integrate AI into their operations. The implications of these findings are significant for both business management and public policy. From a managerial perspective, the results underscore the importance of investing in training programmes and initiatives aimed at upgrading the skill set of employees and managers to effectively use AI in business operations. On the policy front, the conclusions suggest an active role for public administrations in promoting the adoption of AI among SMEs by designing initiatives focused on improving key digital competencies.

**Keywords:** Artificial intelligence, SME, digital competence, digital skill, digitalisation, information technology, GAN

**JEL Classification:** D22, M21, O30

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## **Introduction**

The application of Artificial Intelligence (AI) in business will become a critical factor in the coming decades for the advancement of productivity and competitiveness of companies across all sectors (Brynjolfsson, Rock and Syverson, 2017; Damioli, Van Roy and Vertesy, 2021; Calvino and Fontanelli, 2023). This process of implementation of AI solutions in companies requires the development of new competencies and skills in their staff and renders certain previous competences and skills as less relevant or obsolete, since several tasks previously carried out by humans will be carried out by automatic systems (Acemoglu and Restrepo, 2019; Felten, Raj and Seamans, 2021; Bodea et al., 2024).

Companies today require managerial teams and employees capable of identifying and exploiting the potential of AI integration into their businesses (Kietzmann and Pitt, 2020; Vrontis et al., 2021; Krakowski, Luger and Raisch, 2022; Giraud et al., 2023). Specific experts in information technology (IT) will be in high demand, although other employees will also need to develop digital skills (Khatri et al., 2020; Alekseeva et al., 2021; Jaiswal, Arun and Varma, 2022). However, there is still insufficient evidence on the critical competencies required for the integration of AI in companies. Therefore, this paper seeks to address this research question.

The literature on the application of AI has so far concentrated on the case of large companies that are more proactive in the use of this technology. On the contrary, small and medium enterprises (SMEs) present significant deficiencies in their digitalisation process as the result of the obstacles associated with their small scale, which limits their access to financial, technological, and human resources (OECD, 2021; Calvino and Fontanelli, 2023). In this sense, there is a specific gap in the literature on the competencies and skills critical to the adoption of AI in SMEs.

The objective of this paper is to investigate the determinants of the adoption of artificial intelligence (AI) in small and medium-sized enterprises (SMEs) in Spain, with special attention to the impact of competences and skills. Data from a representative sample of Spanish SMEs, collected through a survey in 2022, was used for analysis. The study uses a logistic regression model as an econometric technique. Given the low adoption rate of AI solutions among SMEs in Spain, this paper addresses the associated dataset imbalance by using a novel AI technique: Generative Adversarial Networks (GANs).

From a theoretical point of view, this paper contributes to the literature by providing new insights into the critical role of competencies and skills in the adoption of AI in business and highlighting the interaction between enterprise resource planning (ERP) systems, marketing analytics tools, and AI. From a methodological standpoint, this research illustrates the application of GANs to address issues of dataset imbalances in economics and business research. From a practical point of view, this article derives relevant implications for management and public policy, suggesting areas of action to promote the adoption of AI in small businesses.

The rest of the article is organised as follows. Section 1 reviews the literature on the application of AI in SMEs and the role of competences and skills, derived from the research hypotheses for this study. Section 2 describes the data set used and the methodology applied in the analysis. Section 3 presents and discusses the results of the research. The article concludes with some final conclusions and implications for practitioners.

## 1. Review of the scientific literature

The current research landscape reflects a growing interest in the applications of AI in business, which underlines its transformative potential. Artificial Intelligence offers distinct advantages to businesses by enhancing effectiveness and objectivity (Raisch and Krakowski, 2021). Its integration spans various functions and tasks within organisations, including that of marketing (Feng et al., 2021), customer service (Nicolescu and Tudorache, 2022; Xu et al., 2020), and human resources, particularly in decision-making processes related to hiring (Khatri et al., 2020; Van den Broek, Sergeeva and Huysman Vrije, 2021). This integration signifies a collaborative effort between machine intelligence and human input (Herrmann and Pfeiffer, 2022), and highlights the importance of human involvement in AI applications (Berente et al., 2021).

