

# A Study on the Convergence of Policy Demands Regarding Public Risk Expressions of Generative AI—A Computational Analysis Based on Weibo Texts

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## Abstract

This paper analyzes texts attached to generative AI discussions on the Weibo platform (N=1,027) and employs BERTopic topic modeling and Logit regression to examine the association patterns between three types of risk expressions and regulatory demands. The study finds that the three types of risk expressions accounted for 47.7% of the whole sample, including ethical risks at 30.6% (314 posts), job displacement risks at 16.2% (166 posts), and data security risks at 1.0% (10 posts); In the sample, expressions of data security risks and ethical risks showed a statistically significant positive association with the probability of mentioning regulatory demands ( $p < 0.01$ ), while the effect of job displacement risks did not reach statistical significance ( $p = 0.101$ ); because of the extremely low frequency of mentions (only 2 instances each), ethical norms and industrial support demands failed to meet the conditions for statistical inference. Meanwhile, negative sentiment is the core textual feature distinguishing expressions of ethical risks ( $OR = 1.42$ ). This paper reveals the “regulatory convergence” characteristic of risk discourse on the Weibo platform, in which discourses on different risk types exhibit diverse expression patterns regarding policy outlets, which presents an empirical reference for understanding the discursive relationship between public risk expressions and policy demands.

## Keywords

generative artificial intelligence, risk expression, policy demands, regulatory convergence, Weibo, computational social science

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## 1. Introduction

### 1.1 Research Background

The theory of risk society has provided a sound theoretical framework for the study of how people perceive new technologies. The swift worldwide adoption and use of generative AI technologies, including ChatGPT, have seen a number of potential risks, such as data breaches, bias in algorithms, job displacement, and deepfake material, being actively discussed on social networks, such as Weibo. There are millions of net citizens who openly voice their fears, suspicions, and aspirations about technological advancement by posting, commenting, and reposting, which creates a large and varied amount of native online discourse. Being the biggest open social media network in China, Weibo is a hub of authentic concerns and governance expectations of a huge

number of users concerning the influence of technology on their lives; as such, it is a major arena for observing public risk perceptions and policy demands.

The central question of this study is: when the public expresses risk concerns about generative AI on Weibo, do their policy demands tend to converge toward “regulatory” discourse? We term this phenomenon “regulatory convergence”, whereby discussions of different risk types form a stable association with regulatory discourse at the policy outlet level.

Academic literature and industry have been increasingly aware of social media texts as an important channel for monitoring and studying people’s opinions on various issues in the sphere of digital governance and information science.[1] At present, studies of the attitude of people to the concept of artificial intelligence and quantitative analysis of electronic texts still produce findings that can be divided into three mainstream streams: first, creation of theoretical frameworks in the context of AI risk perception [2,3], second, quantitative analysis and measurement of social media sentiment texts [4,5,6], and third, development and analysis of AI governance policy systems [7,8]. Such studies offer several viewpoints to comprehend how societies perceive new technologies.

## 1.2 Literature Review

The empirical research conducted in this area has revealed two different measurement strategies. One is based on conventional questionnaires, which concentrate on personal inner psychological views of risk. Through the use of standard scales, these studies have developed a three-dimensional cognitive model, which includes a technological, ethical, and social dimension to profoundly assess the internal psychological condition of people [2,3]; nevertheless, they have drawbacks, including small samples, high-costs, and low timeliness. The other method uses big data technology to obtain the public texts available on social media sites (Weibo) and uses computational tools of topic modelling and sentiment analysis to represent the intensity, emotional tendencies, and topic distribution of the online public opinion [4,5,6]. Also, there is one more type of study that examines the macro-level institutional regulation of AI by explaining the theoretical rationale behind the process of converting the issues of concern of the population into regulatory measures [7,8].

It should be observed that these two kinds of measurement entities have an underlying difference between them: questionnaire data is intended to reflect the responses of the respondents in their subjective and internal perspective, but Weibo texts are only able to register the externalized discourses of risks and demands in the public sphere; these two cannot be directly compared. Nonetheless, the most common text-based researches are conceptually confused [4,5], unable to demarcate the limits of the two. Simultaneously, the current research works tend to study public opinion in isolation along one dimension and do not provide the integrated research that would put the risk issue and policy demands into the same analytical framework.

## 1.3 Research Gaps

Based on a literature review, this paper has found three fundamental gaps in the body of knowledge about the topic under consideration:

First, the vast majority of text analyses consider Weibo discourse as a direct perception of the risk by the public and do not make a distinction between these categories. Many quantitative works that use the language of social media texts equate the online discussion of the population directly with personal views of risk [4,5] without explaining the essential dissimilarity between the two objects of measurement both in terms of theoretical meanings and areas of application, which restricts the explanatory strength of research findings.

