WHY DO ENTERPRISES ADOPT AI? GOVERNMENT AI READINESS AND CULTURAL LEADERSHIP CONTEXTS IN EUROPE

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Abstract

This study examines the extent to which the adoption of artificial intelligence (AI) at the enterprise level in Europe is shaped by government institutional readiness and national cultural dimensions. Integrating institutional theory with Hofstede's cultural dimensions model, the research analyzes how the Government AI Readiness Index, Uncertainty Avoidance (UAI), and Long-Term Orientation (LTO) influence AI adoption in 31 European countries in 2025. Using a multiple linear regression model with interaction terms, the study tests the direct and moderating effects of these factors on the proportion of businesses using AI technologies. The results confirm that government institutional readiness exerts a significant positive effect on AI adoption (β = .450, p = .006), explaining 52.4% of the variation in adoption (R^2 = .524, F = 7.147, p < .001). Uncertainty avoidance moderates this relationship (β = -.290, p = .055), diminishing the positive effect of institutional readiness in societies with high UAI. The direct effects of UAI and LTO are not significant in the full model, suggesting that the influence of culture is predominantly conditional. The study demonstrates that the success of public policies promoting AI depends on the alignment between institutional capacity and the national cultural context. The practical implications highlight the need for culturally adapted national strategies, mechanisms to reduce perceived risk, and managerial practices that address the anxiety associated with technological change in contexts with high uncertainty avoidance.

Keywords: *artificial intelligence adoption, institutional readiness, cultural dimensions, strategic leadership, uncertainty avoidance, digital transformation*

J.E.L. Classification: *O33, M15, Z10, O38, M14*

1. Introduction and context of the study

Digital transformation represents one of the most profound structural changes in contemporary organizations, and artificial intelligence (AI) is a central vector of this process. The integration of AI technologies into business operations influences decision-making processes, operational efficiency, innovation, and competitive advantages. However, the level of AI adoption differs significantly between European countries, even within a relatively integrated economic area. These differences raise a theoretical question relevant to management literature: to what extent is organizational behavior regarding AI adoption shaped by the national institutional and cultural context?

The existing literature emphasizes the importance of internal organizational factors in explaining technology adoption, such as resources, digital skills, or strategic leadership. However, organizations operate within an institutional and cultural framework that influences their decisions and perceptions of risk and innovation. From an institutional theory perspective, the government's ability to support AI development through public policies, digital infrastructure, and coherent regulations can reduce uncertainty and stimulate technological investment. At the same time, cultural dimensions theory suggests that societal values shape risk tolerance and the time horizon of strategic decisions.

Based on these considerations, the main objective of the research is to analyze the impact of government readiness for artificial intelligence on AI adoption among European enterprises and to investigate the moderating role of national culture in this relationship. The study aims to integrate the institutional and cultural perspectives to explain inter-state variations in the level of AI adoption in 2025.

Based on the theoretical framework, the following hypotheses are formulated:

H1: A higher level of government readiness for artificial intelligence is positively associated with the level of AI adoption in enterprises.

This hypothesis derives from institutional theory, according to which a favorable political and administrative framework reduces uncertainty and facilitates organizational innovation.

H2: A high level of uncertainty avoidance is negatively associated with AI adoption in enterprises.

AI adoption involves a significant degree of ambiguity and risk, and societies characterized by uncertainty aversion may exhibit greater resistance to disruptive technologies.

H3: Long-term orientation is positively associated with AI adoption in enterprises.

A future-oriented cultural perspective favors strategic investments in emerging technologies, even in the face of delayed benefits.

H4: Uncertainty avoidance moderates the relationship between government readiness for AI and AI adoption, in the sense that the positive effect of institutional readiness is weaker in societies characterized by high levels of uncertainty avoidance.

This hypothesis reflects the contingent nature of the relationship between institutions and organizational behavior, suggesting that the effectiveness of public policies depends on their compatibility with the national cultural profile.

By testing these hypotheses, the study aims to contribute to management literature by highlighting that AI adoption at the organizational level is the result of an interaction between institutional infrastructure and the value structure of society, and not just internal or purely economic factors.

2. Literature review

The adoption of artificial intelligence at the enterprise level represents a complex phenomenon that transcends simple technological decisions, being deeply rooted in the interaction between organizational capabilities, institutional context, and prevailing cultural values. The specialized literature has approached this issue through multiple theoretical lenses, each offering complementary perspectives on the mechanisms that facilitate or inhibit the integration of emerging technologies in organizations. The Technology Acceptance Model developed by Davis [1] laid the foundation for understanding how perceived usefulness and ease of use influence behavioral intentions to adopt, and subsequent research has extended this framework to integrate broader contextual factors. Pan [2] demonstrates through cross-country analysis that cultural characteristics significantly moderate consumers' behavioral intentions toward mobile payments, finding that uncertainty avoidance negatively moderates the relationship between perceived ease of use and behavioral intention, suggesting that national cultural values fundamentally alter how the perceived benefits of a technology translate into effective adoption.

