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Récits politiques et réglementaires de l'intelligence artificielle : une étude comparative

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Résumé :

Bien que les impacts de l'intelligence artificielle (IA) sur le marché, l'économie ou les clients soient souvent étudiés, on ne sait que peu de choses sur la manière dont les gouvernements soutiennent l'utilisation de l'IA par le biais de discours politiques et réglementaires. Cette recherche s'appuie sur une analyse textuelle de 936 politiques d'IA, mises en œuvre dans 70 pays/régions, pour en étudier les stratégies d'IA. L'analyse textuelle computationnelle menée a permis d'identifier trois dimensions discursives de l'IA, et de conceptualiser trois orientations stratégiques symboliques. Nos résultats contribuent à une meilleure évaluation des différentes approches gouvernementales en matière de gouvernance de l'IA. Cette recherche contribue enfin à une meilleure compréhension de la manière dont les gouvernements définissent leur orientation technologique et stratégique, offrant ainsi des perspectives importantes aux domaines des systèmes d'information et de l'administration.

Mots-clés :

Intelligence artificielle ; Analyse textuelle computationnelle ; Politique industrielle ; Symbole ; Orientation stratégique

Policy and Regulation Narratives of Artificial Intelligence: A Comparative Study

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Abstract:

Although the impacts of artificial intelligence (AI) on the market, the economy, or customers are often studied, little is known about how governments support the use of AI through policy and regulation narratives. We undertake a textual analysis of 936 national and regional AI policies implemented in 70 countries/regions and focus on AI strategies. Computational text analyses led to the identification of three dimensions of AI government discourses and enabled us to conceptualize three symbolic strategic orientations. These results contribute to a better assessment of the different government approaches to AI governance. This research also contributes to a better understanding of how governments frame their technological and strategic orientations, offering important insights to both the information systems and administration fields.

Keywords:

Artificial Intelligence; Computational Text Analysis; Industrial Policy; Symbol; Strategic Orientation

I. Introduction

Process automation, cognitive insight and cognitive engagement enabled by generative AI are growing in organizations (Gruetzemacher et al., 2021; Vassilakopoulou et al., 2023). Although AI has well-documented impacts on productivity in private organizations, its adoption in public administrations varies depending on national technological and regulatory readiness (Duan et al., 2019; Rondeau et al., 2005). Recently, the rise of generative AI has further intensified governmental debates, leading to new regulatory frameworks and strategic adjustments. However, our study examines AI policies at a broader level, encompassing diverse applications beyond generative AI. Understanding the conditions that enable the widespread adoption and development of AI across different national contexts (Rahrovani et al., 2014) remains a critical area of research.

Despite the growing body of research on AI governance, limited attention has been given to how governments articulate and frame their AI policies through strategic narratives. Existing studies have largely focused on regulatory mechanisms and economic impacts (Wamba et al., 2021; Vassilakopoulou et al., 2023), yet the symbolic and discursive dimensions of AI policy-making remain underexplored, with even scarcer literature on IS support in the context of public administrations and public policy (Fagnot et al., 2018; Attour et al., 2021). This study addresses this gap by examining how governments construct policy narratives to signal their strategic orientations toward AI, thereby shaping both domestic governance and international positioning. To address this gap, our study seeks to answer the following research question: *How do governments support the use of AI through policy and regulation narratives?* By analyzing national and regional AI policies, we aim to uncover the underlying dimensions of governmental AI discourse and their implications for policy design and implementation.

Given the need to document and explore the symbolic significance of “*poorly regulated, poorly understood, and yet highly idealized trends such as AI*” (Martineau and Tsoni, 2019, p.109), in this paper, we investigate the discursive and symbolic dimensions of AI policies and the strategic orientations targeted by OECD

countries (Organisation for Economic Co-operation and Development). Our database consists of 936 national and regional AI policies from 70 countries/regions that have been implemented by OECD member and partner countries up to May 2024. The information is available at the project level, with a description of the project, and can be filtered depending on the target groups and policy instruments or by theme. We first undertake a computational text analysis of the corpus to uncover underlying patterns and textual dimensions (Yoon et al., 2014; De Miranda Santos et al., 2006). This first set of results allows us to identify three dimensions in government discourses regarding AI policies. We then categorized countries based on their use of policy instruments to support and control AI developments: how they framed their technological implementation, the nature of the policies implemented, and the theme of the policies. The results enable us to identify categories of countries based on their role in the governance of AI and their signaled symbolic strategic orientations.

Our contributions are of interest to information systems management scholars. First, we are among the first studies to compare country-level policies (Gruetzemacher et al., 2021; Wamba et al., 2021) and to document the strategic orientations of public administrations (Attour et al., 2021; Fagnot et al., 2018). Second, our findings contribute to refining our understanding of how the government influences the development of innovations such as generative AI (Yang and Huang, 2022; Zhang et al., 2022; Rowe et al., 2020). Finally, we contribute to a growing strand of research in IS that explores the symbols related to technologies (Dudézert et al., 2019; Martineau & Tsoni, 2019).

The remainder of the article is organized as follows. The next section presents the literature review. The subsequent section introduces the dataset and the methodology. The results are then presented and discussed. A conclusion follows.

II. Literature review

2.1. Activities of governments in promoting AI and their strategic orientation

The sparse literature on information systems has focused on how governments manage and promote technological change. Research has focused on how governments promote temporary e-gov technologies and processes in crisis contexts (Adrot and Figueiredo, 2013; Mani et al., 2023), how governments adopt new technologies (Saint Amant, 2005; Caron-Fasan and Lesca, 2012), and how local public entities appropriate technological innovations and processes (Fautrero et al., 2021). However, the extent to which governments frame, through regulations, their support for the development of technologies such as AI in society is still understudied (Duan et al., 2019; Väyrynen et al., 2022); we lack research on initial conditions that lead to the widespread use of technological innovations (Rahrovani et al., 2014). In the literature on industrial and innovation policies, there are traditionally three types of government activities related to technological innovations such as AI. The first activity is *supervision*: governments do not intervene (or no longer intervene) in industrial policy but assess, control and intervene in the case of potential market failure, while sensing new regulatory opportunities (Bove, 2020; Buchanan, 2003). This supervision activity is reflected in the IS literature, particularly in Godé's (2008) work on coordinating ICT for welfare, which emphasizes supervision and standardization over other forms of coordination in the context of specific e-government practices. The second activity, *planning*, involves direct and continuous organization and control of industrial production; governments often own companies, create barriers to entry, and select the industries to be protected. This activity is particularly important in developing economies, where the visible hand of the state can have an impact on industrialization and technological change (Amsden, 2003; Cheung, 2022). In their account of the preadoption of strategic scanning information systems, Lesca et al. (2015) emphasized the impact of inconsistent planning for technological change: initially, the French government adopted planning activities, prioritizing and protecting local industries with respect to greenhouse gas emitted to manufacture and transport products to France; however, the French government's subsequent move toward supervision activity led to implementation struggles due to unstable coercive pressures and unclear regulatory incentives

(p.34). Finally, the last activity is *facilitation*, which aims to create favorable tax conditions or subsidize innovative industries that are close to the technological frontier in a proactive manner (Farmer et al., 2021; Krugman, 1980). Facilitation may involve creating a nurturing business environment, network connections between firms or between firms and universities, and interactions between producers and consumers. In the context of IS implementation with local government entities, Fautrero et al. (2021) demonstrated that urban living labs may be instances of facilitation: establishing connections between stakeholders, facilitating innovation, and encouraging sociotechnical integration. Governments can undertake multiple activities at the same time or sequentially, depending on the implemented instrument policy. However, beyond activities, governments develop strategic orientations toward AI.

There have been countless strategic orientation frameworks published in academia and practice throughout the years. However, Miles and Snow's framework (1978; 2003) has been identified as best suited and adapted to public organizations (Bryson et al., 2008; Walker, 2013). Miles and Snow argue that an organization's success depends on external (environment) and internal (strategy, structure, and ideology) processes. Many researchers have investigated this typology with respect to the specific characteristics of public sector organizations (Meier et al., 2007; Wronka-Pośpiech and Wronka-Pośpiech, 2016; Hawrysz, 2020). There are three efficient strategic orientations (or types of strategies) that public organizations can adopt: Prospectors, Defenders, Analyzers (Walker, 2013). These three strategies, if properly implemented, can lead to effective performance in organizations (Miles et al., 1978; Miles and Snow, 2003; Sabherwal and Chan, 2001). As Walker (2013) stated, these strategy types are "*a summary or shorthand of the ways in which organizations coalign with their environments*" (p.4).

Defenders employ rational processes (Elbanna, 2006): they engage in extensive formal planning, gathering and analyzing substantial data on requirements and citizen needs. They assess various options to address these needs, employing advanced techniques to evaluate the costs and benefits of each choice (Elbanna 2006; Walker, 2013). Moreover, they employ a centralized structure to ensure control over these services

and concentrate on core service goals to sustain their performance. In that context, technologies may be used to reinforce standards and disseminate a culture of datafication (Lepage-Richer and McKelvey, 2022).

Prospectors continually search for market opportunities and regularly experiment with potential responses to emerging environmental trends (Miles et al., 1978; Miles and Snow, 2003; Maury, 2022). They often stress product development, funding, performance measurement and consultation with stakeholders (Aljuhmani et al., 2024). They also adopt flexible and decentralized organizational structures (Bryson et al., 2008), leading to more applied strategies. Such decentralization could lead to public–private partnerships and new forms of cross-functional collaboration (Bodo et al., 2021; Walker, 2013).

Analyzers operate in two types of product market domains, one relatively stable and the other changing (Miles and Snow, 2003: 29); they are also able to adapt their structures to create innovative solutions to public problems. Analyzers balance efficiency and learning and use tight cost control with flexibility and adaptability (Safi et al., 2022). They often efficiently produce stable product lines while maintaining an emphasis on research, creativity and innovative risk-taking (Bryson et al., 2008). They ultimately develop specific policies to control potential market failures, usually resulting in fewer and smaller changes than other organizations do (Tourani, 2022).

Overall, this literature review supports our proposal by highlighting two important issues. First, in line with Vassilakopoulou et al. (2023), we argue that the influence of governments on AI development has been overlooked in IS research, despite current and numerous government interventions (i.e., planning, supervision, and facilitation). Second, we argue that a classification approach is best fitted to frame and understand the complex behaviors, activities and strategies enacted by governments.

2.2 Discourses and symbols of strategic orientations toward AI

In their AI policies, some governments may adopt discourses that focus on controlling the use of AI in society, whereas others might be more focused on the funding and development of AI by facilitating or directly planning its development. The creation of agencies or authorities participates in the institutional

tales of AI. Halaweh (2018) highlighted the first initiative, coming from the UAE, to appoint a state minister for AI. As the country was embracing AI, impacts on society were noted, and the storytelling of new jobs, positive firm development, education improvement and happiness unfolded. The ability of governments to create an accountable environment for the use of AI has been underlined, but it has also raised the question of its performativity (Dumez and Minvielle, 2017). Although there are numerous benefits of AI for governments—AI technologies aid governments in increasing their efficiency, improving the quality of citizen services, and saving government spending (see Mehr, 2017 or Vassilakopoulou et al., 2023, for instance)—it always begins with a discourse that might lead to a change in vocabulary without substantial changes in practices (Dumez and Minvielle, 2017).

