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Strategically constructed narratives on artificial intelligence: What stories are told in governmental artificial intelligence policies?

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ABSTRACT

What stories are told in national artificial intelligence (AI) policies? Combining the novel technique of structural topic modeling (STM) and qualitative narrative analysis, this paper examines the policy narratives in 33 countries' AI policies. We uncover six common narratives that are dominating the political agenda concerning AI. Our findings show that the policy narratives' saliences vary across time and countries. We make several contributions. First, our narratives describe well-grounded, supportable conceptions of AI among governments, and show that AI is still a fairly novel, multilayered, and controversial phenomenon. Building on the premise that human sensemaking is best represented and supported by narration, we address the applied rhetoric of governments to either minimize the risks or exalt the opportunities of AI. Second, we uncover the four prominent roles governments seek to take concerning AI implementation: enabler, leader, regulator, and/or user. Third, we make a methodological contribution toward data-driven, computationally-intensive theory development. Our methodological approach and the identified narratives present key starting points for further research.

1. Introduction

Artificial intelligence (AI) refers to machines' ability to learn from experience, adjust to new inputs (Duan, Edwards, and Dwivedi, 2019), or do things normally done by human minds, such as visual perception, speech recognition, decision-making, and translation between languages (Rai, Constantinides, and Sarker, 2019). The opportunities are immense, among others, for advancing health and wellbeing (Sun and Medaglia, 2019), education (Scheepers, Lacity, and Willcocks, 2018), transportation and energy consumption (Kreutzer and Sirrenberg, 2020), manufacturing (Li, Hou, Yu, Lu, and Yang, 2017), finance (Bahrammirzaee, 2010), leisure (Liebman, Saar-Tsechansky, and Stone, 2019), or government (Kankanhalli, Charalabidis, and Mellouli, 2019). Yet applications of AI also involve substantial risks for both the real and the virtual world (Bostrom, 2014). AI poses major challenges to and causes uncertainties for governmental leaders, since they progressively face the consequences of algorithmic inequality (Díaz Andrade and Techatassanasoontorn, 2020), reinforced totalitarianism (Diamond, 2019), oligopolistic market structures (Montes and Goertzel, 2019), labor displacement (Agrawal, Gans, and Goldfarb, 2019), or national or global political unrest (Anderson, Rainie, and Luchsinger, 2018).

With AI's rise in many areas of societal, ethical, economic, or security interest (Dwivedi et al., 2019), policymakers are recognizing the need to issue guidelines and policy frameworks (Gilpin et al., 2018). Thus, numerous national AI policies have recently emerged (OECD, 2019). They incorporate the vision and objectives concerning how AI should be realized (as well as the boundaries) at the state level. Governments actively influence the ways AI are adopted and used by businesses and society. While the need for policy guidance is substantial, to date, the policy-related research into AI remains very limited (Dwivedi et al., 2019). In fact, there is a lack of research on what opportunities and challenges government actors attach to AI and which directions and measures they intend to adopt. In our view, an analysis of relevant policies could make an important contribution here. Policy analysis matters because it is often the starting point for operationalizing strategic intent. Thus, how AI is framed and communicated in policies is key to any subsequent implementation. To enhance our understanding of how governments make sense of AI, we examine national AI policies and reveal the metaphor-rich discursive constructions used by state actors to shape their own and others' understandings of AI.

Against this backdrop, we explore commonly used narratives in governmental AI policies. Like all other narratives, policy narratives are

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stories about a particular subject, and involve actors, contexts, and actions. These stories are told to, among other things, create shared understandings (Shanahan, Pelstring, and McComas, 1999), shape problem definitions as well as the ranges and types of solutions (Layzer, 2006), and influence internal and external audiences' perceptions, attitudes, and behaviors (Reber and Berger, 2005). Policymakers also use narratives to directly or indirectly influence the actions of actors and to advance their policy goals (Gray and Jones, 2016). Thus, policy narratives are strategically constructed and carry purpose and intention (McBeth and Shanahan, 2004). Exploring narratives is an integral part of policy research. The analysis of policy narratives can provide insights into a current political issue, shed light on a policy context, clarify the main actors and key arguments for and against an issue, and present scenarios of possible future developments (Fischer and Forester, 1993; Jones, Shanahan, and McBeth, 2014; Stone, 1989, 2012). The importance of narrative research for explaining new technological phenomena has been recognized in the literature (Bartis and Mitev, 2008; Hedman, Bødker, Gimpel, and Damsgaard, 2019; Rowe, 2012). In identifying and examining commonly used narratives in AI policy, we pay attention to how these narratives evolve, how they manifest in different AI policies and, given the many opportunities and threats of AI discussed in the literature, what roles are attributed to government in AI implementation.

We make three primary contributions. First, our narratives describe well-grounded, supportable conceptions of AI in governments, so as to contextualize and order a novel, multilayered, and controversial phenomenon (Hedman et al., 2019). Building on the premise that *human sensemaking* is best represented and supported by narration (Bruner, 1990), we address the contemporary topics and applied rhetoric of governments to either minimize the risks or exalt the opportunities of AI. Second, we show which roles a government may assign itself in AI. We show that governments often take different roles, such as enabler, regulator, or leader, depending on the challenges and possible responses to AI contained in their policies. Third, we also make a methodological contribution toward data-driven, computationally-intensive theory development (Berente, Seidel, and Safadi, 2018). Policy research typically implies reviewing large bodies of text (we analyzed 37 governmental AI policies, with a total of around 450,000 words, i.e. *1000 A4 pages of 450 words each*). There are human capacity limitations for processing all this information. Instead of applying systematic search strategies (Rowe, 2014) or coding procedures (Bandara, Furtmueller, Gorbacheva, Miskon, and Beekhuyzen, 2015) for organizing and confining the source materials to a volume that is manageable for humans, we used *machine learning* to analyzing the entirety of information and for exploring the hidden thematic structures across the policy documents. To make the machine learning output interpretable and meaningful for humans, we combined computational and policy-related methods and distilled six narratives that are common in extant governmental AI policies.

The remainder of the article is organized as follows: In Section 2, we define the research gap and describe the possible roles and responsibilities of governments in AI. In Section 3, we provide a detailed description of the computational and interpretative research steps before portraying the identified AI policy narratives. We conclude by discussing our findings, limitations, and possibilities for future research.

2. Background

There is a heated debate in the research community about what AI is and is not. Since it is not our purpose toengage with the debate about the definitions of AI, but rather to focus on how AI is framed in AI policy, two commonly cited definitions form a conceptual foundation for this paper. According to McCarthy's (2007) pristine conception, AI is defined as "the science and engineering of making intelligent machines." Similarly, Minsky defines AI as "the science of making machines capable of performing tasks that would require intelligence if done by [humans]." (Minsky, 1968). Since its outset, AI research has made considerable progress in getting AI systems to perform a range of information-processing tasks (as humans do). The controversy between the 'bright' and the 'dark' sides of technological progress (Markus, 2017), which we will delineate next, has long been discussed in the academic literature (Bunge, 1976) and in fiction — it has recently received renewed attention in the literature owing to the emergence of robotics, the Internet of Things, big data, and now AI (Willcocks, 2020).

For years, AI's benefits for statecraft have been a concern for policy researchers (Barth and Arnold, 1999). However, with decreasing costs of computing and data storage, it is only now that governments may afford widespread AI implementation, which has attracted researchers' attention (Markus, 2017; Newell and Marabelli, 2015). Among others, AI may help governments to better handle citizens' requests (Maedche et al., 2019), enabling low-cost and customized education programs (Margetts and Dorobantu, 2019), detect fraud and corruption (Digiampietri et al., 2008), improve emergency response (Ogie, Rho, and Clarke, 2018), or support the proactive management of a smart city's cyber-physical infrastructures (Gatzweiler, 2017; Yigitcanlar, Desouza, Butler, and Roozkhosh, 2020). In sum, the literature on AI displays a multitude of use cases, applications, and potentials, -based on which governments may be able to subvert inertia and transcend current ways of governing.