Neumann et al. [3] explicitly use the Technology-Organization-Environment framework in comparative analysis of AI adoption in public organizations, demonstrating that determinants vary according to implementation stage and specific organizational context. This multi-level approach highlights that institutional and cultural variables are not simple controls, but interact dynamically with organizational capabilities in adoption processes. Schildt [4] applies institutional logic analysis to digitalization research, demonstrating how institutional frameworks shape the adoption and diffusion of digital technologies in organizational settings, offering transferable constructs to AI adoption research.

Fdez. de Arroyabe et al. [5] apply institutional analysis to demonstrate how regulatory frameworks and institutional pressures shape AI adoption dynamics in SMEs across the EU context, offering empirical evidence of the mechanisms through which institutional factors influence technology adoption decisions. Contextual institutional factors and governmental action operate simultaneously as facilitators and constraints in the AI adoption process. Policy coordination at the European level and national AI strategies materially affect adoption at the enterprise level, with the EU Coordinated Plan and member state strategies listing priorities in the areas of skills, research, regulation, and infrastructure [6]. The Government AI Readiness Index [7] provides a comprehensive framework for assessing countries' institutional preparedness for AI adoption, measuring factors such as governance structures, digital infrastructure, and policy frameworks that enable or constrain enterprise-level technology integration.

Digitalization and digital infrastructure represent essential proximal enablers of AI adoption. Aivaz and Tofan [8] demonstrate the synergy between digitalization and the level of business research and development allocations at the European level, emphasizing that investments in digital infrastructure and research are complementary and essential for advanced technology adoption. Ionescu et al. [9] demonstrate through cross-country analysis that innovation framework conditions and institutional factors are critical predictors of corporate digital technology integration in European countries, emphasizing the role of innovation framework conditions as facilitators of sustainable digital transformation. Eurostat data on AI adoption in European enterprises [10] provides empirical evidence of significant cross-country variations in enterprise-level AI utilization.

Cultural values profoundly shape propensity toward innovation and moderate how institutions and technologies influence adoption. Hofstede's cultural dimensions model offers a robust framework for understanding these variations, with two dimensions being particularly relevant for AI adoption: long-term orientation and uncertainty avoidance [11]. Long-term orientation reflects a society's strategic orientation toward the future, including perseverance and investments in future benefits, and multiple cross-country analyses report positive associations between LTO and national innovation outputs and diffusion of new technologies [12]. Cornell University, INSEAD, and WIPO [13] confirm through the Global Innovation Index that cultural orientation toward the future facilitates sustained investments in research and development and adoption of emerging technologies, this dimension being particularly relevant for AI, a technology that requires significant initial investments and whose full benefits manifest over the medium and long term.

Uncertainty avoidance measures the degree to which members of a society manifest aversion to uncertainty and ambiguity, with evidence linking higher UAI to lower innovation outputs and implying a stronger need for institutions that mitigate risk to enable technology adoption [14]. Sartono et al. [15] empirically demonstrate that uncertainty avoidance significantly moderates the relationship between digital trust and intention to adopt Industry 4.0 technologies, confirming the relevance of this cultural dimension for AI adoption. Rubino et al. [16] demonstrate through cross-country analyses that Hofstede dimensions - particularly masculinity and uncertainty avoidance, negatively influence European firm digitalization, while indulgence influences it positively, offering direct empirical evidence for culture effects on digital adoption in the European context.

Organizational readiness and internal capabilities represent critical proximal determinants of AI implementation success. Machado et al. [17] present conditions derived from case studies and a questionnaire for assessing digital organizational readiness in manufacturing, applicable to dimensions and measurement of AI readiness. Hradecky et al. [18] propose an AI Adoption

Readiness Model in the exhibition sector, offering constructs and empirical evidence specific to Western European firms regarding organizational readiness factors. Leso et al. [19] develop and validate through mixed methods a conceptual model on the contribution of organizational culture, structure, and leadership factors in the digital transformation of SMEs, offering valuable evidence for organizational-level hypotheses.

Strategic leadership and organizational culture play fundamental roles in facilitating digital transformation and AI adoption. Van Dun and Kumar [20] investigate the role of transformational leadership and emotional intelligence as social enablers of Industry 4.0 technology adoption, linking managerial practices to systemic readiness and organizational transformation contexts. Faiz et al. [21] analyze the role of digital leadership capability in mastering business model innovation, demonstrating the importance of managerial decision-making and adaptive leadership styles in the context of digital transformation.

Digitalization affects not only the business environment but also fundamental social sectors such as education and population living standards. Aivaz [22] analyzes the impact of ICT on education and living standards in Romania, demonstrating that digital infrastructure and digital skills are essential determinants of socio-economic development, with digitalization investments having multiplier effects that influence not only technology adoption in organizations but also society's capacity to benefit from digital transformation. Bogoslov et al. [23] examine perspectives on artificial intelligence adoption for European Union elderly in the context of digital skills development, linking digital competencies and policy factors to technology adoption patterns among older populations and highlighting the importance of inclusive AI implementation strategies in Europe.

