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Why do manufacturing firms struggle with artificial intelligence?

Abstract

Purpose

This study examines the key barriers hindering the adoption of industrial Artificial Intelligence (AI) in European manufacturing firms. It aims to classify these barriers and analyze their influence on adoption decisions, offering a nuanced understanding that can support managerial strategies for AI implementation.

Design/methodology/approach

Drawing on data from the 2022 European Manufacturing Survey (EMS), the study analyzes responses from 472 firms across Spain, Slovenia, Slovakia, and Croatia. Factor analysis was used to group perceived barriers into three categories: lack of Resources, Environment/Ecosystem limitations, and lack of Usefulness/Fit. Logistic regression models with interaction terms assess the direct and moderating effects of these barriers on AI adoption.

Findings

The study identifies lack of Resources—particularly financial capital, infrastructure, and skilled personnel—as an absolute barrier that directly inhibits AI adoption. Lack of Usefulness/Fit only hinders adoption when resources are also lacking, forming a conditional absolute barrier. Conversely, Environment/Ecosystem limitations and data quality concerns emerge as relative barriers, affecting firms already on the adoption path. Leadership support mitigates environmental challenges and plays a crucial moderating role in successful implementation.

Originality

The study introduces a novel conceptual distinction between absolute and relative barriers to industrial AI adoption, offering practical insights into how manufacturing managers can navigate AI adoption by identifying which barriers require foundational resolution versus those that arise later in the implementation process. This distinction adds a new dimension to the understanding of AI adoption barriers, highlighting the varying degrees of impact depending on an organization's stage in the AI adoption process.

Keywords:

Industrial artificial intelligence, Barriers, Manufacturing, Digital technologies, European manufacturing survey

Quick Value Overview

Interesting because: This study explores why manufacturing firms struggle to adopt artificial intelligence (AI) despite its well-documented benefits for productivity and competitiveness. It introduces a novel distinction between absolute and relative barriers to AI adoption. Unlike prior studies that list barriers individually, this research uncovers their interdependencies and stage-dependent effects, showing that not all barriers equally impede adoption. By combining empirical rigor with cross-country analysis, the paper provides an evidence-based framework that explains how different types of barriers shape the AI adoption journey.

Theoretical value: The study adopts a multi-theoretical approach, combining insights from the Resource-Based View (RBV) and the Technology Acceptance Model (TAM) to propose a novel, process-oriented framework of AI adoption. It introduces the distinction between absolute and relative barriers, extending the existing frameworks by showing that adoption outcomes depend not only on resource availability but also on how organizations perceive, prioritize, and manage barriers across different stages of adoption.

Practical value: For managers and policymakers, the findings offer a clear prioritization of action. Firms should first mitigate absolute barriers by investing in resources, skills, and infrastructure, then focus on managing relative barriers such as data quality and ecosystem coordination. Policymakers can foster adoption through targeted funding, workforce training, and regulatory clarity, ensuring balanced AI readiness across manufacturing sectors.

1. Introduction

Industrial artificial intelligence (AI) stands as a pivotal component for the manufacturing sector, enhancing the performance of manufacturing firms by promoting green product and process innovation (Lin et al., 2024), increasing organisational creativity (Mikalef & Gupta, 2021), serves as a foundational enabling technology within the framework of smart manufacturing (Bustinza et al., 2024), significantly bolstering quality control, expediting design processes, curbing resource wastage, facilitating production reuse and enabling predictive maintenance, among other benefits (Ahmad et al., 2022). Implementing AI can therefore benefit businesses by raising corporate success and offering a strategic advantage (Ghani et al., 2022; Ransbotham Sam et al., 2017).

However, AI adoption in manufacturing has been slower than expected, despite high industry expectations (Ghani et al., 2022; Peres et al., 2020). For instance, while 48% of global CIOs planned to deploy AI by 2020, only 8% of firms in the EU and 6% in the USA had integrated it into core operations (European Commission DESI index, 2024; Laurence Goasduff, 2019; McElheran et al., 2023). This gap between ambition and implementation underscores the need to better understand and address barriers to AI adoption.

As one of the newest technologies, AI adoption is subject to multiple potential barriers. Literature on barriers to digital technology adoption, particularly within Industry 4.0, is extensive (Horváth & Szabó, 2019; Jankowska et al., 2023; Mukherjee et al., 2023; Raj et al., 2020; Stentoft et al., 2021). On the other hand, research specifically addressing barriers and challenges to AI adoption, as part of Industry 4.0, is scarce (Lee et al., 2023) while addressing barriers to AI adoption is crucial (Shahzadi et al., 2024).

Existing studies primarily enumerate barriers but often fail to examine their interrelations, categorization, prioritization, or practical implications (Cubric, 2020; Kar & Kushwaha, 2021; Tariq et al., 2021a). This limitation hinders a comprehensive understanding of how these barriers collectively impact AI adoption. Additionally, most studies consider AI adoption in general, without distinguishing between different types of AI applications (Kar et al., 2021; Lopez-Garcia and Rojas, 2024; Tariq et al., 2021a). This study addresses these gaps by focusing specifically on industrial AI—particularly its applications in automation, quality control, and process optimization within manufacturing environments.

Perceived barriers play a pivotal role in shaping the trajectory of AI adoption. If these barriers are perceived as insurmountable, organizations may be hesitant to embrace AI solutions, negatively affecting their adaptability to technological advancements and competitiveness (Kar et al., 2021). Moreover, a significant research gap exists in formulating effective strategies to overcome AI adoption barriers, particularly in understanding the relationship between barrier perception and actual adoption decisions (Cordeiro et al., 2023; Rjab et al., 2023). While some studies argue that barriers do not significantly affect digital technology adoption (Jankowska et al., 2023; Stentoft et al., 2021), others highlight the influence of financial constraints or technological limitations, on adoption decisions (Cordeiro et al., 2023).

This study seeks to bridge these gaps by categorizing AI adoption barriers and empirically examining their relationships. By leveraging exploratory and confirmatory factor analysis alongside regression modelling, this research uncovers patterns that remain underexplored in prior studies. Moreover, the study introduces the concept of absolute and relative barriers—distinguishing between barriers that fundamentally impede AI adoption and those that primarily affect firms that have already embarked on AI implementation: Absolute barriers are fundamental obstacles that directly prevent organizations from adopting AI, whereas relative barriers do not necessarily prevent the adoption but become significant primarily for organizations that have already integrated AI, representing obstacles that AI adopters must address for successful and sustained implementation.

In this context, the aim of this study is to map the current state of AI barriers in manufacturing in the EU and answer the following questions:

- How can barriers to AI adoption be classified?
- What is the influence of the different barrier categories on AI adoption?

To answer these questions, this article analysis data from the European Manufacturing Survey (EMS) 2022 edition, which comprises 472 surveys of firms located in Spain, Slovenia, Slovakia and Croatia. Factor analysis and logistic regression were used to analyse the data.