The antithesis to a bright AI-based future has been an Orwellian state, where the main purpose of AI is for governments to collect and process data to retain power and control over its citizens (Power, 2016). Given that AI applications are often developed in public-private partnerships, one literature strand has focused on undesirable and negative effects from 'bad' programming, illegal data access, or data repurposing by commercial third-parties (e.g. Agarwal, 2018; Dwivedi et al., 2021; Sun and Medaglia, 2019; Susar and Aquaro, 2019). Another literature strand has focused on AI's broader societal impacts. As the recent case State versus Loomis showed, outsourcing of public decision-making to machines could undermine the values that are fundamental to a democracy, such as equality and transparency (Liu, Lin, and Chen, 2019). Biases of algorithms against race, gender, or beliefs – even unintentional ones – have therefore been the key concerns when studying the dark side of AI in the public sector.

2.1. The four roles of government in AI

Research into government policies has indicated that government's roles deserve special attention (Goh, 2005b; Liu, Simon, Sun, and Cao, 2011), since government involvement can have both negative and positive effects on technology advances (Guenduez, Mettler, & Schedler, 2020). Since AI's impacts are not limited to the public administration and can have far-reaching societal implications, governments are required to actively reflect on setting the 'right' boundaries and measures (Taddeo and Floridi, 2018). In this sense, the literature on AI's bright and dark sides has also implicitly or explicitly been a discussion about the state's roles and responsibilities in the context of AI (Cath, Wachter, Mittelstadt, Taddeo, and Floridi, 2018).

Before we explore the different narratives that underlie AI policies, we will first clarify the possible roles of government concerning AI implementation. Here, we draw on both the literature on government's roles in technology generally (e.g., Borras and Edler, 2020) and studies on government's roles in AI in particular (e.g., Fatima, Desouza, and Dawson, 2020; Ulnicane, Knight, Leach, Stahl, and Wanjiku, 2021). As we illustrate in Fig. 1, based on our review of the literature, we can identify four basic roles that a government may play in AI.

A first role that governments may play is that of *regulator*. In this capacity as "rule-setter" (Cho, 1992), a government legislates various regulatory acts and provides a regulatory environment to reduce possible risks and hazards (Fatima et al., 2020; Ulnicane et al., 2021). For instance, France has established an Ethics Committee for AI, which has proposed the establishment of a fair assessment system to ensure the adequacy and impartiality of data and to avoid unduly misleading the

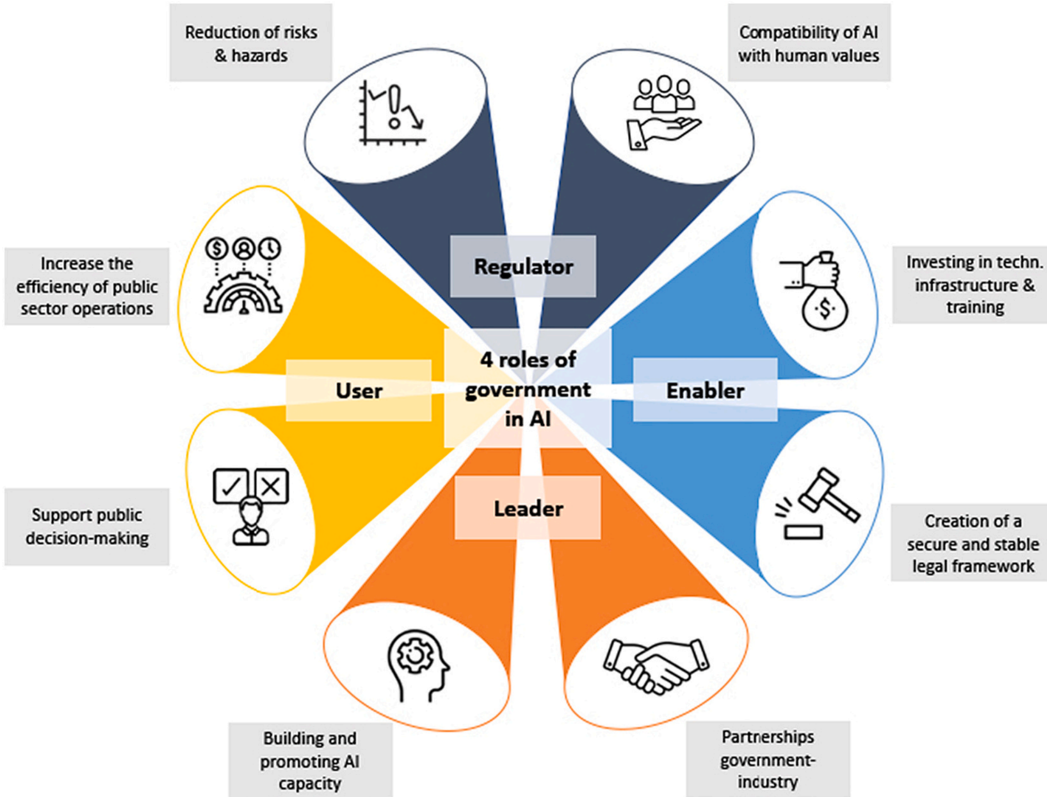

Fig. 1. The four roles of government in the AI context.

public (Kirchner, 2020). In its role as regulator, the government ensures the compatibility of AI with societal values by keeping technology benign and focused on improving all its citizens' lives (Dwivedi et al., 2019).

The second role governments may play is that of key *enabler (*Goh, 2005a;Liu et al., 2011*)*. In this role, governments can dismantle, reduce, and minimize potential barriers, obstacles, and restrictions, supporting businesses and facilitating the use and diffusion of AI. Concerning AI, by investing in domestic technical infrastructure and the training of citizens, a government may ensure that its nation's full potential is used to advance the country's development and implementation of AI (Susar and Aquaro, 2019). By creating secure and stable legal boundaries and a favorable business environment for the private sector to be innovative, governments can also ensure that intellectual property is respected, and can encourage and attract new AI-based businesses (Fujii and Managi, 2018).

The third role of the government in AI is that of *leader*. In this role, a government may be actively involved in the research and development of AI-based applications. It may assume the leader role in certain domains (e.g. cyber-defense, urbanization, disaster management) and may expand to domains outside the "classic dominion" of governments by collaborating with researchers, laboratories, startups, and even large corporations (Chen and Wen, 2020). In Europe alone, the financial support and encouraging uptake by the public and private sectors was estimated to be at least €20 billion by end 2020 (European Commission, 2018). In the U.S., the "future of AI" is backed by $1.2 billion federal funding for AI-based research and training programs (Holdren and Smith, 2016).

The fourth role of a government is that of a *user* of AI technology (Borras and Edler, 2020). To date, a myriad of such application cases have been described in the literature. Internal efficiency gains are often mentioned as the main motivation to adopt AI (Androutsopoulou, Karacapilidis, Loukis, and Charalabidis, 2019). To a lesser extent, the motivation for AI adoption has been to resolve complicated policy questions, enhance participation, or for public decision-making (de Fine Licht and de Fine Licht, 2020).

2.2. The research gap

In response to the speed at which AI is confronting governments, numerous AI-related policies have been published in the past three years (see Table A.1 in the Appendix). These policies provide insights into the national agenda for AI and outline what roles governments will (actively) assume and how they intend to coordinate AI implementation efforts for the public good (Berryhill, Heang, Clogher, and McBride, 2019). So far, only a handful of studies have examined these national AI policies. Fatima et al. (2020), for instance, showed that AI policies are a rich source of information for understanding how governments view the opportunities for public sector modernization and digital transformation (Vial, 2019). Similarly, an in-depth analysis of the AI reports issued by the White House, the European Parliament, and the UK House of Commons by Cath et al. (2018) showed that these policies seem to use more or less the same rhetoric and discuss ethical, social, and economic issues common to Western countries. This is consistent with the findings of policy research, which found that policymakers often use (and continually repeat) strategically constructed narratives in order to influence the implementation of a particular policy (Gray and Jones, 2016; McBeth and Shanahan, 2004). However, for the AI context, we know little about these constructed narratives and governments' preferred rhetoric (Dwivedi et al., 2019). To date, no study has examined or described these AI policy narratives. Starting from this research gap, we ask:

What are the commonly constructed narratives that underlie national AI policies?

What roles of government are contained in these narratives?