Second, risk issues and policy demands usually are researched independently and the absence of literature exploring their relationship in a single text. The majority of public opinion studies have concentrated on the negative risk discourse or policy recommendations [5, 6] without an angle that would match the expression of risks and policy demands in the same text context which makes it hard to identify the inherent relationship between them.

Third, other researchers have used single-period cross-sectional data to make causal or mediating inferences, though cross-sectional data cannot be used to make such inferences. Some studies aim at identifying the causal mechanism or mediating path of the phenomenon of risk perception influencing policy demands by using single-period cross-sectional text data. Nevertheless, fixed cross-sectional public opinion information is not

adequate to satisfy the high standards necessary to test causal identification and mediation effects: these inferences go beyond the degree of causation that the methodology can sustain.

## 1.4 Research Questions and Theoretical Expectations

Due to the discussed research gaps, the present study has taken native discussion texts concerning generative AI on the Weibo platform as its basis of data and will use computational text analysis approaches in order to answer the following main research questions:

Central Question: Are public statements regarding risks of generative AI a form of regulatory convergence in terms of policy demands? To rephrase, are the concerns about risks on various levels of dimension convergent at the discursive level towards regulation as a policy outlet?

Additional questions: (a) What are some of the primary classes of generative AI risk expressions present in Weibo texts? (b) What kind of textual characteristics (length, sentiment) can be correlated with the occurrence of various kinds of risk expressions?

This leads to two competing theoretical expectations:

Expectation 1: Differentiated Demand Pathway. The various kinds of risks are associated with different kinds of policy demands in different ways: ethical risks require the demand of ethical norms, data security risks require the demand of regulation, and risks of job displacement require the demand of industrial support. This expectation assumes a natural fit between problem types and policy tools.

Expectation 2: Regulatory Convergence Pathway. Irrespective of the nature of the risks, all the policy discourses of the public are directed to a single channel, which is regulation. This expectation holds that public discussion on social media tends to reduce complex issues to a single narrative of “regulatory failure”.

This empirical design of the present study will also be able to simultaneously test these two competing expectations. In case Expectation 1 is true, it would imply that the three types of risk expressions predicted the three types of policy demands differently; in case Expectation 2 is true, the three types of risk expressions consistently led to regulatory demands.

## 1.5 Research Significance

The conceptual importance of this research is that it separates risk perception as measured by questionnaires and risk expressions on Weibo, thus preventing their conflation; introduces the term, regulatory convergence, which explains the simultaneous presence of various forms of risk expression and regulatory discourse; and clarifies the weaknesses of cross-sectional texts in causal inference. Practical relevance is: the results of the study may be able to offer information based on the discourse of Weibo that could be useful for the regulatory policies, industrial policies, and ethical norms concerning generative AI.

## 2. Literature Review

### 2.1 Research on Public Risk Expressions Regarding Generative AI

#### 2.1.1 Multi-level, Composite Types of Public Risk Perception

On the topic of the study of public attitudes towards new technologies, scholars agree that the risks related to generative AI are perceived by the population as multi-level, multi-faceted, and complex, and the concern of the population is divided into two kinds of real-life situations, namely individual life and macro-social situations. The relevant studies have not been limited to the creation of general macro-level frameworks; instead, they have been able to divide particular problems of risk into specific categories of content fabrication, privacy breaches, and job displacement, which only confirms the fragmented and heterogeneous nature of public concerns. In the micro-level view of individual rights, many of the risk concerns of the public stem not only from technical problems that directly harm their interests (e.g., personal data breaches or algorithmic bias) but also include macro-social concerns such as changes to the job market and destabilization of online public discourse caused by the massive spread of technology.

The empirical study using large volumes of text posted on social media sites also indicates that there exist considerable disparities in the degree of coverage of various risk problems in the online sphere of public discussions, and the themes containing generative misinformation are more prone to cause a negative sentiment in the population [4,5]. Moreover, the process of differentiation of groups varies by cognitive level: the difference in individual characteristics like age and work results in discrepancies in which risks are prioritized by society [2].

### **2.1.2 Approaches to Measuring Risk Expressions in the Social Media Context**

Due to the popularity of social media, research methodologies are changing beyond the traditional questionnaire-based techniques to computational textual analysis [4, 5, 6]. Although a traditional questionnaire technique has been shown to be able to measure an individual's internal psychological state in depth, it is vulnerable to limitations such as small samples, high costs, and poor timeliness [2]. Conversely, computational analysis algorithms based on social media texts can record the overt expressions of the population in discourses in the public space in real-time and at a larger scale [4, 5].