The strategic orientations of AI governance are not only shaped by regulatory imperatives but also embedded within broader frameworks of institutional legitimacy and symbolic performativity. Following Dumez and Minvielle (2017), we argue that policy discourses on AI not only describe existing technological strategies but also actively construct and shape governmental positions by signaling priorities, reinforcing state credibility, and aligning national strategies with global technological narratives. Indeed, strategic orientations and public policies toward AI may often exhibit symbolic characteristics, particularly when governments prioritize legitimacy over technical efficiency (Rahrovani et al., 2014). This occurs in contexts where immediate pressures—such as demonstrating global competitiveness, satisfying public expectations, or aligning with international norms—take precedence over the substantive integration or optimization of AI technologies. For example, a government might adopt AI strategies or policies that emphasize ethical AI principles, AI-driven governance, or initiatives such as AI-focused ministries and innovation hubs to signal modernization and technological leadership (Halaweh, 2018). However, these actions may not necessarily translate into meaningful or widespread deployment of AI technologies across public sectors. Instead, they serve to manage stakeholders' impressions—such as citizens, investors, and international bodies—enhancing the government's reputation and legitimacy without necessarily delivering on the promised technical or

efficiency benefits (Dumez and Minvielle, 2017). In such cases, the symbolic adoption of AI policies becomes a performative act aimed at achieving social fitness, conforming to institutional pressures, and ensuring political and economic stability, whereas the actual transformative impacts of AI may remain limited or superficial.

Technological artifacts are not only functional but also deeply embedded in symbolic systems that influence their perception and appropriation (Dudézert et al., 2019). Chapel et al. (2022) demonstrate how digital technologies serve as tools for legitimation in public administration, a perspective that helps contextualize AI discourses as mechanisms for political signaling and governance alignment. Similarly, AI can be formalized as a symbol of a solution, utopia, or threat (Martineau & Tsoni, 2019). Governments that present AI as a solution or a utopia tend to emphasize innovation, economic competitiveness and technological leadership, whereas those viewing AI as a potential threat prioritize regulatory frameworks and sovereignty. Discourses such as AI policies create a narrative of transformation, even when their practical implementation or technical efficacy might be secondary concerns. Just as technological tools can be employed as “totems” to signify collective identity or strategic alignment within organizations (Dudézert et al., 2017), AI policies can operate as markers of strategic vision, legitimizing a government’s position on the international stage and among its constituents.

To deepen our understanding of AI policy and strategic orientation, it is essential to study the narratives that governments construct around AI adoption. These narratives, steeped in symbolic meaning, are not merely rhetorical tools; they actively shape how policies are perceived, enacted, and legitimized. By examining the stories governments tell—about AI’s potential to drive modernization, improve efficiency, or uphold ethical principles—we gain insight into the sociopolitical forces driving these policies and the performative dimensions of their implementation.

III. Data and methods

3.1. Database

The data used for this research come from the OECD AI policy observatory, which was launched in February 2020. A census of policies was undertaken yearly from 2019–2024. Our version results from data collected in May 2024, with policies as the unit of analysis: we aggregated 936 AI policies from 70 different countries (including the two regions that developed transnational capabilities and policies for AI: the African Union and the European Union). Each policy has a description page containing different information on target groups (e.g., SMEs, citizens, and researchers), sectors (e.g., agriculture and energy), policy instruments (e.g., regulation, the creation of a public body, and grants), and themes (e.g., public research, the ethics of emerging technologies, business innovation, and specific objectives). Because countries are free to report the policies and strategies of their choice, there are differences in terms of the years covered by countries, but most of the policies were implemented between 2018 and 2024.

Some projects were only concerned with problem formulation and hence had early end dates (2015–2021), whereas long-term projects targeted 2030. Policies typically spanned approximately 9.3 years on average. Figure 1 provides a better understanding of how the OECD policy posture on AI influences national AI policy development (start date).

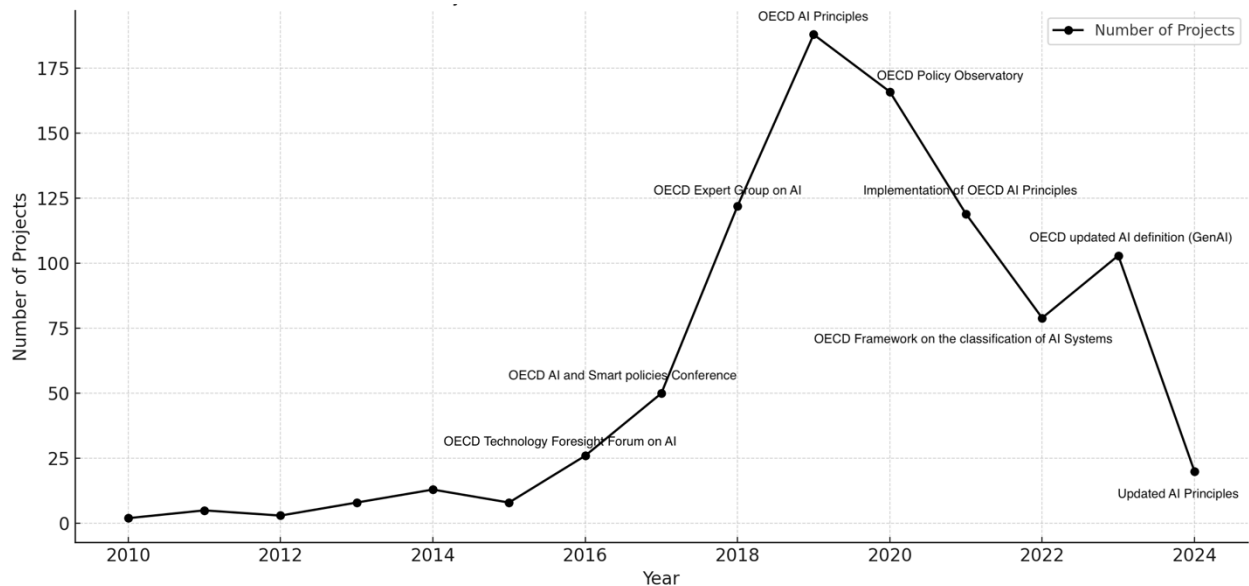


Figure 1: Key events of the OECD and the evolution of national AI policies

The rise in AI policies began after the public gathering of all OECD countries in 2016 and 2017, when the OECD organized public debates on AI (see Figure 1). Debates were supported by analytics and recommendations from the OECD Committee on Digital Economic Policy. The latter provided an overview of major policy considerations that were later implemented by OECD countries¹. In 2018, the OECD established an expert group on AI (AIGO) to scope principles fostering trust in and adoption of AI. This initiative culminated in the adoption of the OECD AI Principles in May 2019, but the groundwork laid in 2018 spurred countries to begin aligning their policies with anticipated international standards². In 2020–2022, several discursive initiatives were launched, and OECD countries were able to compare their AI policies (AI Policy Observatory in 2020; report on the implementation of OECD AI Principles in 2021). The swift development and widespread adoption of generative AI technologies, such as ChatGPT, from 2023–2024 have highlighted both the transformative potential and the associated risks of AI. This has prompted the OECD to revise its definition (2023) and principles (2024) to incentivize governments to prioritize the establishment of robust, ethical, and inclusive AI policies to harness benefits while mitigating challenges such as disinformation and bias. Figure 1 underscores the symbolic power of international consensus and collective action. By participating in the OECD census and recording their AI policies, member countries signaled their alignment with key OECD events. Public debates, public analytics, and public reports served not only as platforms for knowledge exchange but also as mechanisms for constructing a shared narrative around AI as a driver of economic and social progress. This highlights how international forums can act as symbolic stages that amplify the perceived importance and credibility of AI-related initiatives.

3.2. Methods

3.2.1. Cleaning and preprocessing the corpus

¹ See for instance: <https://oecd.ai/en/assets/files/OECD-LEGAL-0449-en.pdf>

² See: <https://oecd.ai/en/about/background>

Computational text analysis has become increasingly popular in management research and is used to study content or sentiment in large text-based datasets (Yoon et al., 2014). Computational text analysis is particularly useful for uncovering patterns in a text dataset (De Miranda Santos et al., 2006). We used Wordstat 2023.2 and Orange Data Mining 3.37 for preprocessing and natural language processing. The database from the OECD AI policy observatory (936 policies from 70 countries/regions) constitutes our corpus. We selected a subset that contains text: descriptions of projects, objectives, and background details (when available). This corpus is composed of 936 records (i.e., lines in an Excel spreadsheet). We preprocessed the text, removing stop words, special characters, punctuation, accents, and URLs; we also undertook standard normalization of words to split the corpus into smaller units (Jurafsky and Martin, 2000). The final corpus included 331,533 words.

3.2.2. Descriptive analysis

We adopted an open approach to this corpus, as our goal was to uncover its underlying textual dimensions. To achieve this goal, we first employed an unsupervised approach to topic modeling, specifically latent semantic indexing (LSI) (Papadimitriou et al., 2000). LSI goes beyond basic lexical matching methods by capturing synonymy and polysemy within a corpus. For example, in our analysis, terms such as “digital transformation” were treated synonymously with “technological transformation,” “data-based transformation,” and “IT-enabled transformation.” This capability allowed us to investigate the conceptual meaning embedded in the records rather than relying solely on surface-level lexical matches. To complement the insights gained from LSI, we incorporated latent Dirichlet allocation (LDA), a probabilistic method that provides a flexible perspective on the corpus by identifying latent topics within the text (Blei et al., 2023). Unlike LSI, which emphasizes semantic relationships, LDA models the corpus probabilistically, identifying underlying themes as distributions of words over topics and topics over documents. This combination of LSI and LDA offered a dual perspective: LSI revealed conceptual associations, whereas LDA revealed thematic structures, providing a more nuanced understanding of the textual dimensions.

However, we encountered a fundamental challenge with this dataset: its asymmetry. Some countries provided extensive descriptions of their policies, whereas others offered only minimal details. This imbalance could lead to overemphasis on frequency and document length, biasing the results if we relied solely on LSI and/or LDA. To address this issue, we turned to the Sorensen similarity index (Jimenez et al., 2016) to explore topics discussed in AI policies. The Sorensen index allowed us to balance the analysis by focusing on shared textual content, regardless of document size. Unlike methods that heavily weigh frequency or volume, the Sorensen index emphasizes commonalities over absolute differences, ensuring that shorter records are not undervalued in the analysis. This was particularly critical in harmonizing the insights from asymmetric data, as it enabled us to capture thematic overlaps and conceptual connections across the corpus, even when textual volume varied significantly. Then, further analyses were performed through multidimensional scaling (Cox and Cox, 2008). Our approach allowed us to emphasize strong thematic relationships and cooccurrences of policy instruments across countries, which might otherwise have been masked by differences in scale. Figure 4 (dimensions of AI) was constructed from these results; see also Figure A1 and Table A1 in the Appendix. We also used the Silhouette score (Shahapure and Nicholas, 2020) to provide a measure of cluster separation (see Appendix, Table A2): the average Silhouette score was 0.65 (precisely, 0.82 for Dimension 1; 0.57 for Dimension 2; 0.60 for Dimension 3). We also compared our results with the Jaccard similarity index (see Figure A2 in the appendix); although both the Sorensen and Jaccard indices are similarity measures, the latter measures the proportion of shared elements relative to all the elements in either set. The Jaccard index was less adapted than the Sorensen index in our case, as the relative size of the union matters less than the overlap (Jimenez et al., 2016). However, it provided a complementary assessment that cross-verified our results, as both figures (Figure A2 in the Appendix for Jaccard and Figure 4 for Sorensen) are consistent.