The interaction between AI and its applications with both managers and employees is crucial. Managers play a pivotal role in overseeing AI implementation and ensuring alignment with organisational goals, while employees contribute domain expertise and feedback, which is essential for the refinement of AI systems. This symbiotic relationship underscores the dynamic nature of AI integration in business settings, where human supervision and collaboration are integral to harnessing its full potential. As the field continues to evolve, understanding the intricate interplay between AI and human stakeholders becomes increasingly important for the effective use of AI technologies in business contexts. This recognition of the complementary roles of AI and human input paves the way for more nuanced and impactful applications across various organisational functions.

On the one hand, previous research shows that it is necessary for managers to acquire and enhance new AI skills to sustain their businesses (Krakowski, Luger and Raisch, 2022). In this regard, AI can demand new qualifications, introduce new tasks, and demand improved skills (Griva et al., 2021; Vrontis et al., 2021). The literature suggests that managers should enhance not only their technical competencies, such as understanding AI and its tools, data visualisation, and analytical knowledge, but also their non-technical competencies, including empathy, imagination, leadership, and critical thinking (Giraud et al., 2023). Both technical and non-technical skills are necessary for the application of AI in companies, since technical skills are valuable for understanding and utilising AI, while non-technical skills are crucial for the successful implementation of AI (Giraud et al., 2023). The recent literature also addresses the challenges presented by AI in the context of evolving work methodologies (Goto, 2022). AI liberates managers from repetitive tasks, thereby enabling them to concentrate on issues of a more intricate nature (Hagemann, Sünnetcioglu and Stark, 2019). Consequently, AI can influence administrative skills and can potentially replace tasks such as information gathering and simple decision-making. However, there remain managerial skills and tasks that currently cannot be substituted or influenced by AI and its tools. These include aspects such as imagination and leadership (Giraud et al., 2023), team motivation, inspiration, and empathy (Plastino and Purdy, 2018), as well as emotional intelligence and critical thinking (Mattingly and Kraiger, 2019).

On the other hand, in relation to employees, AI and its applications diminish the employee's responsibilities by handling basic tasks, thus improving efficiency in the firm through an increased focus of employees on other creative tasks and responsibilities (Acemoglu and Restrepo, 2018). Moreover, AI enables low-skilled employees to handle complex tasks that previously might have required specialisation or training (Mayer, Strich and Fiedler, 2020; Strich, Mayer and Fiedler, 2021). At the same time, while AI facilitates tasks by handling

and reviewing them efficiently, it can also evaluate and monitor employee work performance (Harms and Han, 2019) and daily activities (Malik et al., 2022). Furthermore, AI has the ability to offer guidance and recommendations to employees to improve time management, goal setting, and task selection (Malik et al., 2022). Furthermore, AI can also assist employees in developing their self-management abilities by providing feedback and acknowledging their achievements (Tong et al., 2021).

However, previous studies indicate that managers are the main contributors in the process of implementing AI and its tools (Sousa and Rocha, 2019; Giraud et al., 2023). In the context of the AI revolution, managerial proficiency requires the acquisition of not only standard skills, such as organising, leading, and monitoring, but also a comprehensive understanding of AI and the synergies between humans and AI (Basu et al., 2022; Herrmann and Pfeiffer, 2022). Therefore, obtaining new and innovative knowledge and skills will require training programmes and/or relevant university education (Kietzmann and Pitt, 2020; Vrontis et al., 2021). In the case of SMEs, the personal profile of the business owner/manager plays a crucial role in the organisation and development of the company (Romero and Martínez-Román, 2012; Martín-Martín, Maya García and Romero, 2022). Companies with business owners/managers who have a strong educational background may be better positioned to access the skills necessary to implement AI in their businesses. In addition, today's top business schools, such as Oxford Saïd, MIT Sloan, Cambridge Judge, London Business School, and Harvard Business School, all provide executive education programmes, both online and in person, for managers and entrepreneurs in the field of AI and related areas. Therefore, this illustrates the high demand that exists for the development of AI skills. Based on the aforementioned considerations, this research postulates the following hypothesis:

H1: SMEs whose business owners or managers have a university degree or have completed an advanced level vocational education and training programme are more likely to implement AI in their businesses.

