China's AI Policy: An NLP Approach to Assessing China's Priorities and Governance

Hannah Bailey[1], Hannah Rose Kirk[1], and Phil Howard[1]

[1] *Oxford Internet Institute, University of Oxford*
{hannah.bailey,hannah.kirk,phil.howard}@oii.ox.ac.uk

1 Introduction

Artificial intelligence (AI) technologies are a resource of autonomous, self-learning agency with the power to radically transform societies, and the distribution of power among groups in these societies (Floridi and Cowls 2019, Hagerty and Rubinov 2019). AI is used by a variety of actors in both democracies and authoritarian states. However, who uses AI, and to what end differs markedly between democracies and authoritarian states. In this paper we examine how, and to what end, China, as an authoritarian state, is pursuing the development of artificial intelligence technologies.

While AI has a variety of potential applications, there are two of particular interest to authoritarian states. First, AI technologies are often referred to as general purpose technologies (GPTs), as they have the potential to radically transform economies by reforming the means of production (Ahmed *et al.* 2019). For authoritarian states such as China, economic growth driven by AI has the potential to boost productivity, in lieu of potential deficiencies in the labour force or capital investment (He and Bowser 2017). Second, authoritarian states often lack reliable mechanisms for establishing and maintaining regime security. By enhancing the ability of a regime to monitor a population and predict citizen behaviour, AI technologies can pre-empt unrest, shape public opinion and improve regime stability (Ahmed *et al.* 2019). We recognise that AI can serve other policy objectives, however for this paper we examine the tension between the application of AI for economic growth versus social control. This paper investigates which of these two objectives China prioritises in its pursuit of AI capacities.

The inherent opaqueness of China's political system makes it difficult to evaluate its policy objectives. Previous literature investigating China's AI policies has focused on examining a select number of high profile policy documents issued by central government bodies (Yang and Huang 2022, Gao, Huang, and Zhang 2019, H. Roberts *et al.* 2019, Zeng 2020, Schiff *et al.* 2020). This literature argues that, while China's AI innovation has the potential to influence social governance structure's, the Chinese Communist Party's (CCP's) primary objective is to use AI as a tool for economic growth (Ding 2018, Horton and Zeng 2021). Contrary to popular belief, however, China's governance structure is highly pluralistic and influenced by a variety of socio-political actors who in turn shape the political decision-making process (Brødsgaard 2016). China's governance structure is often referred to as a form of 'fragmented authoritarianism', where policy outcomes at provincial, city and local governments often deviate from central-level directives (Lieberthal and Lampton 2018a, Sinoeconomics 2020). Given this fragmented governance structure, when we evaluate China's AI policies it is important to track AI directives across all areas of government, rather than focusing solely on central-level directives.

In this paper, we identify both the substantive content of China's AI policies, and the governance dynamics that drive these policies. We use natural language processing (NLP) methodologies to quantitatively identify which AI technologies and applications China is prioritising in its policy directives. We also evaluate which levels of government are driving this AI policy agenda.

(2022)

Corresponding author
Hannah Bailey

2 AI Policy

2.1 AI Policies in Authoritarian States

AI is a potentially powerful tool that nation-states can use to: (1) improve their productivity and overall economic performance; or (2) enhance their regime security through information control. Here, we will unpack each of these objectives.

As the technical capacities of AI have improved and the cost of implementing these technologies has decreased, investment in AI has increased. The cost to train an image classifier has decreased by 64% and training times have improved by 94% since 2018 (Zhang *et al.* 2022). Meanwhile, by one estimate, global private investment in AI doubled between 2020 and 2021, reaching $93.5 billion (Zhang *et al.* 2022).

Increased investment in AI is largely motivated by the potential for these technologies to boost productivity by functioning as a GPT. Historically, GPTs such as steam engine technology, electrification, and information technologies, facilitate automation which in turn fosters productivity growth (Rosenberg 1983, Crafts 2004, Oliner, Sichel, and Stiroh 2007). However, since the 2007-2009 global recession, global productivity growth has experienced the steepest and most persistent decline in decades (Basu *et al.* 2020). A variety of factors have contributed to this decline, including diminishing returns from technological innovation, and a lag in the development of new digital technologies (Basu *et al.* 2020). AI technologies have the potential to reverse this decline in productivity growth through automation.

Aside from the immediate benefits for AI to enhance domestic productivity growth, investment in AI promises other positive externalities, or beneficial spillover effects. For instance, these include greater technological self-reliance (Ho 2020), alongside the ability to export these technologies. These externalities are particularly beneficial for authoritarian states, which may wish to reduce their dependency on technologies from competitor democratic states and increase their economic leverage over other states by exporting AI technologies.

While AI technologies have the potential to improve a country's aggregate economic performance, as noted above, they are also potential tools for authoritarian regime security through information control. Authoritarian regimes operate on the notion that governing authority is exercised from above, regardless of popular consent. AI technologies can enable smaller groups of elite actors to maintain this authority by substituting human labour with technology-enabled policing (Ahmed *et al.* 2019).

A security infrastructure consisting of human agents, such as police or military forces, is costly economically and can potentially in and of itself pose a threat to the regime (Feldstein 2019). That is, a large police or military force is useful to a regime only insofar as it is loyal to the regime; if that loyalty evaporates, this human resource can become a threat to the regime (Svolik 2012). The use of AI, in contrast, is comparatively inexpensive and does not require loyalty. AI technologies can surveil, repress and intimidate potential regime threats without posing principal-agent threats to the regime itself wherein the agent turns on the principal. Moreover, by reducing the number of actors required to secure the regime, AI enables an ever smaller number of elites to retain power.

Whereas human operators are limited in terms of time and energy, AI technologies can automate targeted surveillance and predictive policing operations on a large scale (Feldstein 2019). By constantly monitoring a population, AI surveillance and repression technologies can even create a chilling effect, which results in the population self-policing its activities (Feldstein 2019).

AI is thus a multifaceted tool, which offers states both economic benefits and security benefits. It is of course feasible to pursue both these benefits simultaneously; however, the strategic objectives that underpin each are very different and in reality state actors may at times prioritise one set of objectives over another. We explore the possibility that China may thus prioritise an AI policy which focuses on economic benefits over security benefits, or vice versa.

2.2 China's AI Policies

Since 2017, AI advancement has become a national priority for China. In 2017, China's State Council issued a central-level strategy document titled "AI Development Plan" (AIDP) mapping out key benchmarks for its domestic AI industry (Webster *et al.* 2017). This plan marked a pivotal moment in China's development of AI policy, as it sent a clear signal that AI was a national strategic priority. Prior to 2017, there were some efforts to advance AI technologies at the local level and within particular industries, but few macro-level plans for developing AI technologies (Yang and Huang 2022, Horton and Zeng 2021). The AIDP, however, was intended to generate "China's industrial upgrading and economic transformation" and was included in President Xi Jinping's future vision for China (Webster *et al.* 2017, Yu and Jing 2017). The AIDP outlined four objectives: (1) to maintain international competitiveness and optimise an AI development environment by 2020; (2) to have achieved a "major breakthrough" by 2025 in AI theory; (3) to increase the worth of its AI industry to over 400 billion yuan; and (4) to become the world's leading innovator in AI by 2030 (H. Roberts *et al.* 2019).