Hierarchical clustering approaches were considered alternatives; however, they were ultimately deemed less suitable for this analysis. Hierarchical clustering, although effective for organizing data into nested groups,

lacks the ability to integrate semantic nuances and capture the fine-grained relationships present in our policy data. Specifically, hierarchical clustering relies on predefined distance metrics and rigid tree structures, which can oversimplify complex relationships between countries' policy instruments. In contrast, the Sorensen similarity index allowed us to highlight shared conceptual overlaps without overemphasizing document length or frequency disparities. Moreover, the hierarchical approach is highly sensitive to dataset asymmetries, such as countries with significantly longer policy descriptions than those with minimal descriptions. This could lead to biased clusters dominated by larger datasets, masking meaningful patterns in smaller datasets. This choice of methodology allowed us to group countries in a way that better aligned with the specific nature of the policy data. These text-mining techniques helped us group topics and make a global assessment of the dataset (descriptive statistics and a global understanding of the topics across the dataset).

3.2.3. Categorizing countries

We adopted a two-step process to categorize countries. First, we explored dimensions related to policy formulations and government discourses on the design of AI policies. To assess AI discourse dimensions, we used the results of the Sorensen similarity index, which defines the affinity for one topic rather than another. This led us to identify several dimensions based on latent topics (see Figure 4).

Second, each project from each government in the corpus was associated with one to ten policy instruments. The latter are government tools used to *implement* what they formulated in their discourses. Policy instruments are the result of government activities and depend on strategic orientation. This enabled us to group countries with similar patterns of policy instruments. We finally undertook a word enrichment analysis based on these categories. Through this assessment, we identified groups of countries that were better aligned with one strategic orientation from Miles and Snow (1978; 2003): words such as “planning”, “plan”, and “agenda” are much more significant in subcorpus 1 than in the two other subcorpuses. We also searched each subcorpus to improve our interpretation of the results and verify that our typology was aligned. This process led us to formalize Table 5 in the Discussion.

3.2.4. Word enrichment analysis

For each subdataset, such as a group related to the patterns of policy instruments used, we explored associated words. We researched a list of words with lower p values for the selected category than for the entire corpus (Jurafsky and Martin, 2000; Wang et al., 2015). A lower p value indicates a greater likelihood of the word being significant for the category, i.e., not randomly occurring in a section of text. We selected only words with a p value of 0.01, which is in line with experts' guidelines (Manning and Schütze, 1999). To ensure semantic validity, we also undertook manual reviews to judge whether the computational outcomes adequately represented the subdataset, following Jurafsky and Martin's (2000) recommendations; indeed, manual examination to ensure that topics make sense and to confirm meaning is considered a good practice in assessing the validity of findings from computational methods (Manning and Schütze, 1999).

3.2.5. Design choices and the validity of computational text analysis

Applying computational text analysis involves multiple design choices that may have an impact on the validity, generalizability, and reliability of the study. Building on Günther and Joshi's (2020) suggestions, we acknowledge the following four principles:

- *Choice*: We adopted an inductive approach, focusing on uncovering underlying textual dimensions rather than imposing rigid frameworks or assumptions.
- *Reliability and generalizability*: We selected the Sorensen similarity index for its relevance to our dataset (Geva et al., 2019). Additionally, we conducted a sample qualitative review of short and long documents to validate that underrepresented countries were not disproportionately clustered. The impact of this corpus imbalance on the results is further discussed in the Discussion section. Moreover, we were transparent about context-specific adjustment (i.e., the way in which we undertook preprocessing, analysis, and word enrichment) to allow other researchers to assess the applicability and relevance of our findings (Shadish et al., 2002). We checked the consistency of our measure with the Jaccard index (see Figure A4 in the Appendix), provided a visual representation of the relationships between topics (see the intertopic distance map, Figure A1 and Table A1 in the Appendix) and verified the Silhouette scores (see Table A2 in the Appendix).

- *Internal validity:* We manually validated the topic modeling output to ensure greater internal validity (Huang et al., 2018). Indeed, topic modeling can occasionally produce results that lack semantic coherence or align poorly with the research context. By incorporating manual validation, we aimed to mitigate these challenges and ensure that the topics identified were both meaningful and accurate representations of the underlying corpus. We reviewed the top-ranking terms identified for each topic (semantic coherence). To validate the relevance of the identified topics, we cross-checked them against the original records that were strongly associated with each topic: the empirical section below showcased several examples of this process, providing descriptions of policies related to each orientation. Once validated, we revised the topic labels to more accurately reflect their content and meaning. This step ensured that the topics were not just abstract collections of words but also interpretable themes that could guide subsequent analysis. By addressing potential inaccuracies or misalignments in the unsupervised output, we strengthened the credibility of the findings and reinforced both the interpretability and relevance of our results.
- *External validity:* We compared the model output with external data that were not part of the sampled data, as recommended by Bao and Datta (2014). For example, we contrasted our categories of countries with categories of countries related to their GDPs' effects on R&D and innovation spending and external research on AI, such as the Oxford AI Readiness index.³ We reviewed the OECD website and resources on AI policies to reinforce our assessment of the corpus (see Figure 1 for example), particularly on events that may influence discourses related to AI. We also investigated whether the topics uncovered in our analysis were mentioned in the 440 responses to the EU Consultation on Artificial Intelligence dataset and confirmed that our topic model uncovered topics in line with management and industry trends.

IV. Results

³ <https://www.oxfordinsights.com/government-ai-readiness-index/>

The results are divided into two parts. In the first subsection, we present our descriptive analysis and the results from our similarity indexing to assess government discourses toward their own strategic orientation. In the second subsection, we categorize countries based on the word enrichment analysis to characterize the AI dimensions and government interventions in AI policy.

4.1. Exploration of the topics in the corpus

Here, we focus on the topics of the whole corpus of policies to detect variations in the policies advanced by countries. As stated before, in terms of project distribution over time, most AI projects were undertaken between 2018 and 2024. While exploring our corpus, we observed the symbolic role played by AI (supporting national strategies) and policy instruments (supporting AI) and some of the most common objectives of projects undertaken by public bodies. For example, the expression “Invest in AI” (Invest+AI), which appears 324 times in the corpus, was assessed in relation to countries (see Figure 2). In addition to being cited in the description of policies in the corpus, this expression is embedded in the dataset in multiple nominal categories of OECD projects (“OECD AI Principle Addressed” but also “Policy Instrument” and whether there was “Funding for Private Sector”) and appeared in the “Budget Expenditure” sections related to each project of the dataset. In fact, investment communicates more than just the allocation of resources: it reflects a strategic commitment. Among these investment initiatives, most relate to governments’ initiatives (e.g., Bulgaria’s GATE for smart cities, launched in 2019; or Canada’s directive on automated decision-making, which was one of the pioneering policies in 2016 to focus on AI investment for the public sector), followed by industry (e.g., Turkey’s Artificial Intelligence Ecosystem Call 2023, launched in 2022, intended to support industry collaboration) and education (e.g., Netherland’s National Education Lab AI, founded in 2022, aimed at improving the quality of primary and secondary education). Figure 3 depicts the evolution of policies related to AI investment over time.

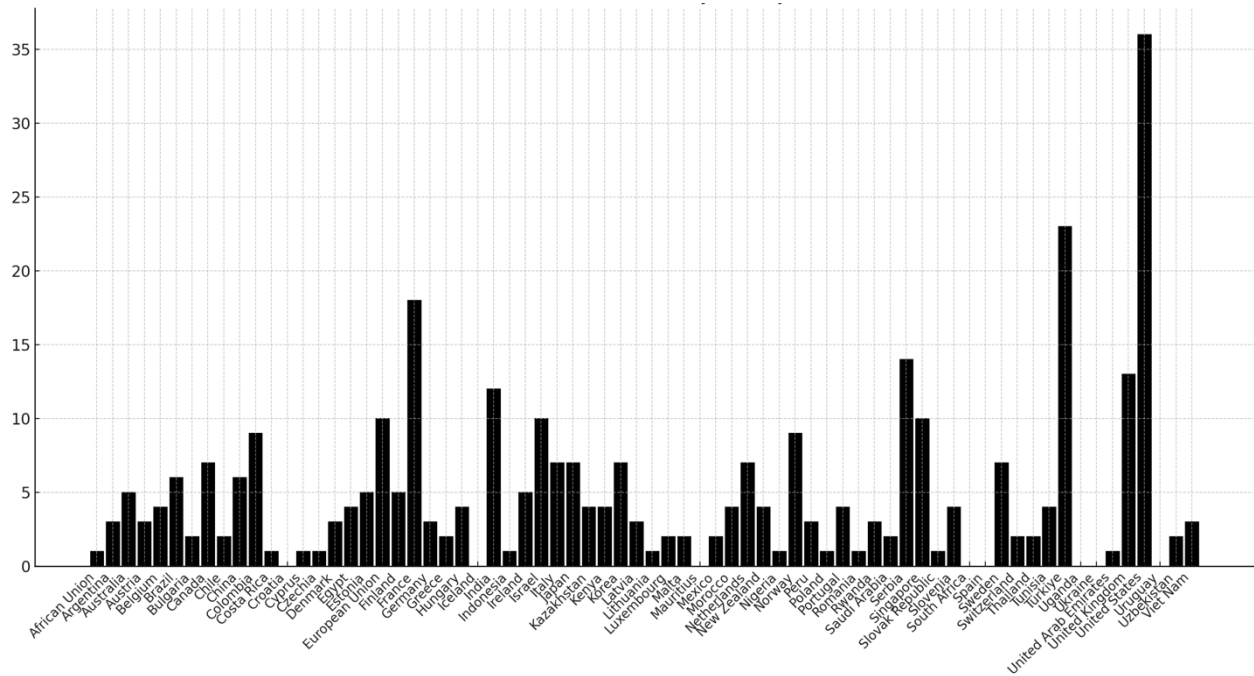


Figure 2: Frequencies of the expression “Invest in AI” mentioned in countries’ AI policies

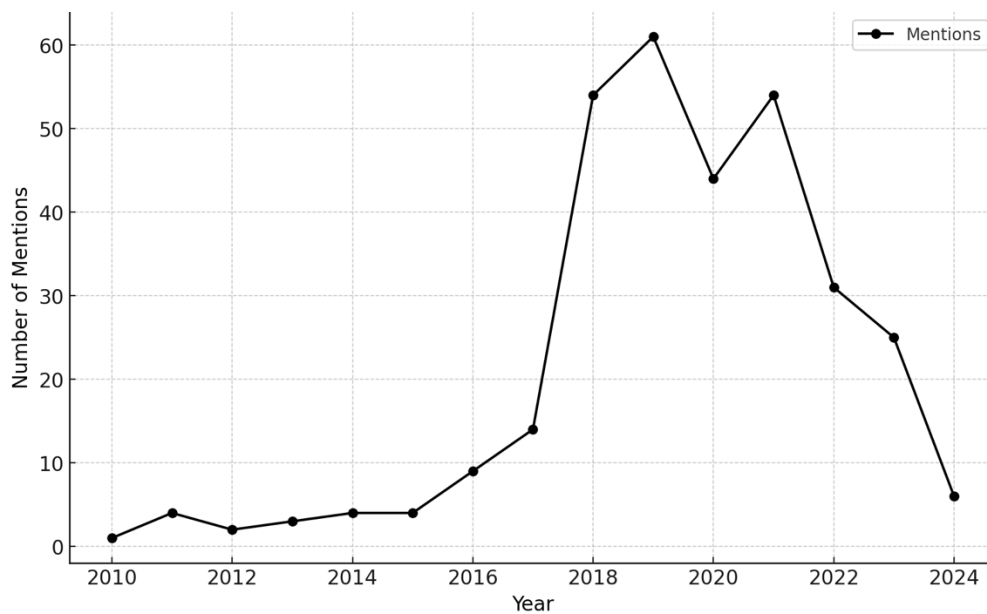


Figure 3: Mentions of the expression “invest in AI” over time in policies

A noticeable increase in mentions occurred from 2016–2017, suggesting the beginning of heightened awareness and commitment to AI-related policies (following OECD events and joint initiatives; see also Figure

1). In 2018–2019, the sharp rise in mentions of investment in AI policies reflects a global consensus on the importance of investing in AI among OECD countries, driven by both economic competition and the transformative potential of AI across sectors (public sector, industry, education).