To address these questions, we combine the structural topic model (STM) with the narrative policy framework (NPF), which we will now discuss in some detail.

3. Methodology

To identify the narratives that are commonly found in governmental AI policies, we applied a sequential mixed-method research design (Creswell, 2003), combining the computational method of topic modeling and policy-related qualitative methods (Fig. 2). This approach is particularly appropriate when combining STM and narrative analysis in policy research (Isoaho, Gritsenko, and Makela, 2021). We will now provide a detailed description of each step. We discuss additional details on data collection, data analysis, and data interpretation in the Online Appendix as supporting information (SI).

3.1. Corpus

We used the *OECD AI Policy Observatory* data on AI, which provides extensive information on government strategies, policy briefs, and related documents concerning the implementation, use, or effects of AI in the public sector, economy, and society. Our search process started in January 2021 and ended in April 2021. After pre-screening all documents, we retained 37 official documents that were published between 2017 and 2020. We excluded documents not written in English, such as the AI policies of Mexico or Poland, from further analysis. Our final text corpus (around *450,000 words,* i.e. *1000 A4 pages of 450 words each*) consisted of 37 AI policy documents from 33 countries (see the SI Appendices A.1 and A.2).

3.2. Data preparation and text processing procedure

Prior to the analysis, we processed all documents with standard procedures, as suggested by Lucas et al. (2015, pp. 256–258) and Roberts et al. (2019, pp. 7-8). To use the computational method of topic modeling to analyze the text corpus, we first had to convert the downloaded documents into machine-readable text. To improve the data quality before conducting the topic modeling, we then prepared the textual data. We removed all special characters and all boilerplate text, such as running titles, pagination, references, or appendices. We then lemmatized and tokenized the text by removing common stop words, stemming and lowercasing the words, and then breaking it down into 1817 paragraphs, each consisting of 250 words. More detail about the text processing appears in the SI Appendix A.3.

3.3. Structural topic modeling

To identify and explore the topics in AI documents, we applied STM, a statistical generative model of word counts that is particularly useful for discovering latent narratives in textual data (Isoaho et al., 2021). Instead of direct observation and pattern matching by researchers, STM draws on a probabilistic process and uses the entire text corpus for inferring topics and estimating their distribution. STM "considers each document as being composed of terms, each topic as a distribution over terms, and each document as a combination of topics" (Chen, Zou, Cheng, and Xie, 2020, p. 4; Roberts et al., 2019).

We used the R software package stm to estimate the topic models (Roberts et al., 2019). Before modeling and extracting the topics, we set the optimal number of topics as required by STM as an unsupervised modeling method (X. Chen et al., 2020; Ebadi et al., 2021). Since an exclusive reliance on statistical measure could result in less semantically meaningful topic models (Levy and Franklin, 2014), we followed Chen et al. (2020) and conducted a two-step analysis to determine the optimal number of topics. We first applied the stm package for estimating the numbers of topics K. The evaluation of the topic model coherence indicated that 5 to 9 topics are most useful for a coherent estimated model. Then, in a second step, we qualitatively examined the topics. We analyzed representative top words, paragraphs, and word clouds of estimated models concerning their distinct narratives and whether, together, they could form a meaningful topic. This led to the concretization of $K = 6$ as the optimal number of topics (see the SI Appendix B.1).

As with other topic models such as Latent Dirichlet Allocation (LDA), STM is designed to discover and explore the 'hidden' thematic structure of a given text corpus. An affordance of STM, compared to other topic modeling approaches, is that it allows to include document-level metadata as covariates in the topic models (Roberts et al., 2014; Roberts et al., 2019; Roberts, Stewart, and Airoldi, 2016), to detect relationships between covariates and the text corpus's content. The inclusion of covariates allows for more informative model analysis (Gilardi, Shipan, and Wuest, 2021). From a statistical perspective, including covariates into the model helps to better estimate the topic proportions and the topic content (Roberts et al., 2016). We chose the year of the publication as the covariates to compare topic prevalence over time.

3.4. Derivation of the policy narratives

STM provides quantitative results as words and paragraphs revealing common patterns that need to be examined qualitatively to uncover common narratives. To derive the common narratives underlying AI policies, we relied on the NPF, a systematic approach to the study of policy narratives (Jones and McBeth, 2010) that presumes that

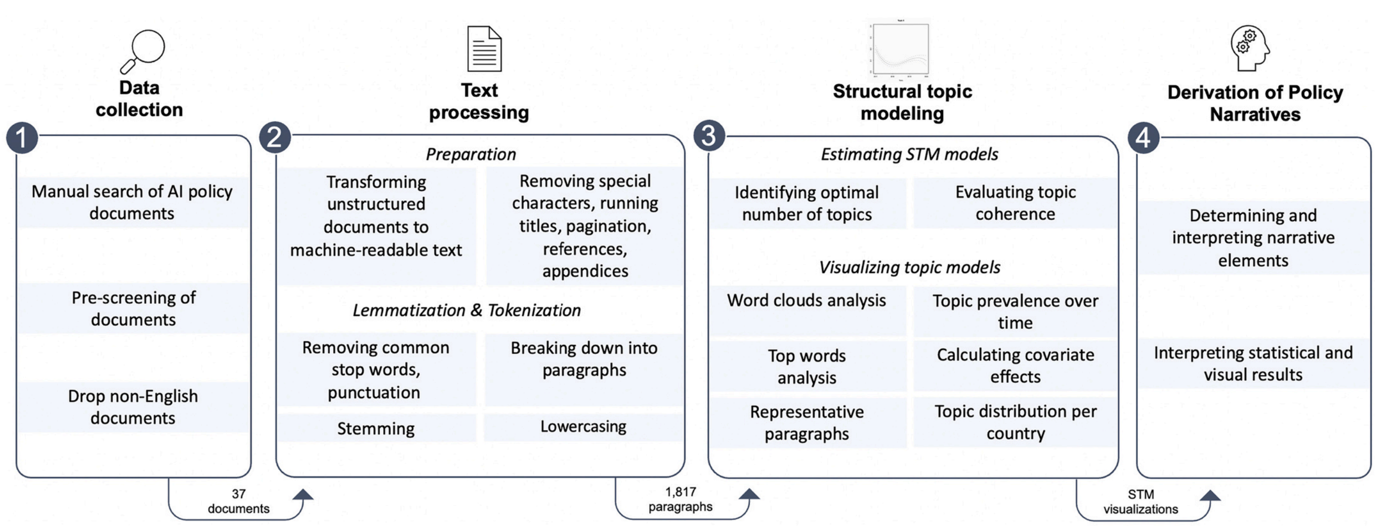

Fig. 2. Illustration of the research process for identifying the narratives used in AI policies.

narratives have the following components:

- *Setting.* The setting provides the context within which a story is told. Elements of the setting include scientific facts, standards, rules, and/or assumptions that most relevant policy actors agree with or that matter in a given policy area. These elements are often taken for granted but can also become controversial or the focal point of the policy narrative.
- *Characters.* The NPF identifies different characters, including a victim who is or could be harmed (in our case, by AI implementation), a villain responsible for the harm, and a hero who ends or promises to end the harm. These characters can be individuals, groups, or whole organizations.
- *Plot.* The plot serves to link characters with one another and with the settings, and assigns blame through asserting a certain causality and intention.
- *Moral.* A policy narrative's moral is presented as a policy solution or a call for a particular action.
- *Roles of the government.* We differentiated four roles that governments can have in AI: regulator, enabler, leader, and/or user (see Chapter, 2.1).

Specifically, we determined narrative elements by first qualitatively analyzing the top words per topic given by the STM output (see the SI Appendices B.2, B.3, and B.4). Top words include the *high-probability* words, which are very common in a topic, and the *frex* words, which are very specific to a topic. We also interpreted the word clouds for each topic that show the words with the highest likelihood of occurrence in the topic (see Fig. B.3 in the SI Appendix B.3). Since interpreting words in isolation from the textual material in which they appear may lead to misinterpretations (Isoaho et al., 2021), we further analyzed exemplary paragraphs in which these words occur. Two of these paragraphs for each topic appear in the SI Appendix B.4. Mapping the computational results from STM with the predefined NPF narration structure, we now turn to the description of the resulting underlying narratives in AI policies.