This study makes several key contributions to the understanding of AI adoption barriers in industrial settings. First, it provides a rigorous empirical examination of perceived barriers, identifying and classifying them through factor analysis and statistical validation rather than relying solely on theoretical assumptions. Second, it introduces an expanded theoretical framework that integrates the Resource-Based View (RBV) and the Technology Acceptance Model (TAM) to categorize barriers more systematically. Third, it introduces a novel perspective by distinguishing between absolute and relative barriers, enabling better prioritization of AI adoption challenges. Fourth, it examines the interdependencies among barriers, shedding light on how they collectively shape AI adoption decisions. Lastly, this study focuses specifically on industrial AI adoption, providing a more relevant and specialized perspective for overcoming sector-specific challenges.

2. Literature overview

2.1 Theoretical models for AI adoption

The most employed theoretical frameworks to guide investigations into technology adoption (Baig et al., 2019) are: the technology-organisation-environment (TOE) framework (Tornatzky et al., 1990), the technology acceptance model (TAM) (Davis, 1989), the diffusion of innovation theory (DOI) (Gillani et al., 2020; Rogers, 1995) or institutional theory (Scott & Christensen, 1995). Complementarily, a general theory such as the resource based view (RBV) (Barney, 1991), can also be instrumental to set the basis to explain the processes of technology adoption.

Most research on barriers and adoption of digital technologies is exclusively based on one of the selected theories, most commonly the TOE theoretical framework (Awa et al., 2016; Chiu et al., 2017; Pillai et al., 2022; Pumplun et al., 2019; Rjab et al., 2023; Sharma et al., 2020), whereas some others combine them, for example TOE and TAM (Chatterjee et al., 2021) or TOE and DOI (AlSheibani et al., 2018; Oliveira et al., 2014). The argument for the combination of such theoretical frameworks is that it is challenging to apply existing adoption models to AI adoption in organizations due to the technology's complexity (Chatterjee et al., 2021) and the rapid evolution of information technology (Oliveira & Martins, 2011; Thong, 1999), which requires to revisit and expand single frameworks, particularly the ones related to data as AI (Pumplun et al., 2019).

2.2 Taxonomies for barriers to AI adoption

Extant literature offers numerous taxonomies for barriers to AI adoption. Rjab et al., (2023) classify them as primary and secondary, while the European Commission (2020) distinguishes between internal (firm-related) and external barriers. Other frameworks propose groupings such as process, technology, economic, regulation, and culture at micro, meso, and macro levels (Spaltini et al., 2024), or global, organisational, and development levels (Perno et al., 2022). More recently, Godinho Filho et al. (2025) distinguished between foundational barriers, which cut across industries, and application-specific barriers linked to particular technologies.

Building on the TOE framework, many studies adopt the technological, organisational, and environmental classification (Shahzadi et al., 2024), with extensions including innovation (Baig et al., 2019; Oliveira et al., 2014), social and economic (Cubric, 2020), security (Hsu & Yeh, 2017), and process-related dimensions (Dennehy et al., 2021).

Yet few works prioritise or analyse dependencies among barriers; when they do, approaches such as interpretive structural modelling or cross-impact matrices are used (Kar et al., 2021; Senna et al., 2022). These studies call for more statistical modelling to confirm such relationships, which this paper addresses.

2.3 Barriers to AI adoption: a theoretical classification

Some authors argue that the challenges in adopting AI mirror those found in implementing any new technology (Venkatesh, 2022), suggesting AI adoption faces similar barriers than other technologies do. However, there are incipient discussions around barriers specifically unique to AI are still in their infancy, with limited research exploring this aspect. Alsheibani et al.(2018) suggest uncertainty of AI capability and business value as distinguishing features of AI compared to other digital technologies, while Pumplun et al. (2019) pinpoint data-related issues, including General Data Protection Regulation (GDPR) compliance, as specific hurdles in AI technology adoption.

Research related to barriers to AI suggests that the lack of skills, lack of visibility of benefits, integration complexity, cost, strategic planning and fear of the unknown are among the most cited factors influencing AI adoption in the literature (Ahmad et al., 2022; Dennehy et al., 2021; Tariq et al., 2021a). As a result of a thorough revision of the literature on barriers to AI adoption, 12 distinct types of barriers have been conceptually identified as presented on Table 1. This classification has been used to define a question on barriers to AI adoption integrated in the survey to manufacturing firms.

Table 1. Classification of barriers to AI adoption

	Barrier	Definition	Authors
B1	Lack of skilled personnel	AI expertise shortage impedes	(Ahmad et al., 2022; Alsheibani et al., 2019; Bhalerao, 2022; Chouhan et al., 2025; Cordeiro et al., 2023; Cugno et al., 2021;

		implementation and effective usage	Jankowska et al., 2023; S. Kar et al., 2021; Oberländer et al., 2020; Pumplun et al., 2019; Sharma et al., 2020; Tarafdar Monideepa et al., 2019; Tariq et al., 2021b; Ulrich et al., 2021)
B2	Lack of coherent digital strategy	Missing plans create confusion and misalignment with AI objectives	(Begnini et al., 2023; Bhalerao, 2022; Hamm & Klesel, 2021; S. Kar et al., 2021; Nguyen et al., 2019; Tariq et al., 2021b)
B3	Lack of usability	Complex AI interfaces deter manufacturing employees, hindering seamless integration into the workflow	(Awa et al., 2016; Begnini et al., 2023; Chatterjee et al., 2021; Črešnar et al., 2023; A. K. Kar & Kushwaha, 2021; S. Kar et al., 2021; Stentoft et al., 2021)
B4	Lack of defined benefits	Unclear business case and relative advantage hinders AI investment, as benefits are not evident to the company	(Awa et al., 2017; Cordeiro et al., 2023; Črešnar et al., 2023; Cugno et al., 2021; Dennehy et al., 2021; Ghobakhloo et al., 2022; Horváth & Szabó, 2019; Lai et al., 2018; Tariq et al., 2021b)
B5	Complexity of implementation, coordination and learning	Overwhelming setup and training challenges manufacturing operations	(Chatterjee et al., 2021; Dennehy et al., 2021; Horváth & Szabó, 2019; S. Kar et al., 2021; Lai et al., 2018; Oliveira et al., 2014; Susanty et al., 2025)
B6	Poor data quality, reliability, poor data integration	Inaccurate data undermines AI reliability and trust. Disconnected data sources hinder comprehensive AI analysis	(Bettoni et al., 2021; Dennehy et al., 2021; Lai et al., 2018; J. Lee et al., 2018; Pumplun et al., 2019)
B7	Lack of IT infrastructure - devices, software, platforms	The company's IT infrastructure is inadequate for the implementation of AI	(Begnini et al., 2023; Cugno et al., 2021; Hamm & Klesel, 2021; Jöhnk et al., 2021; S. Kar et al., 2021; Lai et al., 2018; Pillai et al., 2022)
B8	Lack of leadership support	Without top-level endorsement, AI initiatives stall and are not put in action	(Alsheibani et al., 2019; Baig et al., 2019; Chatterjee et al., 2021; Ghani et al., 2022; Hamm & Klesel, 2021; Jöhnk et al., 2021; S. Kar et al., 2021; Sharma et al., 2020)
B9	Lack of financial resources	Insufficient funds delay or block AI projects	(Baig et al., 2019; Begnini et al., 2023; Bhalerao, 2022; Chouhan et al., 2025; Cugno et al., 2021; Hamm & Klesel, 2021; Horváth & Szabó, 2019; Jöhnk et al., 2021; Pumplun et al., 2019)
B10	Concerns over control of data, security, privacy and reputational risk	Reputational damage can deter manufacturing companies from adopting AI due to potential risks and liabilities associated with these issues	(Ahangar et al., 2025; Ahmad et al., 2022; Baig et al., 2019; Godinho Filho et al., 2025; Hsu & Yeh, 2017; Kamble et al., 2018; Pumplun et al., 2019)