Figure 4 shows the outcome of our exploratory analysis, categorizing dimensions related to policy formulations: government discourses on the design of AI policies.

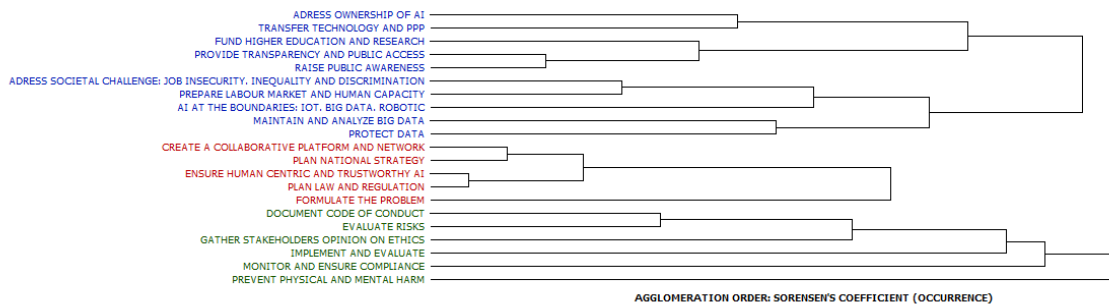


Figure 4: Dimensions of AI (red: Dimension 1; green: Dimension 2; blue: Dimension 3)

Dimension 1: signaling strategic focus and collaboration. This cluster includes topics related to strategic planning processes, a cornerstone for ensuring that AI technologies align with societal values and goals. It emphasizes discourses on developing cooperative frameworks, formulating legal strategies, and ensuring that human-centric values are maintained within AI policies. There is a strong emphasis on collaboration, both at the institutional and policy-making levels, to address AI’s challenges. Topics in this cluster position governments as strategic planners and builders. The discussed regulatory frameworks require both the involvement of stakeholders and signaling the construction of a trustworthy AI ecosystem.

Dimension 2: signaling ethics, compliance, and risk management. This cluster highlights discourses set to codify ethical AI use, assess associated risks, and enforce compliance mechanisms to safeguard societal and individual well-being. Ethical concerns and risk management are paramount, reflecting a growing awareness of AI’s potential harms, including biases, mental health impacts, and physical safety risks. The need for robust monitoring and compliance mechanisms indicates that AI deployment requires ongoing vigilance

and accountability. It positions governments as stewards of public interest in the face of technological uncertainty.

Dimension 3: signaling societal impact and emerging technologies. The focus of this cluster is on addressing societal challenges, signaling transparency in AI operations, and managing emerging technological intersections such as the IoT and robotics. Topics in this cluster reflect a forward-looking stance, with narratives on addressing societal challenges (e.g., ownership, inequality, and public awareness). There is clear recognition of the technological convergence between AI and other domains, such as the IoT, robotics, and big data. Transparency and accessibility are recurring themes, suggesting a need to bridge the gap between technological advancements and public trust. This aligns with the narrative of governments as enablers of transformative yet responsible innovation.

Figure 4 offers insights into how countries framed their AI projects over time, simultaneously addressing core project management constructs (discourses related to planning and design in Dimension 1; building and implementing in Dimension 2; and maintaining AI programs in Dimension 3) but also addressing several critical problems with AI programs (with topics such as law and regulations in Dimension 1; ethical evaluation in Dimension 2; and transparency and discrimination in Dimension 3) and milestones related to collaboration (creating collaboration platforms in Dimension 1; gathering expert and stakeholder opinions in Dimension 2; and addressing public opinion and awareness in Dimension 3). Figure 4 presents an exploratory mapping of the dominant discursive dimensions in AI policies. These dimensions emerge from a computational analysis of the whole corpus and serve as an initial context for understanding how AI is framed in government policies. The connection between these discursive dimensions and symbolic strategic orientations is explored in Section 4.1.2, where we analyze how governments articulate specific AI policy narratives to construct national strategies and regulatory stances.

4.2. Policy discourses and symbols by countryThe categorization was based on the way in which countries framed their policy instrument strategies (see methodology), which led us to identify three groups

of countries (see Figure 5 below). Countries were regrouped based on similar strategies adopted in terms of policy instrument allocations.

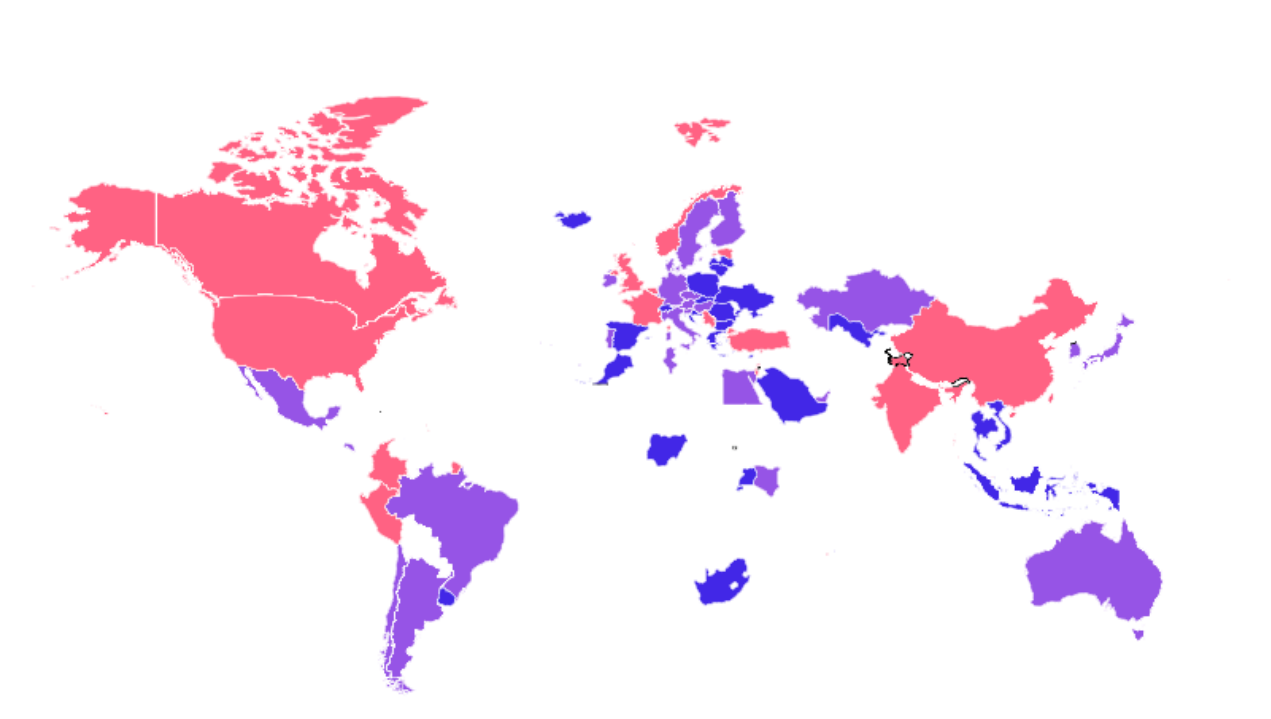


Figure 5: Policy discourses and symbols by country, based on policy instrument allocations
(Defender in blue; Prospector in purple; Analyzer in pink)

4.2.1. Defenders

The first group is composed of countries with policy discourses that align particularly well with the Defender strategic orientation. It is composed of 27 countries (and regions): the African Union, Bulgaria, Croatia, Cyprus, Greece, Iceland, Indonesia, Latvia, Lithuania, Luxembourg, Mauritius, Morocco, Nigeria, Poland, Romania, Rwanda, Saudi Arabia, the Slovak Republic, South Africa, Spain, Switzerland, Thailand, Uganda, Ukraine, Uruguay, Uzbekistan, and Viet Nam. The most representative words for this group are presented in Table 2.

This group consists of countries that emphasize centralized planning and regulatory stability in AI governance. These governments construct AI as a symbol of national sovereignty and regulatory control (in the form of institutional legitimacy). By structuring AI policies around legal frameworks, standards, and oversight mechanisms, Defender-oriented governments signal their role as custodians of stability and standardization. The performativity of AI policy in this group lies in its proactive assertion of regulatory power: policies are not just descriptive but actively shape the AI governance landscape by framing AI as a technology that must be controlled and integrated within national legal frameworks. For example, Saudi Arabia’s Vision 2030 program presents AI as a regulated domain that must align with strict government planning. Similarly, Switzerland’s AI initiatives focus on data protection, compliance, and national oversight, reinforcing the idea that AI must be contained within controlled and predictable policy environments.

Most Representative Words for Defenders	Bi-Grams (Most Associated Co-Occurring Words)
Agenda	Plan
Connectivity	Priorities
Development	Lab
Hub	Data
Incubator	Accelerator
Instruct	/ (None)
Plan	Action
Priorities	Strategic
Telecommunications	/ (None)
Transform	Digital

Table 2: Word Enrichment Analysis, Defenders (p < .001 for all bi-grams)

Table 2, which highlights the most representative words for Defenders, shows how these countries prioritize centralized planning, formalized agendas, and structured digital transformation. The use of terms such as “agenda,” “plan,” “lab,” and “hub” reflects a discourse heavily focused on control, strategy, and the creation of national infrastructure. The repetitive use of words related to planning and transformation constructs a narrative of strategic foresight and preparedness.

