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Destined for Balance? Centralized and Decentralized Approaches to AI Governance

Chenghao Sun and Xiyan Chen

School of Social Sciences, Tsinghua University, China

Correspondence: Chenghao Sun (sunchenghao@tsinghua.edu.cn)

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Abstract

The rapid development of AI and rising concerns over its ethical risks have driven states to adopt centralized or decentralized governance approaches. This article examines the factors influencing states' choices of governance approaches. We hypothesized that states' choices are influenced by three key variables: per capita gross national income, research and development (R&D) capacity, and the level of ethical risks. The fuzzy-set qualitative comparative analysis (fsQCA) method is adopted to analyze how these independent variables impact states' governance choices. Our findings suggest that states that have higher income and stronger R&D capacity tend to adopt a more decentralized governance approach. On the contrary, if a state's income level is high while its R&D capacity is weak, it is likely to take a more centralized approach. Also, there are situations in which states' R&D capacity is relatively weak but their ethical risk level is comparatively high. These states usually employ a relatively centralized approach to ensure technological innovation and risk control. Generally, the influences of a state's income level and R&D capacity outweigh the influence of its ethical risk level. Our framework is tested through case studies of the US, China, Germany, France, Singapore, India, Brazil, and Russia. Inspired by the governance choices of the deviant cases, we also found that a balanced governance approach can facilitate AI innovation while safeguarding human rights and freedom. This requires states to reallocate their governance power and achieve a balance between central and local governments, as well as public and private sectors.

Keywords

artificial intelligence; centralization; ethics; governance; research and development

1. Introduction

With the rapid development and growing adoption of artificial intelligence (AI), its ethical risks have been receiving increasing attention. There arises a question for states about how to govern the emerging technology domestically. Scholars initiated debates over centralized and decentralized governance approaches. Some scholars believe states prefer a centralized approach, which is beneficial to improving resource extraction and integration ability, ensuring consistency in standards, and preventing ethical risks (Cihon et al., 2020; Dafoe, 2018; Hutchcroft, 2001; Radu, 2021). They think a decentralized approach increases the probability of leaking sensitive information and causes alignment problems. It does not necessarily guarantee diversity of data sources and the non-discrimination principle in the AI system (Clifton et al., 2022).

Other scholars regard the decentralized approach as more democratic than the centralized one (Montes & Goertzel, 2019). As Brynjolfsson and Ng (2023) noted, although centralized decision-making can be more efficient, it also leads to concentration of power and resources, which proves to be harmful to democracy. They also highlighted that a centralized approach may hinder innovation in the emerging technology industry, while a decentralized one will not only promote technology research and development (R&D) but will also ensure lower ethical risks (L. Cao, 2022; Chen et al., 2021; Wright, 2023).

Based on the normative analysis of strengths and weaknesses of centralized and decentralized approaches, some scholars seek to examine the types of approaches states have employed by exploring national strategies, regulations, laws, and codes of conduct (Daly et al., 2019; Dixon, 2023; Djeffal et al., 2022; Papyshev & Yarime, 2023; Radu, 2021). But they scarcely explain why states choose a centralized or a decentralized AI governance approach. Therefore, our study follows in the footsteps of previous studies and applies the fuzzy-set qualitative comparative analysis (fsQCA) method to answer the remaining question. We found that there are three factors influencing states' AI governance approaches. The first is the level of per capita gross national income (GNI). Second, from the perspective of technological innovation, states' R&D capacity impacts their choice of governance approach. Third, in terms of safety and security, states' governance approaches can be influenced by the ethical risk levels of data and algorithms.

The article is structured as follows. In the second section, we elaborated on the definitions, characteristics, and evaluative metrics of the dependent variable, i.e., the centralized or decentralized governance approach. We also proposed hypotheses in this section. In the third section, we introduced the reasons behind our choice of the cases and how to operationalize the dependent and independent variables. In addition, the results of the analysis of the necessary and sufficient conditions are reported. In the fourth section, we tested the hypotheses by comparing the cases. In the fifth section, we discussed the fact that the deviant cases indicate a balanced approach to facilitate AI development and reduce ethical risks. This finding has significant implications for global AI governance. Finally, we conclude by acknowledging the limitations of our study and elucidating the implications of the article.

2. Conceptual Framework and Hypotheses

Technology governance presupposes technological progress—without advances or real-world applications, governance is moot. However, regulation has always struggled to keep up with the multiplying harms and risks of AI due to its rapid development and deployment (Kaliisa et al., in press). To analyze how states choose AI governance approaches, we take the degree of centralization or decentralization of their governance approaches as a dependent variable. States' income level, R&D capacity, and ethical risk level are taken as independent variables.

2.1. States' AI Governance Approaches

Before examining why states adopt certain AI governance approaches, it is necessary to define and characterize the prevailing governance configurations. Centralized governance is a top-down approach consisting of a hierarchical system in which the power to govern AI is concentrated in a few entities, such as central government agencies (McNealy, 2022). On the contrary, a decentralized approach is characterized by the absence of a central authority. Thus, governance power is distributed among multiple entities, including local governments, small and large corporations, and research institutions (Liu et al., 2024). However, in practice, the distinction between states' AI governance approaches is not a dichotomy (Pierre & Peters, 2005). Most states require both centralized and decentralized approaches to govern AI effectively, with the relative importance of each shaped by states' historical and institutional contexts.

Based on the aforementioned definitions and characteristics, we construct a multi-dimensional evaluative framework for assessing AI governance configurations. The first dimension is the role of central government, including how much AI governance power is concentrated in the central government or a central agency (Liu et al., 2024). When a central authority concentrates more governance resources and decision-making power, the states' AI governance approach leans toward a centralized configuration. If power is more evenly distributed, the configuration will be more decentralized.

The second dimension considers the engagement of local governments and non-state actors. States that adopt a more decentralized AI governance approach tend to promote multistakeholder collaboration in AI innovation, pursuing rapid technological iteration. In contrast, states that employ a more centralized approach place less emphasis on such collaborative innovation.