B11	Lack of support within the supply chain (suppliers, customers)	Lack of partner alignment slows AI integration in manufacturing	(Bauer, 2020; Ghani et al., 2022; Haans et al., 2016; Koka & Prescott, 2002)
B12	Concern over the ecological impact	AI's energy consumption and carbon footprint raise concerns in terms of sustainability.	(Godinho Filho et al., 2025; Nishant et al., 2020; Rjab et al., 2023)

Source: Authors own work.

3. Methodology

The source of the data used in this study is the European Manufacturing Survey (EMS), administered by the Fraunhofer Institute for Systems and Innovation Research. The survey gathers comprehensive data on innovations within the manufacturing sector. The primary objectives of the EMS project include gaining a deeper understanding of the application of production and information technology, implementing organisational strategies, and integrating best management practices.

The eight-page, 25-section survey targets manufacturing companies and follows strict protocols to ensure cross-country comparability. A standardized questionnaire is first developed in English, translated into national languages, and back-translated to maintain accuracy. Pre-testing is conducted in each country, and data harmonization techniques are applied to address linguistic and contextual differences (Bikfalvi et al., 2014).

The authors of this study, in addition to data collection and processing, participated in the design of the 2022 edition of EMS, contributing to the development of the survey questions related to barriers to AI adoption. This involvement ensured that the identified barriers were well-grounded in both theoretical insights and practical industry challenges. The subsample of the EMS used in this study was collected in 2022 and consists of 472 surveys, distributed as follows: Spain 86, Croatia 138, Slovakia 102, and Slovenia 146. To ensure data quality, the dataset was screened for completeness and consistency. Cases with missing items in terms of structural information were excluded. Outliers and contradictory responses were removed.

3.1 Operationalisation of variables

3.1.1. Barriers

From the reviewed literature, 12 barriers were identified to be related to AI implementation in the companies, as summarised in Table 1. These barriers were used for exploratory factor analysis and regression modelling to define barriers classification and dependencies. A 5-point Likert scale was used to evaluate the 12 barriers to explain the perception of how they affect AI adoption.

3.1.2. AI adoption

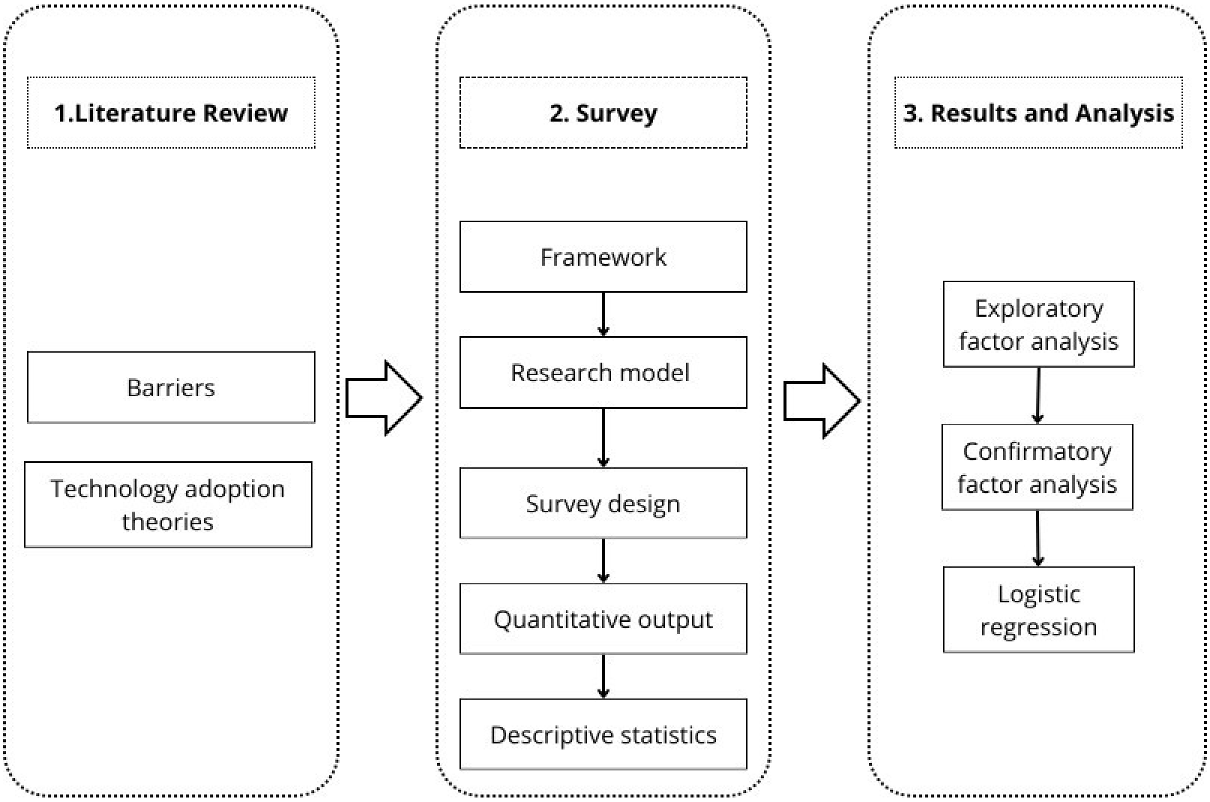
In the logistic regression, the dependent variable was a binary indicator of AI adoption (0 = no use; 1 = at least one use in production). Adoption was assessed through the question: "*Do you use specific software solutions with self-learning functionality in any of the following six production areas: production process management, quality control, maintenance, internal logistics, energy management, or process improvement/innovation?*"

For control variables in regression testing the influence of barriers to AI adoption, country, sector and number of employees to assess the size of the company (Cordeiro et al., 2023; Gillani et al., 2020;

Lerch et al., 2022) were used to ensure that the contextual factors were considered, since they may impact firms’ behaviour and performance. Export and import rates were used to control the impact of companies' levels of openness and the degree to which they depend on internal versus external resources in their utilisation of digital technologies (Stentoft et al., 2021). A descriptive overview of the variables used in the study can be found in Table 2 in the Data Analysis section.