Nevertheless, in most cases, the current literature has a conceptual problem where it conflates the concept of Weibo risk discourse with that of individual risk perception [4,5]. To be more precise, Weibo texts are just the messages people decide to share with others publicly, but they are not an accurate representation of their internal risk perception but an externalized form of risk expression. The need to clarify such a conceptual boundary is essential before carrying out strict empirical studies. A thorough analysis of the current literature indicates that the scholarly society has already established the multi-layered and multifaceted characteristics of the perception of risk [2, 3] and has systematically classified different subcategories of risk issues [4,5]. Nonetheless, the current literature mostly has a poor integration of the dimensions as there are also very few that investigate the differentiated public policy demands that emerge due to different kinds of risks.

## **2.2 Research on Public Policy Demands Regarding Generative AI**

### **2.2.1 Classification of Internet Users' Policy Demands**

The available studies show that the policy requests of netizens on generative AI are characterized by different attributes and generally divided into three categories [7,8]: First, regulatory demands, which require the government to increase the regulation of generative AI research, development, and implementation, to pass appropriate laws and regulations, and to eliminate the threats that may come with the abuse of the technology. Second, demands on industrial support, which are the desire that the government will initiate measures to promote the growth of the local AI industry and raise the status of the country in the world AI competition. Third, ethical norms, which focus on the need to develop industry ethical rules to control the actions of AI creators and consumers and make sure that technological progress is consistent with human principles.

### **2.2.2 Characteristics of Discourse Expression on the Weibo Platform**

Being an open forum for discussion, the discourse of Weibo on these demands is also marked by immediacy, interactivity, and emotional intensity [7,5]. The demands made by netizens are frequently associated with particular risk events or problems, which leads to a chain reaction in the form of: risk event-risk expression-policy demand. Also, there is a great disparity between the impact of opinion leaders and common netizens in expressing demands; the position of opinion leaders tends to determine the orientation of public opinion and thus results in more general social debates.

## **2.3 Research on the Relationship Between Risk Expressions and Policy Demands**

### **2.3.1 Theoretical Explanations for How Risk Concerns Give Rise to Policy Demands**

In theory, the level of perception of risk by the population is an essential condition in the formation of policy demands [7,1]. After people feel that some risk exists, they are driven to find protection and solutions, and thus they demand policies through different channels. The notion of this risk perception-demand expression is one of the key underlying principles of civic engagement and policy formulation.

The academic literature has determined three classical mechanisms that relate to the relationship between risk and demands [7,8,1]: the digital pressure relief mechanism- in which a feeling of insecurity due to the

risks of technology causes people to look up to institutions to offer them security; the institutional demand activation mechanism- when exposure to any risk leads to the creation of a demand on the government to regulate and provide institutions; and the online pressure expression mechanism- where social media becomes the central medium in which the population turns personal concerns into common demands. Existing studies have mostly focused on this line of reasoning on a macro-theoretical level, but the absence of empirical analysis on a micro-level of the question of whether various kinds of risks trigger various kinds of policy demands is still apparent.

### 2.3.2 Two Competing Theoretical Predictions

Based on the above literature, two competing theoretical expectations can be summarized:

Expectation 1: Differentiated Demand Pathway. Various risk categories have varying policy demand categories in different ways: ethical risks correspond to ethical norms; data security risks are related to regulation demands; and employment displacement risks relate to industrial support demands. This expectation assumes a natural fit between problem types and policy tools.

Prediction 2: Regulatory Convergence Pathway. In spite of the nature of the risks involved, all the policy discussion channels in the public sphere lead to one destination: regulation. This expectation holds that public discussion on social media tends to reduce complex issues to a single narrative of “regulatory failure”.

The empirical design of this study will simultaneously test these two competing expectations.

## 2.4 Related Research on Computational Analysis of Weibo Texts

### 2.4.1 Mainstream Computational Methods for Public Opinion Text Mining

The existing computational methods of Weibo text analysis are topic modeling (e.g., LDA, BERTopic), sentiment analysis, social network analysis, and text classification [4,5,6]. Of these, BERTopic or a Transformer-based topic modeling approach is able to handle short texts and produce very interpretable topics, which makes it especially appropriate to analyze short-text-based platforms like Weibo [5,6].

### 2.4.2 Empirical Implementation Cases of AIGC Public Opinion Big Data

Several researchers have performed empirical research on the sentiment of the population in relation to AIGC through the application of computational techniques. One such study examined Weibo messages, and it was discovered that privacy and ethics were the central risk discourses that are often shared by netizens [5]. Other research has also applied quantitative analysis to establish that the loss of jobs is the critical risk problem provoking negative emotions among netizens [9, 6]. The quantitative model of public perception of attention-satisfaction was created by Li Guan et al. using the Weibo platform [4]. Such studies serve as reference points of methodology and useful sources of information in this paper.