4. Findings

4.1. Narratives in national AI policies

With our computational and policy-based research approach, we identified six distinct AI narratives (as summarized in Table 1), which we will now discuss in detail. We will then discuss these narratives. Following Pratt's (2009) recommendation regarding data reporting, we provide exemplary quotes for all of the relevant narrative elements that support our interpretation both in our paper and in the Appendix (see Table C.1 in the SI Appendix).

4.1.1. Narrative 1: Building an AI marketplace

The *setting* of the first narrative foregrounds the importance of a domestic AI marketplace for nation-states in the global AI race: *"countries around the world are investing heavily to take advantage of the significant economic and social opportunities that a digital economy can bring"* (Australia, 2018). According to the national AI policies, these nations are seeking to create fruitful conditions through investments to attract innovative companies and startups from the AI field and therefore to gain a competitive advantage in the global AI environment. Thus, companies, startups, and society are highlighted as important *characters* in this narrative. The *plot* emphasizes that sustainable economic success depends largely on a country's ability to take advantage of technological progress, to improve a location for innovative companies in the AI field and to create new opportunities that improve citizens' digital skills. In this way, innovative companies and pioneers may appear, a location can be strengthened in international terms, and citizens' daily lives can be improved. The *moral* narrative 1 emerged from this. It highlights the need for a clear action plan to strengthen national economic competitiveness. The aim is to attract innovative companies and startups as well as the best talent to the country to harness the opportunities presented by technological progress. The government plays a key role in this. The Government's *resulting role* can be summarized as *enabler* of AI in the sense that it attracts high-growth AI companies and startups by creating an environment that is conducive to innovation. This is shown among others by the example from the UK's AI strategy: *"Along with our*

Table 1
Identified narratives in national AI policies.

	Settings	Characters	Plot	Moral	Role of government
Narrative 1: Building an AI marketplace	The importance of a domestic AI marketplace for nation-states in the global AI competition	Businesses and startups develop an edge in the domestic digital economy	Sustainable economic success depends on countries' ability to take advantage of technological progress, improve the location for innovative companies, and close the digital divide	The need for action plans by the government to strengthen the national economy's competitiveness	Enabler
Narrative 2: Counteracting the winner takes all practice	A vast amount of data is generated, collected, and processed by only a few very large companies	Large companies and state actors	Companies only use data for their own purposes and are unwilling to make it available to everyone	The need for data-sharing with the public sector for reuse and the public good	Regulator
Narrative 3: Engaging in strategic collaboration for AI R&D	Existing national and international alliances, cooperations, and collaborations	Industry, academia, and government make collective efforts toward developing an AI ecosystem	A collaborative approach is needed to realize AI's potentials for society	Engaging in strategic AI partnerships with actors on a national and international level.	Leader
Narrative 4: Creating ethical and trustworthy AI	Existing fundamental human rights, regulations, and core national principles and values	Individuals, communities, groups, society, AI designers, and AI operators	AI challenges fundamental human rights, applicable regulations, and core national principles and values	AI requires a focus on human values and fundamental rights as well as the explanation of (dis) advantages	Regulator
Narrative 5: Educating AI professionals	The importance of training AI professionals for the national job market	The domestic job market, educational Institutions such as schools and universities; students	There is a growing need for qualified AI professionals	The lack of human talent in the AI field must be counteracted through education	Enabler
Narrative 6: Advancing the deployment of AI in practice	AI as a core driving force for the fourth industrial revolution	IT companies, research institutes, industries, and the government	The need for nations to be at the forefront in research, development, and application of AI	Ideal framework conditions must be created so that AI can be applied rapidly and that the country can play a leading role in the global AI race	Enabler

commitments to a visa system that welcomes the best talent, we will establish the UK as the go-to place to headquarter an AI business" (United Kingdom, 2017).

4.1.2. Narrative 2: Counteracting the winner-takes-all practice

The second narrative is entirely within the *setting* that vast amounts of data are generated, collected, and processed by large companies, such as *Facebook, Amazon and Google.* The key actors in this narrative are private companies that hold crucial data and have a dominant market presence. Current government policies seek to work against the *winner-takes-all* practice. These companies, together with state actors, are the main *characters* in this narrative. The *plot* brings together the *setting* and *characters* and highlights that these companies use the collected data exclusively for their own purposes. The second narrative points out that governments require such data "*to avoid value being vacuumed off by a private actor in a paramount position*" (France, 2019). Thus, it stresses the need for these data to also be shared with governments, which forms this narrative's *moral*, for instance to *"enhance public benefit*" (Norway, 2020), "*for the purposes of public sector projects in the public interest*," or for "*a particular private sector artificial intelligence development project*" (Republic of Serbia, 2019). Thus, national AI policies emphasize the need for an *"obligation to provide the data to the state authorities without reimbursement." (Republic of Serbia, 2019).* Government's *resulting role* in narrative 2 is that of a *regulator* responsible for enforcing data provision from the private sector. In this regard, *"the practice of donating data for reuse as a form of corporate responsibility should be established and promoted"* and *"potential incentives such as rewards or tax benefits for companies that are opening, i.e. providing access to their data should also be analyzed"* (Republic of Serbia, 2019). In this context, it is considered critical that data trust and anonymization be guaranteed: *"data must be shared in such a way that individuals and businesses retain control of their own data. Privacy and business interests must be safeguarded."* (Norway, 2020). However, since the data basis is considered key to the use of AI, this narrative also considers coercive mechanisms as a way to build the data basis for AI applications: *"data sharing may be imposed if necessary; for example for reasons of public interest*" (Norway 2020).

4.1.3. Narrative 3: Engaging in strategic collaboration for AI R&D

Narrative 3's *setting* is formed by existing national and international cooperations, collaborations, and alliances created to pursue shared interests and solve shared challenges. These can be cooperations and alliances at the supranational level such as the EU or OECD, but also existing bilateral partnerships. This narrative seeks to extend, complement, and deepen these existing collaborations into the AI field: *"establishing AI as the subject of bilateral and multilateral strategic partnerships, opening and coordinating the promotion of specific topics at working level."* (Czech Republic, 2019). The key *characters* in this narrative include academia, but also the partner countries' industries and governments. The *plot* makes it clear that a strategic approach and collaborative efforts are needed to realize the potential of AI and solve common challenges. For instance, the Czech Republic's national AI policy highlights the *"cooperation and active participation in working groups on AI within the EU*," *"active participation in the implementation of the coordinated plan for AI*," *"co-ordination with the specialized ministries*," and *"involvement in the strategic discussions in committees, working groups and OECD political plenums"* (Czech Republic, 2019).

This collaborative approach also embraces this narrative's *moral*, which highlights the importance of exchanging best practices as well as having a coordinated approach and joint action plans, especially in research and innovation in the AI field. This is also underlined by Spain's National AI Policy: "*At the international level, Spain should promote and participate, through its RDI agents, in European and international proposals and programs deriving from the Coordinated AI Plan that guarantee the EU's global competitiveness in this sector, such as, among others, the exchange of good practices, positioning with respect to new public-private partnerships or the elaboration of a common strategic program of research, data, ethics or AI education at the European level"* (Spain, 2019). In the *resulting role* of *leader*, government is central in this narrative. Government leadership is needed to create and promote partnerships between different actors and generate synergies, which in turn will boost knowledge exchange in AI. Examples include initiating a platform for sharing good AI practices and establishing government-led funding agencies to carry out its policy to promote national and international cooperation programs in the AI field.