In addition to the AIDP, the Ministry of Information and Technology also issued the "Three-Year Action Plan for Promoting Development of a New Generation Artificial Intelligence Industry" (Action Plan). While the AIDP outlines a set of high-level goals, the Action Plan provides details on how these goals should be enacted (Hine and Floridi 2022). Following the expiration of the 2017 Action Plan in 2020, no subsequent plan has been issued. Instead, AI has been encompassed into China's central-level science and technology objectives in the 2021 "Fourteenth Five-Year Plan for the National Economic and Social Development of the People's Republic of China and the Outline of the Long Term Goals for 2035" (Five-Year Plan) (Hine and Floridi 2022). This decision coincides with a period where the broader AI policy environment in China has become more pragmatic about AI technologies and their implementations, and so policy decisions became more targeted (Yang and Huang 2022).

Overall, these select central government documents indicate that China's AI development strategy is focused on developing world-leading AI technologies, and using this technological innovation to maximise economic growth (Ding 2018). Multiple reports claim that the effective implementation of AI could improve China's lagging productivity growth (PwC 2017, Barton *et al.* 2017). Moreover, both the AIDP and the Action Plan prioritise economic targets and objectives for AI development.

Since China's reform and opening in 1978, the CCP has relied on its ability to oversee strong economic performance and improve the quality of life among China's population. China's productivity output has been a major concern for the CCP, as economic growth is a key component of CCP legitimacy and regime security (Shirk 2007). China's fear is that it may fall into the so-called "middle-income trap", where a developing country is able to attain a certain level of economic growth before plateauing at a per capita income level below 12,000 USD (Overholt 2018). To avoid this trap and maintain the CCP's economic legitimacy, China needs to enact economic reforms that boost productivity. This has led Beijing to pursue AI as a means to boost economic productivity and prevent unrest.

At the same time, AI applications could also enhance the CCP's regime security without relying on economic growth as a mediating factor. The State Council's AIDP declares its desire for AI to play a pivotal role in maintaining social stability by integrating AI with local-level public goods, such as medical care, law enforcement and judicial services (Webster *et al.* 2017). China's social credit systems are an example of how the CCP can use AI for social management, as a means to prevent unrest. The social credit system is a collection of local-level infrastructures to bolster law enforcement efforts through the collection and analysis of individual behaviour (Daum 2017). AI is used to monitor and shape individual behaviour through a process referred to as "social management" (社会管理) (Ahmed *et al.* 2019). Social management is a process designed to prevent dissent and pre-empt social conflict as a means to ensure "state security" (国家安全) (Ahmed *et al.* 2019). There are, so far, two "credit cities" that have been publicly praised by the central government: Suzhou and Fuzhou. "Credit cities" refer to cities where local governments and technology companies share data from individuals and businesses to evaluate their trustworthiness (Ahmed *et al.* 2019). While the social credit system continues to face centralisation and data processing hurdles, it appears that China is aiming to develop AI tools to maintain social stability and the CCP's regime stability.

Recent academic literature indicates that China's AI policy documents encourage the application of AI technologies for economic growth and social stability . While some of this literature argues that the CCP prioritises AI applications for economic growth over social stability (Ding 2018, Barton *et al.* 2017), it is important to note that the conclusions made in this literature are largely based on the analysis of a select number of key central-level directives. However, China's central and local level policies are often at odds with each other. China's governance structure is often referred to as "fragmented authoritarianism", wherein the central government outlines overarching policy objectives and then delegates their implementation to local level governments (Lieberthal and Lampton 2018b). While China's governance structure is often thought of as top-down, in reality it consists of top-down guidance with local-level initiatives (Zeng 2020).

This raises a number of questions. First, are AI policies at the local level pursuing the same agenda as the central-level directives? Second, are the key AI policy decisions made at the central or local level? And third, does China's overarching policy agenda prioritise the development of AI applications for economic growth over social stability? To address these questions, we pose two hypotheses that test the findings of the existing literature on China's AI policies, and China's governance structure at large.

Hypothesis 1: Central government AI policies shape local-level policy implementation decisions.

Hypothesis 2: China's local and central level policies prioritise the development of AI applications for economic growth over social stability.

3 Data and Methods

To test these two hypotheses, we compile a novel dataset of all China's central- and local-level policy documents mentioning AI. We then use NLP methods to quantify the topics discussed in these documents, and the sequencing of idea creation and diffusion in China's AI policies. In this section, we describe the method for compiling and cleaning our corpus of policy documents and our NLP approach.

3.1 Data Collection and Processing

We construct a corpus of policy documents from PKU (Peking University) Law [1], a large database for Chinese laws, regulations and policy documents from 1949 to present. In this paper, for ease of reference, we refer to this collection of laws, regulations and policy documents as simply "policy documents". PKU Law is widely used to research a range of disciplines, including law, politics, social policy and business (Nan *et al.* 2020, Zhu, Liu, and Hu 2021, Chen, Mao, and Morrison 2021).

We collect all central and local-level government documents from 1949 to 2021 that mention the term "artificial intelligence" (人工智能) at least once. This gives us a total number of 12,116 documents. We remove duplicates, leaving 11,905 total documents in our corpus. Fig. 1 shows the distribution of these central and local level policy documents over time. Between 1949 and 1981 there were no mentions of AI. Between 1982 and 2006 mentions of AI occur infrequently, with one or no mentions for each year. In 2015, two years prior to the publication of the AIDP and the Action

1. https://www.pkulaw.com/

Plan, there is a notable increase in mentions of AI in both central and local level policy documents. The frequency count of Chinese policy documents mentioning AI peaks in 2020, with 504 central level documents mentioning AI and 2,790 local documents. For every year since 2009, more local level policy documents mention AI than central level documents. This is likely the reflection of a large number of localities each producing documents, as compared with the smaller quantity by central government.

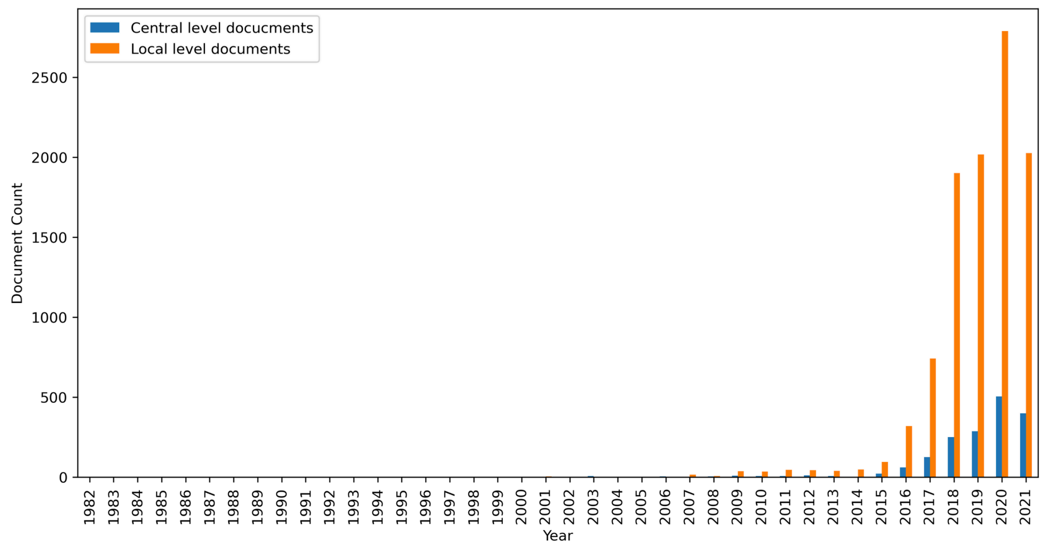

Figure 1. Frequency Distribution of China's local- and central-level policy documents mentioning "artificial intelligence" over time.