In the era of AI, employee skills that incorporate AI can make a significant difference. Prior studies indicate that digital skills become increasingly important during the implementation of AI (Oberländer, Beinicke and Bipp, 2019; Carlisle, Ivanov and Dijkmans, 2023). Additionally, this process requires programming skills, as emphasised in previous research (Subaveerapandiyam, Paladhi and Maruthaveeran, 2024). Therefore, leveraging IT specialists within the company can significantly facilitate the digitalisation process, especially when applying AI. IT specialists are defined, in the context of this research, as employees whose job is directly related to IT, such as the development, operation, or maintenance of IT systems or their application (Instituto Nacional de Estadística, 2019). On the basis of these premises, the following hypothesis is postulated in this research:

H2: SMEs with IT specialists on their staff are more likely to implement AI in their businesses.

Furthermore, upgrading the skill set of employees remains crucial (Jaiswal, Arun and Varma, 2022). The literature has identified various employee skills relevant to AI and is considered significant. These include critical thinking abilities (Delanoy and Kasztelnik, 2020), problem-solving capabilities (Seeber et al., 2020), digital skills (Allmann and Blank, 2021), soft skills (Hart et al., 2021), and continuous learning capabilities (Jaiswal, Arun and Varma, 2022). In this regard, companies will need to conduct internal training activities or provide

employees with access to external training to support them in acquiring the necessary skills for implementing AI in their businesses. On the basis of these considerations, the following hypothesis is proposed:

H3: SMEs that conduct IT training activities for their staff are more likely to implement AI in their businesses.

Additionally, companies must reach a certain level of digital maturity to successfully implement AI in their operations (Lichtenthaler, 2020). In this sense, SMEs that have already adopted advanced digital management tools, such as enterprise resource planning (ERP) systems and marketing analytics tools, could be better prepared to embrace AI in their organisations and to take advantage of its potential. Previous work suggests that ERP systems and AI are interrelated (Jawad and Balázs, 2024; Puthuruthy and Marath, 2024). Furthermore, the relationship between marketing analytics and AI has been studied in the literature, illustrating a strong connection (Hossain et al., 2022; Petrescu and Krishen, 2023). In this respect, the following hypothesis is postulated:

H4: SMEs with advanced skills in digital management, using ERP systems and marketing analytics tools, are more likely to implement AI in their businesses.

SMEs often face challenges in acquiring the skills and knowledge necessary to implement AI in their businesses due to resource constraints. This contributes to the existing gap in digitalisation levels between SMEs and large corporations (OECD, 2021). In this context, collaboration between universities and companies can be regarded as a vital engine driving technological change and its adoption (Sedlacek, 2013; Wirsich et al., 2016). SMEs can benefit from collaboration with universities, research centres, and other public infrastructures to promote digital entrepreneurship and facilitate the digital transformation of existing companies through the adoption of AI (Chan, Krishnamurthy and Sadreddin, 2022). In this sense, the following hypothesis is presented:

H5: SMEs that collaborate with universities and research centres on digitalisation-related issues are more likely to implement AI in their businesses.

## **2. Research methodology**

In this section, the data used in this research are first presented, followed by an explanation of other aspects of the methodology employed.

### **2.1. Data description**

Data for this research were obtained from a survey conducted in the second quarter of 2022 on Spanish SMEs with at least one employee and up to 200 employees. Small and medium-sized enterprises participating in the survey were randomly selected from the Iberian Balance Sheet Analysis System (SABI) database. Our stratified sample is representative of the SME population in Spain with an error of  $\pm 5.0\%$  at a confidence level of 95%, by applying simple random sampling and considering that the population is binomial ( $p = q = 0.5$ , the most unfavourable situation). The survey technique employed was that of computer-assisted telephone interviewing (CATI). In the fieldwork, there was a response rate of 21.5%. No relevant bias was detected between respondents and non-respondents. The final data set for this analysis is made up of 836 valid observations.

The initial data set comprised 54 variables. Through a rigorous selection process involving experts and the application of suitable statistical techniques to identify the most relevant variables pertaining to the endogenous variable that concerns the use of AI in SMEs, a subset of 10 exogenous variables has been chosen to elucidate the dependent variable.

The dependent variable in this study (AI) is a binary variable that captures whether, in the three previous years (2019-21), the company had used AI techniques, such as automatic learning and machine learning, processing and/or generation of natural language, voice recognition, and other methods for the analysis of big data.