The third dimension is the transparency and auditability of AI systems, gauging how much system design and function, personal data use, and automation processes and levels involved in decision-making are disclosed to stakeholders (ISO, 2022, p. 30). A decentralized approach puts more emphasis on the openness of AI systems and on external accountability. On the contrary, a centralized approach is inclined to ensure the opacity of AI systems to maintain control of AI development and governance.

2.2. Hypotheses

Zeng et al. (2024) introduced the AI Governance International Evaluation (AGILE) index to depict the global landscape of national AI governance. The findings revealed a positive correlation between the index and states' income situation. This suggests that development forms the foundation for effective governance. According to modernization theory, with the development of states' economy, social structures become complex, labor processes begin to require the active cooperation of employees, and new groups emerge and organize (Przeworski & Limongi, 1997). As a result, the governance system will become decentralized. On this basis, we propose the first hypothesis:

H1: The higher a state's income level, the greater its tendency to adopt a decentralized AI governance approach.

As Vijayakumar (2021) noted, technological progress serves as a crucial mechanism for economic growth because it offers opportunities for enhancing productivity and creates new business models. But the situations in states with varying levels of R&D capacity can be very different. For advanced economies, AI will increase efficiency, total output, and per capita income by saving on labor (Boix, 2022). Furthermore, Vijayakumar (2021) suggested that AI advancements in one industry are often accompanied by similar progress in other domains. The economic advantages brought by advanced AI R&D capacity will benefit political, military, and social development, and international status. First, AI revolutionizes the process of data collection and analysis. For instance, politically, AI can empower political participation (Savaget et al., 2019). Socially, it allows more timely and accurate poverty identification and classification (Visvizi, 2022). In addition, AI can enhance automatic decision-making and task execution. For example, militarily, AI supports efficient and effective use of unmanned autonomous systems and can undertake dull, dangerous, and dirty tasks (Schraagen, 2023). More importantly, harnessing the aforementioned advantages, states will gain leadership and influence globally in both soft and hard power domains (Rebolledo, 2025).

Multiple actors have participated in the R&D process of AI technology, including government agencies, the private sector, academic institutes, and NGOs. Although the contributions of all parties should not be underestimated, there is no denying that the private enterprises are the main driving force behind AI R&D. For instance, Vijayakumar (2021) proved that annual private investment in AI is positively related to GDP growth in terms of both current and lagged effects. Moreover, local governments have a deeper understanding of the AI development situation in their own jurisdiction. Introducing regulation in a relatively small area can be beneficial to local autonomy and capacity building. Therefore, to fully tap into enterprises' potential for innovation, cut down coordination costs, and enhance national strength, some states with strong AI R&D capacity tend to take the decentralized approach. They distribute the governance power to businesses and local governments.

For middle- and low-income economies, AI R&D capacity is relatively weak. It's difficult for them to generate as much profit as the advanced economies do because the positive impact of automation will be mediated by the cost of moving up in the production ladder from low-value-added to high-value-added activities (Boix, 2022). What's more, due to the improvement of productivity by applying AI, advanced states will "re-shore" production domestically to minimize distribution and transportation costs. This may further lead to economic backsliding of middle- and low-income states. However, Vijayakumar (2021) proved that automation is costly in the short term but beneficial in the long term. Firms that initially invest in automation can gain a competitive advantage over firms that lag behind. Moreover, more R&D-intensive firms pay higher wages on average, with lower-skilled workers benefiting more from working in these firms than higher-skilled workers (Aghion et al., 2017). As a result, although states with low R&D capacity may not benefit from AI development in the short term, in reality, they still put emphasis on technological innovation and strive to catch up with advanced economies. For them, fragmented resources can reduce innovation efficiency, especially when the R&D capacity of companies and research institutes needs enhancement. Since government investment (X. Y. Cao et al., 2023) and cautious data integration and sharing (Omaar, 2024) help improve R&D efficiency, central governments of middle- and low-income economies may play a dominant role in AI development. In this sense, we formulate two hypotheses:

> H2a: The stronger the AI R&D capacity of a state, the more it tends to adopt a decentralized AI governance approach.

> H2b: The weaker the AI R&D capacity of a state, the more it tends to adopt a centralized AI governance approach.

The development and application of AI generate unexpected consequences and pose new forms of risk. Politically, AI can be used to produce fake news, which is much more persuasive than human-generated news (Kouroupis, 2023). Political communication is seriously damaged since it loses its natural, direct, and original dimensions (Kouroupis, 2023). Thus, the fairness of elections will be undermined, and democracy will also be tampered with through the deceiving of voters. Militarily, an AI model trained on biased historical data may not withstand contact with the realities of the world as it currently is (Schraagen, 2023). Besides, concerns exist that uncontrolled AI in autonomous weapons systems could result in catastrophic outcomes. Socially, AI trained by biased data may be harmful to job recruitment and criminal justice (Farina et al., 2022).

The risks need to be addressed by developing suitable means of governance (Taeihagh, 2021). The visibility, prioritization, and political framing of the risk level vary by governance system and media ecology. These constructions, rather than the "risk itself," influence states' governance orientation. In contexts where ethical risks are constructed as high, states tend to take a decentralized approach to manage risks case by case without hindering innovation. Conversely, when constructed risks are low, states aim to keep the risks at a low level and balance innovation with public interests, so they seek to adopt a more centralized governance approach to ensure that progress remains controlled and cautious (Rebolledo, 2025). Accordingly, we put forward two hypotheses:

> H3a: The more publicly politicized and institutionally acknowledged ethical risks are within a state, the more likely the state is to adopt inclusive or balanced governance measures.

> H3b: In states where ethical risks are suppressed or reframed as security threats, centralized governance is more likely.

3. Data and Method

The majority of research on AI governance takes the form of qualitative analysis (Birkstedt et al., 2023; Dafoe, 2018; Mäntymäki et al., 2022). We try to combine the case-oriented qualitative and variable-oriented quantitative methods to comprehensively analyze states' AI governance approaches.