Policy discourses emphasize the central role played by governments in digitally transforming countries with AI. Indeed, Defender countries pinpointed a top-down and centralized approach to the AI agenda. The Slovak Republic’s “*Action Plan for Digital Transformation*” ended in 2022 and was followed by a 2030 national R&D program, which described in greater detail how the government planned to “*digitally transform the economy [...] strengthen the basis for a digital and data economy*” and “*support [...] digital transformation of firms*”. In Morocco, the Al-Khawarizmi program, created in 2019 and scheduled to end in 2024, was intended to create a hub for “*AI skills that the country needs to develop a prosperous economy based on digital transformation and the knowledge economy*”. In this context, “digital” and “transform” represent the symbolic power of AI as a driver of national change. A similar endeavor was undertaken by South Africa in 2022, with the creation of the Artificial Intelligence Institute of South Africa (*Artificial Intelligence Hub*), “*to mark a new era in the country’s digital transformation agenda.*” Words such as “lab” and “hub” emphasize central nodes of innovation. Digital hubs also relate to the government’s willingness to create a central, single focal point through which all activities and communications pass, enabling centralized control and coordination of activities related to AI.

Projects were described with a focus on formal planning, building on the vocabulary of strategy and program planning; for instance, Lithuania described its “*vision of the future [for 2030]. Lithuania is also ready to move forward with its own strategic plan for the future of artificial intelligence*”. In the case of Bulgaria, the core project is named “*concept for the development of AI in Bulgaria until 2030*” and describes the project origins, objectives and stakes for the country: “*In June 2020, a team of representatives of the Bul-*

garian Academy of Sciences (BAS), together with external experts, developed a draft document on the development of AI in Bulgaria until 2030 called ‘Artificial Intelligence for Smart Growth’. It intends to “*create research, expert, business and management capacity, supporting the coordination of measures and activities set as a priority in relevant national strategic documents; and to provide modern communications and scientific infrastructure for AI development and deployment.*” As a last example, Saudi Arabia’s projects were focused mostly on building a “*Vision for 2030*” or “*setting the strategy for 2030*” and first building the central and government-managed capabilities to set the AI agenda in motion. Such descriptions of AI projects focus less on actions and applied solutions (i.e., data, applications and information systems) and more on centralized frameworks and strategic visions. Thus, countries in this group were more aligned with the Defender strategic orientation. Policy discourses emphasized the focus on the central role played by the government and on formal planning.

4.2.2. Prospectors

The second group is composed of countries with policy discourses that align particularly well with the Prospector strategic orientation. This group is composed of 26 countries: Argentina, Australia, Austria, Brazil, Chile, Costa Rica, Czechia, Denmark, Egypt, Finland, Germany, Hungary, Ireland, Italy, Japan, Kazakhstan, Kenya, Korea, Mexico, the Netherlands, New Zealand, Portugal, Slovenia, Sweden, Tunisia, and the United Arab Emirates. The most representative words for this group are shown in Table 3.

This group consists of countries that prioritize funding initiatives, public–private partnerships, and cross-functional collaborations to support AI and national growth. AI policy in these countries operates as a symbol of economic transformation and technological leadership, aligning with legitimacy through innovation. Governments adopting a Prospector orientation performatively construct AI as an inevitable driver of future prosperity, projecting an image of inevitable AI-driven success and mobilizing stakeholders to align with the government’s vision. Through financial incentives, public–private partnerships, and ecosystem development, these countries position AI as a market enabler rather than a regulatory challenge. This aligns with a utopian framing of AI, where technology is portrayed as a transformative force that governments must

embrace to remain globally competitive. For example, Germany’s AI strategy explicitly integrates AI into industrial growth policies, emphasizing public–private synergies to foster large-scale adoption. Similarly, the Netherlands’ AI vision highlights financial support and collaborative platforms to ensure that AI serves as a pillar of national competitiveness.

Most Representative Words for Prospectors	Bi-Grams (Most Associated Co-Occurring Words)
Alignment	Fund
Business	Angel
Coalition	/ (None)
Collaborative	Platform
Company	/ (None)
Dialog	Social
Fund	Allocate
Partnership	Consortia
Private	Investor
Quantifiable	Target

Table 3: Word Enrichment Analysis, Prospectors ($p < .001$ for all bi-grams)

Table 3 presents terms that reflect a narrative of active exploration and innovation. Terms such as “fund” and “allocate” highlight the strategic emphasis on financial support for AI development, portraying governments as enablers of technological progress, whereas “partnership”, “dialog”, and “coalition” evoke images of interconnected ecosystems where public and private actors collaborate to drive AI innovations. These countries are particularly attentive to building partnerships with industry and the global market, focusing on fostering decentralized innovations via public–private partnerships (PPPs). Our analysis shows that these countries were focused primarily on businesses and that the private sector synonyms identified in the word enrichment analysis included expressions such as “businesses”, “companies”, “suppliers”, and “SMEs”).

Terms such as “platform,” “investor,” and “consortia” signal active engagement with market dynamics. Projects focused on providing “*financial support to business R&D and innovation*” and reinforcing PPPs. For example, several early Danish projects (three in 2018) planned to develop “*public–private partnerships*” and “*public–private collaboration models*”. With PPPs, countries engage in efforts to attract international companies. Similarly, Finland was concerned mainly with “*attract[ing] investments in Finland*” (2018) but highlighted the need to “*ensure top-level expertise and attract top experts*” (2019, 2020). Dialogs and discussions on AI strategies were also enacted with the public and society. Brazil launched several consultation projects (2019, 2022) aimed at setting up a “*dialog with society on AI themes (such as public consultations, audiences, sector meetings and workshops, etc.)*”, such as Mexico’s 2022 project to “*open dialog on AI and its impacts*”.

Collaboration and cross-functional exchanges were also reinforced within Prospector countries, with the creation of coalitions and national collaboration toward large-scale national and regional AI programs. New Zealand’s 2023 “*cross-agency program on AI*”, or Australia’s 2023 “*algorithm research*” scheduled as a cross-functional government project, are examples of initiatives enabling better collaboration and coordination within a country. These countries also declared many AI initiatives over the past five years, with greater focus on funding allocation and how projects were financed. Germany, for instance, boasted a significant number of funding projects (2019, 2021, 2022), aiming to synchronize “*funding strategies and [...] provide a marketplace for ideas and facilitate access to funding opportunities*”. The Netherlands’ vision of generative AI, created in 2024, also intended to provide an “*enabling policy environment for AI*” and “*align with a series of investments worth millions of euros*”.

Finally, projects have adopted a more practical perspective, focusing on measuring and quantifying the implementation of AI, in alignment with the needs of enterprises. Italy’s 2022 “*AI Strategic Program*” sets out to apply “*AI in the private sector*”, with “*quantifiable targets*”. This was at the core of Ireland’s “*Enterprise Digital Advisory Board project*”. Created in 2021, this project draws members from Irish industry to assess the adoption of AI by Irish enterprises and to promote “*an AI program for enterprise of targeted*

funding and advisory measures for AI adoption.” The Egyptian Charter for AI, created in 2023, also considered “*measuring a country’s readiness for AI investment and adoption.*” Policy discourses emphasized measurable, quantifiable and tangible actions, such as funding volume, the number of partnerships formed, and the development of collaborative platforms. By adopting this language, governments performatively demonstrate their active participation in fostering AI ecosystems. Countries in this group were aligned with the Prospector strategic orientation. Although planning activities are also part of their discourse, the focus is primarily on decentralization, cross-functional knowledge exchange (e.g., PPPs, dialogs, collaborations), funding allocation and management, and showcasing a proactive, applied approach to implementation (e.g., measuring, aligning).

4.2.3. Analyzers

The last group is composed of countries with policy discourses that align particularly well with the Analyzer strategic orientation. This group is composed of seventeen countries (and regions): Belgium, Canada, China, Colombia, Estonia, the European Union, France, India, Israel, Malta, Norway, Peru, Serbia, Singapore, Türkiye, the United Kingdom, and the United States. The most representative words for this group are presented in Table 4.

This group consists of countries that adaptively balance AI as both an opportunity and a responsibility. AI policy in these countries functions as a symbol of ethical leadership and adaptive strategy, reflecting a form of legitimacy through governance excellence. Unlike Defender-oriented countries, which emphasize strict control, or Prospector-oriented countries, which stress market potential, Analyzer governments frame AI as a dual phenomenon requiring strategic flexibility. They actively shape AI governance by embedding it in discourses related to ethical, regulatory, and adaptation (internal and external sensing behaviors). AI is a solution that must be carefully managed. For example, Canada’s and France’s AI policies consistently highlight the necessity of ethical AI frameworks and accountability measures, not only as compliance require-

ments but also as symbols of responsible technological stewardship. Similarly, Singapore’s AI Verify initiative reinforces the performative nature of AI regulation by providing a structured assessment model that serves to institutionalize ethical AI practices.

Most Representative Words for Analyzers	Bi-grams (Most Associated Co-Occurring Words)
Accountability	Safety
Audit	/ (None)
Autonomy	Freedom
Community	Peer
Discrimination	Bias
Diversity	Fairness
Performance	Output
Protection	Right
Regulatory	Oversight
Transparency	Robustness

Table 4: Word Enrichment Analysis, Analyzers (p < .001 for all bi-grams)

The key terms in Table 4, such as “accountability,” “audit,” “transparency,” “regulatory,” and “protection,” signal a discourse centered on oversight, adaptability, and responsible governance. Analyzer-oriented language reflects a balanced approach that emphasizes both the control of risks and the exploration of opportunities in AI. This discourse is indicative of a government strategy that is focused on mitigating the potential harms of AI (e.g., biases, discrimination, and misuse) while ensuring that its benefits are realized in a controlled and secure manner.

Countries in this group demonstrated considerable policy diversity and a focus on complexity and multiplicity. They emphasized complexity and requisite variety, enacting a larger scope of policy instruments to

cover the diversity of AI challenges, as well as the advancement of AI initiatives. A 2018 US project highlighted the complexity of the problem scope: *“The goal is to use AI to solve large and complex problem sets that span multiple services, cultivating a leading AI workforce, and leading in military AI ethics and safety”*. Two projects from the EU (2019, 2020) also emphasized *“highly complex technology”* and *“layers of complexity and uncertainty”*: *“the scientific evidence which is called upon to help address such problems is often equally complex and typically contains various kinds and degrees of uncertainty that are inherent to science”*. To address this complexity, countries in this group particularly focus on adapting AI to their local issues. Most pinpointed the importance of national resources and aimed to contribute to global research while aligning regulations with national priorities. For example, India seeks to *“keep in view the social, cultural, economic, legal and religious aspects of our country”*. China has created several projects (one in 2019 and two in 2021) *“to deal with challenges related to AI such as algorithmic discrimination, deep fake, unequal AI operation”*. Some of Serbia’s policies also intended to standardize fairness without discrimination (2019) or using AI to support biodiversity projects (2022). The UK, like the US, launched several initiatives in 2020 and 2022 to encourage *“students from underrepresented groups (women, black, disabled and lower socioeconomic backgrounds)”* to *“diversify the skills pipeline for AI to ensure that the AI workforce is representative of the society it serves”*.

