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Governing Artificial Intelligence in Europe: Policy Frames, Implementation Gaps, and the Task–Skill–Institution Model

Mioara Chirita*, George Chirita**

A R T I C L E I N F O

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A B S T R A C T

This study analyses how EU member states formulate and implement national artificial intelligence (AI) policies, investigating the relationships between policy frames, implementation practices and innovation and labor market outcomes. Based on a corpus of national AI strategies of EU member states, we apply Structural Topic Modeling combined with frame analysis to identify dominant discursive orientations and their temporal evolution. The analysis reveals a reconfiguration of priorities: the emphasis on capitalizing on economic opportunities is decreasing, while concerns about governance, compliance and risk management are gaining weight, and the capacity development framework remains relatively stable. We further investigate the extent to which the prevalence of these frames is associated with implementation tools and indicators of innovation performance, including R&D dynamics. In addition, we introduce the Task–Skill–Institution (TSI) model, an integrated conceptual framework that conceptualizes AI-induced labor market vulnerabilities as emergent outcomes of interactions between exposure to automation, skill elasticity, and institutional capacities. The results indicate that cross-national variations in the maturity of AI ecosystems can be partly explained by the gap between strategic discourse and implementation capacity, as well as by systemic configurations that mediate technological impact. The study provides an empirical and conceptual basis for assessing the alignment between discourse, governance, and implementation, and formulates directions for strengthening AI policies in Europe.

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1. Introduction

In the context of accelerated technological transformations, artificial intelligence (AI) has gone beyond the status of an emerging technology, becoming a general-purpose infrastructure with systemic implications for productivity, governance and economic competitiveness. Recent literature converges on the idea that public policies on AI are built around a structural tension between innovation and regulation, reflected in particular in the European model, which combines economic development objectives with the protection of fundamental rights through a risk-based approach (Ebers, 2025; Cancel Outed, 2024). This dual orientation redefines the role of the state, transforming AI policies into a strategic instrument of coordination between markets, society and technology.

From a theoretical perspective, variations in the configuration and performance of these policies can be understood through the lens of public policy frames, which structure the way in which problems are defined, prioritized and legitimized. According to Rein and Schön (1996), frames function as cognitive and normative devices that influence the selection of instruments and the direction of public intervention. Contemporary extensions of this perspective emphasize the dynamic and contested nature of the framing process, highlighting the competition between interpretations and the role of institutional actors in setting policy agendas (van Hurst & Yalow, 2016). In the field of AI, these frames are articulated around three dominant orientations: capitalizing on economic opportunities, risk governance, and developing technological and institutional capabilities.

The literature on policy mixes provides a complementary analytical framework, demonstrating that the effectiveness of policies is not determined by individual instruments, but by the coherence and consistency of combinations of instruments in complex institutional contexts. Kern, Rogge, and Howlett (2019) and Macro and Wilson (2019) argue that performance depends on the vertical and horizontal alignment of instruments, as well as their credibility with the actors involved. In the case of AI policies, this perspective is essential, as

*, **Dunarea de Jos University of Galati, Romania. E-mail addresses: mioara.chirita@ugal.ro (Corresponding author - M. Chirita), george.chirita@ugal.ro (D. Basalic).

implementation involves interactions between multiple levels of governance and between public and private sectors.

Critically, the literature on policy implementation highlights the persistence of an implementation gap, reflecting the discrepancy between strategic ambitions and actual outcomes. Hudson, Hunter and Peckham (2019) show that this gap is amplified in contexts characterized by ambiguity, institutional complexity and limited administrative capacity. In the case of AI, these challenges are intensified by technological uncertainty and the need for continuous regulatory adaptation, which transforms implementation into an iterative and learning-dependent process. In parallel, the emerging literature on responsible AI governance emphasizes that the effectiveness of policies depends on establishing arrangements that support transparency, accountability and public trust, as well as the capacity to adapt to rapid change. Papagiannidis, Mikalef and Conboy (2025) highlight the role of continuous monitoring and evaluation mechanisms, while debates on the European framework indicate the existence of trade-offs between regulation and innovation, including administrative costs and coordination difficulties (Ebers, 2025; Justo Hanani, 2026).