Before using NLP methods, we first clean the text in these policy documents. The cleaning process entails three steps. First, we remove URLs, numeric digits, punctuation, white space and non-Chinese characters. Second, we tokenise each document into word segments. Word segmentation is a problem for Chinese which results from the lack of space to delimit words. We use a specific tokenizer designed for Chinese NLP in the `jieba` python package to segment the Chinese characters in our data into word segments. Third, we remove any commonly occurring stop-words.

To test our two hypotheses, we implement a novel approach to NLP methods. Other researchers use topic modelling to gauge text content and Kullback-Leibler Divergence (KLD) to quantify novelty, transience and resonance across texts over time (Kullback and Leibler 1951, Barron *et al.* 2018). Our contribution is to merge STM with measures of resonance and then construct a feedback loop which includes regression analysis in order to assess determinants of resonance. In the sections that follow we unpack each step of the analysis.

3.2 Structural Topic Modeling

To assess the topical context in which AI is discussed in our corpus of policy documents, we estimate a Structural Topic Model (STM) (M. E. Roberts *et al.* 2014). An STM, and topic models more generally, allow the researcher to identify latent variables in a corpus of text using unsupervised machine learning (Blei 2012). Unsupervised learning is a preferable method in this analysis as, unlike supervised machine learning, it does not require the researcher to pre-determine the topics through a process of manual coding (Grimmer and Stewart 2013). The process of predetermining topics is less desirable as the researcher's perspective or pre-existing expectations may influence the findings (Jacobi, Atteveldt, and Welbers 2016). An unsupervised approach also allows the potential for uncovering previously unknown topics within a text. In using an unsupervised approach, topic modelling clusters textual data from a set of documents into topics, where a topic is a set of words that together form a semantically coherent theme within the documents. Each document, which in this case constitutes a Chinese policy document, is a distribution over these identified topics.

Topic models require the researcher to specify a k number of topics to be estimated. To determine the k value, we use: (1) an assessment of the coherency and distinction of the characteristic words within each topic; (2) fit statistics, including coherence, held-out likelihood, residuals and held-out likelihood, for a series of alternative models with varying numbers of topics (M. E. Roberts *et al.* 2014); and (3) manual examination of the most representative documents for each topic. This approach results in 15 topics for the present corpus.

The STM output contains the most representative words and documents for each topic. From this output, the researcher must then manually label each topic. To label each of the 15 topics in our model, we employ a robust annotation scheme using three independent annotators. The three individuals who served as annotators are proficient in Mandarin (Chinese). During the labelling process, each annotator had access to the seven most representative words and three most representative documents per topic. After independently labelling each topic, the three annotators constructed final topic labels based on majority agreement.

3.3 Novelty, Transience and Resonance

The STM output provides a list of the topics discussed within China's AI policy documents, and the relative prevalence of these topics across the corpus. The STM also provides document-level distributions over topics. We use the STM output to: (1) identify the topics discussed within China's AI policy documents; and (2) measure the degree to which documents are novel, transient or resonate with one another. These two measurements test each of the two hypotheses posed in this paper.

Novelty, transience and resonance are each measures of document similarity over time (Barron *et al.* 2018). Novelty, here, refers to how similar each document is to the documents that precede it. High levels of novelty indicate that a document is less similar to previous documents, and thus introduces novel concepts. Transience is a measure of the similarity of a document to the documents that follow. A document that is highly transient is less similar to the documents that are published after, indicating that the pattern content of that within the document is not retained.

While some policy documents may be novel, the content it introduces may be highly transient, and therefore not be replicated in future policy documents in other localities. This policy document would be surprising given the policy documents that preceded it, and equally surprising given future policy documents, because the new information is transient. Other policy documents, however, may be more effective insofar as these documents shift wider policy discourse to a new issue. This shift could be observed as a surprise asymmetry surrounding the document, given the documents that came before and after. We define this textual asymmetry as resonance. Resonant policy documents are both novel insofar as they introduce surprising content, and are not particularly transient, thereby influencing the content in future policy documents. Resonant documents are therefore pivotal points in policy making. In this paper, we use measures of novelty, transience and resonance to quantify how patterns of language, uncovered by the STM, are propagated in China's AI policy documents.

We calculate novelty, transience and resonance using Kullback-Leibler Divergence (KLD), which measures how much one probability distribution differs from another (Kullback and Leibler 1951). In the case of language modelling, we can use KLD to quantify the extent to which the expectations of an optimal learner, trained on the text pattern in one particular document, are violated by a second document.

We calculate the KLD between policies using the document-level probability distributions outputted by the STM. Novelty between two documents is measured by the KLD of $s^{(j)}$ relative to $s^{(j-1)}$,

$$KLD\left(s^{(j)}|s^{(j-1)}\right) = \sum_{i=1}^{K} s_i^{(j)} \log_2\left(\frac{s_i^{(j)}}{s_i^{(j-1)}}\right).$$

This measure examines novelty between two documents. We average this measure over documents within a longer time window, to examine the extent to which a current policy document discusses unexpected topics, given, say the policy documents from the last two years. We refer to novelty as $\mathcal{N}$ and time as j on a scale w,

$$\mathcal{N}_w\left(j\right) = \frac{1}{w}\sum_{d=1}^{w} KLD\left(s^{(j)}|s^{(j-d)}\right).$$

Transience is calculated in the same manner as novelty, but for a time window into the future, rather than the past. This allows us to measure to what extent the topical patterns in this document persist into the future. We refer to transience as $\mathcal{T}$,

$$\mathcal{T}_w\left(j\right) = \frac{1}{w}\sum_{d=1}^{w} KLD\left(s^{(j)}|s^{(j+d)}\right).$$

Resonance is novelty, $\mathcal{N}$, minus transience, $\mathcal{T}$. Resonant documents indicate pivotal policy documents that are both highly novel and heavily influence future policy documents in the corpus. We refer to resonance as $\mathcal{R}$:

$$\mathcal{R}_w\left(j\right) = \mathcal{N}_w\left(j\right) - \mathcal{T}_w\left(j\right).$$

In this paper, we calculate the degree of novelty, transience and resonance between each of China's local and central policy documents mentioning AI. To address *Hypothesis 1*, we calculate these variables in two steps. First, we measure the novelty, transience and resonance of each central-level policy document, given the local-level documents that precede and follow its publication. This allows us to see the degree to which the content contained within the central document is similar to that used by local policy documents published before it, and influences future local level policies. In a second step, we calculate novelty, transience and resonance for both local- and central-level documents, given the policy documents that precede and follow. These two steps allow us to see the degree to which novel central-level government AI policies shape local-level policies, and, in contrast, how a policy document mentioning AI at any governance level influences any other policy document that follows.

Finally, we use these results, together with the results from the STM, to examine the variables that determine resonance in AI policy making in China. We then use OLS regression modelling to investigate whether central-level directives shape the content of local-level AI policies, or whether there are other factors that have a greater impact on resonance.