These countries also launched initiatives focused on community building. Belgium emphasized that *“one other important aspect of the Brussels approach to AI is community building. The Region expects to continue building on the success of the Data Science Community, made of AI experts and practitioners.”* The UK underlined its aim to *“collaborate within the AI community”* and to *“work with [...] the data science community, to identify barriers to sharing data”*. Singapore intended to *“foster a community to contribute to the use and development of AI testing frameworks, code base, standards, and best practices”* (2023). Malta’s 2016 and 2023 projects around the community echo labor mobility incentives, as they intend to fast track residence permits for people working in the field of AI: *“it aims to bolster the attractiveness of Malta for non-EU founders, their core employees and immediate family members to relocate to Malta”*.

Finally, countries in this last group undertook audits not only to address the challenges of accountability and responsibility (e.g., liability for unethical and misuse) but also to assess the performance of projects in action. “Accountability,” “audit,” and “regulatory oversight” evoke a narrative of due diligence, positioning governments as guardians of ethical and responsible AI use (Table 4). For example, Singapore created the AI Verify project in 2022 to “*validate AI system developer’s/owner’s claims about the approach, use, and verified performance of their AI systems*”. Both Malta (2018) and the US (2021, 2022) set out audit and certification programs for AI and digital innovations. One US project provides resources on “*auditing, testing and evaluation, bias mitigation, and security*” of AI innovations, whereas another “*requires that all automated employment decision tools undergo a bias audit*”. France (2016), Norway (2022), Peru (2019), and Singapore (2021) have also launched initiatives to increase transparency and track and report on users’ complaints related to AI programs, whether AI-based surveillance in the workplace or consumer-related surveillance. Their discourses are aligned with the Analyzer strategic orientation. The diversity and complexity of topics show their orientation toward adaptation (e.g., fostering autonomy, adapting to local needs) and the sensing behavior enacted to increase their requisite diversity (building a community) or regulatory opportunities (data protection). Moreover, they signaled their control for potential market failure (e.g., audits, performance assessment).

V. Discussion

Our typology provides descriptive and explanatory insights into the dimensions and interrelatedness of AI discursive policies. We characterize the discourses of AI regulation. Our findings indicate that some countries issue policies aimed at addressing existing challenges, indirectly supporting innovation, or regulating the use of AI within their economy.

For our analysis, we adapted the framework of Miles and Snow (1978; 2003) to examine government symbolic strategic orientations. Indeed, public and private organizations differ. Unlike private-sector organizations, governments operate under institutional constraints, political accountability, and diplomatic pressures that influence their strategic positioning. Miles and Snow’s framework provides a useful lens for understanding broad strategic orientations; however, governmental strategies are inherently more fluid and shaped by geopolitical considerations and public policy mandates. Therefore, our adaptation of this framework seeks to identify patterns in government discourse rather than impose rigid classifications. Public organizations face political pressure and mandates rather than competitive pressures, which can lead to a defensive stance toward AI development and limit innovation (Vassilakopoulou et al., 2023). In addition, measuring performance is more challenging for public organizations because of legally binding rules and procedures aimed at ensuring accountability but restricting adaptability (Walker, 2013). Successive policy building over time can also enable public organizations to adopt a loosely coupled approach between actions and discourses (Rahrovani et al., 2014). Despite these challenges, public organizations have unique characteristics, such as extensive time and resource allocation and opportunities for large-scale cross-sectorial collaboration, which can foster AI-based innovation. This includes collaboration within government entities, with private firms and nonprofits, as well as with international organizations and other governments. Table 5 summarizes the findings and our operationalization of symbolic strategic orientations. These categories include activities (e.g., supervision, planning, facilitation) and practices (e.g., public–private partnerships, funding) that are not exclusive to certain strategic orientations (Irùn et al., 2020).

Symbolic Strategic Orientation	Exhibited activities	Desired Characteristics	Symbol
Defender (Elbanna 2006; Walker, 2013)	Planning (organize and control) (Amsden, 2003; Cheung, 2022)	Formal planning of AI; centralized structures.	Custodian of stability and standardization.
Prospector (Al-juhmani et al., 2024;	Facilitation (proactivity), Planning (organize and control)	Proactive and incremental implementation of AI; strong focus on funding AI;	Innovator and pioneer.

Maury, 2022)	(Cheung, 2022; Farmer et al., 2021)	decentralized and cross-functional structures.	
Analyzer (Safi et al., 2022; Bryson et al., 2008)	Facilitation (proactivity), Supervision (sensing) (Bove, 2020; Farmer et al., 2021)	Sensing new trends related to AI; control of AI market failure; adaptative structures.	Adaptive strategist.

Table 5: Symbolic strategic orientations

In terms of symbols, Defenders are custodians of stability and standardization, prioritizing centralized planning, formal control mechanisms, and long-term strategies to ensure consistency, reliability, and security in the adoption and governance of AI technologies. Defenders may intervene to secure the relationship between the government and different AI stakeholders, focusing on planning and securing digital transformation, with a centralized approach (Cheung, 2022). AI is developed in a centralized manner and may be set up to support standardization (Lepage-Richer and McKelvey, 2022).

Prospectors have the opposite orientation, fostering decentralization and distribution of knowledge and valorizing funding in a proactive way to develop a network of collaboration on AI (Maury, 2022; Aljuhmani et al., 2024). Decentralization reinforces modularity, enabling new forms of collaborative production of knowledge (Bodo et al., 2021). Prospectors are innovators and pioneers, actively exploring new opportunities, fostering collaboration, and driving decentralized innovation to position themselves at the forefront of technological advancement.

Finally, Analyzers influence AI stakeholders toward considering advanced issues in AI and control for outliers; they intend to foster adaptation to local issues from a global perspective (Safi et al., 2022; Tourani, 2022). The adaptation of structures, enabled by an ambidextrous approach, reinforces local innovation and collaborative performance (see, for example, Yu et al., 2014). Analyzers are adaptive strategists, balancing stability and innovation by integrating structured oversight with the flexibility to address emerging challenges and local needs.

5.1. Theoretical Contributions

5.1.1. Framing the social, material and symbolic dimensions of AI policies through dialogism

As outlined in the methodology section, our text mining process identified three dimensions of policy formulation (see Figure 4), which enabled us to group countries into three strategic orientations based on how they framed policy instrument discourses for their AI projects. The results further allowed us to identify “stages” of AI policy discourse, reflecting the evolving focus and strategic priorities of governments over time.

In the first stage, government discourses emphasize laying the groundwork for AI initiatives. These efforts include designing industrial AI policies, establishing initial programs, and formulating strategies. At this stage, governments signal the strategic importance of AI by identifying the core competencies necessary to achieve long-term digital goals. The second stage focuses on implementing these strategies. Policies and discourses at this stage discuss the operational activities and challenges related to AI, such as ethics, risks, and compliance. Governments engage in partnerships with technical experts, define operational scenarios, and initiate trials to advance AI programs. This phase represents the transition from strategy formulation to application, with a clear focus on operationalizing plans. In the third stage, the emphasis shifts to advanced issues, such as the standardization, security, and safety of AI and the adaptation, sharing or reuse of AI capabilities. AI policy discourses emphasize proactive approaches to optimize efforts and improve AI programs, with flexible data structures to achieve greater impacts. Strategies and policies signal relationships with partners that are mature and well established; centers of excellence may govern new AI developments and leverage standardization, privacy and security related to particular AI projects. There may still be minor limitations in terms of roadmaps, data capabilities, and technological resources. Nevertheless, countries are signaling that they are coping with these limitations by optimizing their efforts, improving their AI programs, adapting them, and backing them with dedicated programs of investment aimed at enhancing AI’s capabilities while maintaining ongoing endeavors toward digital transformation.

However, government discourses do not follow a linear “maturity stage” model. Most government discourses evolved over time. For example, some governments initiated global agendas in 2018, then applied

these agendas in 2021, and finally outlined the next steps in 2024. Simultaneously, they developed multiple discursive stages for different projects, demonstrating that AI policy formulation is dynamic and nonlinear, reflecting a dialogical process where multiple advancements and competing interests coexist.

Our case shows that most of the governments from our dataset adapt policy formulations dynamically (Rondeau et al., 2005). Hence, these discursive dimensions enact a form of dialogism, a simultaneity of multiple advancements and competing interests (e.g., industry partnership and ownership of AI), with uncertainty, complementarity and dialectics (Morin, 1977). As an example, recent advancements in generative AI have prompted several governments to reassess their regulatory approaches, particularly concerning ethical considerations, misinformation risks, and national competitiveness, and to develop new discourses related to generative AI. However, our analysis focused on overarching discursive policy trends rather than isolating a specific AI subcategory: although some policies in our corpus explicitly reference generative AI, the majority reflect broader AI governance strategies. AI policy formulation involves multiple actors, including governments, industry leaders, academics, and civil society. Each stakeholder is acknowledged from a distinct perspective, which is reflected in government discourses. The coexistence of these perspectives (specific/general, with multiple stakeholders and multiple discourses) results in complex narratives (Martineau and Tsoni, 2019; Morin, 1977), where policy narratives are not static but continuously evolve through interactions between competing priorities, such as economic growth, ethical governance, and societal inclusion. This finding aligns well with recent work on the appropriation of technologies and digital transformation, where the appropriation process is constantly evolving, complex, continuous, and involves multiple interconnected stakeholders (Coron and Richet, 2021).

Complexity in sociotechnical systems emerges from the entanglement of social, symbolic, and material dimensions (Benbya et al., 2020). The complexity of AI policy formulation arises from the entanglement of material (infrastructure, facilities), social (users, citizens), and symbolic components (legitimacy, trustworthiness). The latter influences the perception and appropriation of technological artifacts (Dudézert et al., 2019). AI policy thus serves as an adaptive mechanism, where governments iteratively refine their policy

discourses in response to stakeholder feedback (social), technological advancements (material), and societal shifts (symbolic). This dialogism is maintained through synergy, i.e., the coordination of seemingly contradictory elements such as maturity and immaturity, to achieve mutually beneficial outcomes (Smith and Lewis, 2011). This synergy can be achieved through collaborative actions, such as partnerships, or structural mechanisms, such as task forces and centralized management (Mawadia et al., 2019). However, unlike organizational contexts where dialogical communication is more reciprocal (Mawadia et al., 2019), in this case, the discourse often remains top-down, driven by governmental or institutional priorities. In this context, adaptation is essential, as governments navigate the complexities and paradoxes inherent in policy formulation and implementation. By doing so, governments can align policy discourses with actionable goals, ensuring that AI programs evolve to meet societal and technological demands.

5.1.2. Toward symbolic strategic orientations

In a form of Barnesian performativity, discourses aimed at framing a symbolic strategic orientation can lead to the adoption of new activities and practices (Dumez and Minvielle, 2017). These discourses do not merely describe existing realities but actively shape them, encouraging stakeholders to align their behaviors and decisions with the expectations embedded in these narratives. In the context of AI policy, performativity implies that governmental discourses on AI do not simply reflect preexisting technological strategies; rather, they participate in producing and legitimizing these strategies through symbolic and rhetorical means. As Dumez & Minvielle (2017) argue, policy narratives can create a sense of urgency or inevitability around technological adoption, influencing institutional agendas, investment flows, and regulatory frameworks even before tangible implementations take place. This performative dimension is particularly evident in AI governance, where governments leverage policy discourses to signal strategic intentions and project national leadership and align themselves with international AI development trends. Performativity operates through the institutionalization of AI discourse, where policies, strategies, and advisory committees reinforce the credibility of government actions, even when practical implementations remain uncertain or fragmented. As seen in Chapel et al. (2022), public administrations often employ digital technologies as tools of legitimacy,

where the articulation of AI policies serves as a mechanism for demonstrating governance competence and forward-thinking leadership.