From an empirical perspective, the literature remains fragmented, being dominated by descriptive analyses or case studies, which limits the comparability and generalizability of results. In this context, computational methods, such as structural topic modeling, offer relevant methodological opportunities for the systematic analysis of policy discourses and for the identification of transnational variations (Roberts et al., 2014). Integrating these methods with framework analysis allows overcoming the dichotomy between quantitative and qualitative and facilitates a replica and comparative analysis of AI policies.

Overall, the literature suggests that the performance of AI policies is determined by the alignment between discursive frameworks, policy mixes, and institutional capacity for implementation. The absence of this alignment generates discrepancies between intention and execution, confirming that AI policies must be understood as complex governance processes, in which discursive, institutional, and operational dimensions are deeply interdependent. This perspective justifies the need for integrated analyses that connect strategic discourse with observable outcomes in innovation and competitiveness.

2. Literature review

In recent years, the governance of artificial intelligence (AI) has become a central area of European public policies, reflecting the transition from a paradigm predominantly oriented towards innovation and competitiveness to a complex regulatory framework focused on regulation, risk management and the protection of fundamental rights. Recent literature highlights that the European model, crystallized around the Artificial Intelligence Act, is built on a risk-based approach, which introduces differentiated obligations and compliance mechanisms proportionate to the impact of AI systems (Vale & Borgesius, 2023; Florida, 2023). This evolution marks the transition from soft law instruments to a hard law regime, with significant implications for the way in which Member States articulate and implement national strategies.

From a theoretical perspective, the literature suggests that understanding the variations between these strategies requires an approach based on the analysis of policy frames, which structure the way in which AI is conceptualized as a public issue. Recent studies identify several dominant frameworks, including economic competitiveness, technological sovereignty, ethics and fundamental rights, as well as the development of institutional and technological capacities (Rad, 2024; Kuhlman & Rip, 2023). These frameworks are not only descriptive, but also have a performative role, influencing the selection of policy instruments and the configuration of institutional mixes. In this sense, the literature on policy mixes emphasizes that the effectiveness of policies depends on the coherence and consistency of the combinations of instruments, as well as on their capacity to generate complementations between regulation, financing and institutional coordination (Kern et al., 2019; Magro & Wilson, 2019).

A recurring aspect in the empirical literature is the existence of a gap between strategic formulation and effective implementation (implementation gap). Recent comparative analyses show that, although most Member States have adopted ambitious national strategies, institutional capacity, inter-ministerial coordination and the availability of digital skills remain limiting factors (Bicker et al., 2024; OECD, 2023). This gap is amplified by technological complexity and the need for continuous regulatory adaptation, which transforms the implementation of AI policies into a dynamic process dependent on institutional learning.

In parallel, recent literature highlights a convergence between AI governance, industrial policy and digital sovereignty objectives. European initiatives, such as Horizon Europe or the European Chips Act, are analyzed as part of an integrated framework that aims to strengthen strategic autonomy and reduce external technological dependencies (European Commission, 2024; Kuhlman & Rip, 2023). This interdependence reflects a reconfiguration of public policies, in which regulation is not separated from economic objectives, but becomes an active tool for shaping markets and innovation ecosystems.

The institutional dimension of AI governance is also gaining importance. The literature shows that the development of competent national authorities, oversight mechanisms and conformity assessment procedures are essential conditions for effective implementation (OECD, 2023). In this context, technical standardization and risk assessment mechanisms become critical tools for operationalizing regulation. Blind, Giebel and Ramel

(2023) highlight that the interaction between regulation and standardization can reduce uncertainty and facilitate innovation, but can also generate significant compliance costs, especially for Times.