4 Results

In this section, we start by examining graphically the topics discussed in all of China's central- and local-level policy documents that mention AI. We measure how discussions of these topics vary between central- and local-level documents. Thereafter we present the novelty, transience and resonance scores for these documents, and, using regression models, analyse the relationship between resonance, topical focus, and governance level.

4.1 Topics Discussed in AI Policy

We begin by examining the topics contained within the entire corpus of China's local- and central-level policy documents mentioning AI. Fig. 2 shows the sixteen labelled topics from the STM, their overall topic proportions, and their three most representative words. The figure shows that a variety of different topics are discussed within policy documents mentioning AI. Thematically, Fig. 2 illustrate a mixture of topics related to economic development (i.e., 'Industry', 'Finance and Law' and 'Specific Companies'), social issues (i.e., 'Law Enforcement', 'Service Sector', 'Administrative Processes', 'City Governance', 'Medical Treatment' and 'Hospital Procedures'), research and education (i.e., 'Research and Development', 'Research and Innovation', 'Education', 'Career Training' and 'Educational Textbooks'), and other topics such as 'Digital Infrastructure' and 'Showcasing Events'.

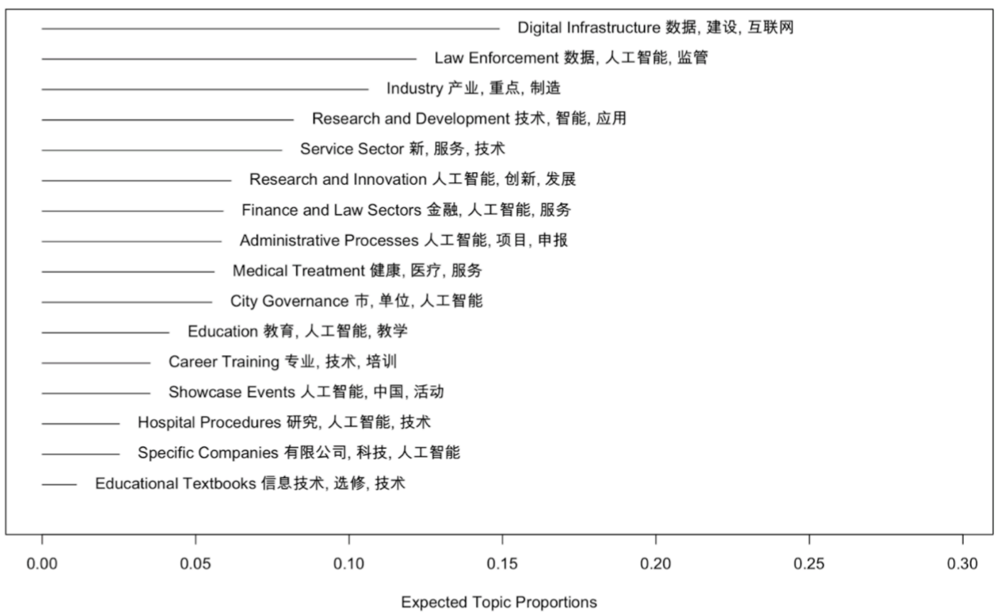

Figure 2. STM Topic Output and Prevalence over the Entire Corpus of China's Central and Local Level Policy Documents Mentioning AI

The most prevalent topic in the corpus, 'Digital Infrastructure', suggests that constructing the physical infrastructure to support future technology innovation and AI applications is a priority for China. Notably, the second most prevalent topic overall discusses 'Law Enforcement'. This topic broadly discusses the application of AI and data-driven innovation to law enforcement and regulation bodies to improve prediction systems. The high prevalence of this topic indicates that the development of AI tools for social control may be a priority for governing bodies within China.

Other topics, however, also discuss the economic applications of AI, including the third most prevalent topic, which discusses AI innovation for industry. Overall, this shows that governing bodies in China discuss the applications of AI to a wide range of sectors, including sectors that may seek to develop AI for social control as well as sectors that aim to use AI to enhance economic performance and for research purposes.

In Fig. 3 we examine the distribution of these topics between central and local policy documents. We calculate the percentage distribution by topic for each level of government. So, for instance 'Specific Companies' comprises approximately nine percent of the overall composition of the central level government topics, and seven percent of the overall local level government topics.

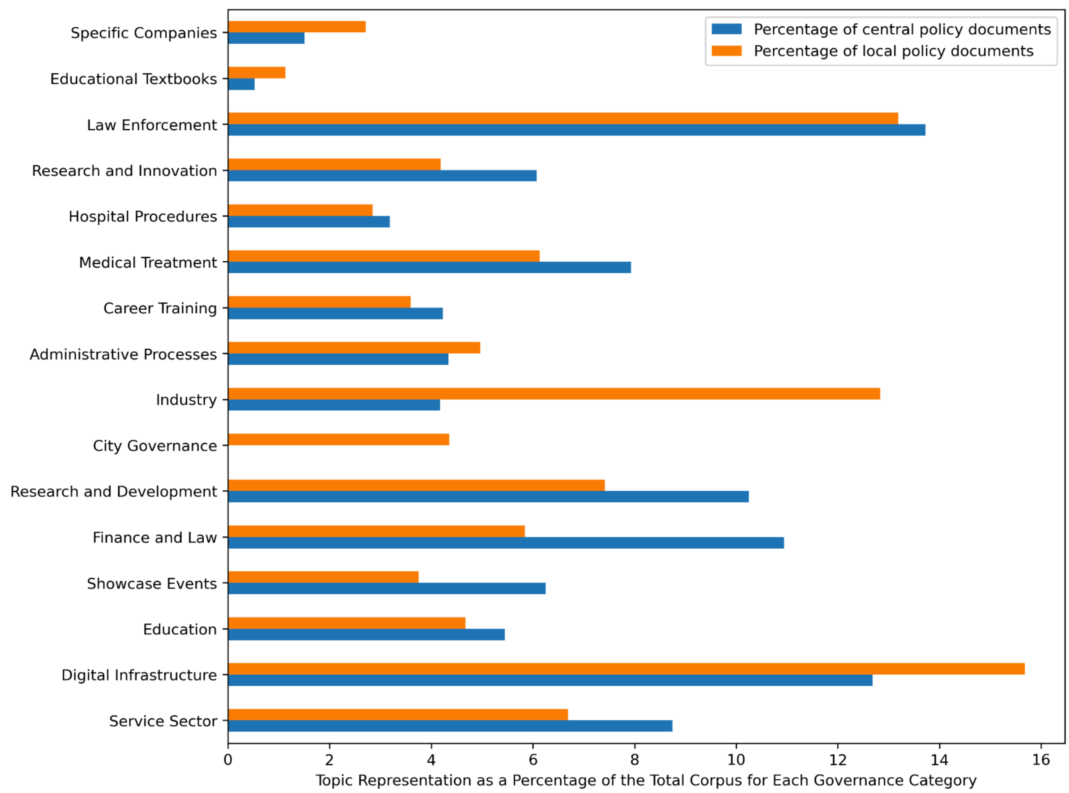

Figure 3. STM Topic Distribution by Governance Level.

