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Exploring the Drivers of AI Adoption: A Meta-Analysis of Technological, Organizational and Environmental (TOE) Factors

Jerónimo Paiva

jeronimob12@gmail.com

ISCAP-IPP

Systematic Review

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PREPRINT

Exploring the Drivers of AI Adoption: A Meta-Analysis of Technological, Organizational and Environmental (TOE) Factors

Agostinho Sousa Pinto[1[0000-0003-1454-030X]], António Abreu[1[0000-0001-5958-9188]], Manuel Pérez Cota[2[0000-0003-0471-6981]] and Jerónimo Paiva [1[0000-0002-8300-962X]]

[1] Instituto Superior de Contabilidade e Administração do Porto IPP/ISCAP/CEOS.PP, Porto, Portugal, apinto@iscap.ipp.pt,aabreu@iscap.ipp.pt, jeronimob12@gmail.com

[2] Universidade de Vigo, Vigo, Spain, mpcota@uvigo.gal

Abstract. The Artificial Intelligence (AI) revolution is transforming the corporate sector and rapidly accelerating the process of digital transformation. Based on a selection of 12 studies for meta-analysis with 3398 respondents from various industries and countries, this study investigates the factors influencing the adoption of AI using the Technology-Organization-Environment (TOE) framework. The results show that seven out of eight TOE factors have a statistically significant effect on AI adoption. Technological factors, including Compatibility (CPT) and Relative Advantage (ADV) have a positive impact, while Complexity (CX) was found to be statistically insignificant. Organizational factors, particularly Organizational Readiness (RE) and Management Support (MS) have a positive moderate effect. Environmental factors reveal that Government Support (GOV), Competitive Pressure (COP) and Vendor Partnership (VP) have a strong and positive impact. The study emphasizes the importance of Vendor Partnership and Organizational Readiness as critical factors in fostering AI adoption. Finally, this research will be advantageous for researchers and practitioners looking to explore the determinants driving significant AI adoption.

Keywords: Artificial Intelligence (AI), Generative AI (GenAI), Large Language Model (LLM), TOE Framework, Meta-Analysis, PRISMA

1 Introduction

According to MarketsandMarkets, the global AI market is expected to surpass $190 billion by 2025 with a staggering compound annual growth rate (CAGR) of 36.62% between 2020 and 2025 (MarketsandMarkets 2024). The development and release of Large Language Models (LLMs) have brought AI into the everyday lives of billions of people. Indeed, ChatGPT, the popular chatbot from OpenAI, is estimated to have reached 100 million monthly active users in two months making it the fastest-growing consumer application in history (Hu 2023).

AI adoption presents exciting opportunities (Paiva and Pinto 2024). AI can automate routine tasks, facilitate data-driven decision-making, and create more agile and responsive organizations (Figueiredo and Pinto 2021; Gomes and Seruca 2023; Gomes and

Gonçalves 2024). According to McKinsey, AI adoption is already contributing to double-digit productivity gains for early adopters, with firms seeing up to a 30% improvement in operational efficiency by integrating AI technologies (McKinsey 2024). The widespread adoption of AI has also raised important social and ethical questions related to data privacy, algorithmic bias and the risk of job losses.

Furthermore, the paper uses the TOE framework to analyze the impact of technological, organizational, and environmental factors on AI adoption by corporations. A meta-analysis of 12 empirical studies validates the theoretical model. Following the PRISMA protocol, the methodology assesses literature quality, heterogeneity, effect sizes, and publication bias. The results highlight key findings, with the conclusion addressing limitations and future research directions.

Theory and Hypothesis

Conceptual Background

AI technologies have been around for decades. However, in the 21st century, the latest developments in computer and data processing capabilities have allowed AI technologies to flourish. However, the definition of Artificial Intelligence is a controversial topic, and several definitions of this term have been presented in Table 1.

Table 1 - Key Definitions and Characteristics of AI

Source	Definitions
(McCarthy 1959)	Referred to as "the science and engineering of making intelligent machines.
(Russell and Norvig 2021)	Artificial intelligence (AI) enables the machine to exhibit human intelligence, including the ability to perceive, reason, learn, and interact, etc.
(DeCanio 2016)	AI is the broad suite of technologies that can match or surpass human capabilities, particularly those involving cognition such as learning and problem solving

TOE Framework

Developed by (Tornatzky et al. 1990), the framework provides a comprehensive lens through which organizations can evaluate the adoption of technological innovations within organizations. The TOE framework categorizes the variety of factors influencing technological adoption into technological, organizational and environmental constructs. This framework is quite malleable and flexible and is suited for structured exploration without being tethered to predetermined constructs (Maragno et al. 2023)

Table 2 shows the proposed model that will be empirically validated.