3.2 Modelling

The suggested methodology is divided into several steps. In the first phase, based on the literature review, barriers to AI adoption were identified, as summarised in Table 1. All analyses were performed using the SPSS statistical software. The research approach is shown in Figure 1.



Source: Authors own work

Figure 1. Research approach

3.3 Common method bias test

To reduce common method bias, both procedural and statistical remedies were applied (Podsakoff et al., 2003; Rodríguez-Ardura & Meseguer-Artola, 2020). Respondents were assured anonymity, multiple respondents per firm were allowed, and Harman’s single-factor test showed that the first factor explained only 28.36% of the variance—well below the 50% threshold—indicating that bias was not a concern (Tehseen et al., 2017).

4. Data analysis

4.1 Descriptive statistics

Basic sample descriptions are presented in Table 2. Notably, the majority of the companies fall within the bracket of small to medium-sized, characterised by employee numbers ranging from 20 to

250. The distribution of the sector of the activities, divided into four groups, is predominated by manufacturing companies belonging to the metal, machine and vehicle sectors, at 42%. At least one AI technology is adopted by 22.5% of the European manufacturing companies.

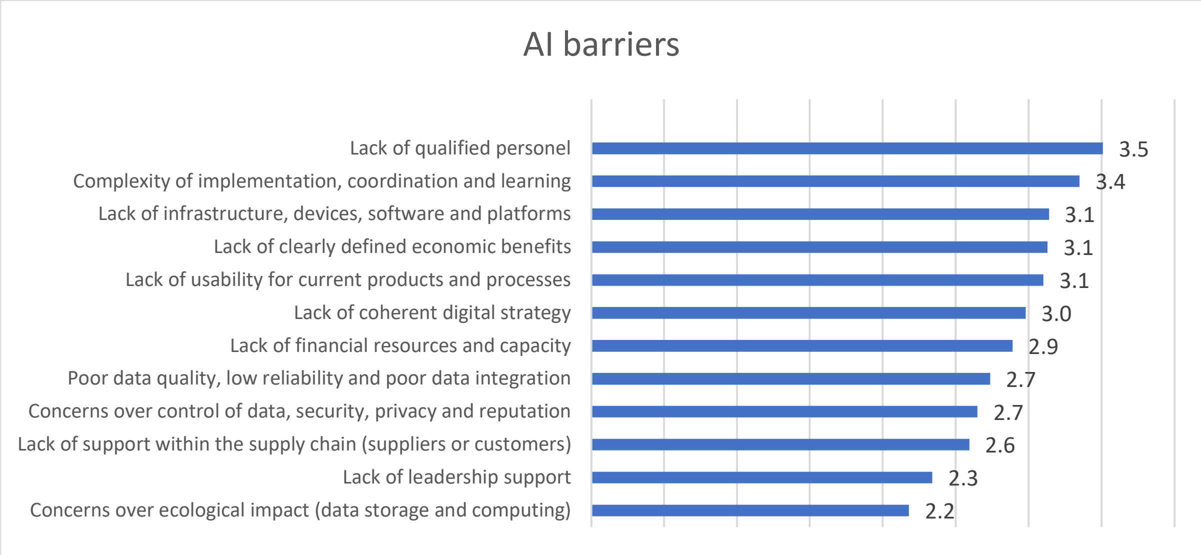
Table 2. Descriptive statistics

	Frequencies	%
Country		
Spain	86	18.2
Croatia	138	29.2
Slovakia	102	21.6
Slovenia	146	30.9
Total	472	100
Size		
< 250 employees	361	82.4
> 250 employees	77	17.6
Total	438	100
Sector		
Chemical, rubber, plastic	58	12.5
Metal, machine, vehicle	196	42.3
Electronic, PC	42	9.1
Other	167	36.1
Total	463	100
AI adoption		
YES	91	22.5
NO	314	77.5
Total	405	100

Source: Authors own work

Figure 2. illustrates the perception of AI barriers among European manufacturing companies. The highest-rated barrier is the lack of qualified personnel, which is consistent with the findings in several studies (Ahmad et al., 2022; Alsheibani et al., 2019; European Commission. Directorate General for Communications Networks, Content and Technology. et al., 2020; Horváth & Szabó, 2019; Tariq et al., 2021a; Ulrich et al., 2021).

In addition to the perception of barriers, the mean and dispersion were tested. The barriers variables had an overall mean value of 2.88 points on the five-point Likert scale, reflecting moderate barrier perceptions. The variance in responses is low, being highest for lack of usability for current products and processes with a value of 1.45. Conversely, the perception of poor data quality, reliability and integration demonstrated minimal dispersion, suggesting a unified understanding among companies regarding the pivotal role of effective data management in successful AI adoption.



Source: Authors own work

Figure 2. Barriers perception among the companies

4.2 Exploratory factor analysis for main barriers dimensions

Exploratory factor analysis was used in this study to combine the barrier variables to form factors that could be used for further analysis and barrier classification. Initially, the calculation of correlations among the variables is imperative, leading to the construction of a correlation matrix. A validation procedure is subsequently conducted, with one of the most commonly employed tests for this purpose being the Kaiser-Meyer-Olkin (KMO) test.

Following these steps, the correlations are calculated as shown in Table 3.

Table 3. Barrier's correlations

	B1	B2	B3	B4	B5	B6	B7	B8	B9	B10	B11	B12
B1	1	0.43	0.29	0.29	0.47	0.40	0.56	0.29	0.48	0.33	0.29	0.24
B2		1.00	0.33	0.41	0.49	0.42	0.52	0.53	0.47	0.40	0.39	0.34
B3			1.00	0.62	0.49	0.38	0.38	0.29	0.29	0.30	0.32	0.22
B4				1.00	0.45	0.46	0.43	0.32	0.29	0.32	0.33	0.28
B5					1.00	0.49	0.45	0.23	0.40	0.37	0.35	0.23
B6						1.00	0.43	0.33	0.37	0.45	0.42	0.41
B7							1.00	0.39	0.51	0.32	0.31	0.27
B8								1.00	0.38	0.36	0.34	0.39
B9									1.00	0.40	0.34	0.31
B10										1.00	0.54	0.72
B11											1.00	0.54
B12												1.00

B1:lack of skilled personnel, B2:lack of coherent digital strategy, B3:lack of usability, B4:lack of defined benefits, B5:complexity of implementation, coordination and learning , B6: poor data quality, reliability, poor data integration, B7:lack of IT infrastructure - devices, software, platforms, B8:lack of leadership support, B9: lack of financial resources, B10:concerns over control of data, security, privacy and reputational risk, B11:lack of support within supply chain (suppliers, customers), B12:concern over ecological impact. *All the values have significance p value <0.05

Source: Authors own work

Within the set, there are no correlation levels over 0.8, which suggests no strong independence among variables. Variables show moderate correlation, which is suitable for further interpretation by factor analysis. A determinant of value of 0.006 was determined, a value over the recommended 0.0001, which also confirms the fit of the data for further factor analysis.