If we examine the three most prevalent topics from Fig. 2, we can see there is a discrepancy in the degree to which local and central level governments discuss these topics alongside AI. Local governments are slightly more likely to discuss AI in the context of 'Digital Infrastructure', which may reflect the direct responsibilities of local governments in terms of implementation. Law enforcement is prevalent among both local- and central-level documents, and accounts for a roughly equal proportion of documents at each governance level. For the topic 'Industry', however, local documents dedicate a much larger proportion of their policy documents to discussing AI in the context of industry when compared to central-level documents. Fig. 3 illustrates that while local- and central-level governments prioritise some applications of AI, such as law enforcement, to the same degree, in other areas they have slightly different distributions over topics. This indicates that these two governance levels may have different policy priorities when discussing AI.

4.2 Central Level Policy Document Novelty, Transience and Resonance

Having examined the broader topical focus of the 11,905 policy documents mentioning AI, we now use the measurements of novelty, transience and resonance outlined above to examine the sequencing of idea creation and diffusion in China's AI policies.

Fig. 4 illustrates the relationship between novelty and transience at the policy document-level. In this figure, each dot represents a central-level policy document, for which novelty and transience is calculated for the preceding and subsequent local-level policies. Here, we examine both novelty and transience over a time window (w) of two years before and after the release date of each policy document. These results are also consistent for a w of six months and four years.

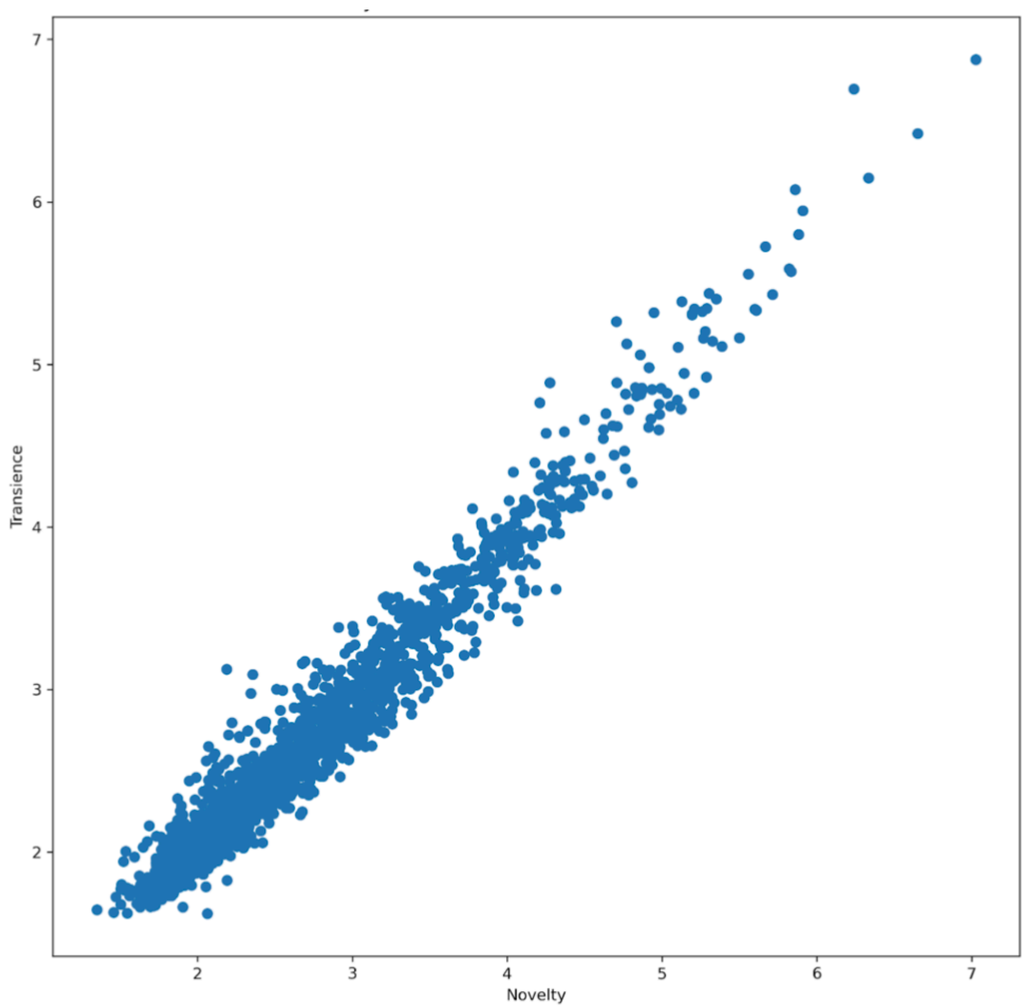

Figure 4. Novelty and Transience Scores for Central Level Documents Mentioning AI

The majority of central-level documents concentrate heavily near the symmetry line, indicating that central policy documents with high novelty have equally high transience. This strong relationship indicates that, contrary to *Hypothesis 1*, novel central-level document directives on AI may not shape subsequent local-level policy implementation decisions. Instead, the central-level AI documents that are similar to the preceding local-level documents are more likely to influence future local-level AI-related policies. Rather than issuing top-down guidance on AI directives that are then successfully implemented by local governments, the central government policies that are carried out by local governments are those that have been discussed before.

4.3 Central And Local Level Policy Document Novelty, Transience and Resonance

Given that Fig. 4 suggests central-level policy documents on AI do not introduce novel ideas that are then implemented at the local level, we instead investigate other factors that may influence resonance among China's AI policy documents. Fig. 5 plots how average document-level measures of novelty, transience and resonance vary by topic prevalence. We might expect that central level policy documents that discuss topics that are highly prevalent might achieve higher resonance among local-level governments.

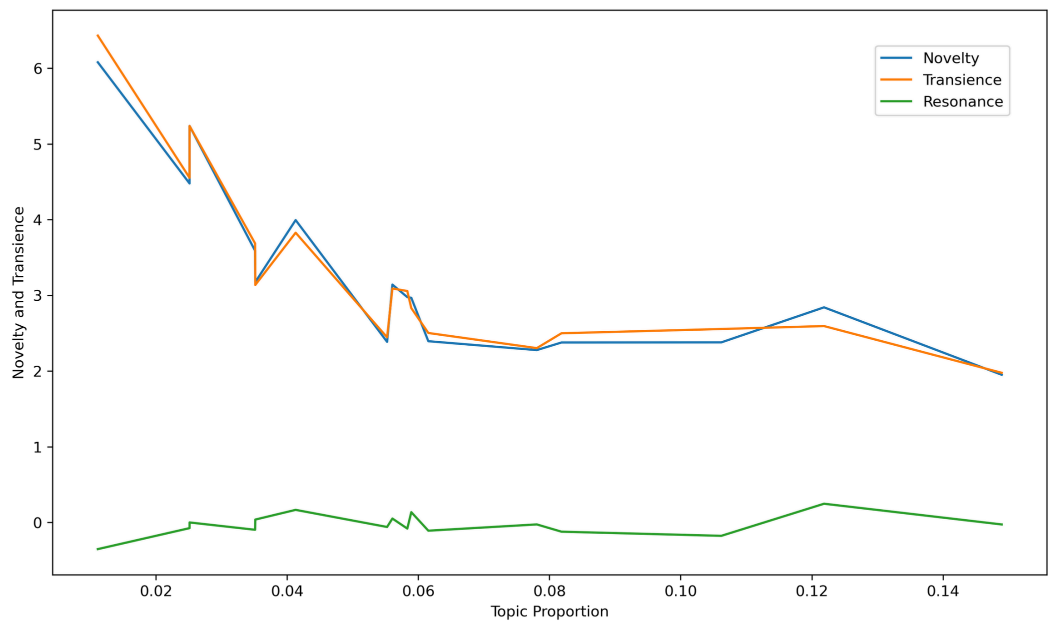

Figure 5. STM Topic Output and Prevalence for China's Central-Level Policy Documents Mentioning AI

Fig. 5 illustrates that both novelty and transience decline overall as topic prevalence increases. This is, however, likely a by-product of the increased number of documents that belong to topics with higher topic proportions and does not apply to resonance. Resonance, by comparison, remains relatively flat, and does not appear to vary along with topic prevalence. This suggests that topic prevalence does not influence the resonance of central-level policy directives on AI.