Table 2 – Exploring the Key Factors Impacting AI Adoption: An Overview of Hypothesis and References

	Factor	Description	Hypothesis	References
Technological	Compatibility	Combability relates to the extent to which the emerging technologies line up with the existing values, needs and experiences of the organization.	H1: Compatibility positively affects AI Adoption.	(Dong and Cao 2022; Badghish and Soomro 2024)
	Complexity	Complexity reflects the level of difficulty is associated with the adoption of new technologies.	H2: Complexity positively affects AI Adoption.	(Allbabidi 2021; AL-khatib 2023; Pan et al. 2023; Zhou 2023; Badghish and Soomro 2024)
	Relative Advantage	Relative Advantage relates to the extent to which a new technology is seen as better than the legacy ones.	H3: Relative Advantage positively affects AI Adoption.	(Dong and Cao 2022; Mukherjee and Chittipaka 2022; AL-khatib 2023; Pan et al. 2023; Badghish and Soomro 2024)
Organizational	Management Support	Management Support is crucial for organizational change, guiding resource allocation for the adoption of new technologies	H4: Management Support positively affects AI Adoption.	(Chen 2019; Allbabidi 2021; Dong and Cao 2022; AL-khatib 2023; Islam et al. 2023; Zhou 2023; Badghish and Soomro 2024; Lim and Seng 2024)
	Organizational Readiness	The availability of financial, human and technological resources that support the adoption of new technologies.	H5: Readiness positively affects AI Adoption.	(Dong and Cao 2022; AL-khatib 2023; Lim and Seng 2024)
	Government Support	Governmental Support refers to the role of the government in stimulating IT innovation by removing barriers.	H6: Government Support positively affects AI Adoption.	(Dong and Cao 2022; Badghish and Soomro 2024; Lim and Seng 2024)
Environmental	Competitive Pressure	Competitive pressures relate to how much an organization responds to pressure from rivals by adopting new technologies more quickly.	H7: Competitive Pressures positively affect AI Adoption.	(Chen 2019; Dong and Cao 2022; Mukherjee and Chittipaka 2022; AL-khatib 2023; Islam et al. 2023)
	Vendor Partnership	Vendor Partnership relates to how the network of business relationship pressures and supplier pressures organizations to adopt innovative technologies like AI.	H8: Vendor Pressure positively affects AI Adoption.	(Dong and Cao 2022; Mukherjee and Chittipaka 2022)

Methodology

Meta-Analysis Method

Meta-analysis is a statistical methodology for combining the results of multiple independent studies to address a common research question or hypothesis. It provides a quantitative synthesis of findings, allowing researchers to identify patterns, assess the consistency of results, and derive more precise and reliable conclusions. By pooling data from various studies, meta-analysis reduces sampling and measurement errors, enhances generalizability, and offers insights into variability through subgroup and moderator analyses (Borenstein et al. 2009; Cooper et al. 2009).

The process of meta-analysis typically involves defining the research scope, systematically identifying and screening studies, coding data, evaluating study quality, and applying statistical techniques to calculate overall effect sizes and test heterogeneity (Glass 1976).

The PRISMA protocol (Preferred Reporting Items for Systematic Reviews and Meta-analyses) was followed to carry out a systematic review and meta-analysis (Moher et al. 2014). This protocol was chosen to make the process of conducting a literature review more transparent and complete. In terms of software, Rayyan QCRI was used to speed up the process of conducting a literature review and Comprehensive Meta-Analysis (CMA) version 3.0 software was used to calculate the effect size.

Literature Search and Inclusion Criteria

First, only conference and journal articles in English were included. Duplicates, theses, dissertations, retracted articles, and non-peer reviewed were excluded. The databases chosen for this scoping review—IEEE Xplore, Web of Science, SCOPUS, Open Alex, and JSTOR—were selected for their comprehensive coverage, credibility, and relevance to the topic. Only articles published between 2014 and 2024 were included.