3.1. Case Selection and Variable Measurement

As for how to choose cases, Berg-Schlosser and De Meur (2009) argued that first, the cases must share enough background characteristics, which in turn can be considered as "constants" in the analysis. So it is indispensable to clearly delimit the outcome of cases before analysis. Second, a maximum of heterogeneity over a minimum number of cases should be achieved.

Based on the twofold guidance, we chose the AI governance cases of the US, China, Germany, France, Singapore, India, Brazil, and Russia. The reasons are that first, AI represents a nascent technological domain, thus not all states have started to govern it. The selected states are relatively advanced in terms of AI development and have embarked on establishing AI governance frameworks. Second, through systemic analysis, we found their AI governance approaches exhibit distinctive characteristics. On this basis, we systematically analyzed and explained why states adopt different governance approaches.

There are several indicators chosen to measure the dependent variable. Firstly, Radu (2021) argued that national documents form the basis for regulatory configurations. Therefore, we used the number of specialized AI governance national strategies and laws in force as of December 2024 as the indicator to measure the capacity of the eight states' central authority in AI governance. The source of the national-level documents is the OECD AI Policy Observatory. Secondly, we used the number of local AI policies and laws in force by December 2024 to measure the extent of local governments' participation in AI governance. The documents are from the official websites of the eight states' local governments. Thirdly, the Global Index on Responsible AI constitutes the largest global data collection on responsible AI. The scores of non-state actors show the performance of the private sector, academia, and civil society. We used the scores as an indicator to measure non-state actors' level of participation in AI governance. Fourthly, states that adopt a decentralized AI governance approach tend to release more open AI models and datasets, and have more active developer communities, while those who implement a centralized governance approach are less likely to keep their AI systems transparent and establish developer communities. Therefore, we used the number of open AI models and datasets, as well as the number of developer communities, to measure the degree of transparency and auditability of states' AI systems. The data are from the report of the AGILE index. Considering that there are multiple indicators used to measure the level of decentralization or centralization, we adopted the entropy weight method (Zhu et al., 2020) and linear weighted sum method (Stanimirovic et al., 2011) to preprocess the data and output the weighted combination of the values.

For independent variables, to begin with, we used per capita GNI to measure the income level of the eight states. According to the World Bank, per capita GNI reflects the average before-tax income of a state's citizens and the state's level of economic development. The per capita GNI of 2023 reported by the World Bank is employed in this study.

Bryan and Teodoridis (2024) asserted that the efficacy of AI governance depends on regulators' knowledge about the benefits of the technology. Furthermore, how much a state can benefit from AI development depends on its progress in AI, which is tied to both academic research and market applications. Therefore, the level of states' R&D capacity is measured by indicators including the number of published articles, granted patents, developed systems (Perrault & Clark, 2024), and supercomputers by 2024 (TOP500, 2024), and the average proportion of total AI private investment to GDP (current US dollars) from 2017 to 2023 (Zeng et al., 2024). Likewise, we adopted the entropy weight method and the linear weighted sum method to deal with the multiple indicators.

In addition to the aforementioned variables, ethics, the moral principles concerning right and wrong, are also important for AI governance. The ethical risks of AI arise from several dimensions, including privacy, fairness, and explainability (IBM AI Ethics Board, 2024; Perrault & Clark, 2024). Risks related to potential harms may affect organizations, consumers, or create broader detrimental effects on society.

There is admittedly a lack of consensus on robust and verifiable methods for measuring ethical risks across different AI use cases (National Institute of Standards and Technology, 2023). The reasons are that first, the speed and scale of the adoption of AI outpace the identification and response to the concerns raised (Taeihagh, 2021). Second, there can be a significant variation in how the components of ethical risks are interpreted (Roberts et al., 2023). For instance, Novelli et al. (2023) criticized the categorization of risks in the EU AI Act as coarse-grained, and proposed an assessment framework based on specific AI scenarios.

Measuring risk at earlier stages of the AI lifecycle can yield different results than at later stages. Moreover, risks presented when AI systems are tested in a virtual environment may differ from the risks posed when that same system is deployed in the real world. Scholars have indicated that risks can be evaluated by observing the existing models' behavior in practice and recorded incidents (Leipzig, 2023; Piorkowski et al., 2023). This kind of measurement in a real-world environment reflects the relatively authentic risk levels of AI models, especially given the black-box nature of AI. Therefore, we measured the ethical risks of AI by considering both subjective and objective dimensions. First, we use the number of AI ethical risk incidents reported by the eight states' governments between 2017 and 2023 to evaluate the risk levels of different states. Since the cases are self-reported by individual countries, this measurement dimension is relatively subjective.

Second, AI ethical risks can also be evaluated based on states' consensus regarding fundamental values, which is more objective. It is commonly recognized that the employment of AI poses the ethical risk of biases (Margetts, 2022; Milan & Beraldo, 2024; Roberts et al., 2023; Taeihagh, 2021). The nondiscrimination of AI is especially important because biased decision-making might worsen already-existing social inequality (Modi, 2023). Moreover, the implications of biased AI are widespread across various domains, including healthcare, employment, criminal justice, financial services, and education. The primary source of bias in AI is societal prejudices reflected in training data, which are amplified and perpetuated through algorithms (Shrishak, 2024). If someone has access to the internet, their data may be collected and used for AI training. Thus, we use the internet gender divide and the share of the underprivileged who use the internet to measure the risk of bias. The data are collected from the OECD's Going Digital Toolkit.

3.2. Analysis and Results

Using the fsQCA method, we analyzed the eight states' approaches to AI governance. The reasons why we chose this method are that first, fuzzy sets are simultaneously qualitative and quantitative, for they incorporate both kinds of distinctions in the calibration of the degree of set membership. Second, the method is suitable for analyzing complex causality in small samples.