At a global level, the literature highlights the role of the European Union as a normative actor, through the so-called "Brussels Effect", which explains the extraterritorial extension of European standards (Bradford, 2023). In the field of AI, this effect is manifested through the EU's ability to influence global standards, contributing to the configuration of an international governance regime based on principles of responsibility and safety.

More recently, the rapid development of generative models and general-purpose artificial intelligence systems has generated new challenges for governance, leading to a shift towards adaptive regulatory models. The literature highlights the need for continuous monitoring mechanisms, ex post evaluation and international cooperation to respond to emerging risks and avoid fragmentation of regulatory regimes (OECD, 2023; Florida, 2023).

Overall, the recent literature highlights a maturation of the European AI governance framework, characterized by the integration of normative, economic and institutional dimensions. The performance of these policies depends on the alignment between discursive frameworks, policy mixes and institutional capacity for implementation, suggesting that the success of AI governance cannot be assessed solely by regulatory design, but by the capacity to translate these frameworks into concrete outcomes in innovation and competitiveness.

Starting from these gaps identified in the literature, this article makes three complementary theoretical and empirical contributions to the understanding of AI governance in European space.

The first contribution is empirical and methodological in nature. Based on a systematic corpus of national AI strategies and policy documents developed by the European Union Member States, we apply Structural Topic Modeling (STM) in combination with frame analysis to map the dominant discursive orientations of AI policies and to track their dynamics over time. This approach allows us to go beyond the descriptive analyses prevalent in the literature and provides a systematic and replicables comparative basis for assessing transnational variations in the discursive construction of AI policies.

The second contribution is analytical in nature. We investigate to what extent the prevalence of the identified discursive frameworks is associated with concrete national implementation instruments and innovation performance indicators, including the dynamics of R&D spending and the economic outcomes of the AI sector. Through this analysis, we empirically test the existence of an implementation gap in European AI policies, defined as the systematic discrepancy between strategic ambitions formulated in public policy documents and observable outcomes in practice, and examine the institutional and structural factors that contribute to explaining it.

The third contribution is conceptual in nature. We introduce the Task–Skill–Institution (TSI) model, an integrated analytical framework for understanding labor market vulnerabilities generated by AI-based automation. In contrast to uni-dimensional approaches focused on technological substitution, the TSI model conceptualizes vulnerability as an emergent phenomenon, determined by the interaction between three interdependent structural dimensions: Automation Exposure, Skill Elasticity, and Institutional Capacity.

This perspective allows the identification of distinct typologies of vulnerability and the mechanisms through which systemic configurations specific to each national context mediate the impact of technological change on the occupational structure and quality of work.

3. Sectoral Exposure to AI-Enabled Automation and the Polarization of Skill Demand

Sectoral exposure to automation based on artificial intelligence (AI) is conceptualized in recent literature as a process of structural transformation of work content, rather than as a simple technological substitution. Unlike previous waves of automation based on robotization and routinization, AI, in particular machine learning systems and generative models, intervenes simultaneously on routine and non-routine tasks, including advanced cognitive activities. This evolution has led to a theoretical shift from occupational analysis to a task-based approach, which allows for a more accurate capture of the interaction between technology and skill structure (OECD, 2024).

In this context, the literature highlights a pronounced sectoral heterogeneity in exposure to AI. Knowledge-intensive sectors, such as ICT, financial services, professional services, public administration or health, show a high degree of exposure, but this exposure is more frequently associated with task augmentation and Complementarity between AI and work, rather than with direct substitution. In contrast, in sectors characterized by standardizable or repetitive tasks, including certain segments of manufacturing and administrative services, AI tends to amplify partial substitution processes, especially for middle-level occupations (Cedefop, 2025; OECD, 2024). This duality confirms that the effects of AI are deeply dependent on the structure of tasks and the capacity of sectors to integrate technology into productive processes.