Regarding the explanatory variables, we first consider the following set of variables associated with competencies within the company:

- **Entrepreneurs/managers with university degrees or higher professional studies (Ent\_edu):** This binary variable captures those SMEs with entrepreneurs/managers who hold a university degree or higher professional training.
- **Medium-level staff with IT expertise (IT\_exp):** This binary variable takes the value 1 for companies that have IT experts in medium-level positions (0 otherwise).
- **IT training initiatives (IT\_train):** This binary variable indicates whether the company had carried out training activities to improve the IT skills of its employees within the three years prior to the survey.
- **ERP Systems (ERP):** This binary variable indicates whether companies have implemented ERP systems.
- **Marketing Analytics Tools (Mark\_analy):** This binary variable indicates whether companies have implemented digital marketing analytics tools.
- **Cooperation with universities and R&D centres (Coop\_univ):** This binary variable captures whether SMEs cooperate with universities and research centres on aspects related to digitalisation.

Firm size (Size), in terms of the number of employees, the age of the company (Age), and dummy variables for sectors (Trade or Services) are also considered in the analysis as control variables.

## **2.2. Generative Adversarial Networks**

In our database, only 85 SMEs have employed artificial intelligence techniques, which represent approximately 10% of the total number of observations. This level of application is consistent with other studies on the adoption of AI in SMEs in Spain (ONTSI, 2023). However, alongside these 85 enterprises that have utilised AI, our data set includes 751 other enterprises that have not used AI, which results in a clear imbalance. This imbalance issue is addressed in this paper through the use of GANs (Goodfellow et al., 2014; Goodfellow et al., 2020), an emerging technique for both semi-supervised and unsupervised learning (Radford, Metz and Chintala, 2015; Donahue, McAuley and Puckette, 2018; Liu et al., 2018).

The application of GANs in data augmentation has shown notable results on the performance of applied predictive models (Douzas and Bação, 2018; Mottini, Lheritier and Acuna-Agost, 2018; Ding, 2019). In the field of social sciences, it is still an emerging technique, but there are several studies in which GANs have achieved satisfactory results and improvements over other methods. Applications that have demonstrated the efficiency of GANs in various economic issues include the detection of banking fraud (Langevin et al., 2022), detection of trading strategies (Koshiyama, Firoozye and Treleaven, 2020), asset price generation (Han, Ma and Zhang, 2022), generation of mobility networks (Mauro et al., 2022), economic scenario generators for market risk assessment (Wang et al., 2024), generation of financial time series (Vuletić, Prenzel and Cucuringu, 2024) or ensuring customer privacy (Anand and Lee, 2023), among others.

These studies support the utility of GANs in economic research, given their ability to address various challenges, including data scarcity, imbalance, missing data, and lack of responses in surveys, thereby producing superior results compared to conventional methods. This is the motivation to employ GANs in this article, where they are used to generate synthetic data to balance the data set.

Generative Adversarial Networks comprise two key components – the Generator and the Discriminator – that operate in an interplay. Initially, the Generator takes in a random noise vector and produces synthetic data. Subsequently, these synthetic data are amalgamated with authentic data to train the Discriminator. The Discriminator’s pivotal task is to distinguish between real and synthetic data. The Generator strives to produce synthetic data convincingly, aiming to deceive the Discriminator, while the Discriminator endeavours not to be misled. This dynamic adversarial process, elucidated by Salimans et al. (2016), Heusel et al. (2017), Ge et al. (2018), and Bynagari (2019), propels the Generator towards enhancing its capability in generating synthetic data that closely mirror authentic data.

The primary objective of this endeavour lies in the replication and validation of original company data. This requires the construction of a model that is capable of faithfully mimicking real-world data. The comprehensive formula, outlined by Gonzalez-Abril et al. (2022), which integrates both the Discriminator and Generator, is as follows:

$$V(\theta^D, \theta^G) = E_{x \sim P_x}[\log D(x)] + E_{z \sim P_z}[\log(1 - D(G(z)))] \tag{1}$$

In this context,  $x$  represents a genuine sample;  $z$  represents a random noise vector;  $D(x)$  is the output of the Discriminator when processing a real sample;  $G(z)$  denotes the output of the Generator derived from the noise vector  $z$ , essentially generating synthetic data;  $D(G(z))$  is the prediction of the Discriminator on the synthetic data;  $P_x$  and  $P_z$  represent the distributions of real and noise data, respectively;  $E_x$  and  $E_z$  correspond to the anticipated log likelihood arising from the different outputs of real and generated data; and  $\theta^D$  and  $\theta^G$  denote the parameters or weights associated with the Discriminator and Generator models, respectively.