In the PRISMA flowchart, the initial search identified 2580 articles. 60 articles were removed for being duplicates (Figure 1). 2422 articles were excluded after screening of titles and abstracts. As a result, 99 articles were selected for full text analysis. After screening the full text of the 99 articles, only 12 articles were included for review.

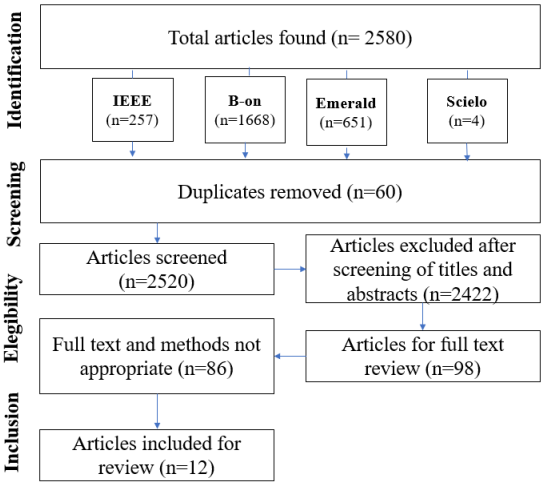


Figure 1 PRISMA Flowchart[1]

Data Coding and Literature Quality Assessment

Data coding involves systematically extracting relevant information from the selected studies. Using the procedure recommended by (Lipsey and Wilson 2001), the data was coded according to the authors, year of publication, sample size, context of the application of AI technologies, the correlation coefficient and main results. Table 3 shows the criteria that was used to assess the quality of the studies included in the meta-analysis.

Table 3 - Criteria used to gauge the quality of the literature

Criterion	Condition	Score
	Random sampling	2 points
Subject Selection	Non-random sampling	1 point
	Unreported	0 points
	Validity score ≥ 0.8	2 points
Data Validity	Validity score between 0.7–0.8	1 point
	Validity score < 0.7 or unreported	0 points
	Fully reported sample and outcome data	2 points
Completeness of Reporting	Partially reported	1 point
	Not reported	0 points

[1] Search Terms: ("TOE Framework" OR "Technology–Organization–Environment Framework" OR "TOE") AND ("AI" OR "Artificial Intelligence" OR "NLP" OR "Natural Language Processing" OR "ML" OR "Machine Learning" OR "DL" OR "Deep Learning")

Criterion	Condition	Score
	Reliability coefficient ≥ 0.8	2 points
Measurement Reliability	Reliability coefficient between 0.7–0.8	1 point
	Reliability coefficient < 0.7 or unreported	0 points

Main Results and Discussion

A grand total of 12 papers were selected for the sample (Table 7). The average score of literature quality was 76,04% and most studies had a quality assessment score of 80% or higher. This indicates that the quality of the literature is quite good. The total sample size was 3398 with respondents from a wide variety of industries and countries. However, many studies focused on the adoption of AI in the continent of Asia, particularly in India, China, Vietnam, Malaysia and the Middle East.

Heterogeneity

Heterogeneity reflects variability in effect sizes across studies and is evaluated using several variables: Cochran's Q-value (Q) and Higgins and Thompson´s statistic (I^2).

The Q value is widely used for heterogeneity tests and tests the null hypothesis that all the studies share the same effect size. Using the significance level p <0.05 indicates that the heterogeneity is statistically significant (Erez et al. 1996). The I^2 quantifies the proportion of variation due to heterogeneity rather than sampling error (Higgins and Thompson 2002; Higgins et al. 2003). I^2 values of 25%, 50% and 75% indicate low, medium and high heterogeneity, respectively.

Table 4 shows the results of the heterogeneity tests. All factors display an I^2 above 90% and high Q_W showcasing very high levels of heterogeneity, even with a limited number of studies. τ values suggest moderate to high variability in true effect sizes, with Government Support (τ=0.267) and Complexity (τ=0.422) having the largest spread. When heterogeneity is present, the main effect test should use a random effects model instead of the fixed effects model (Borenstein et al. 2010). If the studies represent a random sample from a universe of potential studies, the random effects model also provides more generalizable conclusions.