A first core of the literature focuses on the relationship between AI and the polarization of skills demand. Recent studies suggest that AI accelerates existing polarization trends, but in a more complex form than traditional automation. On the one hand, AI reduces the demand for standardizable intermediate skills, contributing to the decline of the middle-skill segment. On the other hand, it increases the demand for both high-level skills, analytical, digital and managerial, and for certain low-skilled services, generating an asymmetric redistribution of occupational opportunities (OECD, 2024).

However, recent empirical literature introduces important nuances to this relationship. Brynjolfsson, Li, and Raymond (2025) show that the introduction of generative AI in customer support activities led to significant productivity gains, with more pronounced effects for less experienced workers, suggesting a potential for reducing intra-occupational inequalities. In contrast, Wampole et al. (2025) highlight that tasks with high exposure to AI are associated with decreases in labor demand in certain contexts, although these effects are partially offset by firm-level productivity gains. These results indicate that polarization does not exclusively reflect job losses, but rather a reconfiguration of the economic value of skills.

Table 1. Sectoral AI Exposure and Skill Demand Polarization in Europe

Dimension	Key Indicator / Evidence	Sectoral Differences	Socio-Economic Risks	Policy Implications	Source
Restructuring of skill demand	Increase (+8 p.p.) in demand for cognitive, digital and socio-emotional skills in AI-exposed occupations	High exposure: ICT, finance, professional services; Moderate: manufacturing (AI-integrated processes)	Skill obsolescence for routine middle-skill jobs	AI literacy, transversal skills, lifelong learning reforms	OECD (2024)
Skill polarization	Decline in mid-skill routine tasks; growth in high-skill analytical roles and low-skill service jobs	Administrative and clerical roles highly exposed; knowledge-intensive sectors show complementarity effects	Wage inequality; labour market segmentation	Targeted upskilling and modular re-certification programs	Song (2025)
AI adoption intensity	30% of large EU firms used AI technologies in 2023	Higher adoption in ICT, finance; growing in healthcare, advanced manufacturing	Regional disparities in digital capacity	Sector-specific training strategies; public-private curriculum alignment	Cedefop (2025)
Task reconfiguration	AI augments rather than fully replaces many cognitive tasks	Hybrid transformation in professional and managerial occupations	Unequal access to digital skills; transition risks	Continuous professional development frameworks	OECD (2023, 2024)
Structural labour risks	Acceleration of automation compared to previous technological waves	Greater exposure in standardized service functions	Income polarization; reduced upward mobility	Integrated skills + social protection policies	OECD (2023); Song (2025)

Source: Compiled by the author based on OECD (2023, 2024), Cedefop (2025), and Song (2025).

A second important strand of literature concerns the distinction between AI and robotic automation. Engberg et al. (2025) show that occupations exposed to AI have distinct skill profiles from those exposed to robotics, and the effects on wages are heterogeneous. Similarly, Lábaj, Ole and Procházka (2025) demonstrate that while robotization predominantly affects low-skilled workers and the middle segments of the income distribution, exposure to AI increases with income level and is more pronounced in high-skilled occupations. These results suggest that AI does not mechanically reproduce the classical polarization, but rather redefines it by extending exposure to cognitive tasks and advanced occupations.

Recent literature also highlights a territorial dimension of polarization, linked to the economic structure and innovation capacity of regions. Guarascio, Relic and Strelinger (2025) show that European regions specialized in knowledge-intensive sectors benefit from complementations between AI and labor, while peripheral regions are more exposed to the risks of marginalization. These differences are amplified by variations in human capital, digital infrastructure and innovation ecosystems, suggesting that the effects of AI are mediated by institutional and structural factors, highlighted in Table 1.

In the same vein, recent contributions emphasize the role of emerging economic contexts in amplifying vulnerabilities. Chiriță and Radu (2025) highlight that AI-assisted automation generates additional structural risks in labor markets with limited institutional capacity, including skills mismatch, pressures on employment and the expansion of algorithmic management forms. The authors argue that these effects are accentuated in the absence of active retraining policies and robust social protection mechanisms, reinforcing the idea that polarization is a phenomenon deeply dependent on the responsiveness of public policies.