4.4 Factors Influencing Resonance in AI Policy Documents

Thus far we have investigated the relationship between central government directives and local level policy implementation decisions to identify which factors influence idea diffusion in China's AI policy decision making. We first explored the relationship between central level policy novelty and transience relative to local level policies, and found limited graphical evidence to suggest that novel central policies which mention AI then subsequently influence local policies. We then explore a second plausible factor that may potentially influence idea diffusion in China's AI policy decision making, namely the prevalence with which the topic is discussed in government policies. Again, we found no graphical evidence that policy resonance at the local level increases with topic prevalence.

Table 1: OLS Regression Results for Productivity and Stability Models for 2 Year Resonance Measure

Variables	Unstandardized Coefficients	(S.E.)	Unstandardized Coefficients	(S.E.)	Unstandardized Coefficients	(S.E.)	Unstandardized Coefficients	(S.E.)
	Model 1-Level of Government		**Model 2-Productivity**		**Model 3-Stability**		**Model 4-Other**	
Intercept	-0.102***	(0.019)	-0.133***	(0.018)	-0.026	(0.016)	-0.038	(0.020)
Government Level Dummy (1=local; 2=central)	0.033***	(0.006)	0.037***	(0.006)	0.006	(0.005)	0.014*	(0.005)
(Log) Document Word Length	0.019***	(0.005)	0.053***	(0.005)	0	(0.004)	-0.002	(0.005)
Service Sector							-0.019	(.014)
Digital Infrastructure			-0.129***	(.011)				
Education							0.32***	(.013)
Showcase Events							-.161***	(.016)
Finance and Law							.376***	(.013)
Research and Development			-0.347***	(.013)				
Industry			-0.174***	(.018)				
City Governance					-0.321***	(.010)		
Administrative Processes							-.150***	(.015)
Career Training							.101***	(.018)
Medical Treatment							.132***	(.012)
Hospital Procedures							0.017	(.017)
Research and Innovation			-0.43***	(.016)				
Law Enforcement					0.45***	(.008)		
Educational Textbooks							-.372***	(.028)
Specific Companies			-0.204***	(.017)				
F-value	21.18		232.296		1579.977		177.031	
P-value	0.001		0.001		0.001		0.001	
Adjusted R-squared	0.004		0.124		0.355		0.144	
N	11475		11475		11475		11475	

As a final step in our analysis, we use Ordinary Least Squares (OLS) regression to examine the effect of key explanatory variables on policy document resonance. This analysis enables us to assess, with greater specificity, the strength of both our earlier hypotheses. To reiterate, the first hypothesis essentially posits that AI policy implementation decisions are a top-down phenomenon, with central government shaping local level decisions. The second hypothesis posits that, regardless of the level of government, China prioritises economic growth and productivity over social stability as it develops AI policies.

The unit of analysis for the regression models is an individual policy document, which for each of our models sums to an N of 11,475. We use a two-year measure for resonance, which allows us a reasonable space of time between the six months and four-year measures discussed earlier. This resonance measure ranges from -2.387 to 1.405. As our predictors, we use the individual topic proportions for each document, across the 16 topics from our STM analysis. Each of these topic proportions, as variables, range from 0 to 1. We also introduce a dummy variable to control for the level of government (local or central). As a second control variable, we include the word length of each document. Because the values for this variable range from 59 to 365,689, we log this measure. In this final analysis, we seek to evaluate (1) whether AI policy implementation is indeed driven by the central government; and (2) whether growth and productivity or social stability is prioritised in AI policies. Support for (1) would be evidenced by a positive and significant coefficient for the level of government dummy. Gauging (2) entails an assessment of the relative strengths of coefficients for topics associated with economic growth and productivity (digital infrastructure, research and development, industry, research and innovation, and specific companies) versus those associated with social stability (city governance and law enforcement). The remaining nine topics as judged by their content do not clearly align with either growth and productivity or social stability. These remaining topics are service sector, education, showcase events, finance and law, administrative processes, career training, medical treatment, hospital procedures, and educational textbooks.

Perhaps not surprisingly, preliminary analysis indicates some degree of multicollinearity among the topic variables, and so we create four distinct models for our analysis to tease out the distinct effects of productivity versus social stability. We recognise that our results are thus less well-specified than what might be obtained from a larger model which includes all the variables. The results for these models are given in *Table 1*. The first model simply includes the level of government and the length of the document. While both coefficients are statistically significant, the coefficients suggest a small substantive effect on policy resonance and moreover the fit of the model is quite poor, with an adjusted R squared value of just 0.004.

Models 2 and 3 are the two models which seek to gauge the relative priorities of productivity versus social stability in AI policies. For the productivity model 2, all the coefficients are statistically significant; however, none of the those for the relevant topics are positive and the overall goodness of fit is weak (Adjusted R squared value of 0.124). These growth and productivity topics in AI policies appear to lessen policy resonance rather than increase it, which suggests that economic growth and productivity are not policies which enhance the resonance of AI policies. Interestingly, however, we note that in this model, level of government is both significant and positive, which suggests that there is a difference between local and central policies, with the latter exhibiting a positive effect on resonance within this model specification. For the social stability model, in contrast, only one variable is statistically significant and positive—law enforcement. Its substantive significance is larger than any other single topic variable, and the model fit is the best of all four models (Adjusted R squared value of 0.355). The F test of overall significance also supports this model for the measure of policy resonance. And, finally, in model 4, the topics education, finance and law, career training, and medical treatment are all significant and positive; however, as these do not directly relate to our analysis here, we do not explore these further.

5 Discussion and Conclusion

This article has examined China's overall AI policy agenda, as well as the factors that lead to successful AI policy diffusion within China's fragmented governance structure. Recent literature on China's AI policies has largely focused on examining a select number of high profile central-level AI directives (Yang and Huang 2022, Gao, Huang, and Zhang 2019, H. Roberts *et al.* 2019, Zeng 2020, Schiff *et al.* 2020). The assumption taken by this literature is that these central policy directives are then directly implemented by local governments within China. However, China's fragmented governance structure means that local level governments have a degree of autonomy to determine their own policy agendas, which may in turn deviate from the central-level directives (Lieberthal and Lampton 2018a, Brødsgaard 2016). This study therefore extends the literature on China's AI policies, and China's governance structure at large by examining how AI implementation ideas diffuse through China's policy making process.