## 3. Research Design

### 3.1 Definition of Core Concepts

Individual Internal Risk Perception:

It means that people have their own subjective psychological evaluations and emotions about the possible negative effects of generative AI technologies [2]. The idea relates to the internal psychological state of the person and can be assessed through standardized questionnaire measures, which are not directly addressed in this research.

Risk Expressions on Weibo:

It describes a statement made proactively by users in online texts, like posts and comments, on the Weibo website that pertains to the dangers of generative AI technology. The textual manifestation of public risk concerns in the public sphere is represented by it and acts as the main independent variable in this research.

Policy Demands:

It is a reference to policy expectations that concern regulation, industrial promotion, and industrial ethics that are expressed by the users at the same time in the same Weibo text [7]. It is the textual expression of the people's governing hopes and becomes the main dependent variable in the current research.

**Regulatory Convergence:**

It is also referred to as a consistent co-occurrence association between various risk statements and the policy discourse related to regulation in social media writing. It is important to note especially that the concept of the so-called convergence of regulations, as it is used in this research, is confined solely to the sphere of discursive co-occurrence, i.e., the propensity of the two sets of terms (risk terms and regulation-related terms) to be present at the same time in a given text. The definition is distinct from the concepts of cognitive level, like attribution in psychology and does not imply any assumptions about the psychological condition, intentions or degree of rationality of the public.

### 3.2 Data Sources and Collection

The research was conducted using the data from the Weibo platform. With the help of the Weibo Advanced Search API, it can be filtered out that the public posts and their comments that included keywords like generative AI, large language models, ChatGPT, Wenxin Yiyan, Tongyi Qianwen, and Sora [4,6]. The research adopted a purposive sampling strategy of typical time periods, focusing on the periods when high-profile generative AI issues were at their peak (e.g., the introduction of Sora in February 2025 and the deepfake scandal in March 2026). The process of collecting data was finished in July 2026.

In order to make sure that the data are representative and timely, text data of various time intervals and groups of users have been incorporated. The data cleaning was done in accordance with the following criteria: (1) elimination of posts that were only made up of emojis or short phrases with no substantive meaning; (2) commercial advertisements and promotional materials were filtered out; (3) deleting duplicate posts that saturated the feed; (4) excluding discussions that did not relate to generative AI. Finally, 1,027 valid samples remained to be analyzed.

### 3.3 Variable Definition and Measurement

**Independent Variables:** Binary variables representing three categories of risk expressions.

To determine the three types of expression of risks, a technique of topic modeling by BERTopic with keyword matching was used [5,6]. A remark worth making is that when analysing the results in Tables 2 and 4, the three types of risk expressions were treated as binary (0 / 1) so that a single text could correspond to several risk categories at the same time, but when analysing the multinomial logit in Table 5, the dependent variables were coded in an exclusive manner. The particular rule is that when a text matches keywords of multiple risk categories, it is classified into only one category depending on priority- ethical risks > data security risks > job displacement risks. This rule of priority is explained by the fact that ethical risks (e.g., plagiarism, copyright issues) are typically the most salient issues in public discussion; they are therefore given priority to ensure that controversial issues are not diluted. Mutual exclusivity of the coding guarantees the independence between categories in the multinomial logit regression, hence eliminating bias in estimates due to the presence of overlapping categories.

**Ethical Risk Indicator (0/1):** Does the content contain such keywords as content authenticity, algorithmic bias, copyright disputes, unclear liability, or value conflicts?

**Data Security Risk Indicator (0/1):** Is it a fact that the content contains keywords related to personal information leaks, data privacy protection, or training data sources?

**Employment Displacement Risk Indicator (0/1):** It can contain keywords indicating either the effect of AI on old jobs or the change in the structure of employment.

**Dependent Variable:** A binary variable representing regulatory demands.

Considering that the frequency of policy demands in Weibo texts is very low, in other words, there are only two mentions of ethical norms (0.2 percent) and two mentions of industrial support demands (0.2 percent), which do not satisfy the requirements of statistical inference, this paper will concentrate its research on

regulatory demands (i.e., the demand for regulatory restrictions, i.e., the request of the government to increase the laws and law enforcement, 36 times, 3.5 per cent) which are coded as a dichotomous variable (0- non-mentioned, 1- mentioned).

Control variable: negative sentiment (0/1).

A sentiment analysis model (SnowNLP) has been applied to provide a sentiment score for every text. In accordance with the conventions of setting thresholds adopted by Li et al. (2020) in the field of sentiment analysis of Chinese social media [10], texts with scores lower than the threshold (0.4) were labelled as negative (1), whereas the rest were classified as neutral/positive (0).