Table 4 - Criteria used to gauge the quality of the literature

Factors	m	Heterogeneity				Tau	
		Q_W	df	p	I^2 (%)	Tau²	Tau
Compatibility	3	75,037	2	0,00***	97,33%	0,358	0,128
Complexity	8	888,859	7	0,00***	99,21%	0,650	0,422
Relative Advantage	7	158,424	6	0,00***	96,21%	0,311	0,097

Management Support	9	328,261	8	0,00***	97,56%	0,374	0,140
Organizational Readiness	4	114,471	3	0,00***	97,38%	0,423	0,179
Government Support	5	237,283	4	0,00***	98,31%	0,517	0,267
Competitive Pressure	6	163,657	5	0,00***	96,94%	0,316	0,100
Vendor Partnership	3	54,258	2	0,00***	96,31%	0,283	0,080

Publication Bias Test

Publication bias occurs when studies with significant and positive results is easier to publish than those with negative or insignificant results (Kepes et al. 2023). Also known as the "file drawer problem", it creates a distorted view of the evidence and a body of literature that does not adequately represent the overall state of research in a certain field. To test for publication bias, five methods were used:

1. Fail-safe numbers (N_{fs}) (Rosenberg 2005): indicates that N_{fs} studies with insignificant results must be included in the meta-analysis to make the overall effect insignificant. If N_{fs} > 5k +10 (k – number of studies), there is no publication bias.

2.Begg and Mazumdar´s rank correlation test (Begg and Mazumdar 1994): A non-significant test results indicates the nonexistence of publication bias;

3.Egger's regression test (Egger et al. 1997; Sterne and Egger 2005): If the linear regression result is not statistically significant, there is no publication bias;

4. Duval and Tweedie's Trim and Fill (Duval and Tweedie 2000): A non-parametric method that aims both to identify and correct for funnel plot asymmetry arising from publication bias. The aim is to estimate the number of missing studies that might exist in a meta-analysis and the effect that these studies might have had on their outcomes.

5. Funnel plot (Borenstein et al. 2009): Using a scatterplot to visually detect the presence of publication bias or heterogeneity.

Given that N_{fs} > 5k +10 for all variables, there is no evidence of publication bias (Rosenberg 2005) (Table 5).Both the results from Begg and Mazumdar's Test (Z) and Egger's tests indicate were not statistically significant (p > 0.05), also indicating that there is no publication bias. The only exceptions were Management Support and Government Support. These variables exhibit significant p-values in the Egger´s tests Management Support and Government Support. However, the results from the other four tests do not show any signs of publication bias. As can be seen in Figure 2, the funnel plot illustrated that the scatter points of all factors are relatively well distributed and symmetrically concentrated. In summary, the results show no significant publication bias, which reinforces the findings of this study.

Table 5 – Publication Bias Test[2]

Factors	m	Nfs and Criterion		Begg and Mazumdar's Test (Z)		Egger's Regression Test Intercept		CI after Trimming and Filling	
		N_{fs}	Criterion	Z	*p*	Intercept	*p*	LL	*UL*
Compatibility	3	216	25	0,000	0,500	27,893	0,295	0,174	0,997
Complexity	8	107	50	0,619	0,268	19,862	0,237	-0,271	0,633
Relative Advantage	7	1479	45	0,901	0,184	12,339	0,185	0,274	0,795
Management Support	9	1240	55	2,189	0,014	21,712	0,025**	0,056	0,602
Organizational Readiness	4	553	30	0,340	0,367	18,999	0,106	0,433	1,274
Government Support	5	556	35	1,225	0,110	27,355	0,049**	-0,162	0,861
Competitive Pressure	6	429	40	0,751	0,226	41,359	0,115	0,136	0,651
Vendor Partnership	3	239	25	0,000	0,500	52,800	0,274	0,242	0,895