Following the correlation matrix, a principal component analysis was performed. The factor extraction was performed using Principal Component Analysis (PCA) with Varimax rotation in SPSS. The number of factors was determined using Kaiser's criterion (eigenvalues > 1) and scree plot inspection, which supported a three-factor solution. The Kaiser–Meyer–Olkin Measure of Sampling Adequacy value was 0.882, which is well above the recommended value of 0.5, confirming the factor analysis fit (Kaiser, 1974). Bartlett's test of sphericity confirms the fit with a significance level of $p < 0.001$. The factor analysis identified three factors that explain 64% of the total variability. Table 4 presents the rotated component matrix with the three factors extracted.

Table 4. Rotated component matrix for barriers

Rotated Component Matrix

		Component		
		1	2	3
B1	Lack of skilled personnel	**0.761**	0.087	0.188
B2	Lack of coherent digital strategy	**0.658**	0.296	0.261
B3	Lack of usability	0.145	0.134	**0.840**
B4	Lack of defined benefits	0.182	0.191	**0.813**
B5	Complexity of implementation, coordination and learning	0.461	0.122	**0.608**
B6	Poor data quality, reliability, poor data integration	0.341	0.407	0.489
B7	Lack of IT infrastructure - devices, software, platforms	**0.747**	0.104	0.315
B8	Lack of leadership support	**0.502**	0.419	0.095
B9	Lack of financial resources	**0.733**	0.245	0.102
B10	Concerns over control of data, security, privacy and reputation	0.230	**0.821**	0.172
B11	Lack of support within supply chain	0.190	**0.704**	0.261
B12	Concern over ecological impact	0.133	**0.884**	0.082
variance explained		23.75%	21.06%	19.18%
total variance explained		23.75%	44.81%	63.99%

Extraction Method: Principal Component Analysis.
Rotation Method: Varimax with Kaiser Normalization.
Rotation converged in 5 iterations.

Source: Authors own work

Factor analysis revealed three dimensions of barriers. **Lack of Resources** covers shortages in skills, infrastructure, finance, strategy, and leadership. **Environment and Ecosystem Limitations** include concerns over ecological impact, data security and privacy, and weak supply chain support. **Lack of Usefulness/Fit** reflects limited usability, unclear economic benefits, and implementation complexity. Since issues of poor data quality, reliability, and integration did not load strongly on any factor, they were treated separately in the regression analysis.

4.3 Barriers construct validation: confirmatory factor analysis

All factors loaded over 0.5 are shown in table 5. Average variance extracted (AVE) was calculated to further confirm the validity of the constructs. In the case of the construct Resources, the AVE was slightly below 0.5 (0.482), so the barrier with the lowest loading (lack of leadership support) was taken out of the construct. After this modification, all constructs showed an AVE of more than 0.5. Next, composite reliability (CR) and Cronbach's alpha α were tested. All the constructs gave results for CR and Cronbach's alpha α of over 0.7, confirming their validity. The results of the reliability test are described in Table 5. The barrier that was excluded (lack of leadership support) was added separately to the posterior regression analysis.

Table 5. Constructs' reliability statistics

Construct/Items	LF	AVE	CR	α
Lack of Resources		0.527	0.812	0.794
lack of skilled personnel	**0.761**			
lack of coherent digital strategy	**0.658**			
lack of IT infrastructure - devices, software, platforms	**0.747**			
lack of financial resources	**0.733**			
Environment and ecosystem limitations		0.65	0.847	0.811
concerns over control of data, security, privacy and reputational risk	**0.821**			
lack of support within supply chain (suppliers, customers)	**0.704**			
concern over ecological impact	**0.884**			
Lack of Usefulness/Fit		0.578	0.802	0.752
lack of usability	**0.840**			
lack of defined benefits	**0.813**			
complexity of implementation, coordination and learning	**0.608**			

Source: Authors own work

4.4 Regression analysis results

Wald statistics and logistic regression were used to test the effect of perceived barriers on AI adoption.

The three constructs of barriers created in the confirmatory factor analysis were entered as independent variables. In the exploratory analysis, the item data quality/poor data integration showed relatively even cross-loadings across all three factors, with no loading above 0.50. This suggests that data quality is intertwined with technical readiness, organisational processes, and environmental context rather than belonging to a single domain. Its treatment as a separate barrier is therefore justified both empirically, due to weak factor loadings, and theoretically, as prior studies emphasise data quality as a multidimensional construct underpinning effective AI use (Bettoni et al., 2021; Dennehy et al., 2021; Heimberger et al., 2024; Pumplun et al., 2019).

The size of the company measured by the number of employees (standardised by natural logarithm), sector, country, export and import were entered as control variables. Lack of leadership support was also included separately, as it was excluded from lack of Resources factor in the confirmatory analysis.

Two regression models were run. The first assessed the barriers separately, and the second estimated the effects of the barriers' interaction. The interactive effects were studies to extend the linear relations from the first model by testing the two-way moderating effect as the possibility of uncovering hidden relationships.

All the variables relating to the barriers in the second regression model were centred and the collinearity was assessed for the second regression model, showing that all the values of the variance inflation factor (VIF) were below the recommended value 5. The linearity of the logit was tested for continuous predictors (firm size, barrier factor scores, export, and import) using the Box–Tidwell procedure. Interaction terms between each predictor and its natural logarithm were entered into the model; none reached statistical significance ($p > 0.05$), confirming that the linearity assumption was met.

Table 6. presents the results of the regression analysis. In Model I, lack of Resources and Data quality exhibited significant negative and positive impacts on AI adoption, respectively. Resources exhibited a significant negative impact ($\beta = –0.329$, $p < 0.05$), with the odds ratio (0.72). Data quality, in contrast, showed a significant positive effect ($\beta = 0.317$, $p < 0.05$), odds ratio 1.37. A lack of significance for Environmental/ecosystem limitations and lack of Usefulness/Fit constructs implies their limited direct influence. The control variables—Country (Spain, Croatia) and Sector (chemical, rubber, plastic; metal, machine, vehicle)—also displayed significance.

Model II introduced moderation effects, emphasizing the substantial negative impact (-0.382**) of lack of Resources*Usefulness/Fit limitations on AI adoption. Significance persisted for lack of Resources and Data quality as significant barriers. Environmental*Leadership support showed a positive significant impact (0.187**), while other interactions remained insignificant. The significance of the control variables remained similar to that of the first model.