After obtaining the weighted values of the dependent variable using the entropy weight method and the linear weighted sum method, we adopted the three-value anchoring method to directly calibrate the data, converting them into fuzzy membership scores that range from 0 to 1 (Rihoux & Ragin, 2009). We took the three-value scheme using the scores 0.95, 0.50, and 0.05 (Ragin, 2008) to indicate the degree of membership in the set of the values of dependent variable. Accordingly, we set the breakpoints at 0.671, 0.137, and 0.067, which means that when the weighted values of the indicators are greater than or equal to 0.671, the states are considered as having full membership in the set of "decentralized AI governance approach." If the values are lower than 0.067, the states are regarded as having full nonmembership in the same set. The crossover point is 0.137, meaning that the states with this value are neither fully in nor fully out of the set. Using the fsQCA software, we calibrated the values in Table 1. Values approaching 1 indicate stronger membership in the "decentralized AI governance approach" set.

The average, maximum, and minimum calibrated values of the dependent variable are 0.47, 0.97, and 0.02, respectively. And the standard deviation of the values is 0.328. So there are obvious differences in the AI governance approaches of the eight states. Among them, the AI governance approaches of the US and China are the most decentralized, while Russia adopts the most centralized governance approach.

Table 1. Measurement and calibration of states' AI governance approaches.

State	Measured Value	Calibrated Value
US	0.490432	0.88
China	0.768079	0.97
Germany	0.278046	0.69
France	0.154122	0.52
Singapore	0.101853	0.18
India	0.101859	0.18
Brazil	0.119386	0.32
Russia	0.048180	0.02

Next, we calibrated the independent variables. For per capita GNI, we employed the indirect method of calibration. In 2024, according to the World Bank, states with a per capita GNI lower than 1,145 US dollars are classified as low-income states. States with a per capita GNI ranging from 1,146 to 4,515 US dollars are lower-middle-income states. States with a per capita GNI from 4,516 to 14,005 US dollars are upper-middle-income states. High-income states are those whose per capita GNI is higher than 14,005 US dollars. According to the concept of infrastructural power—the capacity of the state to penetrate civil society and to implement political decisions logistically (Mann, 1984)—we interpreted income status as a proxy for infrastructural power to determine the governance landscape. On this basis, we adopted a four-value anchoring method, using the numerical values of 1, 0.67, 0.33, and 0 to indicate the degree of membership in the set of "high income states." These four values sequentially represent "fully in," "more in than out," "more out than in," and "fully out" (Rihoux & Ragin, 2009). States with a per capita GNI greater than 14,005 US dollars were coded as fully in the set of high-income states. States whose per capita GNI is greater than 4,515 US dollars were coded as more in than out. Those with a per capita GNI greater than 1,145 were coded as more out than in. And those with a per capita GNI of 1,145 or lower were coded as fully out. The next step is to estimate the indirectly calibrated values of per capita GNI of each case, using per capita GNI as the independent variable and the qualitative codings as the dependent variable. We used the Stata software to construct a fractional logit model using the fractional polynomial regression procedure (Ragin, 2008). The predicted values are reported in Table 2.

For R&D capacity, drawing on the theory of absorptive capacity, which argues that the ability to recognize the value of new, external information, assimilate it, and apply it is critical to innovative capabilities (Cohen & Levinthal, 1990), we adopted a three-value anchoring method. The value of 0.794 corresponded to the score 0.95, indicating that cases with values higher than 0.794 were considered fully in the set of "strong R&D capacity." Additionally, the value 0.017 was scored 0.05, meaning that cases with values lower than 0.017 are fully out of the set of "strong R&D capacity." The crossover point was 0.099, meaning that the cases with this exact value were neither fully in nor fully out of the set. The measured and calibrated values are shown in Table 2. These thresholds ensured that calibration differentiated between global leaders, emerging players, and innovation laggards.

As for ethical risk, the levels of perceived risk influence how complex the governance webs are (Renn, 2008). We continue to use a three-value anchoring method to distinguish between low-exposure, emerging-risk, and high-exposure systems. The value of 0.564 was scored 0.95, indicating that cases with a value higher than 0.564 were fully in the set of "high ethical risk level." The value of 0.0297 corresponded to the score 0.05, meaning that cases with a value lower than 0.0297 were fully out of the set. The crossover point was 0.093, meaning that cases with this exact value were neither fully in nor fully out of the set. The measured and calibrated values are shown in Table 2.

Table 2. Measurement and calibration of states' per capita GNI, R&D capacity, and ethical risk level.

State	Per Capita GNI	Calibrated Value	R&D	Calibrated Value	Ethical Risk	Calibrated Value
US	80,450	1	0.993	0.98	0.582106	0.96
China	13,390	0.834275	0.425	0.80	0.112447	0.53
Germany	54,800	1	0.133	0.54	0.074146	0.29
France	45,180	1	0.078	0.32	0.039882	0.07
Singapore	70,590	1	0.120	0.52	0.024255	0.04
India	2,540	0.331074	0.046	0.12	0.531632	0.94
Brazil	9,280	0.629858	0.017	0.05	0.174996	0.63
Russia	14,250	0.874792	0.018	0.05	0.050464	0.12

After calibrating the dependent and independent vare we analyzed the necessary and sufficient conditions for a state's choice of AI governance approach. Necessary conditions are those that must be present for the outcome to occur, but their presence does not guarantee that occurrence. With fuzzy sets, a possible necessary condition is signaled when the instances of the outcome constitute a subset of instances of a condition (Rihoux & Ragin, 2009). The closer the consistency score is to 1, measuring the extent to which the outcome set is a subset of the condition set, the more likely the condition is necessary for the outcome. For condition (independent) variables that meet the consistency threshold, their coverage must be further examined. The coverage of a condition variable measures the extent to which it explains the outcome variable. We took 0.9 as the consistency threshold and 0.5 as the coverage threshold (Schneider & Wagemann, 2012). According to these standards, only per capita GNI is a necessary condition for a state's decentralized AI governance approach. The value of its coverage is 0.543. This result confirms H1, indicating that if the income level of a state is high, the state will be more likely to adopt a decentralized AI governance approach.