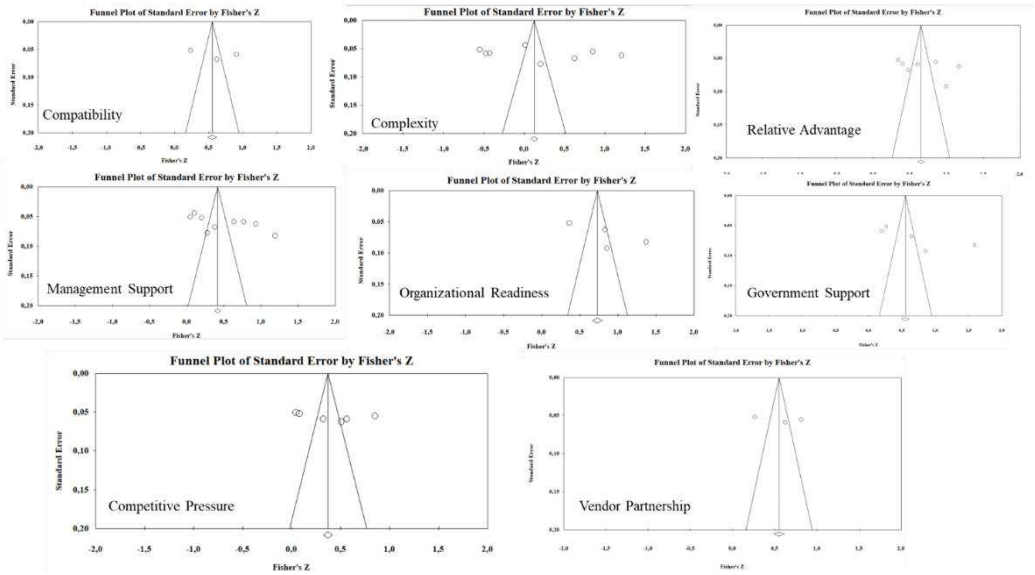


Figure 2 – Funnel Plot

[2] Note: m, the number of effect sizes; Nfs, fail-safe numbers; Z, the standard score; *p* significance level; LL, lower limit; UL, upper limit.

Main Effects

The effect size (ES) quantifies how strong the relationship or differences reported in individual studies to be able to compare across diverse studies. Fisher Z-Transformation of a Pearson correlation coefficient was used to calculate the combined effect size (Fisher 1915). Thus, the Fisher transformation yields a variable whose distribution is approximately normally distributed and with a stable variance. According to (Fisher 1915; Pestana and Gageiro 2014), the thresholds are typically: low correlation ($|Z| < 0.2$), moderate correlation ($0.2 \leq |Z| < 0.5$), and strong correlation ($|Z| \geq 0.5$):

The results show that 7 out of 8 TOE factors analyzed have a statistically significant effect on AI adoption (Table 6). Complexity *(p* = 0,432) was the only variable proven not to be statistically significant with 95% confidence.

Regarding the technological factors, Compatibility (ES = 0,586) and Relative Advantage (ES = 0,689) have a positive effect on AI adoption. Technological compatibility of AI technologies with legacy and existing systems and processes reduces resistance to change and increases the willingness to adopt. Relative Advantage has the strongest effect size of the three technological variables. Indeed, corporations are more inclined to adopt AI if they find it provides clear benefits like greater productivity, cost savings and efficiency. Indeed, AI solutions often outperform existing solutions and reduce the workload, allowing workers to focus on more added value tasks.

As for the organizational factors, Management Support (ES = 0,500) and Organizational Readiness (ES = 0,853) both have a positive effect on AI adoption. Indeed, the involvement and encouragement of corporate leaders is crucial. To adopt AI solutions, management must allocate resources and reduce resistance to change. Organizational Readiness has a strong correlation with AI Adoption, making it the most relevant organizational variable. Indeed, organizations need to have the necessary mixture of infrastructure, skills and financial clout to be prepared for the challenges of AI Adoption.

Regarding environmental factors, Government Support (ES=0,707) and Competitive Pressure (ES=0,394) and Vendor Partnership (ES=0,569) have a positive effect on AI adoption. When organizations face intense competition, they adopt AI technologies to differentiate themselves from the competition. The strong influence of the variable Vendor emphasizes the increasing role of private sector and AI vendors (Amazon, SAP, Oracle, IBM, Palantir, Microsoft). Vendors drive AI adoption by providing tailored solutions, tacking business challenges and setting industry standards. However, Government Support is the most relevant environmental variable, highlighting the role of the state in driving digital transformation. States can draft AI policies and provide subsidies and incentives to reduce the perceived risk and financial burden of implementing AI. As a result, corporations tend to look more to the state than the private sector for leadership in the process of digital transformation.