Human capital readiness through higher education systems represents a critical factor for AI adoption. Râlea et al. [24] use stochastic frontier models to analyze the efficiency of higher education systems in the EU, demonstrating significant variations between countries in the capacity to produce qualified human capital, these differences in educational efficiency being reflected in countries' capacity to adopt and implement advanced technologies such as AI. The study highlights that countries with more efficient higher education systems, which produce graduates with advanced digital and analytical skills, present superior institutional readiness for AI adoption, emphasizing the importance of investments in education not only as a public good in itself but also as a prerequisite for digital transformation and adoption of emerging technologies.

The expansion of AI applications in the digital economy includes innovative domains such as neuromarketing applied to social media. Micu et al. [25] explore neuromarketing challenges in the digital economy, analyzing how AI technologies and neuroscience can be combined to better understand online consumer behavior, demonstrating that AI is not adopted only for operational efficiency but also to unlock new analytical and strategic capabilities in organizations. The study highlights that AI adoption in cutting-edge domains requires not only technological infrastructure but also an organizational culture open to experimentation and innovation, as well as an institutional framework that supports interdisciplinary research.

Trust in technology represents an important mediator between cultural values and effective adoption. Teodorescu et al. [26] analyze consumer trust in AI algorithms used in e-commerce, demonstrating that cultural and educational factors significantly influence the level of trust and, implicitly, the intention to adopt AI technologies, the study highlighting that trust in AI is built not only through technical characteristics of systems but also through contextual and cultural factors that shape user perceptions. Aivaz and Teodorescu [27] demonstrate that the use of digital devices in the academic environment is influenced by cultural and behavioral factors, with students manifesting different attitudes toward technology depending on cultural and institutional context, offering evidence about the importance of educational context in forming attitudes toward digital technologies and AI.

The broader institutional and economic context in which organizations operate significantly influences their capacity to adopt advanced technologies. Jula et al. [28] offer a profound analysis of institutional and economic influences on poverty in Europe, demonstrating that the quality of institutions, economic policies, and infrastructure investments are critical determinants of development, the implications being relevant for AI adoption: countries with stronger institutions, coherent economic policies, and sustained infrastructure investments create a more favorable environment for innovation and technological adoption.

Despite significant progress in understanding AI adoption, the literature presents important gaps that require further investigation. Existing research is predominantly cross-sectional, limiting causal inferences regarding the mechanisms through which institutional readiness and cultural values influence AI adoption, with longitudinal studies needed to track the evolution of adoption over time and identify causal relationships. Although the literature recognizes the importance of factors at the country, organization, and individual levels, few studies formally test multi-level models that integrate these levels of analysis and examine mediation and moderation mechanisms between levels. Most studies apply theoretical frameworks developed for older technologies to AI without operationalizing AI specifics: opacity, autonomy, learning capacity, algorithmic uncertainty, requiring a reconceptualization of adoption constructs to capture the unique characteristics of AI. There is a lack of rigorous evidence regarding the comparative effectiveness of different policy instruments in stimulating AI adoption across firm sizes and sectors, and current research offers static snapshots of how culture and institutions interact, without examining how these interactions evolve over time as technology matures and social norms adapt.

The present research addresses some of these gaps by simultaneously examining governmental institutional readiness and cultural dimensions as determinants of AI adoption at the enterprise level in Europe, using a design that allows testing interaction effects between institutional and cultural factors, thus contributing to a more nuanced understanding of how national context shapes organizational behavior in adopting emerging technologies.

3. Metodology

The dependent variable used in the analysis is represented by the share of enterprises using artificial intelligence technologies in 2025 (Enter_UsingAI2025). The indicator is expressed as a percentage and reflects the proportion of firms in each state that have integrated AI solutions into their current operations. This indicator captures the aggregate level of organizational AI adoption at the national level.

The main independent variable is the Government AI Readiness Index (2025), a composite indicator that measures the institutional capacity of the state to develop, regulate, and support the AI ecosystem. The index includes dimensions such as digital infrastructure, human capital, administrative capacity, and regulatory framework. Higher values indicate a higher level of institutional readiness.

The cultural dimensions are taken from Hofstede's model and include Uncertainty Avoidance (UAI) and Long-Term Orientation (LTO). UAI measures the degree to which members of a society show aversion to uncertainty and ambiguity, and LTO reflects the long-term strategic orientation of society, including perseverance and investment in future benefits.

To test the moderating effect, the Government AI Readiness and Uncertainty Avoidance variables were standardized by transforming them into z-scores (mean 0, standard deviation 1). Standardization was performed to reduce potential multicollinearity issues associated with the inclusion of the interaction term and to facilitate the interpretation of the coefficients.

The interaction term (IntZ) was constructed as the product of the standardized variables of the Government AI Readiness index and UAI. This term captures the conditional effect of culture on the relationship between institutional capacity and AI adoption.

The analysis was performed using the multiple linear regression model, and the model fit was assessed by the coefficient of determination (R^2), the F-test, the regression coefficients, and the collinearity indicators (VIF and conditioning indices). The residuals were also examined to verify compliance with the linear regression assumptions.