Table 6. Summary of regressions models

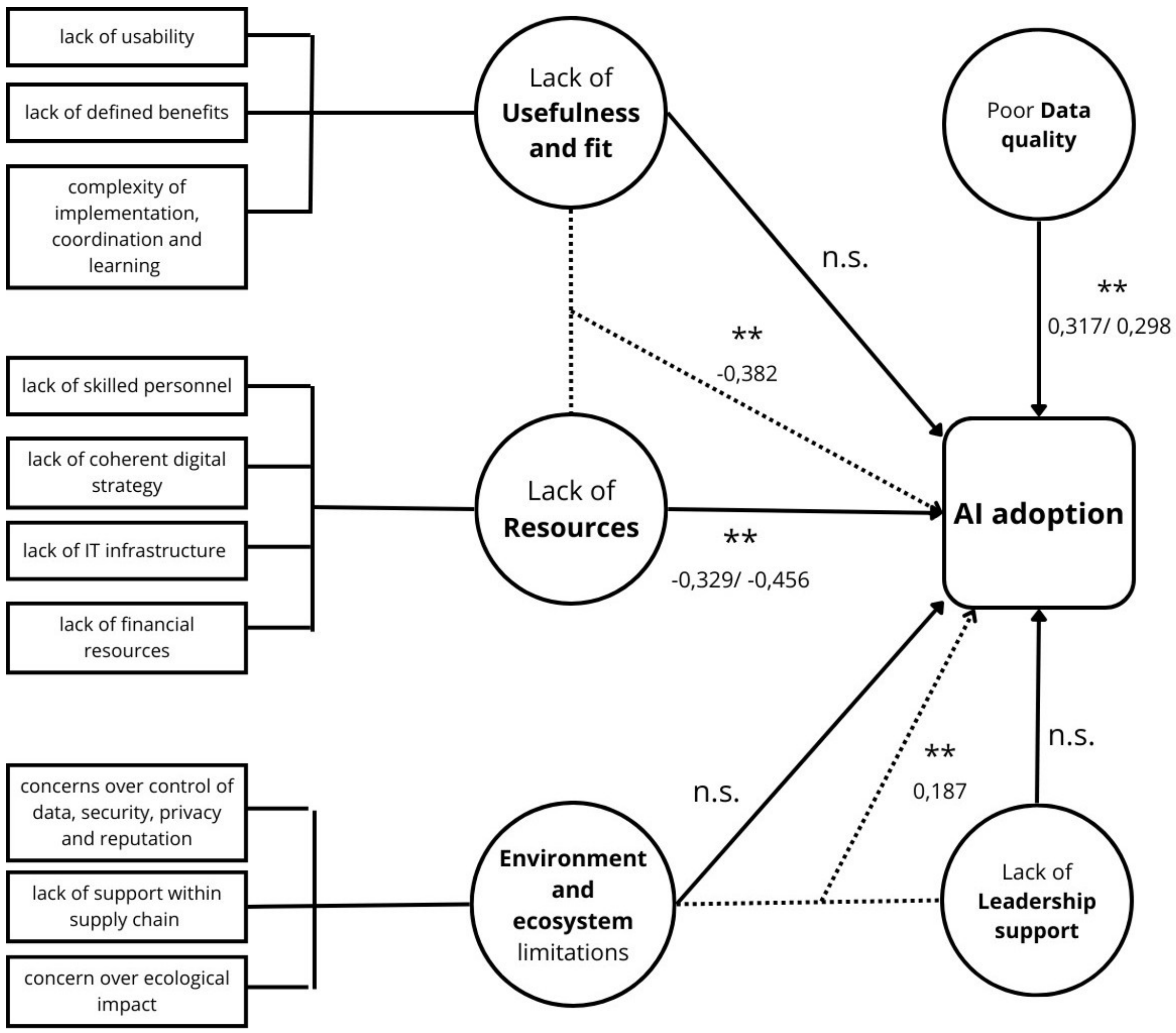
		Model I.	Model II.
	Dependent variable	AI adoption	
	Independent variables	β	
Barriers to AI adoption	Lack of Resources	-0.329**	-0.456**
	Environment and ecosystem limitation	n.s.	n.s.
	Lack of Usefulness/fit	n.s.	n.s.
	Data quality	0.317**	0.298**
	Leadership support		n.s.
Interaction of barriers	Resources*Data quality		n.s.
	Environment*Data quality		n.s.
	Usefulness/fit*Data quality		n.s.
	Resources*Environment		n.s.
	Resources*Usefulness/fit		-0.382**
	Environment*Usefulness/fit		n.s.
	Resources*Leadership		n.s.
	Fit*Strategy		n.s.
	Environment*Leadership		0.187**
	Data quality*Leadership		n.s.
	Control variables		
	Country (Cat)		
	Spain	**	**
	Croatia	-1.205**	-1.256**

	Slovakia	n.s.	n.s.
	Slovenia	n.s.	n.s.
	Sector (Cat)		
	Chem,rubber, plastic	**	**
	Metal, machine, vehicle	-1.124**	-1.158**
	Electronic, PC	n.s.	n.s.
	Other	n.s.	n.s.
	Size(employees)	n.s.	n.s.
	Export	n.s.	n.s.
	Import	n.s.	n.s.
	Number of cases	342	342
	R^2 Cox & Snell	0.075	0.106
	R^2 Nagelkerne	0.115	0.161

Notes: *** p<0.001, **p<0.050, *p<0.100 , Cat – categorical variable

Source: Authors own work

The negative coefficient for lack of Resources suggests that insufficient resources hinder AI adoption. Conversely, the positive coefficients for Data quality could indicate that AI adopters are more aware of the importance of data management than non-adopters. A summary of the research models with the results of the regression analysis is drawn in Figure 3.



n.s.= non-significant. *** p<0.001, **p<0.050, *p<0.100

Source: Authors own work

Figure 3. Research model results

5. Discussion of the findings

5.1 Barriers classification

The implementation of AI is crucial for competitiveness in Industry 4.0, yet organisations must navigate a complex set of barriers hindering adoption. The results of the exploratory factor analysis aim to shed light on the interconnections between barriers, which can be classified into following overarching categories: lack of Resources, Environment/ecosystem limitations and lack of Usefulness/fit. Furthermore, we emphasise that these barriers are intimately linked with data, connecting these categories of barriers, and playing a pivotal role in shaping the landscape of AI adoption.

I. Lack of resources as barriers to AI adoption

Resources constitute a primary set of barriers hindering AI adoption in organisations. These barriers include financial constraints, a shortage of skilled personnel and infrastructure limitations. Financial constraints may be particularly pronounced for smaller companies, where investment in AI technologies can represent a substantial portion of their budgets. A shortage of skilled personnel is another common challenge, since the field of AI demands specialised expertise that may not be readily available in the job market. Infrastructure limitations encompass the need for robust hardware, software and network capabilities to support AI systems.

Data acts simultaneously as a resource and a barrier: AI systems rely on it for training and decision-making, but its collection and management demand substantial investment and expertise. Therefore, the availability and quality of data can significantly impact an organisation's ability to successfully adopt AI.

II. Ecosystem and environmental barriers to AI adoption

The second category of barriers relates to the environment in which organisations operate. Environmental barriers include data privacy concerns, insufficient ecosystem support, and ecological impacts, reflecting the complex interplay between organisations and their external environments (Franco et al., 2024).