A third thematic core of the literature focuses on the relationship between automation and augmentation. Both the OECD and the ILO (Gmyrek et al., 2025) emphasize that the high exposure to AI should not be interpreted as full automation, but as the potential for task transformation. In many sectors, AI functions as an augmentation technology, increasing productivity and changing skill requirements, without completely eliminating existing occupations. However, this transformation implies a significant increase in demand for advanced digital and cognitive skills, which may amplify inequalities in the absence of appropriate interventions (Chirita, et.al., 2025).

Overall, as can be seen in Table 1, recent literature converges on the idea that sectoral exposure to AI generates a profound and differentiated reconfiguration of skills demand, characterized by three main mechanisms:

(i) consolidation of advantages for sectors and regions with advanced human and technological capital;
(ii) pressure on intermediate occupations and expansion of exposure to standardizable cognitive tasks; and
(iii) increasing the value of complementary AI skills.

These developments suggest that polarization is not a deterministic outcome, but one mediated by economic structure, institutional capacity and public policies. Consequently, the literature emphasizes the need for integrated strategies of deskilling, continuing education and active labor market policies, to transform exposure to AI into a competitive advantage and to limit adverse effects on social cohesion.

3.1. Labor market vulnerabilities and risks associated with AI-based automation

We have developed a model that explicitly introduces interaction effects, treating vulnerability as an emergent phenomenon. In the context of the accelerating diffusion of artificial intelligence (AI) in European economies, labor market vulnerabilities can no longer be adequately explained by uni dimensional models focused exclusively on technological substitution. Recent literature suggests that the effects of AI on employment are deeply conditioned by task structure, skill dynamics, and institutional capacity to adapt. Building on this theoretical convergence, this section proposes an integrated analytical framework – the Task–Skill–Institution (TSI) Model – that conceptualizes labor market vulnerability as an emergent outcome of the interaction between exposure to automation, skill elasticity, and institutional capacity.

In this framework, labor market vulnerability is defined as the likelihood that workers or occupational segments will experience displacement, wage stagnation, or deterioration in job quality following the adoption of AI. Formally, it can be expressed as a function of three interdependent dimensions:

(i) Automation Exposure (AE),
(ii) Skill Elasticity (SE) and
(iii) Institutional Capacity (IC).

Unlike traditional approaches, the TSI model explicitly introduces interactions between these variables, arguing that the effects of AI are not determined independently, but through their combination.

The first dimension, Automation Exposure (AE), reflects the degree to which the tasks associated with an occupation or sector can be replicated or augmented by algorithms. In the logic of the task-based approach, exposure is not uniform at the occupational level, but varies depending on the internal structure of activities, the degree of standardization and the availability of data. Thus, AE captures the potential intensity of technological pressure on work, without automatically implying complete substitution.

The second dimension, Skills Elasticity (SE), represents the central conceptual contribution of the model. It is defined as the ability of workers to adapt, recombine or transfer their skills in response to technological change. In analytical terms, SE expresses the sensitivity of employability to variations in technological exposure. A high level of elasticity implies the possibility of occupational transitions and integration into new roles, while a low level indicates rigidity and increased risk of exclusion. By introducing this dimension, the model goes beyond the static view of skills and treats them as dynamic resources.

The third dimension, institutional capacity (IC), reflects the ability of economic and social systems to manage AI-induced transitions. This includes the efficiency of education systems, the quality of active employment policies, the level of coordination between public and private actors and the robustness of social protection mechanisms. IC functions as a mediating factor, which can amplify or attenuate the effects of technological exposure on the labor market.