Table 6 – Results of the Main Effects test

	Effect Size and 95% CI	**Test of Null (2-Tail)**

Factors	m	n	ES	SE	Var	LL	UL	Z	*p*
Compatibility	3	882	0,586	0,210	0,044	0,174	0,997	2,792	0,005**
Complexity	8	2449	0,181	0,231	0,053	-0,271	0,633	0,786	0,432
Relative Advantage	7	1888	0,689	0,120	0,014	0,454	0,924	5,742	0,000***
Management Support	9	2652	0,500	0,126	0,016	0,253	0,748	3,962	0,000***
Organizational Readiness	4	903	0,853	0,215	0,046	0,433	1,274	3,976	0,000***
Government Support	5	1152	0,707	0,234	0,055	0,249	1,164	3,027	0,002**
Competitive Pressure	6	1930	0,394	0,131	0,017	0,136	0,651	3,000	0,003**
Vendor Partnership	3	991	0,569	0,167	0,028	0,242	0,895	3,411	0,001**

Figure 3 summarizes the main results of the meta-analysis.

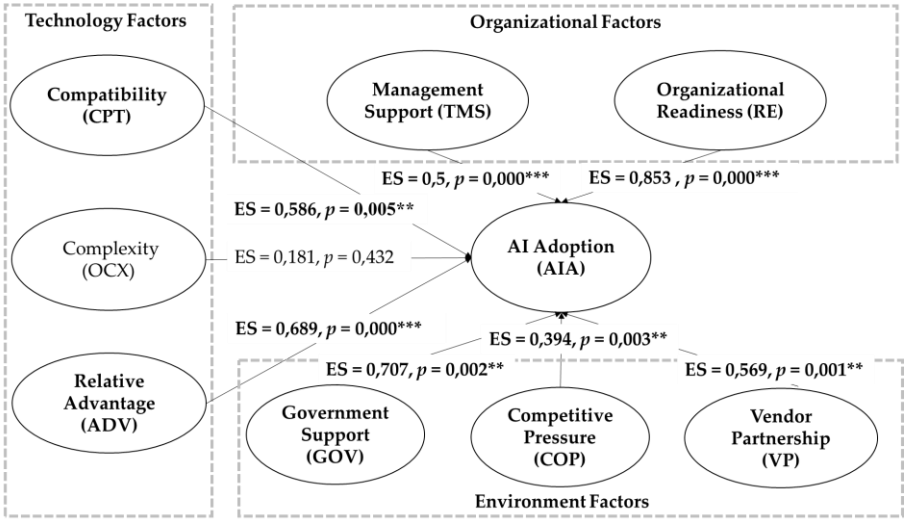


Figure 3 Research Model Assessed

Moderating Effects

(Pan et al. 2023) found that asset specificity mitigates the negative impact of technological competence, while uncertainty increases the role of technological competence but has no effect on relative advantage or complexity. Studies like (Dong and Cao 2022) and (Chen et al. 2021) found moderating variables demographic variables (gender, age, education and job position), firm size, annual sales and enterprise affiliation to be statistically insignificant.

However, this study will not explore the role of moderating variables due to the lack of sufficient studies and only four out of ten studies explored moderating

variables. Indeed, no single moderating variable was examined more than once making it very difficult about their role in AI adoption.

Conclusion

In this study, the authors reviewed 12 published articles with a total sample of 3398 that utilized the TOE framework to investigate the critical factors that lead to the adoption of AI technologies in the corporate sector. The results showed that there is a strong and positive influence of TOE factors (Compatibility, Relative Advantage, Management Support, Organizational Readiness, Government Support, Competitive Pressure and Vendor Partnership) on AI Adoption with 95% confidence. However, Complexity was shown to be statistically insignificant.

Indeed, corporations adopt innovative technologies like AI due to a complex mixture of technological, environmental and organizational factors, which should prompt managers, policymakers and industry leaders seeking to understand why corporations are investing unprecedented resources in implementing AI technologies.

The study has significant managerial implications to enhance the sustainable adoption of emerging technologies like AI. Managers must provide leadership and invest in AI technologies. It is important to take advantage of government subsidies, rebates and discounts to reduce the costs of implementing AI. By following a collaborative multi-stakeholder approach, governments, corporations and R&D organizations can foster greater public confidence in AI adoption.

Limitations and Future Work

There are several important limitations worth noting. Firstly, there is a selection bias because it was not possible to include all relevant literature due to several reasons: language barriers, lack of full text articles and database access. Some studies omitted necessary data for this meta-analysis. Unpublished studies could not be found and were overlooked. Secondly, the meta-analysis included mostly cross-sectional studies which can affect the accuracy of the results. In addition, most studies focused on the adoption of AI in the continent of Asia, particularly in India, China and in the Middle East. This fact should be considered as a potential source of bias. Thirdly, the role of certain moderator variables (industry type, company age, number of employees, etc.…) was not analyzed in depth due to lack of data. Additionally, the factors influencing the adoption of AI by corporations are more complex and diverse. Factors like trialability, employees` knowledge and absorptive capability were not examined. Further research should seek to explore the role of additional moderator variables and factors influencing the adoption of AI technologies. To fill in the gaps in the existing literature, future research should explore the adoption of AI outside of Asia.