Control variables.

The number of characters in the text was added as a way of controlling the effects of non-core factors.

### 3.4 Analytical Model

As the dependent variable (regulatory demands) has a sparse distribution (mention rate of 3.5%), in this paper, the estimation uses a Logit regression model with the following model specification:

$$P(Y = 1) = \frac{1}{1 + e^{-(\beta_0 + \beta_1 X_{ethic} + \beta_2 X_{data} + \beta_3 X_{job} + \gamma \cdot Controls)}}$$

in which Y indicates whether regulatory demands are mentioned (0/1), and  $X_{\{ethic\}}$ ,  $X_{\{data\}}$ , and  $X_{\{job\}}$  are binary (0/1) variables representing the three categories of risk expressions, respectively.

In order to strengthen the confirmation of the robustness of the coefficient estimates, this research used the bootstrap approach (of 1,000 repeated samples) to compute robust standard errors and confidence intervals of the regression coefficients, hence eliminating the possible biases of traditional standard errors when working with a small sample size.

Statement on the Scope of the Study:

The research paper is founded on cross-sectional data that only reflects the magnitude and significance of statistical correlations between the variables, but it does not imply the direction of causation. The Odds Ratio (OR) obtained in the Logit model indicates the factor by which the probability of mentioning regulatory demands varies with the occurrence of a risk expression, not causation.

## 4. Empirical Analysis

### 4.1 Descriptive Statistics

With a combination of BERTopic topic modeling and keyword matching, three types of risk expressions can be found in 1,027 cleaned Weibo posts. The descriptive statistics of each variable are presented in Table 1.

*Table 1: Descriptive Statistics of Key Variables*

| Variable                            | Code                             | Mean   | Standard Deviation | Minimum | Maximum |
|-------------------------------------|----------------------------------|--------|--------------------|---------|---------|
| Ethical Risk Expression             | 0 = Not mentioned, 1 = Mentioned | 0.3057 | 0.4609             | 0       | 1       |
| Data Security Risk Expressions      | 0 = Not mentioned, 1 = Mentioned | 0.0097 | 0.0983             | 0       | 1       |
| Expression of Job Displacement Risk | 0 = Not mentioned, 1 = Mentioned | 0.1616 | 0.3682             | 0       | 1       |
| Regulatory Demands                  | 0 = Not mentioned, 1 = Mentioned | 0.0351 | 0.1841             | 0       | 1       |
| Text length (characters)            | Continuous variables             | 147.98 | 62.61              | 13      | 391     |

*Note: Demands regarding ethical norms were mentioned twice (0.2%), and demands regarding industrial support were mentioned twice (0.2%); these were not included in the table due to insufficient sample size.*

### Statistical Classification of Risk Expressions:

*Table 2: Statistical Classification of Risk Expressions*

| Risk Type                          | Count | Percentage |
|------------------------------------|-------|------------|
| Ethical Risks                      | 314   | 30.60%     |
| Job Displacement Risk              | 166   | 16.20%     |
| Data Security Risk                 | 10    | 1.00%      |
| Neutral or Irrelevant Discussions  | 537   | 52.30%     |
| Total of the three risk categories | 490   | 47.70%     |

These three risks taken together represent 47.7% indicating that almost half of the Weibo posts on the topic of generative AI include expressions of risk concerns [4,5].

Regulatory demands mentions statistics: Regulatory demands were noted 36 times (3.5%), ethical norms were noted 2 times (0.2%), and industrial support was noted 2 times (0.2%). The most frequent kind of demand was regulatory demands, with 90 percent of all mentions.

## 4.2 Results of the Logit Regression Analysis

The research paper has used a Logit model to determine the effect of the three kinds of risk expressions on the likelihood of mentioning regulatory demands. The diagnostics of multicollinearity indicated that the variance inflation factors (VIFs) of all independent variables were near unity (ethical risk VIF = 1.016, data security risk VIF = 1.008, job displacement risk VIF = 1.075, text length VIF = 1.082), which is significantly lower than the critical value of 10, implying that there is no multicollinearity in the model. The regression findings are presented in Table 3.