4.1.4. Narrative 4: Creating ethical and trustworthy AI

Narrative 4 deals with the possible risks associated with the uses of AI. The existing fundamental human rights, applicable regulations, and core national principles and values form the *setting.* The *characters* involved are individuals, communities, groups, society, AI designers, and AI operators. Regarding the latter two, for instance, the following is highlighted: *"the AI designer or operator is responsible to develop governance and control practices to identify and evaluate the potential impacts and trade-offs and to determine the best course of action."* (Malta, 2019). The *plot* spans the arc between a nation's existing principles, rules, and social values and the actors involved. It highlights the fact that AI challenges the fundamental human rights, applicable regulations, and core national principles such as *"physical and mental integrity, personal and cultural sense of identity, and satisfaction of their essential needs"* (Australia, 2018). It is therefore imperative that, as AI spreads, there is a focus on human values, fundamental rights, and the explanation of (dis)advantages of AI. This is narrative 4's *moral*. Measures must be taken to minimize potential negative impacts of AI throughout the AI lifecycle. National AI policies emphasize the need to establish control and protection mechanisms to ensure that AI does not violate basic human rights: *"In January 2019, Singapore published Asia's first Model AI Governance Framework that provides detailed and readily implementable guidance to private sector organisations to address key ethical and governance issues when deploying AI solutions."* (Singapore, 2019). People must maintain control over AI and affected people must always be informed about risks; this is the only way to create a *"trustworthy AI."* To make this possible, *"clear processes should be in place to ensure there is always a human who can be held accountable for the operation of an AI system. Accessible complaints resolution processes should be implemented to ensure effective redress for individuals harmed by AI systems"* (Malta, 2019). Against this background, narrative 4 emphasizes the *role* of the government as *regulator*. By developing rules, standards, guidelines, norms, and ethical principles, it ensures that the negative social impacts of AI development and use are minimized and that citizens' well-being is increased (Spain, 2019).

4.1.5. Narrative 5: Educating AI professionals

This narrative's setting manifests in the scarcity of AI professionals and highlights that the supply of highly skilled AI talent does not meet the demand for it. Thus, narrative 5 focuses on the importance of training AI professionals for the national job market, making it clear that AI has a transformative effect, which affects the domestic job market and educational institutions as main *characters*. The influence of bringing together the *setting* and the actors in the *plot* shows the growing need for qualified AI professionals: *"the aim is to train students in the much more technical occupations of AI, in which, although in-depth knowledge of AI is not a prerequisite, it would be deemed a direct asset by companies"* (France, 2019). Examples from the national AI policies include *"industrialization of AI techniques"* (Japan, 2017)*, "machine learning"* (Portugal, 2019), *"automation"* (Qatar, 2019)*, "robotics and data science"* (Norway, 2020), and *"integration and adaptation of AI components"* (France, 2019). Narrative 5's moral is also derived from this. National AI policies draw attention to the current deficit of human talent in the AI field, which must be remedied through education. National AI policies highlight many concrete measures. One possibility is to dramatically increase the numbers of AI Master's and Doctoral students. It is also important to *"make lifelong learning a core mission of all our schools, especially universities and university-colleges… Early on and throughout their childhood, we need to teach our children 21st-century skills, so that they can really* *understand and talk 'the language' of technology, while also reinforcing their human skills.*" (Belgium, 2019). Finally, "*the current labor force also needs to have the tools needed to succeed in a future with AI. Opportunities for vocational training need to be created, prioritizing those with jobs and occupations that have the greatest risk of automation*" (Belgium, 2019). For the training institutions to be able to set up the necessary courses, political commitment with additional funding is needed. From this, we can deduce the *resulting role* of the government as *enabler*. For instance, Malta's AI policy emphasizes increasing the number of qualified AI specialists: "*the government will also continue to provide scholarships and financial support to carry out post-graduate studies in AI outside Malta under the Tertiary Education Scholarship Scheme*" and will "*provide individuals (…) with a tax credit*" (Malta, 2019).

4.1.6. Narrative 6: Advancing the deployment of AI in practice

Narrative 6 focuses on AI as a key driving force behind the fourth industrial revolution. This is against the background that AI R&D has advanced, as have the areas in which AI can be used and applied- including "*intelligent manufacturing,*" "*intelligent factory*," "*intelligent diagnosis*," "*intelligent service platform*," "*intelligent transportation*," "*intelligent monitoring*," and "*intelligent security*", as highlighted in China's AI policy- are expanding. This development has also led to the intensification of the global AI race. The fundamental change associated with this transformation and the global race to lead to development and application of AI technology forms the *setting* of this narrative.

The *plot* highlights that AI technology must be linked and integrated in various fields in order to strengthen a nation's industrial competitiveness. IT companies, research institutes, industries, and the government – as *characters* in this narrative – are needed if one is to be at the forefront in research, development, and application of intelligent AI systems: "*The focus is on strengthening the convergence of the new generation of major scientific and technological projects. Collaboratively promote research in artificial technology for breakthroughs and product development applications*" (United States, 2019). This requires investment in R&D as well as comprehensive promotion of the applications of new-generation AI in the economy and society. There is also a need for greater collaboration between the individual actors. For instance, in the use and application of AI technologies, the focus is on open innovation projects in which different players across industries can participate. Derived from this is this narrative's *moral*, which states that ideal framework conditions must be created so that AI can be applied as rapidly as possible, for a country to play a leading role in international competition. In intelligent medical care, for instance, developing "*man-machine coordination in surgical robots,*" exploring "*human-computer collaboration in clinical intelligent diagnosis and treatment,*" and strengthening "*epidemic intelligence monitoring, prevention, and control*" (China, 2017) are listed as key strategic directions for the further development and application of AI technology. The *resulting role* of government in this narrative is of *enabler* of AI. To advance the societal implementation of AI, the government must support both R&D (such as basic research) as well as the rapid application of AI. To this end, regulatory settings need to be adapted and appropriate research centers must be created in which

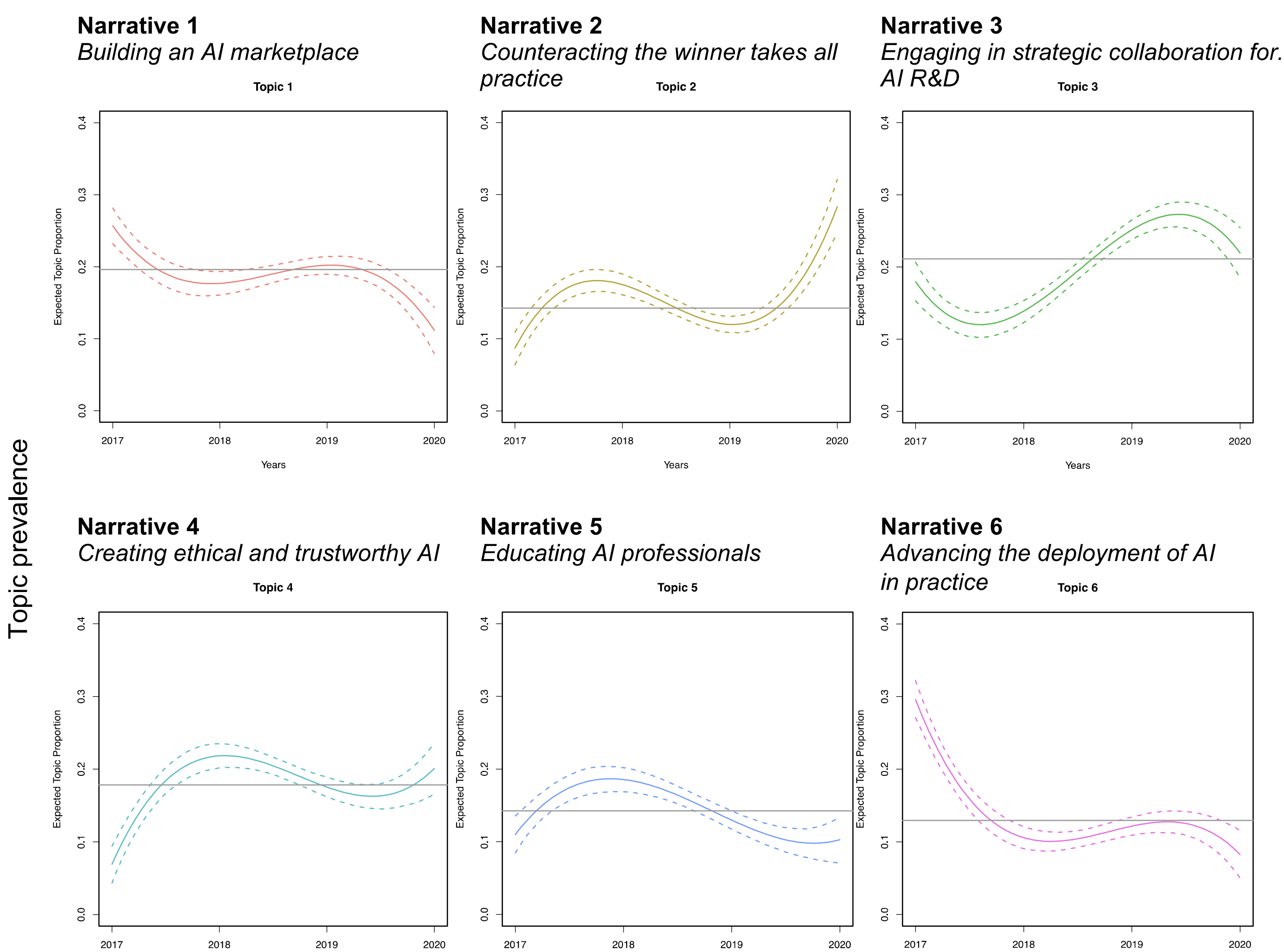

Fig. 3. Topic prevalences of the six narratives over time in all the national AI policies.

actors from academia and industry can cooperate, conduct research, and rapidly advance the application of AI in multiple areas.