The value function undergoes a min-max strategy aimed at maximizing the Discriminator loss while simultaneously minimising the Generator loss,  $\min_{\theta^G} \max_{\theta^D} V(\theta^D, \theta^G)$ .



To apply GANs, observations that exhibit the target characteristic of interest, namely SMEs that have adopted AI solutions, were selected from the database, resulting in 85 observations. The Generator’s structure, denoted as  $G(z)$ , comprises six dense layers. It takes the noise vector as input and produces an output vector of size 10, corresponding to the number of features. On the other hand, the Discriminator’s architecture, labelled as  $D(z)$ , consists of three dense layers, each incorporating batch normalisation and leaky ( $\alpha = 0.01$ ) layers.

The Generator and Discriminator both employ the Adam optimiser with a uniform learning rate set at 0.0001. The Discriminator utilises cross-entropy loss, tailored for its binary classification task. In contrast, the Generator’s loss function relies on mean square error, calculated from the percentiles disparity between the real and synthetic data. This specific loss function is chosen because of its capability to empirically enhance the goodness-of-fit performance of the real and synthetic distributions by adjusting the number of percentiles appropriately.

The dataset undergoes validation before its utilisation. Goodness-of-fit tests are conducted, with the null hypothesis ( $H_0$ ) positing that the set of synthetic enterprises originates from the same distribution as the real enterprises, at a significance level of 5%. Pearson’s chi-squared tests are used for categorical variables and the Kolmogorov-Smirnov tests for quantitative variables (see Table no. 1).

**Table no. 1. Features, number of different values, and p-value**

Feature	values	p-value	Feature	values	p-value
Size	41	7.610086e-02	IT_exp	2	4.654900e-01
Age	39	5.172965e-02	IT_train	2	2.405108e-01
Trade	2	4.560974e-01	ERP	2	5.308537e-01
Services	2	4.228170e-01	Mark_analy	2	8.327084e-02
Ent_edu	2	2.916162e-01	Coop_uni	2	3.746260e-01

### 2.3. Logistic regression

From the generated data set, 669 items of synthetic data have been randomly selected and incorporated into the original database. Therefore, the database used for the logistic regression study consists of 1,508 observations (each observation representing an enterprise) and 10 variables where 754 enterprises exhibit the characteristic studied and 754 do not.

In table no. 2, the behaviour of different variables can be observed in the presence of the study variable ( $AI=YES$ ) and in its absence ( $AI = NO$ ). It can be observed that enterprises that implement AI are led by entrepreneurs with higher education in 87% of cases, compared to 70% in those that do not employ such technologies. Furthermore, 66% of these companies have technicians and mid-level professionals specialised in IT, as opposed to only 27% in companies not utilising AI. It should be noted that in 72% of these companies, training activities are conducted to improve knowledge in IT, while only 36% of companies that do not use AI engage in such activities.

**Table no. 2. Summary of descriptive statistics**

	AI = YES					AI = NO				
	Mean <sup>a</sup>	Median	SD	Min	Max	Mean <sup>a</sup>	Median	SD	Min	Max
<b>Size</b>	32.120	24.670	26.769	1	170	17.360	10	22.975	1	160
<b>Age</b>	20.940	19.230	10.942	3	99	20.890	19	13.172	2	120
<b>Trade</b>	0.110	0	0.316	0	1	0.220	0	0.414	0	1
<b>Services</b>	0.720	1	0.450	0	1	0.500	1	0.500	0	1
<b>Ent_edu</b>	0.870	1	0.332	0	1	0.700	1	0.460	0	1
<b>IT_exp</b>	0.660	1	0.472	0	1	0.270	0	0.446	0	1
<b>IT_train</b>	0.720	1	0.449	0	1	0.360	0	0.481	0	1
<b>ERP</b>	0.750	1	0.431	0	1	0.470	0	0.500	0	1
<b>Mark_analy</b>	0.770	1	0.423	0	1	0.350	0	0.477	0	1
<b>Coop_univ</b>	0.270	0	0.446	0	1	0.100	0	0.299	0	1

(a) In the case of dichotomous variables, the mean represents the percentage of 1. SD = Standard deviation. Min = Minimum. Max = Maximum.