However, these symbolic strategic orientations can also be seen as discursive “illusions”, created and managed to assert and legitimate national policies (Rahrovani et al., 2014; Dudézert and Leidner, 2011). Discourses of strategic orientations formalize AI as a symbolic *solution* by embedding it within narratives of rationality and efficiency. Defenders emphasize AI’s role in centralized planning and standardization, presenting it as a tool for stability and technical mastery (Martineau & Tsoni, 2019). Prospectors frame AI as an enabler of innovation and collaboration, aligning with its formative aspect as an inevitable driver of progress and modernization and rejoining the “digital comes first” paradigm (Baskerville et al., 2020; Rowe et al., 2020). Analyzers balance its quantitative and ethical dimensions, showcasing AI as a rational, pragmatic, adaptive solution for addressing societal and organizational challenges (Martineau & Tsoni, 2019). However, beyond this projection of control and mastery over AI (*AI as a solution*), our findings show that AI appears equally as a *utopic* symbol (see Tables 2, 3, 4): it embodies the vision of a more connected, collaborative, communicative, and “hub” society, aligning with the ideals of a “network society” (Van Dijk, 2020). Its applications often evoke optimism and idealism, portraying AI as a tool for fostering inclusivity, creativity, and participatory engagement across diverse societal domains. By emphasizing its potential to enhance collaboration, empower communities, and democratize access to knowledge and resources, AI reflects the aesthetic and social dimensions of utopia, where technology is seen not only as functional but also as a catalyst for shared progress and collective well-being (Martineau & Tsoni, 2019).

This paper contributes to a strand of research on legitimacy and the construction of symbols in organizations (Chapel et al., 2022; Dudézert et al., 2019). Our case demonstrated that AI was used as a complex “totem” (Dudézert et al., 2017) to signify strategic orientation. It sheds light on this discursive construction in the context of public bodies.

5.2. Theoretical Implications for IS Research

This research replies to a call for more investigations on IS support in the context of public administrations (Attour et al., 2021; Fagnot et al., 2018). We believe that a certain number of academic contributions to the IS literature can be made by analyzing the antecedents of the widespread use of technological innovations (Rahrovani et al., 2014). Indeed, we extend this strand of IS research on the antecedents of technological innovation adoption by demonstrating that AI governance is a matter of not only infrastructure readiness but also discursive construction and symbolic positioning. The way governments frame AI within policy narratives has a direct impact on its adoption and implementation within public institutions.

Our focus on the public sector is also novel in IS research—the latter has traditionally focused on technological adoption and digital transformation in private organizations—as we intended to improve our understanding of how governments design, implement, and legitimize AI policies. In addition, although AI governance is often analyzed from regulatory and compliance perspectives, our findings suggest that symbolic positioning and strategic narratives play key roles in shaping governmental AI strategies. Understanding these narratives can help anticipate potential policy shifts, cross-national AI collaborations, and public–private partnerships. Additionally, our research highlights the performative nature of AI policies, showing that governments do not merely regulate AI but actively construct its role within society. This perspective aligns with the growing body of research on the performativity of digital technologies in IS (Dumez & Minvielle, 2017; Chapel et al., 2022) and opens new avenues for exploring how discourse shapes the adoption and institutionalization of AI technologies.

In this paper, we propose a structured analytical framework for studying AI policies in public administrations based on a strategic classification (Defender, Prospector, Analyzer) from Miles and Snow (1978, 2003). This offers an insightful classification that helps structure governmental approaches to AI regulation, investment, and facilitation. However, unlike traditional applications of this typology, where organizations are assigned a fixed strategy, our findings suggest that governments may adopt complex hybrid strategies or transition between different and multiple orientations over time. These findings could be further explored in future IS research.

5.3. Limitations and areas for future research

As with any work, our findings are subject to a few limitations. Our choice of the Sorensen coefficient was particularly well suited to our corpus and objectives: we aimed to emphasize shared elements and overlaps, placing greater weight on the intersection of sets in the corpus rather than on their differences, to address data asymmetry. Although the application of computational text analysis is increasingly common in innovation management research (Yoon et al., 2014), the approach remains relatively new and can often resemble a “black box,” introducing methodological uncertainties.

These limitations stand in stark contrast to newer approaches in topic modeling that leverage embeddings or neural architecture. Unlike frequency-based measures and traditional topic modeling, neural topic modeling techniques may offer a robust opportunity for further research on the discourse of innovations. We followed Rai’s (2016) observations related to the comparability of measures across observations. To increase the robustness of our approach, we compared the coherence of our results with a similar measure (the Jaccard index). We were also able to manually examine subsets of documents to evaluate the alignment between the similarity index and our assessment. This assessment of textual similarity suggested that the measure was robust in capturing meaningful relationships. However, this approach was feasible only because of the size of our corpus (936 IA policies) and would not have been achievable with a larger corpus.

Another major limitation of our dataset is the fact that the census depends on the willingness of OECD countries to disclose or describe their AI policies. This asymmetry in policy length may lead to an overrepresentation of countries with detailed AI strategies. The dataset was also affected by the withdrawal of the Russian Federation from the OECD AI policy database and the impact of the Ukraine–Russia war on AI investments in Eastern Europe and North Asia in the 2022–2024 period. This influences our results by amplifying the perceived diversity of strategic orientations in countries with detailed AI strategies. This may also influence our understanding of firm-level business policies, management and local IS strategies inherited from national AI initiatives (see Zhang et al., 2022; Yang and Huang, 2022: for instance). To mitigate

this, we cross-validated our clusters using external policy indices and AI development indicators. These comparisons suggest that although some variations in detail persist, the overarching categorization of AI governance strategies remains robust. Future research expanding the scope to underrepresented regions, such as the Russian Federation and North Asia, could further enhance the generalizability of our findings and reinforce the robustness of our contributions.

Although our classification into three strategic orientations (Defender, Prospector, Analyzer) provides a structured analysis of AI policies, several countries exhibit hybrid characteristics that do not fit neatly into these categories. These atypical cases highlight the dynamic and evolving nature of governmental AI strategies, which are influenced by external pressures (international cooperation, technological developments, and economic constraints) and internal factors (institutional structures, political priorities, and technological capabilities). Indeed, some countries adopt a mixed strategy, integrating different elements of Defender, Prospector, and Analyzer orientations based on their national priorities. For instance, Switzerland is associated primarily with a Defender approach, characterized by strong regulation and a commitment to structuring AI development within a robust legal framework. However, recent initiatives, such as funding programs for AI startups and the development of technology hubs (e.g., Swiss AI Lab IDSIA), reflect a Prospector dimension oriented toward innovation and collaboration with the private sector. This duality demonstrates a strategy that is both cautious and proactive, where Switzerland seeks to balance strict regulation with support for innovation. Some countries do not fit neatly into a single category because they are undergoing a transition between different strategic orientations, either due to political changes or a lack of AI policy maturity. Hungary has published ambitious AI policies, adopting rhetoric close to that of Prospectors, yet its implementation capacity remains limited. This gap between discourse and institutional capacity makes it a case where political symbolism may be ahead of actual capabilities. These discrepancies are further explained in the next Section (Practical Contributions), where we compare our results with industry insights, such as the Government AI Readiness (GAR) index.

We also firmly believe that future research could develop this preliminary typology of symbolic strategic orientation through a comparison of the different means of supporting the development of AI, with a focus on a specific regulation, such as the EU AI Act. As it contributes to a better understanding of how governments frame their technological and strategic orientation, we have confidence in the fact that it offers important avenues to both the IS and administration fields. Another possibility for future related research is to assess how AI policies match a country's economic complexity index⁴ (ECI) evolution over time. Indeed, ECI is a key indicator of the prospect of a country's future development and therefore could explain a country's strategic discourse toward disruptive opportunities (Aghion et al., 2017).

5.4. Practical Implications

Symbolic strategic orientations toward AI shape societal expectations and significantly impact businesses and policy-makers, who must balance idealized narratives on AI with practical challenges and governance responsibilities. To assess the performativity of AI policies, we compared our results with industry insights, such as the Government AI Readiness (GAR) index. Almost all countries have a concordance between their readiness for AI and their related political and strategic discourse. Overall, Defender discourses include a mix of emerging markets and moderate performers. The former are countries that are developing AI capabilities with room for improvement. Moderate performers, such as many Eastern European countries, have established but not leader AI infrastructures and capabilities. The Prospector and Analyzer categories are relatively similar in terms of their GAR index scores, each featuring a combination of top performers and emerging markets. Top performers, such as those in the U.S., China, France and Japan, have strong AI infrastructures, advanced education systems, and strong governance systems. The governments' AI strategies in these countries are different from those in other countries with lower GAR scores, demonstrating

⁴ Economic development requires the accumulation of productive knowledge and its use in both more and more complex industries. Harvard Growth Lab's Country Rankings assess the current state of a country's productive knowledge through the economic complexity index (ECI). Countries improve their ECI by increasing the number and complexity of the products they successfully export (source: <https://atlas.hks.harvard.edu/rankings>).

that diverse models of state intervention can effectively shape AI development and governance. For example, China, as an Analyzer, adopts a massive and globalized approach to AI to rapidly scale AI technologies and a broader application of AI across various strategic sectors, with rapid deployment. This is aligned with Zhang et al.'s (2022) and Yang and Huang's (2022) findings on how specific government policies in China influence the decision of Chinese firms to invest in the long run.

Discrepancies highlighted generic performativity (Dumez and Minvielle, 2017): a discourse might lead to a change in vocabulary without substantial changes in practices. These discrepancies are mediated through a process of loose coupling (Orton and Weick, 1990): "technique gets adopted only superficially, in a ritualistic way" (Kislov et al., 2017, p. 1167). In our case, we may see a loose form of coupling between public discourses on AI and effective AI readiness: some countries, such as Hungary or Peru, may have assumed an AI-ready posture consistent with societal pressures to address a complex reality (Wamba et al., 2021; Chandler, 2019) while still adapting their effective response to "digital first" challenges (Baskerville et al., 2020), such as AI. Conversely, a country such as Switzerland has shown a different form of loose coupling between discourses and action, suffering from dampened coordination and a weak relationship between the content of the government vision supporting the development and implementation of AI and the existing digital capacity and infrastructure development.

The symbolic meaning attributed to technologies such as AI is not static but evolves based on the context, users, and the technology's lifecycle. As highlighted in the previous section, when different stakeholders perceive a technology simultaneously as a solution and utopia, the complexity of managing these diverging symbolisms increases dramatically (Martineau and Tsoni, 2019). From a policy-maker perspective, this necessitates tailored strategies that account for localized interpretations, emphasizing the need for discursive approaches and symbol boundaries that adapt to specific citizen groups, professions, or industries.