For sufficiency, if a condition (independent) variable or a configuration of condition variables is a sufficient condition for the outcome (dependent) variable, it means that all cases where the condition or the configuration of conditions is present must necessarily exhibit the outcome variable. However, cases showing the outcome do not necessarily exhibit the conditions (Ragin, 2000).

Table 3. Results of the necessary condition analysis.

Outcome (Dependent) Variable	Condition (Independent) Variable	Consistency	Coverage
Degree of Decentralization (Y)	Per Capita GNI	0.963903	0.543370
	~ Per Capita GNI	0.182374	0.515582
	R&D	0.773936	0.860947
	~ R&D	0.505319	0.411255
	Ethical Risk	0.619681	0.650838
	~ Ethical Risk	0.611702	0.520362
Degree of Centralization (~ Y)	Per Capita GNI	0.848048	0.539089
	~ Per Capita GNI	0.281669	0.897951
	R&D	0.358491	0.449704
	~ R&D	0.889151	0.816017
	Ethical Risk	0.500000	0.592179
	~ Ethical Risk	0.705189	0.676471

Notes: "~" represents negation; the membership of a case in the negation of fuzzy set A simply subtracts its membership in set A from 1.

We used the truth table of independent and dependent variables for sufficient condition analysis. Due to our small sample size, we set the frequency threshold as 1 (Rihoux & Ragin, 2009). Also, we set the threshold of raw consistency as 0.8 (Rihoux & Ragin, 2009) and the threshold of PRI consistency (Proportional Reduction in Inconsistency) as 0.65 (Greckhamer, 2016). Then, we used the fsQCA software to generate three solutions: the complex solution, the intermediate solution, and the parsimonious solution. Because of the limited diversity of our sample, there exist logical remainders. The complex solution excludes all counterfactuals in logical reminders, while the intermediate solution contains easy counterfactuals, and the parsimonious solution contains both easy and difficult counterfactuals. So the assessment of sufficiency of the conditions relies mainly on the intermediate solution, supplemented by the parsimonious solution. The results are reported in Tables 4 and 5.

Table 4. Sufficient conditions for a decentralized AI governance approach.

	Parsimonious Solution				Intermediate Solution		
	Raw coverage	Unique coverage	Consistency		Raw coverage	Unique coverage	Consistency
R&D	0.773936	0.773936	0.860947	Per capita GNI * R&D	0.773936	0.773936	0.860947
Solution coverage	0.773936	solution consistency	0.860947	Solution coverage	0.773936	solution consistency	0.860947

Note: "*" represents the logical AND.

According to Table 4, we found that the configuration of high income and strong AI R&D capacity is a sufficient condition for a decentralized AI governance approach. Moreover, strong R&D capacity is the core condition. Solution coverage and consistency of the parsimonious and intermediate solutions are greater than 0.75, so the results demonstrate relatively strong explanatory strength (Schneider & Wagemann, 2012). The results confirm H2a—greater AI R&D capacity correlates with a higher likelihood of adopting

Table 5. Sufficient conditions for a centralized AI governance approach.

	Parsimonious Solution			Intermediate Solution			
	Raw coverage	Unique coverage	Consistency		Raw coverage	Unique coverage	Consistency
~ R&D	0.889151	0.889151	0.816017	Per capita GNI * ~ R&D	0.744275	0.383206	0.858531
				~ R&D * ethical risks	0.476415	0.115346	0.897778
Solution coverage	0.889151	solution consistency	0.816017	Solution coverage	0.859621	solution consistency	0.862715

Notes: "~" represents negation; "*" represents the logical AND.

decentralized AI governance. But H3a is not verified, suggesting that a high level of ethical risks has little impact on whether states choose a decentralized AI governance approach or not.

We also found, as Table 5 shows, that the configuration of high income and weak AI R&D capacity is a sufficient condition for a centralized AI governance approach. Aside from this, the configuration of weak AI R&D capacity and high ethical risk level is another sufficient condition for states to adopt a centralized AI governance approach. Furthermore, weak R&D capacity is the core condition of the two kinds of configurations. The results are reliable because solution coverage and consistency of the parsimonious and intermediate solutions are greater than 0.8. Thus, H2b is verified. It is noteworthy that a high level of ethical risk positively influences states' centralized AI governance approach, which is contrary to H3b.

To test the robustness of the three configurations, we reset the threshold of consistency to 0.85, with other thresholds held constant. The outcome of the necessary condition analysis remains the same. What's more, the configurations of high income and weak AI R&D capacity and weak AI R&D capacity and high ethical risks level are still sufficient conditions for more centralized governance approaches. The solution coverage is 0.859621, and the solution consistency is 0.862715. However, the configuration of high income, strong AI R&D capacity, and high ethical risks level, rather than the configuration of high income and strong AI R&D capacity, is a sufficient condition for a decentralized AI governance approach. The solution coverage is 0.531915, and consistency is 0.947867. Consequently, the configuration of high income and strong AI R&D capacity is not robust, but high income and strong AI R&D capacity are still important determinants.

4. Case Study

In this part, we triangulated fsQCA results with case studies by, first, mapping sufficient pathways shown by the fsQCA software to empirical evidence from policy documents, and second, contextualizing deviant results. The types of cases are shown in Table 6.

The comprehensive analysis of necessary and sufficient conditions suggests that governance configurations are shaped not only by functional considerations but also by historical and institutional legacies of industrial, digital, and political reforms (Pierson, 2000). First, if the income level of a state is relatively high and it has

Table 6. Typology matrix of AI governance configurations by institutional control and innovation coordination.

	High Innovation Coordination	Low Innovation Coordination
High Institutional Control	Singapore	Russia, Brazil, India
Low Institutional Control	US, China, Germany	France

strong AI R&D capacity, the state will adopt a more decentralized approach to governing AI technology, reflecting both its contemporary capacities and the evolution of multistakeholder governance norms. Cases exhibiting membership scores greater than 0.5 in both the condition and the outcome sets are the US (0.98, 0.88), China (0.80, 0.97), and Germany (0.54, 0.69).