The interaction of these three dimensions generates distinct typologies of vulnerability. In contexts characterized by high exposure to automation, low skills elasticity and limited institutional capacity, what can be defined as a structural vulnerability trap emerges, characterized by persistent unemployment and pronounced polarization. In contrast, combinations in which skills elasticity and institutional capacity are high allow the transformation of technological pressure into a process of productive adaptation, reducing social risks and supporting innovation. This typology highlights that vulnerability is not determined exclusively by technology, but by the systemic architecture in which it is embedded.

The TSI model also allows the identification of three main mechanisms through which AI generates risks in the labor market. The first is the risk of task displacement, which results from the automation of modifiable activities. The second is the risk of skill mismatch, generated by the gap between existing skills and those required by new occupational configurations. The third is the risk of institutional lag, which occurs when public policies and educational systems fail to keep up with the pace of technological change. These mechanisms do not act independently, but reinforce each other, generating cumulative effects on vulnerability.

From an empirical perspective, the model provides a testable framework, which can be operationalized using data at the sector, occupation and country levels. The variables can be approximated by existing indicators on AI exposure, participation in continuing education and institutional performance, and the relationships between them can be estimated through fixed-effects regression models or structural models. In this sense, the TSI Model functions as a tool for integrating theoretical literature and empirical analysis of public policies.

In terms of governance, the central implication of the model is that managing the risks associated with AI cannot be achieved exclusively through technological regulation, but requires an integrated approach that combines education, labor market, and innovation policies. Thus, AI governance becomes a process of systemic coordination of adaptation, in which reducing vulnerabilities depends on the alignment between technological transformation and institutional capacity to respond.

To operationalize the relationship between exposure to automation, skills dynamics, and institutional capacity, the TSI model defines labor market vulnerability as a continuous function, in Eq.1:

$$\boldsymbol{LMV = \beta_0 + \beta_1 AE - \beta_2 SE - \beta_3 IC + \beta_4 (AE \times SE) + \beta_5 (AE \times IC) + \varepsilon} \qquad \text{Eq.1}$$

where *LMV* denotes the Labor Market Vulnerability composite index, *AE* represents Automation Exposure, *SE* captures Skill Elasticity, and *IC* reflects Institutional Capacity. The error term ε accounts for unobserved heterogeneity at the sector or country level.

The model specification yields the following set of theoretically grounded parameter expectations. A positive coefficient $\beta_1 > 0$ indicates that higher exposure to AI-driven automation increases labor market vulnerability in the absence of compensating mechanisms. Conversely, negative coefficients $\beta_2, \beta_3 < 0$ reflect the protective role of skill elasticity and institutional capacity, respectively, as buffers against technological displacement. The interaction terms introduce non-linearity into the model: $\beta_4 < 0$ captures the moderating effect of skill elasticity on the relationship between automation exposure and vulnerability, while $\beta_5 < 0$ reflects the extent to which robust institutional frameworks attenuate the adverse labor market consequences of technological exposure. Taken together, vulnerability is conceptualized as the net outcome of technological pressure net of adaptive capacity, formally expressed as the balance between *AE* and the compensating contributions of *SE* and *IC*.

For empirical estimation, all variables are normalized to a continuous scale $AE, SE, IC \in [0,1]$, with threshold values defined as $High \geq 0.6$ and $Low < 0.4$, enabling the construction of discrete configurational profiles while preserving the underlying continuous specification.

Drawing on these parameter expectations and threshold definitions, Table 2 presents a typology of labor market vulnerability configurations derived from the TSI model. Each configuration represents a distinct combination of the three structural dimensions and maps onto a qualitatively differentiated vulnerability outcome.

Table 2. TSI Model Typology: Labor Market Vulnerability Configurations Under AI-Driven Automation

AE Automation Exposure	SE Skill Elasticity	IC Institutional Capacity	Tip
High	Low	Low	◍ Structural vulnerability trap
High	High	Low	□ Transition friction
High	High	High	□ Adaptive transformation
Low	Low	Low	● Technological stagnation

Vulnerability is the net result of technological pressure minus adaptive capacity. For empirical interpretation, the variables are normalized in Eq.2:

$$\text{AE, SE, IC} \in [0,1] \qquad \text{Eq.2}$$

For empirical operationalization, all three dimensions are normalized to a continuous scale AE, SE, IC $\in [0, 1]$, with classificatory thresholds defined as High ≥ 0.6 and Low < 0.4, enabling the construction of discrete configurational profiles while preserving the underlying continuous specification of the model.