4. Results

Empirical analysis was conducted to assess the influence of government readiness for artificial intelligence and cultural dimensions on the level of AI adoption in European enterprises in 2025. The results obtained are presented below, in the logical order of the analytical stages.

Tabel No. 1. Descriptive Statistics

	Mean	**Std. Deviation**	**N**
Enter_UsingAI2025	19.926452	10.2541983	31
Zscore: GovAIReadIndex2025	.000000	1.0000000	31
Zscore: UAI	.000000	1.0000000	31
LTO	50.65	10.310	31
IntZ	-.2830	.85683	31

Table No. 1. presents descriptive statistics for the variables included in the model. The mean AI adoption rate in 2025 is 19.93%, with a standard deviation of 10.25, indicating considerable variability among the states analyzed. The GovAI and UAI variables are presented in standardized form (mean 0, standard deviation 1), as they were used to construct the interaction term. LTO has a mean of 50.65 and moderate dispersion. The interaction variable (IntZ) reflects the product of institutional readiness and uncertainty avoidance.

Tabel No. 2. Correlations

		Enter_UsingAI2025	**Zscore: GovAIReadIndex2025**	**Zscore: UAI**	**LTO**	**IntZ**
Pearson Correlation	Enter_UsingAI2025	1.000	.540	-.494	.480	-.287
	Zscore: GovAIReadIndex2025	.540	1.000	-.292	.341	.137
	Zscore: UAI	-.494	-.292	1.000	-.470	.265
	LTO	.480	.341	-.470	1.000	-.051
	IntZ	-.287	.137	.265	-.051	1.000
Sig. (1-tailed)	Enter_UsingAI2025	.	<.001	.002	.003	.059
	Zscore: GovAIReadIndex2025	.001	.	.055	.030	.232
	Zscore: UAI	.002	.055	.	.004	.075
	LTO	.003	.030	.004	.	.392
	IntZ	.059	.232	.075	.392	.
N	Enter_UsingAI2025	31	31	31	31	31
	Zscore: GovAIReadIndex2025	31	31	31	31	31
	Zscore: UAI	31	31	31	31	31
	LTO	31	31	31	31	31
	IntZ	31	31	31	31	31

Correlational analysis highlights a strong positive relationship between government readiness for AI and AI adoption in 2025 ($r = .540$, $p < .001$), suggesting that states with higher institutional capacity experience greater levels of AI technology integration within their organizational environments.

Uncertainty avoidance is negatively associated with AI adoption ($r = -.494$, $p = .002$), while long-term orientation shows a significant positive relationship ($r = .480$, $p = .003$). The interaction term is negatively correlated with AI adoption, preliminarily indicating the existence of a possible moderating effect.

The regression model was estimated using the Enter method, with all variables being entered simultaneously into the analysis. The dependent variable is AI adoption in 2025, and the predictors include standardized government readiness, standardized uncertainty avoidance, long-term orientation, and the interaction term.

Tabel No. 3. Variables Entered/Removed[a]

Model	Variables Entered	Variables Removed	Method
1	IntZ, LTO, Zscore: GovAIReadIndex 2025, Zscore: UAI[b]	.	Enter
a. Dependent Variable: Enter_UsingAI2025			
b. All requested variables entered.			

The estimated model explains 52.4% of the variation in AI adoption ($R^2 = .524$), and the adjusted coefficient indicates robust explanatory power (adjusted $R^2 = .450$). The high value of R suggests a strong association between the included predictors and the dependent variable.

Tabel No. 4. Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.724[a]	.524	.450	7.6016258
a. Predictors: (Constant), IntZ, LTO, Zscore: GovAIReadIndex2025, Zscore: UAI				
b. Dependent Variable: Enter_UsingAI2025				

The ANOVA test confirms the overall significance of the model ($F = 7.147$, $p < .001$), indicating that the included predictors contribute significantly to explaining the variation in AI adoption in 2025.

Tabel No. 5. ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	1652.055	4	413.014	7.147	<.001[b]
	Residual	1502.403	26	57.785		
	Total	3154.458	30			
a. Dependent Variable: Enter_UsingAI2025						
b. Predictors: (Constant), IntZ, LTO, Zscore: GovAIReadIndex2025, Zscore: UAI						

The analysis of the coefficients indicates that government readiness for AI has a positive and statistically significant effect on AI adoption ($\beta = .450$, $p = .006$), confirming the determining role of institutional capacity. Uncertainty avoidance does not have a significant direct effect, and long-term orientation, although positive, does not reach the conventional threshold of significance.
The interaction term is negative and close to the threshold of statistical significance ($\beta = -.290$, $p = .055$), suggesting that the positive effect of institutional readiness on AI adoption is diminished in societies characterized by high levels of uncertainty avoidance. This result supports the idea of a conditional relationship between institutions and organizational behavior.