The reasons why these states adopt a decentralized governance approach are as follows. First of all, preceding decentralized governance steps induce further movement in the same direction. Also, due to their relatively high income level, the division of labor has become more specialized, and social structures have become complex. In the US, the tradition of dispersed authority—rooted in its federal system and reinforced by past digital governance policies—facilitates a decentralized approach. Multiple stakeholders have participated in AI governance, consistent with the US National Artificial Intelligence Research and Development Strategic Plan (National Science and Technology Council, 2023). There is no federal law or executive order to govern AI. However, states in the US have already enacted laws. Besides this, many US technology corporations have issued ethics statements on their AI activities, like Microsoft's AI Principles. Also, US not-for-profit organizations and foundations have actively supervised the AI governance process (Daly et al., 2019). In August 2023, Accountable Tech, the AI Now Institute, and Electronic Privacy Information Center (EPIC) jointly released the "Zero Trust AI Governance" framework.

In China, experimental localism, long used in economic policy pilots, underpins the encouragement of provincial-level AI strategies. For instance, Beijing launched its AI Plus action plan in 2024. Additionally, Shanghai enacted the first provincial-level AI regulation in 2022. Shenzhen also introduced measures to build itself into an AI-pioneer city in 2023. Moreover, China upholds the principle that the market should play a dominant role in determining AI development roadmaps and establishing industrial standards (State Council of the People's Republic of China, 2017).

Germany also puts emphasis on multistakeholder governance: 13 out of 16 German states have developed their own AI strategy or agenda as of 2025. Discussion groups and cooperation platforms have been built, representing multiple actors involved in AI governance. For example, Platform Industry 4.0 (2015), Learning Systems (2017), Digital Hub Initiative (2017), and Regulatory Sandboxes (2018) all help establish distributed nodes to promote interinstitutional communication and cooperation among the private sector, academia, and civil society.

The second reason is that the states with advanced AI R&D capacity seek to sustain their "first mover" advantages in AI and enhance competitiveness. The US benefits from its unparalleled AI R&D capacity and tends to augment its strength to compete with China. Economically, AI innovation in life sciences, personal devices and computing, banking and finance, and energy management is strongly correlated with GDP growth at present and in the future (Vijayakumar, 2021). Militarily, as then US Secretary of Defence Mark Esper said, "Whichever nation harnesses AI first will have a decisive advantage on the battlefield for many,

many years" (Konaev et al., 2020). The US Department of Defence's Data, Analytics, and Artificial Intelligence Adoption Strategy (2023) noted that AI can bring military advantages like enabling efficient and precise strategic decisions, and deploying continuous advancements in technological capabilities to creatively address complex national security challenges. These contribute to deterring potential aggressors and winning great-power competitions with US strategic competitors, especially China. Socially, the US Department of State clarified that AI advances are providing great benefits to social well-being in areas including precision medicine, environmental sustainability, education, and public welfare. Geopolitically, based on the aforementioned benefits, AI can help comprehensively increase national strength and empower the US to consolidate its global leadership.

As the second most advanced state in AI R&D, China has led the development of large language models, which are now widely used in areas such as transportation, e-commerce, education, and office productivity, promoting intelligent upgrading and the digital transformation of traditional industries. Further to this, as a key enabler of new quality productive forces (新质生产力), AI enhances the inclusiveness of China's development by improving resource allocation and service efficiency ("'Rengongzhineng+' funeng xinzhi shengchanli fazhan," 2025). To continue facilitating economic development, enhancing governance capacity to safeguard social stability, and improving global competitiveness, China plans that by 2030, its AI theories, technologies, and applications should achieve globally pioneering levels. This will make China the world's primary AI innovation center. Also, China can achieve visible results with intelligent economy and society applications. Further, these lay an important foundation for China to become a leading innovation-style nation and an economic power (State Council of the People's Republic of China, 2017).

Germany aims to ensure that innovation will not be hindered. In addition to this, it seeks to establish "AI Made in Germany" as an international trademark for modern, secure, and public-interest-oriented AI applications based on the European canon of values (The German Federal Government, 2020).

Singapore is a deviant case. Schneider and Wagemann (2012) stated that cases with membership in condition set > 0.5 and membership in outcome set < 0.5 are deviant cases for consistency. According to the fsQCA software, Singapore's membership in the set of "per capita GNI * R&D capacity" is 0.52, while its membership in the set of decentralized AI governance approach is 0.18. The reason for Singapore to adopt a less decentralized approach is that it tends to strike a balance between AI innovation and public interests. Its path reflects a tradition of centralized developmental planning, as in the Smart Nation initiative. Although there are no specific laws in Singapore that directly regulate AI, the Singapore government has developed frameworks and tools to guide AI deployment and promote the responsible use of AI. For example, the Model AI Governance Framework (Personal Data Protection Commission of Singapore, 2020) was formulated to guide the private sector in addressing ethical and governance issues; AI Verify (The Info-communications Media Development Authority and Personal Data Protection Commission, 2022) aims to help organizations validate the performance of their AI systems against AI ethics principles through standardized tests; and the National Artificial Intelligence Strategy 2.0 was updated in 2023, outlining Singapore's commitment to building a trusted and responsible AI ecosystem.

Second, relatively high-income but lower R&D capacity states tend to adopt more centralized governance approaches to fully tap into their economic potential and accelerate innovation. Typical cases reported by fsQCA are Russia (0.875, 0.980) and Brazil (0.630, 0.680).