*Table 3: Logit Regression Results for the Probability of Regulatory Demands Being Mentioned*

| Variable                         | Coefficient | p-value | OR    | Bootstrap 95% CI (OR) |
|----------------------------------|-------------|---------|-------|-----------------------|
| Core Independent Variables       |             |         |       |                       |
| Data Security Risk Expression    | 2.6701      | <0.001  | 14.43 | [4.94, 37.40]         |
| Ethical Risk Expression          | 0.9921      | 0.003   | 2.7   | [1.38, 5.27]          |
| Job Displacement Risk Expression | 0.5845      | 0.101   | 1.79  | [0.87, 3.53]          |
| Control Variables                |             |         |       |                       |
| Text Length                      | 0.0051      | 0.082   | 1.01  | [1.001, 1.010]        |
| Constant term                    | -4.8173     | <0.001  | —     | —                     |

*Note: Pseudo  $R^2 = 0.1209$ ; LLR  $p$ -value =  $2.858e-08$ ;  $N = 1,027$ ; Bootstrap confidence intervals are calculated based on 1,000 bootstrap repetitions; percentile confidence intervals for ORs are reported; variables in bold are statistically significant*

### Interpretation of Results:

The positive correlation between the expression of data security risks and the likelihood of citing regulatory demands is statistically significant (OR = 14.43, 95% CI: 4.94-37.40,  $p < 0.001$ ). Nevertheless, it must be explicitly pointed out that there were merely 10 examples (1.0%) of data security risk expressions, and only 3 of them also included mentions of regulatory demands. This OR is statistically significant, but the confidence intervals are very large (crossing almost an order of magnitude); as such, very little estimation precision can be made, implying that it cannot be considered as a large effect or as a robust and strong effect. The significance of this finding lies mainly in its suggestive direction (i.e., when the public discusses data security issues, their discourse tends to point toward regulation), while the effect size awaits verification with larger samples.

The odds ratios of ethical risk expressions (OR = 2.70, 95% CI: 1.38-5.27,  $p = 0.003$ ) were also found to be statistically significant in increasing the likelihood of regulatory demands being mentioned, however, its effect size was significantly lower than that of the data security risk.

The influence of the risk of employment substitution (OR = 1.79, 95% CI: 0.87 -3.53,  $p = 0.101$ ) on the regulatory demands was statistically insignificant, which is supported by the fact that the confidence interval of the OR covers 1, and this result is consistent with  $p = 0.101$ , indicating that the effect is not significant. This non-significant result can be explained on at least two different levels: Firstly, in terms of statistical power, regulatory demands were only referred to 36 times (3.5%), and due to the very low statistical power of the study, it may not have been able to detect a weak effect that existed; Secondly, in terms of discourse patterns, the weak relationship between job displacement and regulation in discourse can be attributed to differences in

the nature of the risk issues: employment is a long-term structural issue of society and the discussion of policies related to it usually involves other terms, including “training”, “safety nets”, and “economic policy” [9]; in contrast, regulation, as a short-term risk mitigation mechanism, is more common when talking about the rapid events of a data breach or deepfake. Public discourse practices are connected to various kinds of risks being linked with various forms of policy terminology, which leads to various patterns of expression.

### 4.3 Supplementary Analysis 1: Manual Review of Texts Expressing Regulatory Demands

In order to guarantee the precision in keyword matching, this paper performed a manual contextual analysis of all 36 texts that mentioned regulatory demands to determine if it was indeed alluding to government legislative regulation.

*Table 4: Results of Manual Review of Texts Referring to Regulatory Demands*

| Category                                      | Count | Percentage | Typical Examples                                                                                                                                            |
|-----------------------------------------------|-------|------------|-------------------------------------------------------------------------------------------------------------------------------------------------------------|
| Explicitly Referring to Government Regulation | 26    | 72.20%     | “Global regulation is imminent,” “Calling on governments to take immediate regulatory action,” “Hoping regulations will catch up as soon as possible”       |
| Vague or Non-Regulatory References            | 10    | 27.80%     | Discusses only the risks themselves, without explicitly pointing to the government; or points to platforms or industry standards rather than the government |
| Irony/Negative Tone                           | 0     | 0.00%      | —                                                                                                                                                           |
| Total                                         | 36    | 100%       |                                                                                                                                                             |

As shown by the manual review results, the keyword matching approach achieved fairly high validity, with 72.2% (26 texts) of the regulatory demand texts explicitly referring to government regulation. About 27.8% (10 texts), despite referring to keywords like regulation, are unclear on semantic references or are related to risk descriptions, not policy appeals - this indicates the shortcomings of the keyword matching approach on complex rhetoric. [4,5]

### 4.4 Supplementary Analysis 2: Fisher’s Exact Test for the Co-occurrence of Risk Expressions and Regulatory Demands

In order to ascertain whether the correlation between data security risk expressions and regulatory demands can be explained by outliers in limited data, this paper performs a Fisher exact test on the 0/1 distribution of the two variables.