4.2. Prevalences of the narratives and time trends

STM allowed us to trace the changes in prevalences of the narratives in the text corpus. Having identified and described the narratives, we will now first discuss our topic model results concerning topic prevalences and the time trends. We used this analysis to explore shifts in narratives and the narrative sequence structure. The topic evolution over time is illustrated in Fig. 3, which also displays every topic's median, i.e., the proportion of the narratives across all the documents (see also Fig. B.5 and Table B.6 in the Appendix).

Narrative 3 is the most prevalent topic across all the documents, and

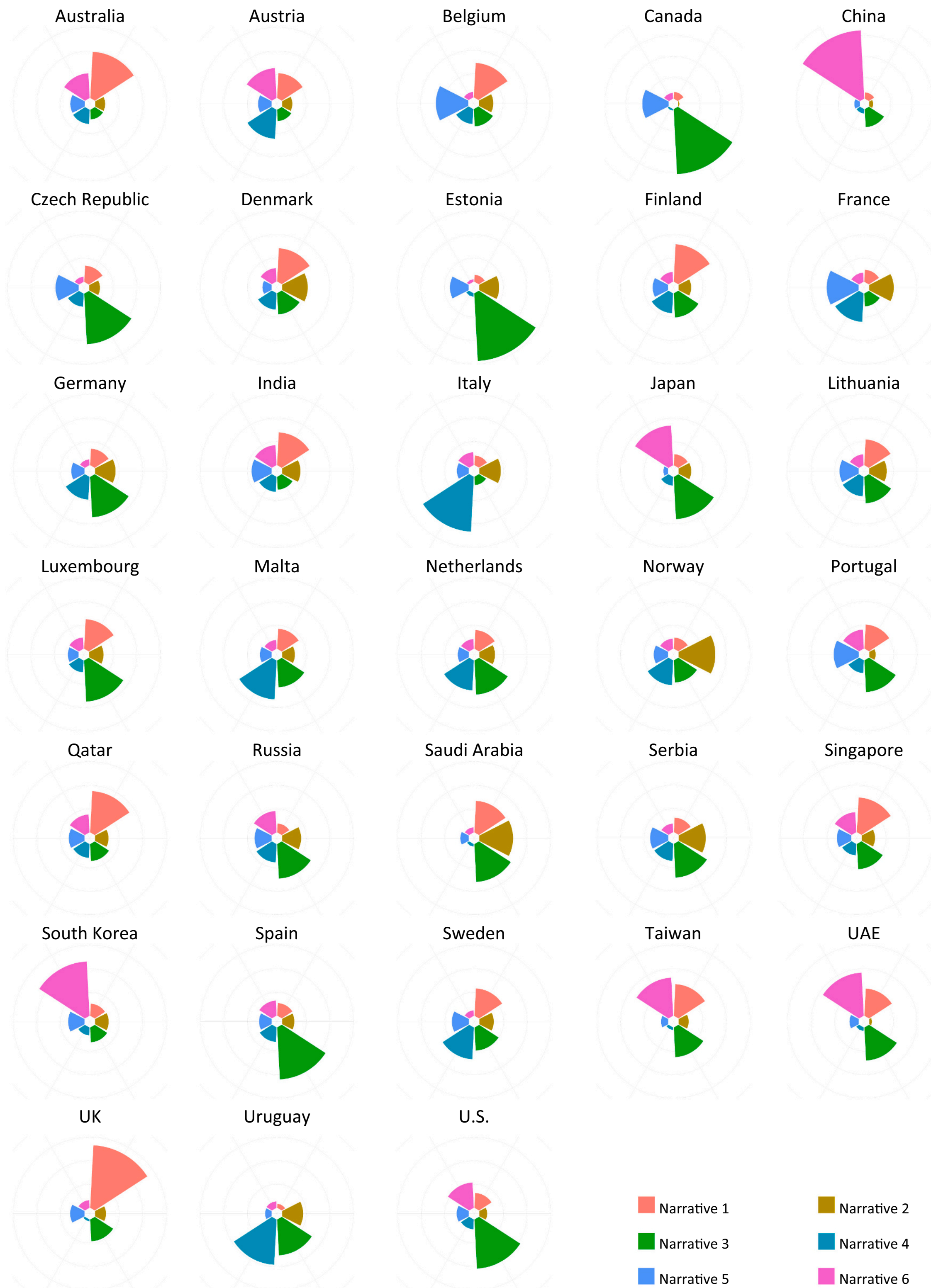

Fig. 4. Distribution of narratives in the national AI policies.

is increasingly mentioned in the newer AI policies. While the importance of strategic collaboration in AI is increasing, the trajectory for narrative 1 points in the opposite direction. This narrative, which emphasizes the importance of building an internal AI market, is very strongly highlighted in the early AI policies, is mentioned in the 2018 publications, is mentioned somewhat more in the policies published in 2019, decreases very sharply in the 2020 AI documents, and receives the least mentions compared to the other narratives. Narrative 6 has a similar course as narrative 1, but is the least prevalent on average. Also, the differences in prevalence over time do not vary as much and the mentions remain at a higher level in 2020 than for narrative 1. Narratives 2 and 4 show a similar course as narrative 3, starting with low prevalence in 2017 and being increasingly mentioned in newer AI documents. Especially the increasing salience of narrative 2 in national AI policies published after 2019 indicates that opposing monopolies by international tech giants became more relevant. Narrative 5 is less varying in occurrence between AI policies from 2017 to 2020, with an only slightly more pronounced emphasis in 2018. This demonstrates that the importance of AI education remaines a fairly stable narrative over time.

Overall, our study reveals that narratives concerning the building of a national AI marketplace (narrative 1) and the rapid deployment of AI (narrative 6) are prevalent in pioneering AI policies. In contrast, narratives challenging the monopoly position of large private firms (narrative 2), emphasizing the importance of strategic collaborations (narrative 3), and focusing on creating ethical and trustworthy AI (narrative 4) are more salient in the newer AI documents. Our analysis shows that educating AI professionals (narrative 5) is a constantly relevant narrative in both older and newer policies. In line with this trajectory, the pioneering AI policies emphasize governments' enabler role (narratives 1 and 6), while subsequent AI policies stress their regulator role (narratives 2 and 4) and their leader role (narrative 3). Looking at the individual graphs, the confidence intervals for 2020 are generally larger than for the other years, because there were only three AI policies in 2020, and therefore analyzed fewer paragraphs ($n = 126$). However, as can be seen from the graphs, the policy documents' time of publication plays a role in how strongly a narrative is emphasized.

4.3. Distribution of the six narratives in the national AI policies

Fig. 4 illustrates the distribution of the six narratives across the 33 countries for which we analyzed the AI documents (for details, see Table B.6 in the Appendix). We discuss our results, looking at the distribution and the salience of the narratives in each country and the similarities as well as differences between the countries. Regarding the distribution, there are countries where the six narratives are evenly salient; these include Denmark, India, Lithuania, Norway, and Portugal. In other countries, particular narratives are strongly pronounced. While for instance in China and South Korea, narrative 6 is strongly emphasized, the UK focuses on narrative 1, Italy on narrative 4 and Canada on narrative 3. Further, the figure reveals that, compared to the other narratives, narrative 5 is never the most prevalent narrative in any country.