The President of the Russian Federation Vladimir Putin declared in 2017, “Whichever country becomes the leader in artificial intelligence will become the ruler of the world” (“Who Vladimir Putin”, 2017). Russia has a statist tradition of technological development and an ambition to enhance its national power and global status by improving its capacity for AI innovation. Thus, a centralized AI governance approach is employed to achieve its geopolitical goal. State-owned Russian companies that are delegated and supervised by the central government play a dominant role in AI governance. The Russian government believes that, unlike private companies, state-owned enterprises will not exert a destabilizing influence on its political system. For instance, despite Yandex’s status as Russia’s leading tech firm, its uneasy relationship with the Kremlin may limit its interaction with the Russian government and other state-owned firms (Petrella et al., 2021). Depending on the government’s level of trust, state-owned companies can gain policy support from the government, which will be beneficial not only for achieving Russia’s strategic goals, but also for the companies’ interests. Russian state-owned bank Sberbank has been the main driving force of the National Strategy for the Development of Artificial Intelligence. The strategy facilitates research on algorithms and mathematical methods, as well as the improvement of both the quality and scale of AI-related talent development (Prezident Rossiyskoy Federatsii, 2019). The company has also played a leading role in drafting and advancing the AI Roadmap in Russia. More than 20% of the investment budget allocated by the Roadmap will be spent on Sberbank’s internal operational processes, while other spending will boost the ecosystem that Sberbank can benefit from (Petrella et al., 2021).

Although the Russian government has realized the importance of the private sector in technological innovation, the function of private companies is limited. Also, cooperation between state-owned and private companies is ineffective. For example, while the AI Alliance Russia, supervised by the Ministry of Economic Development, said that it will foster collaboration on AI between the public and private sectors, little visible cooperation has occurred (Petrella et al., 2021).

Similar to Russia, the Brazilian central government takes the lead in AI governance to accelerate its AI development. Advances in AI are expected to benefit Brazil across the social, economic, and diplomatic sectors. However, Brazil faces significant challenges that impede its AI innovation, including a lack of AI talent and the inability to install high-performance supercomputers dedicated to AI and to expand data centers. To optimize resource management and overcome these challenges, Brazil adopts a relatively centralized AI governance approach. It has developed the Brazilian AI Plan under the guidance of the National Council for Science and Technology. The Plan emphasizes leadership of the Brazilian government in promoting partnerships between different actors in the AI innovation and regulation ecosystem (Conselho Nacional de Ciência e Tecnologia, 2025).

A deviant case is France, whose membership in the condition set is 0.68 while its membership in the outcome set is 0.48. France seeks to equip itself with a competitive AI research capacity and to disseminate AI within the economy. It also facilitates the responsible development of AI by ensuring multistakeholder participation. As a result, although France’s income is relatively high and its R&D capacity is relatively weak, its AI governance approach is less centralized. In 2017, the French government launched the National AI Strategy as part of “France 2030,” which calls for the initiation of AI projects. For instance, the IA Booster France 2030 program is aimed at stimulating the innovation and effective governance of French small and medium-sized enterprises. Moreover, in July 2023, the French Data Protection Authority (CNIL) opened a public consultation on its AI action plan to ensure the rights of end-users. It sought the opinions of all concerned public and private actors.

Third, states with weak AI R&D capacity and high ethical risk adopt a more centralized AI governance approach to incentivize technological innovation and control risks. India (0.88, 0.82) is a typical case. Half the Indian population lacks access to the internet—the excluded half is primarily women, rural communities, and Adivasis (Sambasivan et al., 2021). As reported by the OECD, the difference between the share of men who are internet users and the share of women is 10.1 percentage points as of 2024, substantially higher than OECD members' average of 2.9 percentage points. Additionally, data from Statista shows that in 2023, 51% of people in India perceived that AI would replace their current job, compared to 36% globally. Considering that a company's self-management rules are ineffective in curtailing AI ethical risks (Joshi, 2024), the Indian government tends to control the risks through a centralized approach. For example, in 2023, a revised Digital Personal Data Protection Act was passed to safeguard personal data used in AI R&D.

Although India recognizes that the ethical risks of the emerging technology may cause harm, it gives more priority to facilitating technological advancement through centralized governance. Following the traditional tenets of liberal economy, Indian policy discourse is predominantly economically focused, considering the economic gains that AI offers to India, such as increased productivity, new revenue streams, and cost savings in public services (Bhalla et al., 2024). For instance, the National Strategy for AI (NITI Aayog, 2020) stated that the role of the state should be conceived as a "facilitator" or "enabler" for private enterprises to propel innovation and economic growth. Furthermore, the Indian government intends to open up "non-personal" and anonymized datasets from the vast files of information collected by public agencies for data mining and analysis (Ministry of Electronics and Information Technology, 2022).

5. Discussion

5.1. The Future of AI Governance

According to the results reported by the fsQCA software, states' income level and AI R&D capacity play important roles in impacting states' AI governance choices. In contrast, the influence of the ethical risk level is marginal. This shows that states put more emphasis on AI development than on risk management. Due to the black box nature of AI technology, it is hard to fully understand how AI operates. Besides this, AI has grown rapidly in recent years, so AI governance struggles to keep pace with its development (Meek et al., 2016). According to the "Collingridge dilemma" (Genus & Stirling, 2018), intervening in AI development with risk control measures either too early or too late will be detrimental to society. Therefore, it is understandable why states are cautious in risk control when AI is only partially understood. Additionally, since AI has not demonstrated substantial risks or disastrous consequences, policymakers, the private sector, and the public do not take the issue seriously enough.

However, a common characteristic shown in the deviant cases is that their ethical risk consideration is beyond that of the typical cases. As a result, their AI governance approaches are either less decentralized or less centralized than the typical cases. This indicates that in the future, if ethical risks become more evident and states have to put more emphasis on risk management, they may adopt a balanced governance approach. For instance, during the Covid-19 pandemic, Chinese central and local governments, as well as civil society, jointly employed an Integrative Coordination Governance approach (Dang et al., 2021). Through this approach, the governments were in charge of discovering social problems in real time and proposing solutions accordingly, while technology companies and NGOs were responsible for optimizing algorithms to adapt to the demand for governance. Meanwhile, under the supervision of the governments, companies reduced the ethical risks caused by AI as far as possible, which is beneficial to long-term development.