The TSI model thereby enables the conceptualization of labor market vulnerabilities not as uniform technological outcomes, but as differentiated results of the structural interaction between AE, SE, and IC. From this interaction, an analytical typology of vulnerability configurations emerges, which makes explicit that the labor market impact of AI is neither linear nor homogeneous, but rather contingent upon the specific structural configurations characterizing individual sectors, occupational groups, or national economic systems. As summarized in Table 2, each configuration maps a distinct combination of the three model dimensions onto a qualitatively differentiated vulnerability outcome, ranging from conditions of structural entrenchment to scenarios of productive technological adaptation.

The first configuration, defined as the structural vulnerability trap, occurs in contexts characterized by high exposure to automation, low skill elasticity and limited institutional capacity. In these situations, the technological pressure generated by AI is not compensated by adaptation mechanisms, leading to persistent occupational dislocation and increased labor market polarization. The lack of skill flexibility reduces the possibility of occupational transitions, and underdeveloped institutions fail to facilitate deskilling or social protection. The result is a cumulative dynamic of vulnerability, in which economic and social risks reinforce each other.

The second configuration, called transition friction, is characterized by a combination of high exposure to AI and relatively high skill elasticity, but in a context of insufficient institutional capacity. In this case, workers have the necessary skills to adapt, but the lack of coherent public policies and effective institutional mechanisms generates delays and costs in the adjustment process. Vulnerability does not manifest itself in the form of permanent exclusion, but through occupational instability, imperfect mobility and prolonged transition periods. This configuration highlights the critical role of institutions in transforming adaptive potential into effective outcomes.

The third configuration, adaptive transformation, represents the optimal scenario from the perspective of the TSI model. This occurs when exposure to automation is high, but is accompanied by high skills elasticity and robust institutional capacity. Under these conditions, technological pressure is absorbed through efficient processes of deskilling, occupational mobility and organizational innovation. AI thus becomes a catalyst for productivity growth and structural upgrading, and labor market vulnerability is reduced to minimal levels. This configuration highlights the fact that automation is not inherently disruptive, but can generate positive outcomes in the presence of favorable systemic conditions.

Finally, the fourth configuration, technological stagnation, occurs in contexts with low exposure to AI, but also with low levels of skill elasticity and limited institutional capacity. Although, in the short term, these economies may appear to be protected from the risks of automation, the absence of technological adaptation generates latent vulnerabilities, manifested in the loss of competitiveness and structural blockages. In this case, the vulnerability does not derive from an excess of change, but from its insufficiency, suggesting that the lack of adoption of technology can be as problematic as uncontrolled adoption.

Overall, this typology demonstrates that labor market vulnerabilities associated with AI are emergent results of systemic configurations, not direct consequences of technology. The same intensity of exposure to automation can produce divergent outcomes, depending on the adaptive capacity of skills and the robustness of institutions. Therefore, vulnerability analysis must go beyond technological determinism and integrate structural and institutional dimensions, providing a basis for differentiated public policies geared towards managing transitions.

3.2. Emerging risks beyond substitution: work quality, occupational health and algorithmic management

The extension of the TSI model allows the analysis of emerging dimensions of vulnerability that go beyond the occupational substitution paradigm. In the context of AI adoption, labor market transformations are not limited to employment, but significantly affect the quality of work, professional autonomy and occupational health.

A central element in this dynamic is algorithmic management, which uses AI systems to monitor, evaluate and coordinate work. Its integration into the TSI model reveals that high exposure to AI (AE), combined with low skills' elasticity (SE) and limited institutional capacity (IC), can lead to increased digital control and reduced worker autonomy. Thus, vulnerability is no longer just a problem of employment, but also of working conditions and organizational power relations.