In addition, companies that employ AI exhibit competences in ERP systems in 75% of cases, compared to 47% in companies where AI is not present. Companies that have adopted AI also score higher in terms of competences in analytical marketing tools, with 77% of them as opposed to 35%. Lastly, concerning collaboration with universities and/or research centres on aspects related to digitalisation, they also record a higher percentage, albeit with smaller differences in this case. Regarding the control variables, it can be observed that, in the service sector, the use of AI is more extensive, and it is in larger companies where AI is used more. Regarding the age of the companies, the two values are very similar.

Logistic regression analysis is used and the maximum likelihood method is used for parameter estimation. The equation of the model is as follows:

$$\ln\left(\frac{p}{1-p}\right) = \beta_0 + \beta_1 Size + \beta_2 Age + \beta_3 Trade + \beta_4 Services + \beta_5 Ent_{edu} + \beta_6 IT_{exp} + \beta_7 IT_{train} + \beta_8 ERP + \beta_9 Mark_{analy} + \beta_{10} Coop_{univ} + u \tag{2}$$

where  $p = P(AI=1|X)$  is the probability that the AI variable takes the value 1 in the presence of the explanatory variables, calculated as follows:

$$p = P(AI = 1|X) = \frac{\exp(\beta_0 + \sum_{i=1}^{10} \beta_i x_i)}{1 + \exp(\beta_0 + \sum_{i=1}^{10} \beta_i x_i)} \tag{3}$$

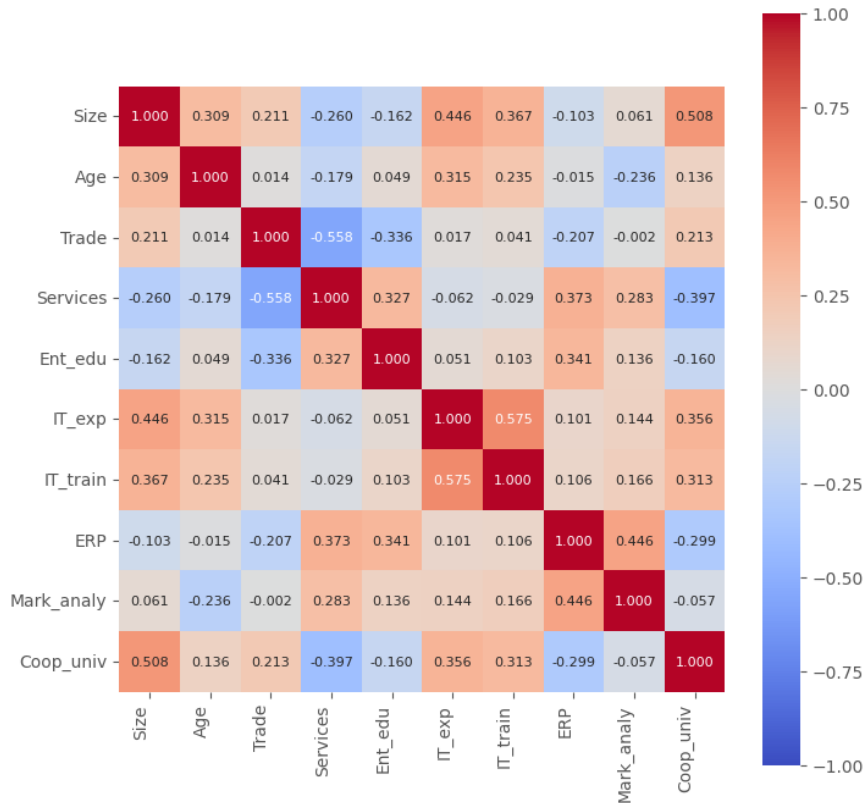
where,

$\beta_0$ : the intercept term of the model

$\beta_i$ : coefficients of the explanatory variables

X: set of explanatory variables  $\{x_1, x_2, \dots, x_{10}\}$

There are no issues of collinearity among the explanatory variables (see figure no. 1).



**Figure no. 1. Matrix of correlations**

**3. Results and discussion**

The results of the econometric analysis are presented in table no. 3. The omnibus test (chi-squared) enables verification that the model helps explain our dependent variable, AI, since it is significant (p-value < 0.001). Furthermore, the explanatory variables manage to account for between 39.4% and 52.5% of the variance of our dependent variable. In the classification table presented in table no. 4, it can be observed that the model has a high sensitivity of 94.3% and a specificity of 77.2%, with an overall classification accuracy of 85.7%.