When looking at the prevalences of the individual narratives across the countries, narrative 1 is very pronounced in the UK, Australia, Finland, and Singapore. Since narrative 1 focuses on the own domestic market and the location's attractiveness, this indicates these countries' efforts to become a business hub for startups and companies specializing in AI, create jobs, and add economic value, positively impacting the country's economic development.

Narrative 2 is salient in the AI policies of Norway, Saudi Arabia, France, and Serbia, as well as in other countries to varying degrees. Interestingly, it is hardly mentioned in AI policies of the countries where large companies do business with big data. These include above all the U.S. and China, home to for instance Google, Meta, or ByteDance.

Narrative 3, which entails engagement in strategic collaboration for AI R&D is the most salient narrative across all the documents (see Fig. 3 and Fig. B.5 in the SI Appendix B.2). Focusing on the countries, it is the most prevalent narrative in the AI policies of Canada, the Czech Republic, Estonia, Germany, Japan, Lithuania, Luxembourg, the Netherlands, Portugal, Russia, Saudi Arabia, Serbia, Spain and the U.S., as well as the second-most salient narrative in China, Finland, Malta, Singapore, Taiwan, the United Arab Emirates, the UK, and Uruguay. This demonstrates the importance allocated by countries across the world to strategic alliances in AI.

Narrative 4 - ethical, trustworthy AI - shows a high prevalence in Austria, France, Germany, Italy, Lithuania, Malta, the Netherlands, Norway, Spain, Sweden, and Uruguay. An explanation for this narrative's prevalence in these countries may be the Convention of the Council of Europe on personal data protection from January 28, 1981. To date, the Convention for the Protection of Individuals with regard to Automatic Processing of Personal Data has been ratified by 47 states, with Uruguay being the first non-European state (see https://www.coe.int/en/). Looking at narrative 4, the analysis of the individual policy documents for Australia and Malta shows interesting results. Besides Finland, these two countries have also published several policy documents. An analysis of these individual policy documents shows that Australia and Malta have each devoted a policy document to the ethical and normative questions surrounding AI; thus, narrative 4 is particularly salient in these documents (see Fig. B.7 in SI the Appendix B.7). However, narrative 4 is not salient in the AI policies of the UK and Estonia, which are also member states of the Council of Europe. There are especially few mentions of the *ethical and trustworthy* AI narrative in the AI policies of Canada, China, Estonia, Saudi Arabia, Singapore, South Korea, Taiwan, the United Arab Emirates, the UK, and the U.S. Thus, this narrative barely appears in both Eastern and Western countries, democratic or non-democratic alike.

The emphasis on educating AI professionals is only the most prevalent narrative in France's AI policy; it is least common in the policies of Denmark and Luxembourg. In all other countries, like narrative 2, narrative 5 does occur, although not very frequently. This is unsurprising, since their prevalence is low on average across all the documents (see Fig. 3 and Fig. B.5 in the SI Appendix B.2).

Finally, narrative 6 is highly polarizing the spider diagram in some cases, although it is the least prevalent narrative across all the documents (see Fig. 3 and Fig. B.5 in the Appendix). Countries that seek leadership in AI implementation and that therefore strongly emphasize this narrative in their AI policies are China, South Korea, Taiwan, Japan, the United Arab Emirates, and the U.S. Aspiring or existing technology plays a key role in these countries, which strive for regional or even global leadership in AI application. However, in European countries such as Belgium, the Czech Republic, Estonia, Sweden, or the UK, narrative 6 is less prevalent. The prevalence of narrative 6 is extreme, i.e., it is either barely or extensively salient in the national AI policies. Further, when narrative 6 is moderately prevalent, narrative 2 is also moderately present. However, when narrative 6 is very prevalent, narrative 2 shows a low prevalence in the same AI policy, and vice versa. Thus, advancing the deployment of AI in practice and counteracting the *winner-takes-all* either enjoys a balanced emphasis, or the AI policies prioritize one narrative over the other.

5. Discussion and conclusion

Public policy "is whatever governments choose to do or not do." (Dye, 1972, p. 1). It is a purposive course of action taken to deal with a problem or matter of concern (Anderson, 1975, p. 3). With the progressing diffusion of AI-based applications in both the private and public sectors (Hamet and Tremblay, 2017; Hengstler, Enkel, and Duelli, 2016; Huang and Rust, 2018; Jiang et al., 2017; Li et al., 2017), governments face major challenges in containing undesired effects or reinforcing positive effects for the economy, society, and public administrations (Dwivedi et al., 2019). Accordingly, to reduce uncertainties, communicate with internal and external stakeholders, and clarify government's roles and responsibilities, more and more AI policies are being published (Cath et al., 2018; Fatima et al., 2020). Using computational and interpretative methods, we analyzed 37 national policies of 33 countries to identify the prevailing narratives, as well as to provide an overview over the roles that governments have envisioned therein.

5.1. Contributions

We have explored a range of narratives and roles of government in AI policies using STM and NPF. Our study contributes to literature in three ways:

5.1.1. Unveiling the isomorphism in narratives in AI policies

First, we provide an overview over the prevailing narratives in AI policies. The focus on narratives is relevant because public authorities use them strategically in policies to portray policy issues, interpret situations, and promote and legitimize their preferred course of action (Stone, 2012). We identify six distinct narratives, ranging from improving national settings for AI development and deployment, to strategic AI collaborations at the national and international level. Further, by uncovering the prevailing narratives in these countries' AI policies, our analysis has extended the research (Dwivedi et al., 2019; Kankanhalli et al., 2019; Sun and Medaglia, 2019; Susar and Aquaro, 2019) by showing what these governments consider critical in public policy concerning AI and how they seek to harness AI's benefits while countering the threats.

A particularly interesting aspect in this context is that very different governments use very similar narratives in AI policies, uncovering the isomorphism that has received little attention in previous studies. The current research, whether single-case or comparative studies, emphasizes AI policy and implementation as countries' efforts to lead the way. Our analysis shows that, regardless of these efforts, governments are very similar in the language they use. Thus, their AI policies are isomorphic but not identical. We reveal that countries' AI policies follow the motto *same same, but different*. All six narratives are present in every national AI policy. The policies do not differ concerning which narrative (as a form of storytelling) they use, but they do differ concerning how strongly they emphasize them. Therein lies the strategic nature of AI narratives: not whether they are taken up by governments, but how much prominence is given to them. Overall, our findings contribute to a better understanding of how AI is framed in AI polies by highlighting the various narratives in national AI policies and revealing the differences and similarities in their uses across time and countries.

5.1.2. Unpacking government's roles in AI policy narratives

Second, the heated debate regarding the bright and dark sides of AI technology has raised the question which roles and responsibilities governments should take (Agarwal, 2018; Digiampietri et al., 2008; Liu et al., 2019; Maedche et al., 2019; Ogie et al., 2018). Against this backdrop, applying the NPF, we focus on government as a key actor. To establish a role for actors is typical of the NPF (Shanahan, Jones, McBeth, and Radaelli, 2017). We unpack different government roles in AI policies, contributing to the literature on implications of AI for governments (Barth and Arnold, 1999; Cath et al., 2018; Taddeo and Floridi, 2018). We see that government's roles in AI policies are strongly associated with the underlying policy narrative. Our analysis shows that government intervention is required as *enabler* to establish a domestic AI market (narrative 1); to introduce AI promotion activities to satisfy the demand for AI talent (narrative 5); and to widely and quickly deploy AI in the own country in order to gain strategic advantages (narrative 6); as *regulator* to ensure that not only the large private sector players benefit from data collected (narrative 2); and to prevent negative effects by setting conditions for ethical and trustworthy AI (narrative 4); and as *leader* to engage in strategic cooperation and collaboration in AI research and development to work on common challenges (narrative 3).