Tabel No. 6. Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	T	Sig.	Collinearity Statistics	
		B	Std. Error	Beta			Tolerance	VIF
1	(Constant)	7.467	8.109		.921	.366		
	Zscore: GovAIReadIndex2025	4.616	1.533	.450	3.012	.006	.820	1.219
	Zscore: UAI	-1.825	1.674	-.178	-1.091	.285	.687	1.455
	LTO	.227	.157	.228	1.441	.161	.733	1.364
	IntZ	-3.469	1.728	-.290	-2.007	.055	.879	1.138
a. Dependent Variable: Enter_UsingAI2025								

The collinearity indicators show VIF values below 2 for all variables, and the conditioning indices do not signal any serious problems. These results confirm the stability of the estimates and the absence of excessive multicollinearity.

Tabel No. 7. Collinearity Diagnostics[a]

Model	Dimension	Eigenvalue	Condition Index	Variance Proportions				
				(Constant)	Zscore: GovAIReadIndex2025	Zscor: UAI	LTO	IntZ
1	1	2.179	1.000	.01	.00	.01	.01	.05
	2	1.291	1.299	.00	.29	.27	.00	.00
	3	1.010	1.469	.00	.22	.08	.00	.39
	4	.506	2.074	.00	.44	.47	.00	.55
	5	.014	12.384	.99	.05	.17	.99	.00
a. Dependent Variable: Enter_UsingAI2025								

Residual analysis indicates a balanced distribution of errors, with standardized residuals falling within acceptable limits. This suggests that the assumptions of linear regression are satisfied and that the model is appropriate for the data analyzed.

Tabel No. 8. Residuals Statistics[a]

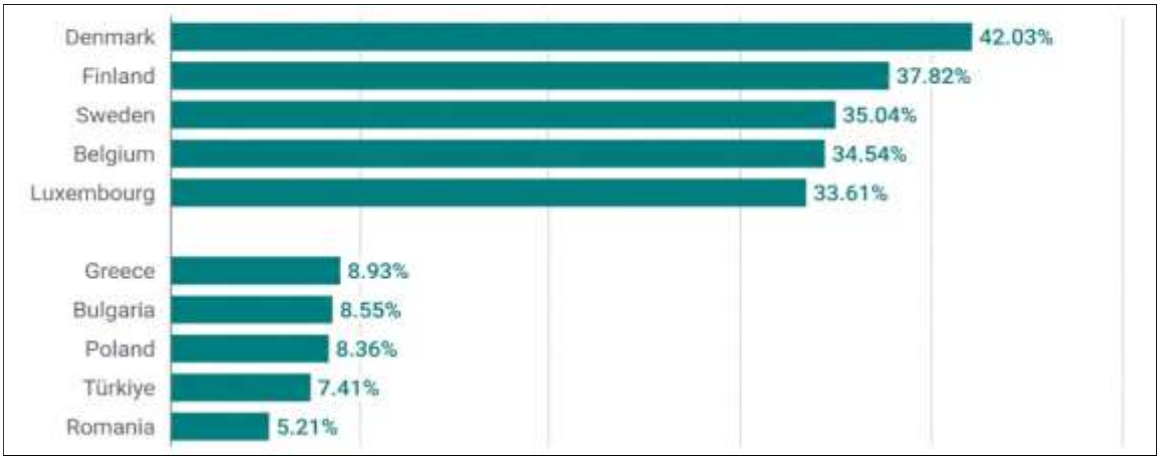
	Minimum	Maximum	Mean	Std. Deviation	N
Predicted Value	8.030354	38.888687	19.926452	7.4208152	31
Residual	-11.4702969	16.6317062	.0000000	7.0767285	31
Std. Predicted Value	-1.603	2.555	.000	1.000	31
Std. Residual	-1.509	2.188	.000	.931	31
a. Dependent Variable: Enter_UsingAI2025					

Overall, the results highlight that the organizational adoption of artificial intelligence in Europe is strongly influenced by the institutional capacity of the state, but its effectiveness is conditioned by the cultural profile of society. Thus, digital transformation at the organizational level appears to be the result of an interaction between institutional infrastructure and national value structures.

