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ASSESSMENT OF FOOD WASTE POLICY EFFECTS BASED ON TEXT MINING ANALYSIS OF PUBLIC FEEDBACK: A CASE STUDY OF CHINA'S ANTI-FOOD WASTE LAW

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Abstract: Food waste poses a major challenge to global sustainable development and food security. China's Anti-Food Waste Law, introduced in 2021, is an important intervention policy that aims to curb food waste by influencing public attitudes and consumption behaviors. Based on social media text mining, this study systematically evaluates the policy effects of the law. By analyzing more than 81,000 microblogs related to food waste from 2019 to 2023, the changes in public discourse, attitudes, and self-reported behaviors before and after the implementation of the law were explored. The study found that government initiatives such as the "Clean Plate Campaign" were widely disseminated on social media and became the focus of public discussion. Topic model analysis revealed that public perception closely aligned with the core principles of the Anti-Food Waste Law, demonstrating that the law had a significant influence on shaping public discourse. Sentiment analysis results showed that public sentiment reached a peak at the beginning of policy implementation, but its positive impact did not last long. Overall, this study verified the application potential of text mining technology in policy effect evaluation and emphasized that sustained public participation is essential for the long-term effectiveness of policies. It is recommended that policymakers continue to carry out highly interactive campaigns through social media to consolidate the social consensus against food waste.

Index Terms **-** Food Waste, Policy Evaluation, Text Mining, Public Sentiment, China's Anti-Food Waste Law, Large Language Models

I. INTRODUCTION

Food waste poses a global threat to food security, environmental sustainability, and economic stability. The United Nations Environment Programme (UNEP) estimates that approximately 17% of food available to consumers is wasted each year [1]. In China, approximately 27% of food annually produced for human consumption (349 ± 4 Mt) is lost or wasted [2]. The generation of food waste not only results in the emission of substantial quantities of greenhouse gases, but also leads to the depletion of significant water and energy resources. This, in turn, has been estimated to result in an annual global economic loss of approximately US$2.6 trillion [3-5]. These trends starkly contradict the targets outlined in Sustainable Development Goal (SDG) 12.3, which calls for halving per capita food waste at the retail and consumer levels by 2030 while reducing losses in production and supply chains [6].In response to this crisis, governments around the world have implemented various policy frameworks to curb food waste. France led the way in 2016 with the world's first Anti-Food Waste Act, which legally prohibits supermarkets from destroying unsold edible food and instead mandates its donation to charities and food banks [7]. In the same year, Italy followed suit with its Anti-Waste Act, which incentivizes businesses to donate leftover food through tax breaks and promotes consumer habits such as "bagging" in restaurants [8]. In Asia, South Korea introduced a volume-based food waste fee system in 2013, which has reduced waste and promoted recycling through strict monitoring and financial penalties [9]. However, the effectiveness of such policies remains controversial, especially in developing economies undergoing rapid dietary transitions. China's 2021 Anti-Food Waste Law exemplifies this challenge. Enacted by the Standing Committee of the National People's Congress, the law imposes stringent measures on food service, including mandatory smaller portion sizes, consumer education campaigns, and fines for establishments that encourage excessive ordering [10].However, despite the gradual improvement of the policy system, the effectiveness of policies depends not only on the rationality of their design but also on the public's cognition, attitudes, and behavioral responses. As the main actors in food consumption, the public's level of cognition, supportive attitudes, and actual actions regarding the Anti-Food Waste Law directly affect the effectiveness of policy implementation. Therefore, evaluating the implementation effects of the Anti-Food Waste Law, particularly by analyzing public feedback, is of great significance for further improving relevant policies.

Although policy interventions are an effective means to reduce food waste, their actual reduction effects still need to be systematically validated. Existing studies have mainly assessed policy efficacy through qualitative and quantitative methods: qualitative studies focus on stakeholders' empirical insights, e.g., Busetti [11] reveals logistical barriers to the implementation of food donation policies in the Italian restaurant industry through semi-structured interviews; and quantitative studies rely on data modeling, e.g., Aitken, et al. [12] find based on U.S. state-level data that states with stronger conservation policies in the states have more food donations. However, traditional approaches face significant limitations in measuring public attitudes and behaviors. On the one hand, objective measures (e.g., waste composition analysis) are difficult to apply on a large scale due to high costs [13]; on the other hand, subjective self-reported data are subject to large biases, with van Herpen, et al. [14] finding that compared to the Physical Waste Survey and the Food Expenditure Survey, self-assessment slightly underestimates the proportion of measured food waste (respectively 13.7% and 16.3%, respectively). These methodological shortcomings make it difficult to accurately obtain data on food waste attitudes and behaviors for large-scale populations, which in turn undermines the reliability of policy assessments.