Our main argument is that, at all levels of government, China produces policies designed to encourage the development of AI technologies to ensure social stability and the CCP's regime security. We find that the overall level of discussion of law enforcement applications of AI within China's policy documents is high in both local- and central-level documents. Moreover, we find that governance level is a factor that has low substantive significance in determining the resonance of an AI policy document on subsequent policy making. Rather, whether a policy discusses AI in the context of law enforcement is the key determinant of a policy document's resonance, regardless of the government level that issued the policy.

This article makes three key contributions to the wider literature on authoritarian government AI policies, and more broadly, NLP methods for social science inference. First, the findings of this study indicate that China, as an authoritarian state with advanced AI capacities, is focused on developing AI tools for social control and regime security more so than for economic growth. Our results run counter to *Hypothesis 2*, which was derived from previous literature examining central-level AI directives.

Second, this study contributes to our understanding of policy making in China. China's fragmented governance structure mean that central-level directives do not reliably diffuse to local level policy initiatives. Rather, we find that local level policies are not the result of implementation of earlier central-level ideas, but have their own priorities and objectives. Local level governments prioritise regime stability within policies that mention AI, indicating that regime security is an important factor driving CCP policy, even at the local level.

Third, we develop an NLP method for detecting idea diffusion within policy documents over time. Our method combines (1) topic modelling, (2) measures of document content entropy to infer the novelty and resonance of one document compared to others before and after it, and (3) regression analysis. This method allows us to quantify idea diffusion at scale, and isolate the factors that contribute to this diffusion.

Overall, this study suggests that China, as an authoritarian state, is prioritising the development of AI tools for social stability and regime security rather than for economic development. Moreover, this desire to develop AI tools to facilitate social control stems from all levels of government. This matters because it runs contrary to the literature on China's AI policies, which suggests that China is prioritising economic applications of AI over social applications. We can use this knowledge to anticipate what AI technologies may be developed within China, and then exported to other countries, as well as the AI technologies that other authoritarian states are likely to employ.

Future research could further explore the interaction between China's policies and the AI products developed by firms and government bodies in China, alongside the allocation of state funding within this industry. AI technologies for social control could have the a wide-ranging impact on citizen behaviour within authoritarian regimes, and the ability of authoritarian states to maintain a strong hold on power with limited resources and personnel. Once developed, these technologies could also potentially be exported to regimes globally, and limit the ability of citizens to act against the ruling regime. It is therefore incumbent on researchers to continue to track and identify the manner in which authoritarian states are developing such capacities, and the impacts of these technologies on populations.

References

Ahmed, S., N. E. Bajema, S. Bendett, B. A. Chang, R. Creemers, C. C. Demchak, S. W. Denton, *et al.* 2019. *Artificial Intelligence, China, Russia, and the Global Order: Technological, Political, Global, and Creative Perspectives* [in en]. Maxwell Air Force Base, Alabama: Air University Press.

Barron, A. T. J., J. Huang, R. L. Spang, and S. DeDeo. 2018. "Individuals, Institutions, and Innovation in the Debates of the French Revolution" [in en]. ArXiv:1710.06867 [nlin, physics:physics, q-bio], *Proceedings of the National Academy of Sciences* 115, no. 18 (May): 4607–4612. ISSN: 0027-8424, 1091-6490, accessed September 9, 2022. https://doi.org/10.1073/pnas.1717729115. http://arxiv.org/abs/1710.06867.

Barton, D., J. Woetzel, J. Seong, and Q. Tian. 2017. *Artificial intelligence: Implications for China.* Technical report. McKinsey. Accessed September 7, 2022. https://www.mckinsey.com/featured-insights/china/artificial-intelligence-implications-for-china.

Basu, A. M., K. Basu, A. Bhattacharya, M. Bouchet, C. S. Brahima, A. Dieppe, K. Derviş, *et al.* 2020. *Reimagining the global economy: Building back better in a post-COVID-19 world* [in en]. Technical report. Brookings: Global Economy and Development.

Blei, D. M. 2012. "Probabilistic topic models" [in en]. *Communications of the ACM* 55, no. 4 (April): 77–84. ISSN: 0001-0782, 1557-7317, accessed September 9, 2022. https://doi.org/10.1145/2133806.2133826. https://dl.acm.org/doi/10.1145/2133806.2133826.

Brødsgaard, K. E. 2016. "'Fragmented authoritarianism' or 'integrated fragmentation'?" In *Chinese Politics as Fragmented Authoritarianism,* 50–67. Routledge.

Chen, Q., Y. Mao, and A. M. Morrison. 2021. "Impacts of Environmental Regulations on Tourism Carbon Emissions" [in en]. Number: 23 Publisher: Multidisciplinary Digital Publishing Institute, *International Journal of Environmental Research and Public Health* 18, no. 23 (January): 12850. ISSN: 1660-4601, accessed September 11, 2022. https://doi.org/10.3390/ijerph182312850. https://www.mdpi.com/1660-4601/18/23/12850.

Crafts, N. 2004. "Steam as a General Purpose Technology: A Growth Accounting Perspective" [in en]. *The Economic Journal* 114, no. 495 (April): 338–351. ISSN: 0013-0133, 1468-0297, accessed September 4, 2022. https://doi.org/10.1111/j.1468-0297.2003.00200.x. https://academic.oup.com/ej/article/114/495/338/5085642.

Daum, J. 2017. "China through a glass, darkly: What foreign media misses in China's social credit." *China law translate* 24.

Ding, J. 2018. *Deciphering China's AI Dream* [in en]. Technical report. Future of Humanity Institute, University of Oxford.

Feldstein, S. 2019. "The Road to Digital Unfreedom: How Artificial Intelligence is Reshaping Repression." Publisher: Johns Hopkins University Press, *Journal of Democracy* 30 (1): 40–52. ISSN: 1086-3214, accessed September 5, 2022. https://doi.org/10.1353/jod.2019.0003. https://muse.jhu.edu/article/713721.

Floridi, L., and J. Cowls. 2019. "A Unified Framework of Five Principles for AI in Society" [in en]. *Harvard Data Science Review* (June). Accessed September 7, 2022. https://doi.org/10.1162/99608f92.8cd550d1. https://hdsr.mitpress.mit.edu/pub/l0jsh9d1.

Gao, Huang, and Zhang. 2019. "Comparative Analysis between International Research Hotspots and National-Level Policy Keywords on Artificial Intelligence in China from 2009 to 2018" [in en]. *Sustainability* 11, no. 23 (November): 6574. ISSN: 2071-1050, accessed January 24, 2022. https://doi.org/10.3390/su11236574. https://www.mdpi.com/2071-1050/11/23/6574.

Grimmer, J., and B. M. Stewart. 2013. "Text as Data: The Promise and Pitfalls of Automatic Content Analysis Methods for Political Texts" [in en]. *Political Analysis* 21 (3): 267–297. ISSN: 1047-1987, 1476-4989, accessed September 9, 2022. https://doi.org/10.1093/pan/mps028. https://www.cambridge.org/core/product/identifier/S1047198700013401/type/journal_article.

Hagerty, A., and I. Rubinov. 2019. "Global AI Ethics: A Review of the Social Impacts and Ethical Implications of Artificial Intelligence" [in en], 27. http://%20arxiv.org/abs/1907.07892.

He, Y., and A. Bowser. 2017. *How China is preparing for an AI-powered Future.* Technical report. Wilson Center. Accessed September 4, 2022. https://www.wilsoncenter.org/sites/default/files/media/documents/publication/how_china_is_preparing_for_ai_powered_future.pdf.