5. Discussions

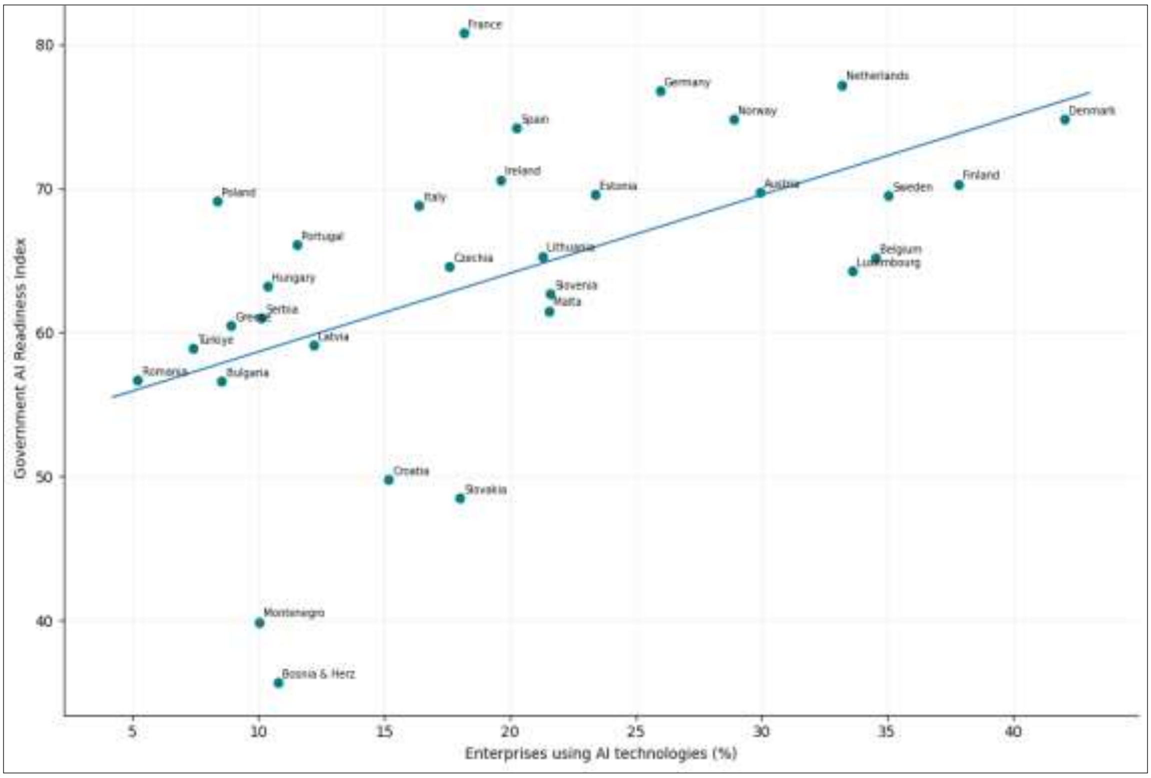
The distribution of enterprise AI adoption across European countries reveals marked differences in adoption ranges, as shown in Figure No. 1, indicating that the diffusion of AI technologies is far from uniform across the continent. While some countries demonstrate advanced levels of enterprise integration, others remain at substantially lower adoption levels, pointing to significant cross-country heterogeneity. These disparities raise a central analytical question for this study: which factors influence the extent to which enterprises adopt AI technologies across different national contexts?

Figure No. 1. A Continent Divided, Enterprises AI Adoption Ranges



The results of the study confirm that the organizational adoption of artificial intelligence in Europe is strongly influenced by the national institutional context, but also conditioned by the cultural characteristics of society. The estimated model explains more than half of the variation in AI adoption levels in 2025, indicating substantial explanatory power for a cross-country study. Figure No. 2 visualizes the cross-country association between enterprise AI adoption and government AI readiness in Europe. The scatter distribution indicates an overall positive relationship, suggesting that higher levels of governmental preparedness tend to coincide with greater enterprise-level AI adoption. At the same time, dispersion around the trend highlights heterogeneity across countries, motivating further analysis of contextual factors that may shape how institutional readiness translates into organizational adoption outcomes

Figure No. 2. Enterprise AI Adoption and Government AI Readiness in Europe

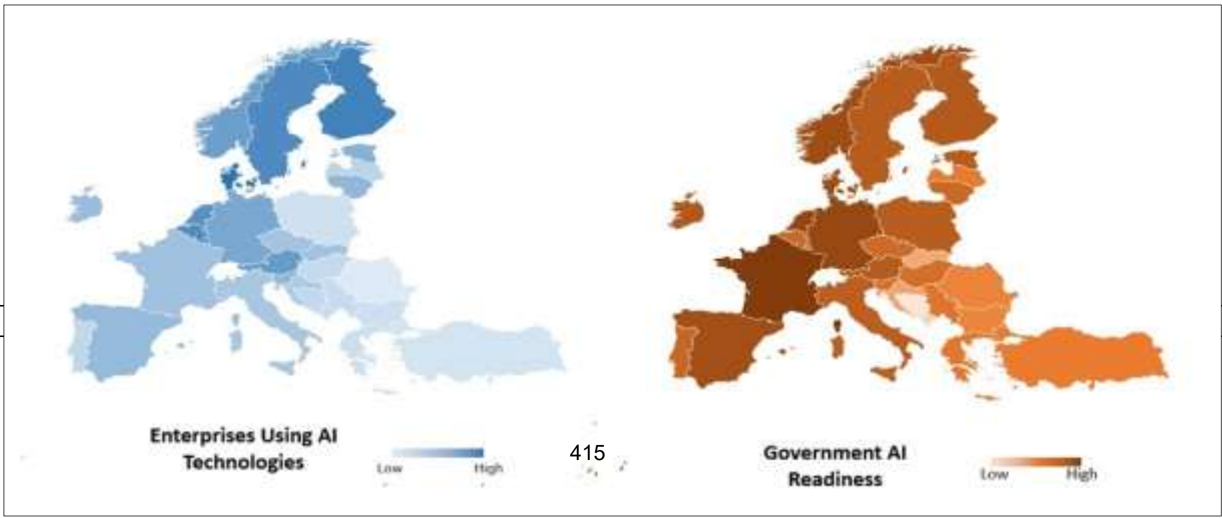


Hypothesis H1, according to which government readiness for artificial intelligence is positively associated with AI adoption at the enterprise level, is empirically supported. The positive and significant coefficient of the Government AI Readiness index confirms the essential role of institutions in facilitating digital transformation. This relationship is also reflected visually in Figure No. 3, where countries with higher levels of government AI readiness tend to correspond to higher rates of enterprise AI adoption, reinforcing the positive association identified in the empirical analysis.