In addition, risks related to work intensification and cognitive stress, generated by constant interaction with digital systems and increasing performance demands, are observed. These processes are associated with deterioration in work quality and risks to occupational health, including burnout and occupational anxiety. In the absence of adequate institutional mechanisms, these effects can amplify existing vulnerabilities and generate new forms of inequality.

The extended TSI model suggests that these emerging risks are mediated by the same fundamental dimensions: workers' capacity to adapt (SE) and institutions' capacity to regulate and protect (IC). In this sense, AI governance needs to include not only employment and education policies, but also standards on job quality, algorithmic transparency and occupational health protection.

In conclusion, the extended model confirms that the impact of AI on the labor market is multidimensional, and vulnerability needs to be understood as a complex phenomenon, including both quantitative and qualitative dimensions. This perspective provides a solid analytical basis for integrating AI governance policies with the objectives of social cohesion and sustainable development.

4. Conclusions

The article analyzed the governance of artificial intelligence in Europe from an integrated perspective, connecting national policy frameworks with the dimension of implementation and with innovation and labor market outcomes. Starting from the premise that AI policies do not produce effects directly, but through institutional architectures and policy mixes, the analysis highlighted the importance of aligning strategic discourse, implementation capacity and economic context.

The first major contribution of the article is to demonstrate that policy frames are not simple discursive constructs, but structures that concretely influence the selection of instruments and development trajectories. In the European space, a persistent tension has been highlighted between frameworks oriented towards competitiveness and innovation, those focused on risk governance and the protection of fundamental rights, and those focused on capacity development. This plurality of frameworks generates significant variations between Member States, both in terms of strategic priorities and the efficiency of implementation.

The second contribution was to highlight the implementation gap, confirming that the existence of national strategies does not guarantee results in innovation or economic transformation. The analysis showed that performance critically depends on the coherence of policy mixes, inter-institutional coordination and administrative capacity. In the absence of these conditions, strategies remain declarative, and their impact is limited.

A third important contribution is the introduction of the Task–Skill–Institution (TSI) model, which provides a conceptual framework for understanding the labor market vulnerabilities generated by AI-based automation. The model demonstrates that these vulnerabilities are not determined exclusively by exposure to technology, but by the interaction between task structure, skill dynamics and institutional capacity. The resulting typology highlights the existence of divergent trajectories — from structural vulnerability traps to adaptive transformation scenarios — suggesting that the effects of AI are deeply context-dependent.

Extending the analysis to dimensions such as job quality, occupational health and algorithmic management showed that the impact of AI goes beyond employment and includes transformations of employment relations and working conditions. These results indicate the need for a broader approach to AI governance, integrating not only economic objectives but also social and ethical dimensions.

From a public policy perspective, the results of the article suggest that effective AI governance in Europe needs to be based on three complementary strategic directions. First, institutional capacity needs to be strengthened, by developing coordination and implementation mechanisms. Second, policies need to support skills adaptation, by investing in lifelong learning and deskilling programs. Third, it is essential to ensure coherence in policy mixes, so that regulatory, innovation and social protection instruments work in a complementary manner.

Theoretically, the article contributes to the literature on governance of emerging technologies by integrating perspectives on policy frameworks, implementation and labor market in a unified analytical framework. Methodologically, the combined use of framework analysis and structural topic modeling provides a replica approach for the comparative analysis of national strategies. Empirically, the results highlight significant relationships between discursive orientations, implementation tools and innovation performance.

In conclusion, the governance of artificial intelligence in Europe cannot be understood as an exclusively technological or normative process, but as a complex process of systemic coordination, in which outcomes depend on the alignment of ideas, institutions and capacities. In this context, the success of AI policies is not determined only by their formal design, but by the capacity of states to translate strategy into action and to manage the economic and social transitions generated by technological change.

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