The role of data in environmental barriers is manifested via data privacy concerns. As organisations handle increasing amounts of sensitive data, maintaining data privacy and security becomes paramount. Adherence to data protection laws, such as GDPR, and establishing robust data security measures are essential for AI adoption while avoiding legal issues and maintaining consumer trust.

III. Barriers related to the lack of usefulness and fit

The third category of barriers pertains to the perceived usefulness of AI technologies. Resistance to change, perceived irrelevance, and unclear business use cases can deter AI adoption. For an innovation to be adopted and used, it must be made known to the relevant individuals within the organization (Jeyaraj & Sabherwal, 2008). Resistance to change often emerges from workforce apprehension about AI technologies replacing human roles or disrupting established processes.

The influence of data in this context is twofold. Data quality and relevance are fundamental in demonstrating the usefulness of AI solutions. Accurate and relevant data are essential for generating valuable insights and predictions. Moreover, data-driven use cases, demonstrating tangible benefits of AI, can help alleviate concerns and encourage adoption.

5.2 Effect of barriers on AI adoption - The concept of relative and absolute barriers

The results allow for a distinction between *absolute* and *relative* barriers to AI adoption, based on their impact. When a significant negative relationship exists, the barrier impedes AI adoption. Our findings identify a lack of Resources and perceived lack of Usefulness/Fit as absolute barriers. Specifically, a lack of Resources acts as an absolute direct barrier. Perceived lack of Usefulness/Fit, however, functions as an absolute barrier only in conjunction with a lack of Resources (i.e., through a moderating effect).

The significant negative effect of resource-related barriers underscores that successful AI implementation depends on a solid foundation of financial, human, and infrastructural capacity. Resource constraints pose serious hurdles that can derail initiatives at early stages, confirming their role as absolute barriers to adoption.

The research revealed an interesting interplay between perceived lack of Usefulness/fit of AI within existing manufacturing processes and the availability of resources in influencing AI adoption. The perceived lack of usefulness or fit becomes a barrier only when combined with scarce resources, suggesting that resource limitations amplify perceptions of AI's limited applicability. This suggests that while the perception of AI's usefulness and fit is important, its absence alone is insufficient to impede adoption when resource constraints are not perceived. The presence of resource limitations appears to transform the lack of perceived usefulness/fit of AI from a neutral factor into a significant barrier to adoption.

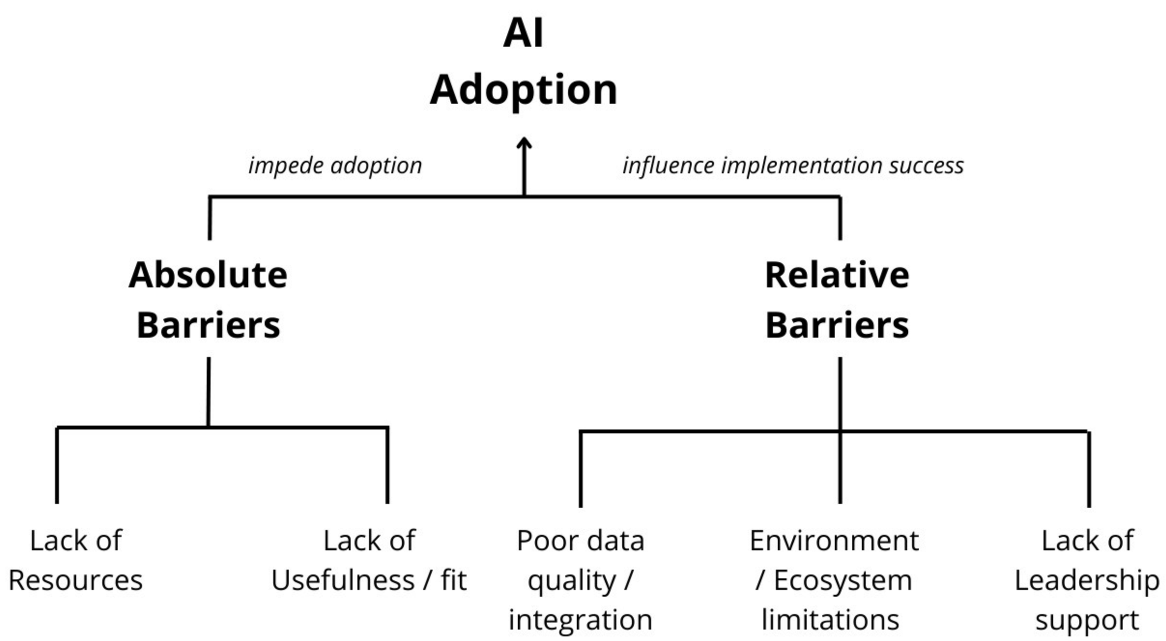
On the other hand, Data Quality/Implementation alone, and Environment limitations and lack of Leadership support in moderation show significant and positive affect on AI adoption, making them relative barriers to AI adoption, being significant for AI adopters rather than non-adopters.

Poor data quality reduces the accuracy and usefulness of AI models, as noisy or incomplete datasets limit their predictive value. The lack of reliability in data—stemming from inconsistent collection procedures or measurement errors—undermines trust in AI outputs and discourages decision-makers from relying on them. Additionally, poor data integration across legacy systems and new digital platforms results in fragmented information flows, preventing firms from developing the comprehensive datasets required for advanced analytics.

The positive effect of data quality and implementation challenges on AI adoption may seem counterintuitive, but it reflects firms' awareness of the hurdles involved. Such awareness—gained from prior data-driven initiatives or industry lessons—encourages a more cautious and strategic approach. Rather than deterring adoption, it prompts investment in data preparation, infrastructure, and talent, making firms better positioned for successful AI implementation.

The positive moderation between environmental limitations and leadership support highlights the stage-dependent nature of AI adoption. Firms already engaged in AI recognise that strong leadership is essential for addressing regulatory and infrastructural constraints. Effective leaders champion adoption while mitigating external barriers through regulatory engagement, clearer data governance, and industry collaboration (Ghobakhloo et al., 2024; Madanaguli et al., 2024). By ensuring compliance, transparency, and cybersecurity, they build trust across the supply chain and create conditions for responsible, scalable AI implementation.

Figure 4. illustrates the categorization of AI adoption barriers, distinguishing between absolute and relative barriers.



Source: Authors own work

Figure 4. Absolute and relative barriers and their effect on AI adoption

While the analysis controlled for national differences, it is important to note that the four countries in our sample represent varying levels of digital maturity. Spain and Slovenia show comparatively higher readiness, while Slovakia and Croatia lag behind the EU average in areas such as digital integration, human capital or connectivity (*DESI)*, 2022). Nevertheless, the empirical results demonstrate that the absolute–relative distinction holds across contexts, underscoring its robustness as a general framework.