This result reinforces the institutional theory perspective, according to which organizations respond to pressures and incentives from the institutional environment. A clear regulatory framework, adequate digital infrastructure, and public support for innovation reduce perceived uncertainty and increase the likelihood of adopting emerging technologies.

Hypothesis H2, which assumed a direct negative relationship between uncertainty avoidance and AI adoption, is not supported by the results. Although the bivariate relationship is negative and significant, the direct effect of UAI becomes insignificant in the full regression model. This suggests that the influence of culture is not predominantly manifested through a direct effect on AI adoption, but rather through a conditional mechanism dependent on interaction with institutional factors.

Figure No. 3. Comparison between the Outcome (Enterprise Using AI) and the Driver (Government AI Readiness)

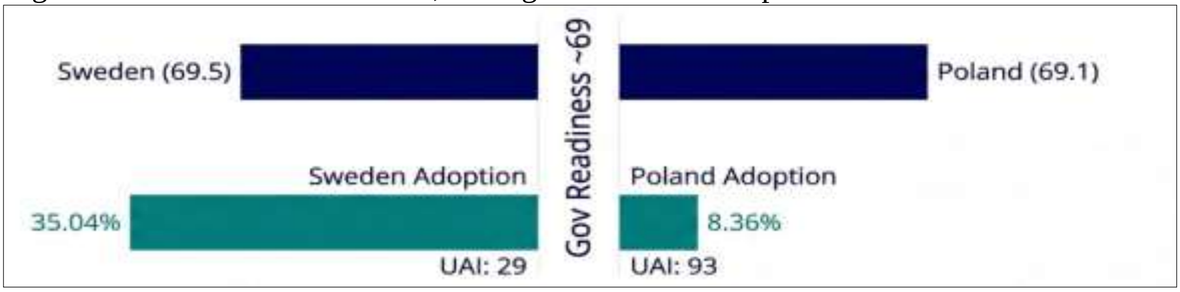


Hypothesis H3, regarding the positive role of long-term orientation, is not directly confirmed in the final model, although the bivariate relationship is significant and the direction of the effect remains positive. This finding indicates that, in the context of AI adoption in 2025, institutional capacity appears to have a stronger influence than cultural predispositions related to the time horizon of investments. However, long-term orientation may continue to play an indirect role in shaping the overall strategic climate. Figure No. 4 visually summarizes this result by illustrating the relative position of long-term orientation within the overall explanatory framework. While the effect remains positive at the bivariate level, its lack of statistical significance in the final model suggests that long-term cultural orientation does not independently drive enterprise AI adoption when institutional readiness is considered. This supports the interpretation that long-term orientation functions more as a background strategic context than as a direct determinant of adoption outcomes.

Figure 4 Long-Term Orientation as a Non-Significant but Contextual Factor in AI Adoption

Hypothesis H4, regarding the moderating effect of uncertainty avoidance on the relationship between government readiness and AI adoption, is marginally supported. The interaction term is negative and close to the conventional threshold of statistical significance, indicating that the positive effect of institutional readiness is diminished in societies characterized by high levels of uncertainty avoidance. This result is particularly relevant from a theoretical perspective, as it highlights the contingent nature of the relationship between institutions and organizational behavior. Public policies aimed at developing AI do not produce uniform effects; their effectiveness depends on their compatibility with dominant cultural values. Figure No. 5, the comparison between Sweden and Poland illustrating divergent enterprise AI adoption despite similar government AI readiness levels. Differences in uncertainty avoidance (UAI) suggest that cultural factors may moderate the relationship between institutional readiness and AI adoption.

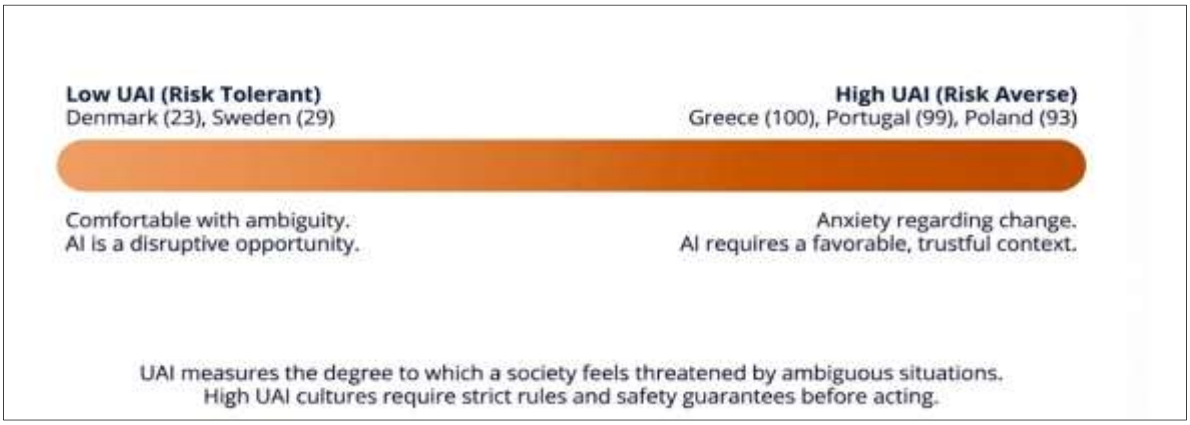
Figure No. 5. Identical Readiness, Divergent Results Example