Regarding the control variables, first, age, and size are significant. The sign is negative in the case of age, indicating that younger companies are those that have the most adopted AI. In contrast, the sign is positive in the case of firm size, indicating that larger companies are more frequently incorporating the use of AI compared to smaller firms. This is consistent with previous evidence (OECD, 2021; Calvino and Fontanelli, 2023) and can be explained by the greater constraints on access to technological, human, and financial resources faced by smaller companies. For sectoral dummies, a statistically significant negative coefficient for the trade variable can be observed. This result suggests the existence of greater challenges or barriers to AI implementation for SMEs operating in the trade sector compared to the industry, which serves as the base category in the estimated model. On the contrary, the

coefficient for the service variable, also significant, has a positive sign, indicating that the use of AI is more widespread among companies in the service sector compared to industrial firms. This result is probably associated with the most advanced knowledge-intensive services.

**Table no. 3. Logistic regression model**

Variables	B	S.E.	p-value	Exp(B)
Const	-4.187	0.338	<0.001	0.015
Size	0.023	0.004	<0.001	1.023
Age	-0.022	0.007	0.001	0.978
Trade	-0.859	0.271	0.002	0.424
Services	1.110	0.209	<0.001	3.035
Ent_edu	1.066	0.224	<0.001	2.904
IT_exp	1.012	0.178	<0.001	2.750
IT_train	0.575	0.167	<0.001	1.778
ERP	0.842	0.184	<0.001	2.320
Mark_analy	1.565	0.168	<0.001	4.784
Coop_univ	1.826	0.242	<0.001	6.209
<b>Goodness of fit</b>				
Chi-squared	755.408	p-value	<0.001	
R <sup>2</sup> Cox and Snell	0.394	R <sup>2</sup> Nagelkerke	0.525	

*n = 1,508 observations. S.E.= Standard Error.*

**Table no. 4. Classification**

Observed (AI)	Prognosed (AI)		% correct
	NO	YES	
NO	582	172	77.2
YES	43	711	94.3
<b>Global percentage</b>			<b>85.7</b>

Regarding the explanatory variables, they are all significant and have a positive sign. These findings provide strong evidence to support all hypotheses postulated in Section 2.

First, our results indicate that SMEs whose business owners/managers have a university degree or high professional training are more likely to adopt AI in their businesses, thus supporting hypothesis H1. This finding underscores the importance of acquiring new and innovative knowledge and skills for entrepreneurs/managers, which can be obtained through university education or training. Entrepreneurs with a strong educational background are better equipped to understand the potential associated with AI adoption and to successfully implement the necessary changes in their companies. This importance of the education level of business owners/managers aligns with previous evidence from studies by Romero and Martínez-Roman (2012) and Martín-Martín, Maya García and Romero (2022).

Similarly, the presence of technical staff with IT expertise and IT training initiatives for employees is observed to exert a strong positive effect on AI adoption, supporting our hypotheses H2 and H3. Companies with IT experts among their staff and those conducting IT training activities exhibit a more positive attitude towards AI adoption and possess the necessary skills to facilitate successful implementation of this technology. This suggests that such companies have greater readiness or capability for AI adoption and highlights the

importance of SMEs prioritising skilled personnel and investing in continuous training to effectively leverage advanced technologies such as AI. This finding aligns with previous literature that emphasises the importance of skills and competencies for AI adoption (Alekseeva et al., 2021; Calvino and Fontanelli, 2023).

In particular, our results indicate that SMEs that use marketing analytics tools and ERP systems are more likely to adopt AI, supporting hypothesis H4. This suggests that firms with more advanced digital skills and higher digital maturity are better positioned to understand and integrate AI technology into their operations, thereby enhancing their ability to adapt to and capitalise on the benefits of AI. Digitalisation is a cumulative and learning process, and it is not advisable to jump into the void when seeking to maximise the probabilities of success. The application of advanced tools for digital management indicates that SMEs already possess the necessary competencies and skills for adopting AI. Additionally, these tools serve as a powerful source for obtaining and structuring large amounts of data, which are necessary for training AI models. This finding is in line with previous analyses that point out the potential interaction between ERP systems, marketing analytics, and AI (Petrescu and Krishen, 2023; Jawad and Balázs, 2024).