Hine, E., and L. Floridi. 2022. "Artificial intelligence with American values and Chinese characteristics: a comparative analysis of American and Chinese governmental AI policies" [in en]. *AI & SOCIETY* (June). ISSN: 1435-5655, accessed June 28, 2022. https://doi.org/10.1007/s00146-022-01499-8. https://doi.org/10.1007/s00146-022-01499-8.

Ho, S. 2020. *China's AI Efforts Suggest Tactics in New 'Self-Reliance' Push* [in en]. Technical report. DigiChina: Stanford University, December. Accessed September 5, 2022. https://digichina.stanford.edu/work/chinas-ai-efforts-suggest-tactics-in-new-self-reliance-push/.

Horton, B., and J. Zeng. 2021. *Can China become the AI superpower?* [In en]. Accessed September 9, 2021. https://www.chathamhouse.org/2021/01/can-china-become-ai-superpower.

Jacobi, C., W. van Atteveldt, and K. Welbers. 2016. "Quantitative analysis of large amounts of journalistic texts using topic modelling." Publisher: Routledge _eprint: https://doi.org/10.1080/21670811.2015.1093271, *Digital Journalism* 4, no. 1 (January): 89–106. ISSN: 2167-0811, accessed September 9, 2022. https://doi.org/10.1080/21670811.2015.1093271. https://doi.org/10.1080/21670811.2015.1093271.

Kullback, S., and R. A. Leibler. 1951. "On Information and Sufficiency." Publisher: Institute of Mathematical Statistics, *The Annals of Mathematical Statistics* 22 (1): 79–86. ISSN: 0003-4851, accessed September 9, 2022. https://www.jstor.org/stable/2236703.

Lieberthal, K. G., and D. M. Lampton. 2018a. *Bureaucracy, politics, and decision making in post-Mao China.* Vol. 14. University of California Press.

———. 2018b. *Bureaucracy, politics, and decision making in post-Mao China.* Vol. 14. University of California Press.

Nan, Y., T. Feng, Y. Hu, and X. Qi. 2020. "Understanding Aging Policies in China: A Bibliometric Analysis of Policy Documents, 1978–2019" [in en]. Number: 16 Publisher: Multidisciplinary Digital Publishing Institute, *International Journal of Environmental Research and Public Health* 17, no. 16 (January): 5956. ISSN: 1660-4601, accessed September 11, 2022. https://doi.org/10.3390/ijerph17165956. https://www.mdpi.com/1660-4601/17/16/5956.

Oliner, S. D., D. E. Sichel, and K. J. Stiroh. 2007. "Explaining a productive decade." Publisher: JSTOR, *Brookings papers on economic activity* 2007 (1): 81–137.

Overholt, W. H. 2018. *China's crisis of success.* Cambridge University Press.

PwC. 2017. *Sizing the prize What's the real value of AI for your business and how can you capitalise?* Technical report. Accessed September 7, 2022. https://www.pwc.com/gx/en/issues/analytics/assets/pwc-ai-analysis-sizing-the-prize-report.pdf.

Roberts, H., J. Cowls, J. Morley, M. Taddeo, V. Wang, and L. Floridi. 2019. *The Chinese Approach to Artificial Intelligence: An Analysis of Policy and Regulation* [in en]. SSRN Scholarly Paper ID 3469784. Rochester, NY: Social Science Research Network, September. Accessed February 5, 2021. https://doi.org/10.2139/ssrn.3469784. https://papers.ssrn.com/abstract=3469784.

Roberts, M. E., B. M. Stewart, D. Tingley, C. Lucas, J. Leder-Luis, S. K. Gadarian, B. Albertson, and D. G. Rand. 2014. "Structural topic models for open-ended survey responses." Publisher: Wiley Online Library, *American journal of political science* 58 (4): 1064–1082.

Rosenberg, N. 1983. "The Effects of Energy Supply Characteristics on Technology and Economic Growth." In *Energy, Productivity, and Economic Growth.* Cambridge, MA: Oelgeschlager, Gunn, / Hain.

Schiff, D., J. Biddle, J. Borenstein, and K. Laas. 2020. "What's Next for AI Ethics, Policy, and Governance? A Global Overview" [in en]. In *Proceedings of the AAAI/ACM Conference on AI, Ethics, and Society,* 153–158. New York NY USA: ACM, February. ISBN: 978-1-4503-7110-0, accessed September 4, 2022. https://doi.org/10.1145/3375627.3375804. https://dl.acm.org/doi/10.1145/3375627.3375804.

Shirk, S. L. 2007. *China: How China's Internal Politics Could Derail Its Peaceful Rise.* Oxford University Press.

Sinoeconomics. 2020. *China' s conflict resolution mechanism* [in en-GB], December. Accessed September 4, 2022. https://sinoeconomics.com/2020/12/06/chinas-conflict-resolution-mechanism/.

Svolik, M. W. 2012. *The politics of authoritarian rule.* Cambridge University Press.

Webster, G., R. Creemers, P. Triolo, and E. Kania. 2017. *Full Translation: China's 'New Generation Artificial Intelligence Development Plan'* [in en]. Accessed September 7, 2022. http://newamerica.org/cybersecurity-initiative/digichina/blog/full-translation-chinas-new-generation-artificial-intelligence-development-plan-2017/.

Yang, C., and C. Huang. 2022. "Quantitative mapping of the evolution of AI policy distribution, targets and focuses over three decades in China" [in en]. *Technological Forecasting and Social Change* 174 (January): 121188. ISSN: 0040-1625, accessed January 24, 2022. https://doi.org/10.1016/j.techfore.2021.121188. https://www.sciencedirect.com/science/article/pii/S0040162521006211.

Yu, X., and M. Jing. 2017. *Xi Jinping gives imprimatur to China' s plan to lead AI investment* [in en]. Section: Business, October. Accessed September 7, 2022. https://www.scmp.com/business/china-business/article/2115935/chinas-xi-jinping-highlights-ai-big-data-and-shared-economy.

Zeng, J. 2020. "Artificial intelligence and China's authoritarian governance." *International Affairs* 96, no. 6 (November): 1441–1459. ISSN: 0020-5850, accessed January 8, 2022. https://doi.org/10.1093/ia/iiaa172. https://doi.org/10.1093/ia/iiaa172.

Zhang, D., N. Maslej, E. Brynjolfsson, J. Etchemendy, T. Lyons, J. Manyika, H. Ngo, *et al.* 2022. *The AI Index 2022 Annual Report.* Technical report. AI Index Steering Committee, tanford Institute for Human-Centered AI, Stanford University. Accessed September 5, 2022. https://aiindex.stanford.edu/wp-content/uploads/2022/03/2022-AI-Index-Report_Master.pdf.

Zhu, K., B. Liu, and Z. Hu. 2021. "Impact of the Implementation of the Anti-domestic Violence Law of the People's Republic of China on Domestic Violence Behavior by Married Couples in Urban Areas" [in en]. Publisher: Francis Academic Press, *Academic Journal of Humanities & Social Sciences* 4, no. 12 (December). Accessed September 11, 2022. https://doi.org/10.25236/AJHSS.2021.041217. https://francis-press.com/index.php/papers/5609#abstract.