The results of this study are different from and extend those of studies that found no significant effect between barriers and adoption (Stentoft et al., 2021). One of the reasons could be that this study examined not only the direct effect of the barriers but also the interaction effect on AI adoption, which is neglected in other studies. On the other hand, the fact that not all perceived barriers prevent AI adoption supports other studies that find that only selected barriers impact the adoption of digital technologies.

Unlike existing frameworks such as TOE, RBV, or TAM, this study introduces the novel distinction between absolute and relative barriers, offering a process-oriented perspective on how obstacles vary across stages of AI adoption. By classifying barriers into absolute and relative, this study extends recent work distinguishing firms at different stages of digital transformation—those intending to adopt and those already adopting (Susanty et al., 2025). This perspective clarifies how barrier perceptions shift along the adoption journey, aligning with readiness and maturity frameworks (Parasuraman, 2000; Schumacher et al., 2016).

6. Conclusion and implications

6.1. Conclusions

The findings of this study contribute to a deeper understanding of the barriers to AI adoption in European manufacturing companies by categorizing these barriers into **three overarching constructs**: lack of Resources, Environment/Ecosystem limitations, and lack of Usefulness/Fit. The results highlight the complexity of AI adoption, illustrating that barriers are interrelated rather than isolated factors, with data playing a central role in shaping these dynamics. This aligns with the findings of Stohr et al. (2024), who demonstrated that it is not enough to single out specific guidelines and success factors for AI implementation; rather, it is necessary to understand the interdependent nature of these mechanisms.

Furthermore, the study introduces the concept of **absolute** versus **relative barriers**, distinguishing between those related to non-adopter that inherently prevent AI adoption (absolute barriers) and those that primarily affect companies that are already engaged in AI adoption – AI adopters (relative barriers). This distinction adds a new dimension to the understanding of AI adoption barriers, highlighting the varying degrees of impact depending on an organization's stage in the AI adoption process. While these prior classifications segment barriers according to their nature (e.g., technological, organisational, environmental) or scope (e.g., internal vs. external, foundational vs. application-specific), our approach differentiates them by their functional role within the adoption journey. In doing so, it extends established frameworks such as TOE, offering a dynamic, process-oriented view of how barriers interact and shift in influence over time.

The study identifies a lack of Resources as a primary absolute barrier, directly impeding AI adoption due to financial constraints, insufficient IT infrastructure, and a shortage of skilled personnel. Additionally, the interaction between resource availability and perceived usefulness indicates that AI adoption is significantly hindered when both these factors are perceived as lacking.

Environmental limitations, such as data privacy concerns, supply chain network support, regulatory constraints, and ecological impacts, were found to influence AI implementation in conjunction with leadership support. The study emphasizes the moderating role of leadership in mitigating environmental constraints, further reinforcing the notion that AI adoption requires strategic guidance and proactive management. The findings also suggest that some barriers, particularly data-related challenges, do not necessarily hinder AI adoption but instead serve as relative barriers. Organizations that have already embarked on AI adoption tend to be more aware of data-related challenges and take proactive measures to address them. The pivotal role of data within the realm of barriers to AI adoption highlights a critical factor that differs from the barriers encountered in the adoption of other technologies, seemingly confirming the findings of Pumplun et al. (2019).

6.2. Implications

Theoretical Implications

The classification of barriers into distinct constructs—lack of Resources, Environment/Ecosystem limitations, and lack of Usefulness/Fit—enhances the theoretical understanding of AI adoption barriers. This classification aligns with and extends existing theoretical frameworks such as the Resource-Based View (RBV), and the Technology Acceptance Model (TAM), offering a comprehensive approach to understanding AI adoption challenges. The findings reinforce RBV by highlighting the importance of internal resources—financial, human, and infrastructural—for AI adoption success. The study also expands upon TAM by demonstrating that perceived usefulness and fit alone are insufficient to drive AI adoption unless adequate resources are available.

The integration of multiple theoretical perspectives rather than relying on a singular framework provides a more holistic understanding of AI adoption barriers, advocating for a multi-theoretical approach in future research. By adopting a multi-theoretical approach, this research acknowledges the interconnected nature of these influences and emphasizes the necessity of a comprehensive framework that considers both internal capabilities and external institutional forces.

Practical Implications

For policymakers, the study underscores the need for targeted interventions to address absolute barriers to AI adoption. Public and private sector collaboration should focus on alleviating financial constraints through funding programs, tax incentives, and subsidies for AI-related training and infrastructure development. Additionally, policies that facilitate access to skilled AI professionals, such as workforce training initiatives and AI education programs, can help mitigate skill shortages. Regulatory clarity is equally important for reducing uncertainty and encouraging adoption.

For business leaders, the findings highlight the necessity of strategic planning in AI adoption. Companies must assess their resource availability and develop a structured roadmap for AI implementation, ensuring that financial, infrastructural, and human capital needs are met. Additionally, the study emphasizes the importance of strong leadership in navigating environmental constraints, reinforcing the role of top management in championing AI initiatives.

The distinction between absolute and relative barriers identified in this study has direct economic and societal relevance. Economically, addressing absolute barriers—such as lack of skilled personnel or inadequate infrastructure—can unlock significant productivity gains and strengthen competitiveness. Societally, overcoming absolute barriers can facilitate smoother workforce transitions through reskilling, support sustainable manufacturing practices via AI-driven efficiency gains, and improve public acceptance of AI by demonstrating tangible benefits in quality, safety, and environmental performance. Relative barriers, meanwhile, highlight the importance of organizational learning and adaptive strategies once firms are on the adoption path. By linking barrier typology directly to actionable interventions, this research offers a framework for coordinated efforts among managers, policymakers, and community stakeholders.

6.3. Limitations and future research

This study acknowledges certain limitations. It focused on European manufacturing companies, so the results may not be directly transferable to other industries and regions. Additionally, AI is a rapidly evolving field, and the significance of various barriers may change over time. While the statistical models demonstrated good explanatory power, the cross-sectional survey design limits causal inference. Longitudinal studies can provide more insights into these dynamics.

While this study provides valuable insights, several avenues for future research remain open. First, further investigation into the role of data as both a resource and a barrier could yield deeper insights into data governance and management strategies for AI adoption. Second, barriers to AI adoption are dynamic rather than static. Longitudinal studies examining how organizations overcome barriers over time could reveal how some obstacles, such as resources, diminish over time while others, like data integration or ecosystem support, become more salient as adoption progresses. Third, expanding the research scope beyond European manufacturing companies to other industries and regions would enhance the generalizability of the findings.

In addition to the country, sector, firm size, export, and import status, other relevant firm-level characteristics were not included. Variables such as digital maturity, technological infrastructure, and employees' digital skills may also significantly influence AI adoption but were not captured in the present dataset. Future research should incorporate these dimensions to provide a more comprehensive understanding of organisational readiness and to refine the explanatory power of adoption models.

Finally, the study advocates for further exploration of the moderating effects between barriers and AI adoption. Understanding how leadership, environmental constraints, and organizational culture interact with resource availability and perceived usefulness could provide additional guidance for businesses and policymakers in fostering AI adoption.

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