Our findings are in line with Ulnicane et al. (2021), who also observed that the oligopoly of a small number of companies that disregard social needs and concerns is a policy problem for which the state was assigned a more active and collaborative role in AI policies for countering it. However, we observe that governments are caught in a dilemma: On the one hand, narratives 2 and 4 call for some prudence, suggesting that a government should act as regulator and should clarify the boundaries of accountability of AI-based solutions, specifically for algorithmic decision-making. On the other hand, the other narratives define governments' roles as leader and enabler - responsible for setting favorable working conditions for a domestic data-driven economy, establishing national and international alliances and partnerships with industries and friendly states, educating AI talent, and advancing the deployment of AI in practice. All countries face this dilemma to a degree. Some countries seek to balance this field of tension by addressing the narratives more evenly in their AI policies, while others tend to take a side and stress a certain narrative.

Overall, governments' role as user is not prominent in the narratives, indicating that governments are prioritizing enabling, regulating, and promoting AI rather than using AI applications themselves. Yet this finding doesn't mean that governments don't use AI. On the contrary, as we highlight in narrative 6, governments see potential in using AI technology for improving services, intelligent security, or epidemic monitoring and control, all of which are policy areas within government's responsibility. Interesting regarding narrative 6 in this context, however, is the fact that the policy documents mention no application in areas such as automated propaganda and disinformation campaigns, social control, surveillance, facial recognition, or social sorting, which are highlighted with concern in the literature in connection with the state as AI user (e.g., Hagendorff, 2020).

5.1.3. New methodological approach to analyze policy narratives

Third, we make a methodological contribution. We employed STM, a novel automated text mining method, to discover narratives and estimate their relationship to document metadata. We rely on the NPF, an analytical tool developed in response to postmodern approaches to understand narratives' roles in policy (Jones and McBeth, 2010, 2020; McBeth, Jones, and Shanahan, 2014). To date, NPF scholars have used various methods to demonstrate the roles that narratives play in public policy (E. A. Shanahan, Jones, and McBeth, 2018). We introduce a new approach to discover policy narratives, analyzing their temporal evolution and their distribution in policy documents. Our methodological approach is more efficient, faster, and less costly compared to completely manual qualitative analyses. Further, since the analysis is conducted automatically, our results are less prone to subjective bias. Also, combining it with qualitative interpretative analysis – as we do here – increases the results' credibility (Isoaho et al., 2021).

Overall, automated text mining techniques such as STM or LDA contribute toward data-driven, computationally-intensive theory development in policy research (Berente et al., 2018). These new techniques allow to obtain comprehensive information from large text corpi of any kind (e.g., news articles, tweets, or other documents) and to not only explore narratives, but also topics, themes, and frames. In our view, text mining techniques will pave the way for more intersubjectively reliable policy research.

5.2. Implications for practice

Policy narratives are strategically constructed and serve specific purposes (McBeth and Shanahan, 2004): they create a shared understanding (J. Shanahan et al., 1999), serve to define problems and shape solutions (Layzer, 2006), influence actors' actions (Gray and Jones, 2016; Reber and Berger, 2005), and thus promote the achievement of policy goals. Our analysis offers insights into AI policy that are relevant to practitioners. We shed light on the different directions that governments across the globe are taking, including the challenges they see, the courses of action they envision, and the different roles governments selfassign in achieving AI policy goals. In our view, it is important for different actors to be aware of the different narratives and related strategic aspirations of governments.

Our study offers interesting insights for policymakers. First, based on our analysis, they can compare what other governments are focusing on in AI, what their priorities are, and the similarities in or differences between their policies. Second, applying the same constructed narratives that are used by other governments (and in possibly very different political and cultural contexts) may be a strategy of blame avoidance (Hood, 2007; Weaver, 1986), a behavior that has also been studied by other IS scholars but for different cases and situations (e.g. Iacovou, Thompson, and Smith, 2009; Lee, Panteli, Bülow, and Hsu, 2018). Following the 'norm' and at times communicating in a totally 'context-free' way seems to make policymakers less vulnerable to being singled out or held accountable for bad or sub-optimal decisions (vice versa, developing exceptional or more country-specific or situation-specific narratives for a fairly new phenomenon would likely provoke undesired reactions from political adversaries, lobbyists, or policy consultants). In this sense, knowing the common AI narratives in use is important for policy professionals, particularly for those who are risk-averse and wish to avoid awkward political debates or who operate in an environment where AI is still in its infancy.

Our analysis provides insights for companies concerning which governments aim to strongly promote the business environment for AI, where governments aim to hold companies more accountable on data, where ethical issues are given more weight, or where practical applications relating to AI are given greater priority.

For research institutions, our results show where international research collaborations in the AI field are targeted more strongly, or which governments particularly emphasize the education of AI specialists. All this information helps these actors to better understand the governments with their various agendas and to consider them in their AI-related actions.

5.3. Limitations and future work

Our study has limitations. First, the results from our STM analysis (as any application of machine learning) depend on the input data one feeds the algorithm. Thus, first, the data basis for our analysis is limited by availability regarding language, number of AI policies, length of texts, and publication date. Certain governments publish policies only in their country-specific language or use English only for consolidated policy briefs. Thus, there are English AI policies from only 33 countries. Also, the text corpi we retrieved from some countries' AI policies are considerably shorter than those of other countries. Further, concerning publication date, we have AI documents of only three countries for 2020, the last observation year in our dataset. Second, another study limitation arises owing to the STM analysis, which identifies narratives that are common to all policies. Since there are no narratives that are specific to one or a few policies, our study covers only a subset of the narratives that are present in individual policies, namely only those they share with other AI policies. Third, with the interpretation of the computational results, we introduce a certain level of subjectivity that is normal for the current state of technological progress and that is necessary for making the findings usable for humans (DiMaggio, Nag, and Blei, 2013).

The identified narratives present a key starting point for further research. Our results indicate that the global race rhetoric for AI - especially pronounced between China and the U.S. (Johnson, 2021) - is short-sighted, since many more countries are participants in the race. Likewise, it is interesting that, besides the competition aspect between countries, the AI policies strongly emphasize strategic alliances in R&D; this is the most salient narrative across all the AI documents. Considering the prevailing *winning the race* rhetoric, this aspect of international collaboration is still underestimated and has barely been discussed in the literature. How this cooperation narrative is concretely implemented in practice and with which effects may be important foci for future research.

Further, our findings on policy narratives also support studies that have provided insights into the real world. For instance, the U.S. – where narrative 3 (a focus on AI R&D) is strongest – is leading in AI R&D and has the most startups in the AI field. In contrast, in the case of China – where narrative 6 (deployment of AI in practice) is strongest – investments in AI are described as application-oriented (Hagendorff, 2020). However, the link between rhetoric and reality may not always be easy to find. More detailed research is needed to show which narratives are found in practice and which are omitted, along with the explanations for one or the other case.

Our analysis also reveals that there is no clear difference between world regions and regime types concerning the narratives they use in their AI policies. Since no two countries are completely identical in the saliences of the narratives they use, we recommend that researchers analyze individual AI policies in-depth. This would allow the different narratives and actors' roles to be examined in greater detail and would allow us to discover further narratives and roles specific to each country. Related to the character of the narratives, the NPF can also be applied to determine whether actors demonize their opponents (i.e., a devil shift by referencing villains) or stress their own heroic role in solving policy problems (i.e., an angel shift by referencing heroes) (Jones and McBeth, 2020). Our results indicate that the devil and angel shifts are also present in the AI context, for instance, referring to researchers as heroes and to big tech companies as villains. An interesting empirical question here is to determine whether governments predominantly engage in angel and/or devil shifting, to what effects, and with whom. Our results indicate that both occur. Empirical analysis and how these narratives contribute to the global AI race, to the formation of international coalitions in R&D, to the implementation of AI would be interesting future research areas.

Finally, we agree with Isoaho et al. (2021), seeing tremendous potential for STM as a novel computational method. STM is less prone to subjective misinterpretation and, especially with large text files, can be used as a as a time-saving and resource-saving complement to well-known qualitative methods, not only for narrative analysis but also for frame analysis, discourse analysis, or thematic analysis.

CRediT authorship contribution statement

Ali A. Guenduez: Conceptualization, Supervision, Methodology, Data curation, Formal analysis, Writing – original draft, Writing – review & editing, Visualization. **Tobias Mettler:** Conceptualization, Formal analysis, Writing – original draft, Writing – review & editing.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

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