Statements and Declarations

Conflict of Interest The authors declare no competing interests.

LLM´s Statement The authors declare that GPT-4 was used during the preparation of this manuscript to improve language clarity and standardize references and formatting according to academic standards. To ensure originality and integrity, ChatGPT was also used to check for plagiarism.

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Appendix

Table 7 - Articles involved in the meta-analysis.

Study	Sample	Respondents	Country	Context	Main Results
(Phuoc 2022)	193	Senior Managers	Vietnam	Various Industries	Statistically significant impact on AI Adoption: Technical compatibility, Relative advantage, technical complexity, Managerial support, Managerial capability, Organizational readiness, Government involvement, Market uncertainty, Vendor partnership.
(AL-khatib 2023)	260	Retail Workers	Jordan	Retail Sector	Statistically significant impact on AI Adoption: Relative advantage, Complexity, Top Management Support, Organizational readiness, Customer Pressures Statistically insignificant: Compatibility and Competitive Pressures.
(Allbabidi 2021)	168	External Auditors	Jordan	Audit Sector	Statistically significant impact on AI Adoption: IT Knowledge, IT Cognitive Style, IT Self-Efficacy, IT Management Support, IT Training, IT Facilitating Resources, Perceived Complexity, Competitive Pressure, Regulation
(Badghish and Soomro 2024)	220	Middle and Top Management.	Saudi Arabia	SME´s Various Industries	Statistically significant impact on AI Adoption: Relative advantage, Compatibility, Sustainable Human Capital, Government Support, Market and Customer Statistically insignificant: Cost, Complexity, Organizational Support,
(Pan et al. 2023)	297	HR and Senior Managers	China	Various Industries	Statistically significant impact on AI Adoption:, complexity; organizational context; technology competence; regulatory; environmental context Statistically insignificant: Relative Advantage; company size
(Lim and Seng 2024)	150	Employees	Malaysia	SME´s Various Industries	Statistically significant impact on AI adoption: Perceived Ease of Use, Management Support, Organizational Readiness, Government Support, External Pressure
(Zhou 2023)	513	Industry Experts	China	Highway Construction	Statistically significant impact on AI adoption: Technical feasibility; Technological advantage; Technological complexity; Technological risk; Technology costs; Organizational structure; Management support; Employee engagement; Policy environment; Market environment; Market demand; Social perception; Cultural differences. Statistically insignificant impact: Organizational culture.
(Dong and Cao 2022)	373	Employees	China	Industrial SME´s	Statistically significant impact on AI adoption: Relative Advantage, Compatibility, Complexity, Observability, Trialability, Top Management Support, Organizational Readiness, Vendor Support Statistically insignificant: Competitive Pressure and Government Support
(Chen 2019)	290	Employees	China	Hospitality	Statistically significant impact on AI adoption: Perceived AI risk; Management support; Innovativeness; Competitive pressure; Regulatory Support Statistically insignificant impact on AI adoption: AI System Quality
(Islam et al. 2023)	389	HR employees	Malaysia	Tourism	Statistically significant impact on AI adoption: Perceived Ease of Use, Perceived Usefulness, Technology Competence, Top Management Support and Competitive Pressure

(Chen et al. 2021)	289	Managers and Engineers	China	Large Telecom Companies	Statistically significant impact on AI adoption: compatibility; relative advantage; complexity; managerial support; government involvement; vendor partnership
(Mukherjee and Chittipaka 2022)	329	Executives and Managers	India	Food Supply Chain Management	Statistically significant impact on AI adoption: Relative advantage; Reliability; Complexity; Cost; Innovation Adoption; Top management support; IT awareness; Skilled employees; Environmental uncertainty; Competitive pressure; Information intensity; Supplier´s pressure
(Tan et al. 2022)	120	Employees	Vietnam	SME´s	Statistically significant impact on AI adoption: Relative advantage, government support, top management support, enterprise readiness