*Table 5: Contingency Table of Co-occurrence Between Data Security Risk Expressions and Regulatory Demands*

|                                   | Mention of Regulatory Demands | No Mention of Regulatory Demands | Total |
|-----------------------------------|-------------------------------|----------------------------------|-------|
| Mention of Data Security Risks    | 3                             | 7                                | 10    |
| No mention of data security risks | 33                            | 984                              | 1,017 |
| Total                             | 36                            | 991                              | 1,027 |

The outcome of the Fisher exact test offers additional support for the co-occurrence relationship between the risk of data security and regulatory demands ( $p = 0.009$ , one-tailed). It is important to mention, however, that the test is conducted using a sparse contingency table (expected frequencies  $< 5$ ) and the fact that the findings are statistically significant does not imply that the effect is robust. There were only 10 references (1.0%) related to data security risks, and among them, only 3 referred to both regulatory demands - such a low absolute frequency means that although the OR of 14.43 is statistically significant, its 95 percent confidence interval of [4.94, 37.40] spans nearly an order of magnitude, indicating extremely limited estimation precision. Consequently, the importance of this result is more in showing a tendency, i.e., that whenever the topic of data security comes up in the community, it frequently leads to regulation, instead of offering conclusive results. The next step in future studies should be to verify the robustness of this effect in larger samples.

### 4.5 Supplementary Analysis 3: Factors Influencing the Differentiation of Risk Expression Types

In order to explore the text characteristics linked to the development of various kinds of risk expressions, this research made use of the concept of risk-free discussions (537 entries) as the reference group, considered

the type of risk expressions as a three-class dependent variable (ethics risk/job displacement risk/data security risk), and analyzed the data using a multinomial logit regression.

*Table 5: Multinomial Logit Regression of Factors Influencing Risk Expression Types (Reference Group: No Risk)*

| Variables          | Ethical Risk (n=314) | Job Displacement Risk (n=166) | Data Security Risk (n=10) |
|--------------------|----------------------|-------------------------------|---------------------------|
| Text Length        | 0.7814               | 1.3758                        | 1.1963                    |
| Negative Sentiment | 1.4162               | 1.057                         | 0.5285                    |

*Note: The values in the table represent Odds Ratios (OR); the reference group is "No Risk" (n=537); risk types are coded as mutually exclusive, with priority ranked as ethical risk > data security risk > job displacement risk; model accuracy is 52.48%; N=1027*

**Analysis of Findings:** As is shown in Table 5, the three risk categories have different features concerning the features of the text.

One of the strongest attributes of ethical risks is negative sentiment. A text that has negative sentiment will have an estimated 41.6 percent increased likelihood of containing an expression of an ethical risk (OR = 1.4162). Meanwhile, texts that address the issue of ethical risks are likely to be less than average in length (OR = 0.7814). It might be linked with what triggers such discussions: discussions of such issues as plagiarism or deepfakes can be caused by a sudden event that causes people to express their feelings through short emotional posts [5,9].

Conversely, the debates on the risks of job displacement are more frequent in the longer literature (OR = 1.3758). The topics of employment problems need the inclusion of job types and referencing data or case studies, thus, the texts tend to be long and the tone of writing relatively rational. Nevertheless, the relationships between these discussions and the demands of regulation are not statistically significant ( $p = 0.101$ ), which means that these discussions do not often result in the direct expressions of the demand for regulatory action.

Only 10 texts were classified as data security risk expressions; given the very small sample, the results are unstable, and no further interpretation is provided here.

## 5. Conclusions and Discussion

### 5.1 Research Conclusions

This research has systematically analyzed the relationship between risk expressions and regulatory demands through the application of BERTopic topic modeling and Logit regression, and strictly demarcated the difference between individual intrinsic risk perception and explicit risk expression in social media based on a dataset of texts talking about generative AI on the Weibo platform (N = 1027). These were the main findings of the study:

First, the risk expressions about generative AI in the Weibo space have focused on two aspects: ethical risks and job displacement risks, whereas the expression of data security risks has been less frequent. Expressions of ethical risks made up 30.6 percent (314 posts), expressions of job displacement made up 16.2 percent (166 posts), and data security risks took up 1 percent (10 posts) each; neutral or unrelated talk constituted 52.3 percent (537 posts). The 3 types of risks together represented 47.7 percent, which shows that almost half of the relevant talks included explicit risk concerns [4,5].

Second, in the present sample, the presence of data security risks and ethical risks was found to be significantly positively correlated with the likelihood of mentioning regulatory demands (data security risks: OR = 14.43, 95% CI: 4.94-37.40,  $p < 0.001$ ; ethical risks: OR = 2.70, 95% CI: 1.38-5.27,  $p = 0.003$ ). Job displacement risk impact was statistically insignificant (OR = 1.79, 95% CI: 0.87-3.53,  $p = 0.101$ ). This outcome must be viewed as only an initial sign since the confidence interval is broad, and the sample number is small in case of data security risks and it must be confirmed by using a greater sample. Ethical-norm and industrial-support demands were mentioned only twice each, which precludes statistical inference.