Moreover, the dynamic and dialectical nature of symbolic meanings underscores the importance of sustained engagement and iterative adjustment (Mawadia et al., 2019). Over time, technologies that initially evoke

resistance or fear may be seen as solutions as users gain familiarity or the organizational context shifts (and vice versa; see, for example, Mani et al., 2023 and Rowe et al., 2020). We recommend that policy-makers integrate mechanisms for continual reassessment and recalibration of symbolic narratives using training, localized advocacy, and iterative design to align perceptions with the local objectives of regional public agencies, local organizations, and citizens.

VI. Conclusion

AI has been recognized as having an impact on innovation, which enhances productivity, reduces public spending, and fosters economic growth. As AI requires large amounts of investment, governments play a key role in its development and adoption (Wamba et al., 2021; Vassilakopoulou et al., 2023). This governmental involvement not only shapes the material aspects of AI development but also influences the symbolic narratives that frame its societal impact and legitimacy. Recognizing this interplay between the symbolic and the material is essential for understanding how AI policies are framed, adopted, and perceived within broader institutional and societal contexts (Martineau & Tsoni, 2019). Exploring the narratives of AI transformation, we described three symbolic strategic orientations (Defender, Prospector, Analyzer) and their symbolic use of AI to build legitimacy and performativity (Chapel et al., 2022; Dumez and Minvielle, 2017). By doing so, this paper replies to a call for more research on IS support in the context of public administrations (Attour et al., 2021; Fagnot et al., 2018) and contributes to the literature on IS by analyzing the antecedents of the widespread use of technological innovations (Rahrovani et al., 2014). In addition to our unique setting (international comparison of many AI national policies and their contents), our research involved exploring how government discourses can shape practices, behaviors, and realities rather than merely describing them.

CRedit author statement

Jean-Loup Richet: Conceptualization, Methodology, Formal analysis, Writing- Original draft preparation, Writing- Reviewing and Editing. **Vincent Dutot:** Conceptualization, Methodology,

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Declaration of use of “Generative Artificial Intelligence” technologies

N/A

VII. References

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APPENDIX

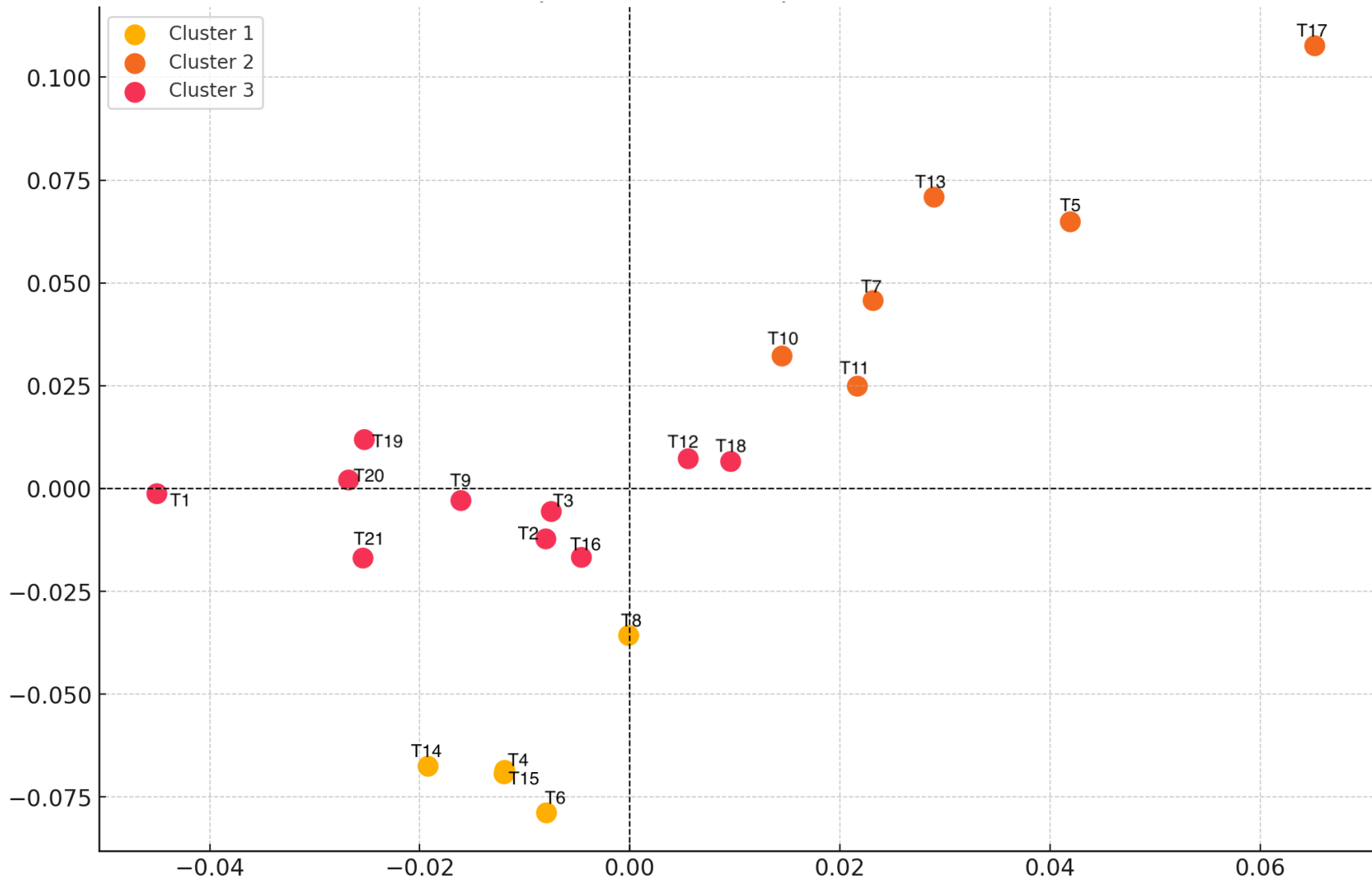


Figure A1: Intertopic Distance Map (Sorensen similarity index)

Shortened Label	Full Topic Name	Cluster
T1	ADDRESS OWNERSHIP OF AI	3
T2	ADDRESS SOCIETAL CHALLENGES: JOB INSECURITY, INEQUALITY AND DISCRIMINATION	3
T3	AI AT THE BOUNDARIES: IOT, BIG DATA, ROBOTICS	3
T4	CREATE A COLLABORATIVE PLATFORM AND NETWORK	1
T5	DOCUMENT CODE OF CONDUCT	2
T6	ENSURE HUMAN-CENTRIC AND TRUSTWORTHY AI	1
T7	EVALUATE RISKS	2
T8	FORMULATE THE PROBLEM	1
T9	FUND HIGHER EDUCATION AND RESEARCH	3
T10	GATHER STAKEHOLDERS' OPINIONS ON ETHICS	2
T11	IMPLEMENT AND EVALUATE	2
T12	MAINTAIN AND ANALYZE BIG DATA	3
T13	MONITOR AND ENSURE COMPLIANCE	2
T14	PLAN LAW AND REGULATION	1
T15	PLAN NATIONAL STRATEGY	1
T16	PREPARE LABOR MARKET AND HUMAN CAPACITY	3
T17	PREVENT PHYSICAL AND MENTAL HARM	2
T18	PROTECT DATA	3
T19	PROVIDE TRANSPARENCY AND PUBLIC ACCESS	3
T20	RAISE PUBLIC AWARENESS	3
T21	TRANSFER TECHNOLOGY AND PPP	3

Table A1: Legend of Figure A1

Topic	Dimension	Silhouette Score
CREATE A COLLABORATIVE PLATFORM AND NETWORK	1	0.899691358
ENSURE HUMAN-CENTRIC AND TRUSTWORTHY AI	1	0.896907216
FORMULATE THE PROBLEM	1	0.518469657
PLAN LAWS AND REGULATIONS	1	0.914814815
PLAN NATIONAL STRATEGY	1	0.899691358
DOCUMENT CODE OF CONDUCT	2	0.761020882
EVALUATE RISKS	2	0.662477558
GATHER STAKEHOLDERS' OPINIONS ON ETHICS	2	0.395683453
IMPLEMENT AND EVALUATE	2	0.278617711
MONITOR AND ENSURE COMPLIANCE	2	0.664105379
PREVENT PHYSICAL AND MENTAL HARM	2	0.686021505
ADDRESS OWNERSHIP OF AI	3	0.692915392
ADDRESS SOCIETAL CHALLENGES: JOB INSECURITY, INEQUALITY AND DISCRIMINATION	3	0.624819625
AI AT THE BOUNDARIES: IOT, BIG DATA, ROBOTICS	3	0.685314685
FUND HIGHER EDUCATION AND RESEARCH	3	0.771352986
MAINTAIN AND ANALYZE BIG DATA	3	0.442080378
PREPARE LABOR MARKET AND HUMAN CAPACITY	3	0.417344173
PROTECT DATA	3	0.41723356
PROVIDE TRANSPARENCY AND PUBLIC ACCESS	3	0.676945668
RAISE PUBLIC AWARENESS	3	0.703703704
TRANSFER TECHNOLOGY AND PPP	3	0.626108999

Table A2: Silhouette Score

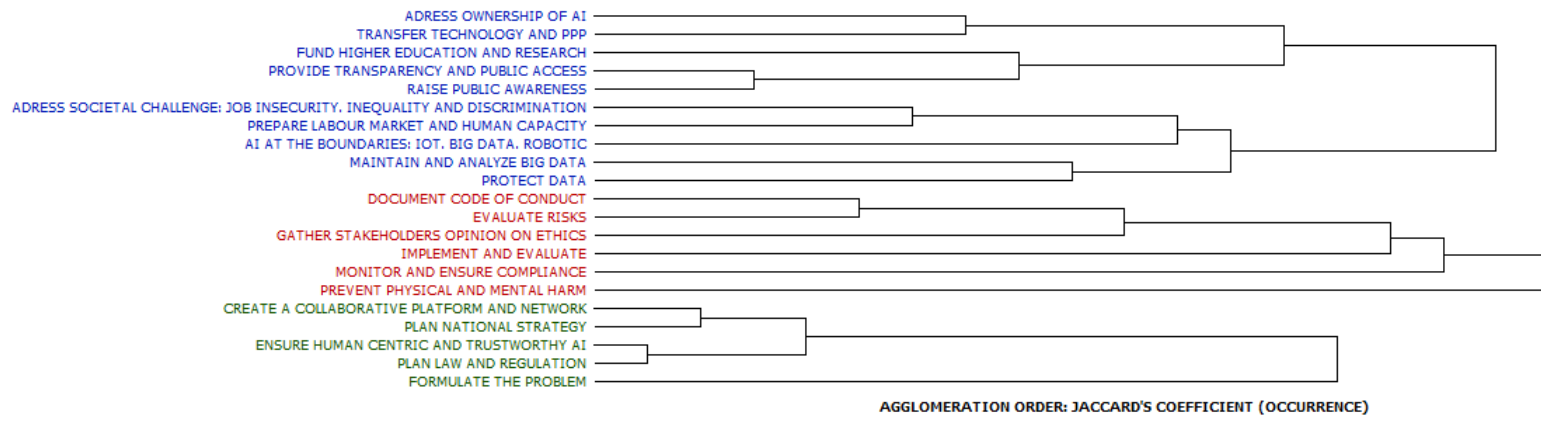


Figure A2: Dimensions of AI (assessment with the Jaccard index)