Overall, the results suggest that AI adoption cannot be explained solely by internal resources or public policies, but must be understood as the result of an interaction between institutional infrastructure and national value structure. Institutions create the formal framework for innovation, but culture shapes the interpretation and internalization of this framework at the organizational level.

From a managerial perspective, these findings indicate that national strategies to promote artificial intelligence must be adapted to the cultural profile of society. In countries characterized by high levels of uncertainty avoidance, simply strengthening infrastructure and regulations may not be enough. Additional mechanisms are needed to reduce perceived risk, provide regulatory clarity, and support programs that diminish the ambiguity associated with emerging technologies.

Figure No. 6. Uncertainty Avoidance as a Cultural Moderator of AI Adoption



To further interpret the moderation effect identified in the empirical analysis, Figure No. 6. conceptualizes the role of the Uncertainty Avoidance Index (UAI) as a cultural continuum shaping organizational responses to AI adoption. Countries characterized by low UAI values, such as Denmark and Sweden, tend to exhibit higher tolerance toward ambiguity and technological disruption, which may facilitate experimentation and faster AI integration. In contrast, high-UAI contexts, exemplified by Greece, Portugal, and Poland, are generally associated with stronger risk aversion and a greater need for stability and institutional guarantees before adopting new technologies. This cultural distinction helps explain why similar levels of government AI readiness may produce different adoption outcomes, reinforcing the argument that cultural factors condition how institutional capacity translates into enterprise-level AI uptake.

By integrating institutional theory with national cultural dimensions, the study contributes to the literature on management and digital transformation by highlighting that the success of public policies in the field of AI depends on the alignment between institutional capacity and cultural context. This perspective provides a useful analytical framework for understanding inter-state variations in the pace of organizational digital transformation.

6. Conclusions and practical implications

This study analyzed the institutional and cultural determinants of artificial intelligence adoption at the level of European enterprises in 2025. The results highlight the central role of the state's institutional capacity in stimulating organizational digital transformation, confirming that a favorable government framework is an essential factor in accelerating AI adoption. At the same time, the analysis shows that institutional effects are not uniform but are conditioned by the national cultural profile, in particular the level of uncertainty avoidance.

The main contribution of the study is to integrate the institutional perspective with cultural dimensions in explaining technological adoption at the organizational level. The results suggest that public policies geared toward AI development do not automatically generate digital transformation, but interact with societal values that shape risk perception and openness to innovation. Thus, AI adoption should be understood as the result of an alignment between institutional infrastructure and national culture.

From a managerial perspective, these findings have relevant implications for both public decision-makers and organizational leaders. In countries with high levels of uncertainty avoidance, simply developing digital infrastructure or adopting national AI strategies may not be enough.

Additional mechanisms are needed to reduce perceived risk, clarify the regulatory framework, standardize, and communicate strategically to increase organizations' confidence in emerging technologies. Similarly, organizational leaders need to pay attention to the internal cultural climate and develop management practices that reduce anxiety associated with technological change while promoting a long-term strategic vision.

Therefore, the study emphasizes that digital transformation is not just a technological or economic process, but a profoundly institutional and cultural one. Effective AI policies must be adapted to the societal context, and organizational strategies must take into account the dominant values of the environment in which they operate.

7. Limitations and future research directions

Despite its contributions, the study has a number of limitations that should be taken into account. First, the analysis is conducted at the aggregate level, using the country as the unit of analysis. While this approach is appropriate for investigating institutional and cultural influences, it does not allow for capturing intra-national differences or variability at the individual organizational level. Future studies could use firm-level data to examine how institutional and cultural factors interact with internal organizational characteristics.

Second, the cross-sectional design limits the possibility of drawing firm causal conclusions. Although the relationships identified are theoretically consistent, longitudinal research could provide a more dynamic perspective on how the evolution of institutional capacity influences the pace of AI adoption over time.

Another limitation relates to the use of national-level cultural dimensions, which may not fully capture the complexity of country-specific organizational values. Future research could integrate measures of organizational culture or managerial climate to provide a more nuanced analysis.

In addition, the explanatory model could be expanded to include other relevant variables, such as the level of economic development, investment in research and development, digital human capital, or the sectoral structure of the economy. Integrating these factors could contribute to a more complete understanding of the national digital ecosystem.

Finally, future research could explore other cultural dimensions, such as individualism or distance from power, to examine whether and to what extent they influence the adoption of emerging technologies.

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