Third, there were no parallel relationships between ethical risks and calls for ethical norms, as well as between the risk of job displacement and calls to support industries. In Weibo discourses, risk types are not matched one-to-one with policy demands, but several risks all lead to regulation [7]. Even though the calls on

ethical norms were very few, it is not necessarily the case that the population does not care about ethics; instead, this probably means that the population does not have a shared language to make such demands.

Fourth, negative sentiment was highly correlated with statements of ethical risks ( $OR = 1.4162$ ), however, no significant correlation was observed with employment displacement risks or data security risks. Discussing ethical risks in terms of textual characteristics tended to be negatively emotional and short, whereas employment displacement tended to be more lengthy and somewhat reasonable in mood.

## 5.2 Theoretical Contributions

This study has theoretical significance in three aspects.

First, it is used to differentiate between risk perception assessed through questionnaires and risk expression on Weibo [2]. The two are usually considered as one and the same in previous studies, but they vary in their nature and measurement.

Second, this study introduces the concept of “regulatory convergence” to describe the co-occurrence of risk expressions and regulatory discourse within the same text. It refers to textual co-occurrence only and does not involve users’ underlying thoughts.

Third, it may be stated that there is no one-to-one relationship between a type of risk and policy demands. Data security risks and ethical risks are closely linked to regulatory demands, but the threat of losing a job is not. One reason is that when discussing various risky issues, the vocabulary used is not the same: data security and ethical issues often go hand in hand with the concepts of legislation and law enforcement, whereas employment-related issues are often discussed in the context of training, safeguards, and economic policy.

## 5.3 Implications for Practice

Based on the findings of this study, two points are worth noting.

First, the debate on risks in Weibo can also lead to regulation [7], however, this is not a complete picture of the policy demands of the population. The policymakers may take into account the mood of society on social networks, though it cannot be considered as the only voice of the people.

Second, even though the number of discussions that involved the discussion of data security risks was low (only 10 posts), the direction of its association with regulatory demands was clear ( $OR = 14.43$ ). The people who speak out about the issue of data breaches and deepfakes usually urge the government to introduce laws that will address the problem. These problems ought to be given priority on the regulatory agenda. Conversely, the association between job displacement and regulatory discourse is weak and statistically non-significant ( $p = 0.101$ ), because of the specific nature of employment issues: they require long-term structural change, discussions are discontinuous, and it becomes hard to develop a focused regulation call. To solve these concerns it might be necessary to depend more on the institutionalized mechanisms of dialogue rather than using public opinion driven emergency response models.

## 5.4 Research Limitations and Future Prospects

This study has the following limitations:

Firstly, the sample size is small, and the distribution of the dependent variables is sparse. The study has made use of merely 1,027 postings on the Weibo platform. As the Weibo population is different from the population of the country, the sample cannot be taken as representative of the so-called Chinese population. Regulatory demands were found only 36 times (3.5 percent), whereas ethical-norm and industrial-support demands occurred only twice, which restricts the statistical validity of the results. The odds ratio ( $OR$ ) of data security risk was 14.43 and had a large confidence interval (95%  $CI$ : 4.94-37.40) which shows that it has poor estimation accuracy. The findings are specific to the 1,027-post sample in this paper and should not be extrapolated to other situations. In addition, this study adopted a purposive sampling of typical time periods, focusing on the periods when high-profile generative AI issues erupted. Such crisis windows might make the discussions more prone to the regulatory discourse, and the findings may not necessarily be indicative of regular discussion patterns. Subsequent studies may consider using multi-batch data gathering, cross-platform comparison, or continuous time sampling to enhance the validation of external validity.

Secondly, there are some limitations to keyword matching. Manual review showed that 10 out of 36 regulatory demand texts were semantically ambiguous or not directed at government regulation, which produced a 27.8 percent mislabeling rate. It implies that keyword matching might miss certain implicit risk expressions (e.g., AI taking away jobs is not one of the predefined keywords) and cannot detect rhetorical devices like sarcasm, hypotheticals, and negations [4,5]. Semantic embeddings with large language models can also be used in future studies to enhance the accuracy of coding.

Thirdly, constraints of cross-sectional data. The current study is unable to disclose the dynamic evolutionary relationship between risk expressions and policy demands. Further studies may be able to apply panel data or longitudinal data to investigate how this relationship has changed over time with more details.

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## Conflicts of Interest

The authors declare no conflict of interest.

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