5.2. Towards a Theory of Balanced AI Governance

Based on the above empirical analysis, the balanced approach is conceived not as a static midpoint, but as dynamic coordination between state and non-state actors, iterative policy feedback loops, and adaptive mechanisms such as regulatory sandboxes or mission-oriented experimentation (Mazzucato, 2016). Such a balance features vertical central–local government coordination to align strategic objectives, horizontal public–private partnerships to leverage expertise and resources, and temporal management of the trade-off between short-term innovation gains and long-term risk mitigation.

A balanced approach proves to be beneficial to the improvement of R&D capacity and ethical risk control. For example, in March 2018, the Russian Ministry of Defense issued a statement ignoring the potential of private companies for AI innovation and self-regulation, while proposing the leadership of the Russian government and state-owned enterprises in AI governance. One year later, the Russian government introduced three AI-specific policy documents that leaned heavily on the private sector, emphasizing the increased decentralization of the Russian AI governance approach. This change acted as one of the causes of the improvement of Russia's R&D capacity from 2018 to 2019. The Stanford AI Vibrancy tool shows that the increase in the number of AI journal publications and patent grants from 2018 to 2019 is greater than the increases both from 2017 to 2018 and from 2019 to 2020. In Singapore, the Monetary Authority of Singapore provides supervisory guidance to all financial institutions. It also works with industry, sharing best practices for risk management efforts and facilitating industry collaboration through programs such as Project MindForge (Monetary Authority of Singapore, 2024). Therefore, the level of AI ethical risk emanating from Singapore's financial sector is relatively low.

The balanced approach reciprocally influences the independent variables, helping address prominent issues quickly and enhancing the effectiveness of regulations. Thus, a balanced approach may not only become a widely accepted domestic AI governance approach, but could also profoundly impact the current global AI governance landscape.

Local, regional, national, international, and non-governmental actors are comprised in the global AI governance ecosystem, which leads to the fragmentation of the system (OECD, 2024). Geopolitical competition further hampers international interoperability, exacerbates ethical risks, and poses barriers to trade and investment. Simply resorting to techno-authoritarianism or unregulated marketism will be ineffective in aiding the emergence of a synergistic, anticipatory, and multistakeholder global AI governance system. Only the balanced approach offers a promising pathway for global AI governance. Its principles align with ongoing initiatives such as UNESCO's Recommendation on the Ethics of AI, emphasizing inclusiveness, accountability, and adaptability. To ensure these principles translate into practice, advanced and developing economies, technology giants, and small and medium-sized businesses should coordinate their interests through global platforms, fostering a governance order that is equitable and resilient.

6. Conclusion

The world is undergoing a fundamental technological shift in the age of AI. Although AI can be harnessed to benefit industries and society, ethical risks including bias, privacy leakage, and job displacement may be harmful to human rights (United Nations System Chief Executives Board for Coordination, 2024). Therefore, proper governance is needed to make the most of the opportunities brought by AI and to mitigate its ethical risks. There are debates about how to govern AI and maximize its advantages (Brynjolfsson & Ng, 2023; Cihon et al., 2020; Dafoe, 2018). Our study aims to contribute to the debates by determining the variables that influence states' AI governance approaches.

Our work combined qualitative with quantitative analysis by adopting the fsQCA method. We chose the US, China, Germany, France, Singapore, India, Russia, and Brazil as the cases about which data were collected, analyzed, and used to test our hypotheses. With the aim of analyzing the underlying factors influencing states' choices of AI governance approaches, we established a framework in which states' income level, R&D capacity, and ethical risk level are taken as independent variables and states' AI governance approach is the dependent variable. We found that states that have higher income and stronger R&D capacity tend to adopt a decentralized governance approach. On the contrary, if a state's income level is high while its R&D capacity is weak, it is likely to take the centralized approach. Also, there are situations in which states' R&D capacity is relatively weak but their ethical risk level is comparatively high. These states usually employ a centralized approach to ensure technological innovation and control risks. Generally, the influence of states' income level and R&D capacity outweighs the influence of their ethical risk level.

Furthermore, we found that there are deviant cases in which states intend to adopt a less decentralized or less centralized approach to balance AI development and risk management. Consequently, we infer that neither a highly decentralized nor a highly centralized approach can effectively reconcile the tension between R&D capacity and ethical risks. Only a balanced approach offers the potential for simultaneously fostering technological advancement and mitigating ethical concerns.

There are limitations in our study. First, although we measured the ethical risks from multiple dimensions, due to data limitations, a more accurate evaluation of a state's risk levels could not be achieved. Second, the research method is also limited. While fsQCA provides systematic pattern recognition, the sample size is small, so diversity of results is not guaranteed. Moreover, we selected typical and deviant cases and potentially overlooked the edge-case insights.

Nevertheless, our results have important implications. The integrated use of fsQCA and case studies enables a comprehensive explanation of states' AI governance choices. In addition, we proved that the combination of per capita GNI and R&D capacity, as well as the combination of R&D capacity and ethical risk level, can impact states' choice of AI governance approach. More importantly, through the analysis of the deviant cases, we found that a balanced governance approach is ideal for promoting innovation and managing risks.

Our framework provides insights for Web 3.0 governance. Governance of decentralized technologies such as blockchain protocols and DAOs (decentralized autonomous organizations) also faces the problem of how to balance development and security. Our findings imply that emphasizing government regulation and multistakeholder participation simultaneously can help mitigate the dilemma and inform the design of more resilient blockchain and DAO governance structures.

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Conflict of Interests

The authors declare no conflict of interests.

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About the Authors

Chenghao Sun is an associate professor and a fellow at the School of Social Sciences, Tsinghua University. He is a council member of the Chinese Association of American Studies. His research interests include China–US relations, transatlantic relations, AI and global governance.

Xiyan Chen is a research assistant at the School of Social Sciences, Tsinghua University, and an analyst at ChinAffairs+. Her research interests include US domestic and foreign policies, AI governance.