Lastly, our results reveal that cooperation with universities and research centres exerts a strong positive effect on the implementation of AI in SMEs, which supports hypothesis H5. Collaboration with universities and research centres facilitates the implementation of AI in SMEs by providing access to the technological and knowledge resources that are critical to the implementation of AI in business. This finding is consistent with Chan, Krishnamurthy and Sadreddin (2022), where SMEs are shown to benefit from the establishment of collaboration with universities and research centres to facilitate their digital transformation. Moreover, the effect associated with this variable is observed to be the greatest based on the odds ratios (see Exp(B) in Table no. 3).

In general, these results underscore the importance of competencies and skills in influencing the adoption of AI within SMEs in Spain. The findings elucidate how digital human capital directly impacts the adoption of AI tools in business.

## **Conclusions**

This article delves into the evolving landscape of competency requirements spurred by AI adoption within companies and deals particularly in the case of SMEs in Spain. In doing so, we highlight the pivotal role of upgrading skill sets, adaptability, and strategic workforce planning to harness the potential of AI while ensuring sustainable growth and competitiveness in today's dynamic business environment.

The approach of SMEs to digitalisation is influenced by the specific characteristics of these types of companies, which can entail certain limitations to adopting AI in their businesses. In this context, our paper highlights some critical competencies and skills that favour the adoption of AI in SMEs. To our knowledge, this study represents the first attempt to examine the competency requirements for AI implementation with a specific focus on SMEs. By empirically investigating the factors associated with AI adoption in SMEs in Spain, our research therefore fills a relevant gap in the existing literature. Our findings not only provide

valuable insights into important competencies for AI implementation, but also offer practical guidance for SMEs looking to embark on their AI journey.

From a methodological standpoint, our study employs an innovative technique known as Generative Adversarial Networks (GANs), which has traditionally found application in fields such as medicine and engineering, and has only recently been adopted in the realm of economics.

Our analysis reveals that SMEs with business owners/managers holding a university degree or high-professional training, those with IT experts on their staff, and those conducting IT-related training for their employees are more inclined to adopt AI technologies. Furthermore, SMEs equipped with advanced digital management skills (using ERP systems and marketing analytics tools) and engaged in collaboration with universities and research centres exhibit a higher propensity for the integration of AI into their operations.

These findings have significant implications for both business management and public policy. From a managerial point of view, the results underscore the critical need for the enhancement of digital skills within companies to facilitate the successful adoption of AI technologies. In this sense, the hiring of IT specialists is crucial for SMEs to adopt AI. They bring expertise in assessing needs, integrating systems, managing data, and ensuring cybersecurity. Their skills are essential for successful AI implementation, driving innovation and efficiency in SMEs. Furthermore, the results presented in this document highlight the importance of investing in training programmes and initiatives aimed at improving the skills of employees and managers to effectively leverage AI in business operations.

In particular, this research shows that implementing ERP systems and marketing analytics in SMEs can significantly favour the adoption of AI in business operations. ERP systems streamline and integrate various business processes, providing a centralised platform to manage resources, finances, and operations. This integration results in a wealth of structured data, which is essential for training AI models. Additionally, marketing analytics tools allow SMEs to gather, analyse, and interpret vast amounts of customer data, leading to better insights and more informed decision making. Together, these technologies create a robust data infrastructure, improving the capacity for AI implementation. Using data from ERP systems and marketing analytics, AI can automate and optimise tasks, predict trends, personalise customer interactions, and improve overall efficiency. Finally, SMEs should also strive to establish closer collaboration with universities and research centres to support their AI implementation projects within their businesses. These cooperative relationships can facilitate SMEs' access to external knowledge, skills, and capabilities that are not available within the organisation.

On the policy front, public administrations can play a crucial role in fostering AI adoption among SMEs by designing initiatives focused on improving key digital competencies. This could involve developing targeted training programmes, providing financial incentives or grants for technology adoption, and facilitating collaboration between SMEs and educational institutions or research centres. Furthermore, the development of AI competences within education systems is strategically important (Grădinaru et al., 2024). By actively promoting the development of digital skills and capabilities within SMEs, policymakers can contribute to driving innovation, productivity, and competitiveness in the broader economy.

This research is not without limitations. In this sense, it should be noted that most of the variables used in the econometric analysis are dichotomous. Future research could use Likert

scales to capture the degrees of intensity of responses. Furthermore, while the analysis presented in this paper offers valuable information on SMEs in Spain, the observed results could be context dependent. More research is needed to generalise the findings and assess their applicability to other countries. Furthermore, future studies could explore whether similar conclusions hold true for larger companies in different industries.

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