In order to break through these limitations, text mining technology provides a new paradigm for policy research by utilizing big data and natural language processing techniques [15]. Compared with traditional methods, its advantages are threefold: first, research design based on open-source data (e.g., social media, news commentaries, and online forums) significantly reduces the threshold and cost of data acquisition. Second, users' discussions on social media tend to be more realistic, reducing the social expectation bias and self-report bias in traditional questionnaires [16]. Finally, text mining can analyze large amounts of data covering different regions, ages, and social groups, providing a more representative sample [17]. Empirical studies have validated the effectiveness of this technique: Song, et al. [18] used LDA thematic modeling to analyze China's food safety policies, identifying several key policy areas such as food additives regulation and food traceability systems; Singh and Glińska-Neweś [19] quantified 43,000 tweets through sentiment analysis to study customers' attitudes towards organic food in a more objective way; Huang, et al. [20], on the other hand, combined social network analysis with LDA modeling to locate five key food safety issues from takeout platform comments. Through text mining methods, such studies not only reduce the cost of data collection, but also dynamically track the evolution of public responses, providing a temporally and spatially continuous observation perspective for food research.

In recent years, Large Language Models (LLMs) have made significant breakthroughs in the field of natural language processing [21]. This technological innovation has contributed to the transformation of research methods in the social and behavioral sciences, with more and more scholars using automated text analysis techniques to quantitatively extract complex concepts such as “mental constructs” from massive amounts of text [22]. Compared with traditional text analysis methods, the core advantages of LLM are twofold: first, its deep learning-based architecture can more accurately capture the contextual semantic associations of text; second, it can complete high-precision analysis without relying on labeled data for model training [22].

Currently, the text analysis capability of LLM has been validated in several types of empirical studies. For example, Wu, et al. [23] used LLM to make unsupervised predictions of potential positions of political figures, demonstrating its potential application in the field of political science, while Yang and Menczer [24] confirmed that GPT-3.5 was able to assess the credibility of news media at a level close to that of a human expert. Through comparative experiments, Gilardi, et al. [25] established that ChatGPT achieves superior accuracy and coding consistency compared to MTurk-based manual annotations on text classification tasks such as topic identification and stance detection, while simultaneously demonstrating significant cost-efficiency advantages. For multilingual and multimodal scenarios, Rathje, Mirea, Sucholutsky, Marjieh, Robertson and Van Bavel [22] tested the ability of the GPT family of models to recognize psychological dimensions such as emotions and moral inclinations, and showed that their performance outperforms traditional lexicographic methods and is comparable or even better than fine-tuned machine learning models. Together, these studies highlight the technical advantages and application prospects of LLM in interdisciplinary text analysis.

Based on the above advancements, this study integrates text mining with large language model (LLM) technology to construct a comprehensive Cognitive-Attitude-Behavior analysis framework. The research first employs keyword frequency analysis to gain insights into the focal points of public concern regarding food waste. Subsequently, topic modeling techniques are utilized to identify the key dimensions of cognitive differentiation, followed by sentiment analysis to explore the emotional mechanisms that facilitate the transformation from cognition to attitude. Finally, LLM is employed to assess the cross-temporal effects of policy interventions on public attitudes and behaviors.

This study not only fills the empirical gap in the evaluation of food waste policies in developing countries but also opens up an innovative method for assessing policy effectiveness by combining text mining techniques with large language modeling.

The structure of this paper is arranged as follows: Section 2 provides a detailed overview of data sources and research methods, including data preprocessing, keyword extraction, sentiment analysis, and the LLM scoring framework. Section 3 reports the quantitative results of keyword trends, topic clusters, sentiment dynamics, and policy impacts. Section 4 discusses the implications of these findings and suggests strategies to improve policy effectiveness. Finally, Section 5 reflects on the limitations of the study.

II. DATA AND METHODS

Data Sources and Processing

The data for this study comes from user discussions related to food waste on the Sina Weibo platform. The selection of Weibo as the research platform is mainly based on the following considerations: (1) Weibo is one of the largest social media in China, with a wide user base as of the second quarter of 2024, when monthly active users of Weibo reached 583 million. (2) Weibo user groups cover a wide range of people of different ages, occupations, and geographic regions, which enhances the representativeness of the sample. (3) The instantaneous discussions and interactions of Weibo users reflect the real public attitudes towards the topic of food waste, which can help to objectively assess the effects of policy implementation.

For Weibo data, we crawled content using the keyword "food waste" from April 29, 2019, to April 29, 2023, yielding an initial sample of 106,544 posts. We then eliminated irrelevant information through keyword matching, resulting in a final sample of 81,286 valid posts for analysis.

At the same time, in order to solve the problem of ambiguous words and unregistered words, we have built custom dictionaries, including: empty plate campaign, etc. To optimize the semantic quality of the corpus, we filtered the stop words using Baidu’s stop word list to remove high-frequency function words with minimal semantic value.

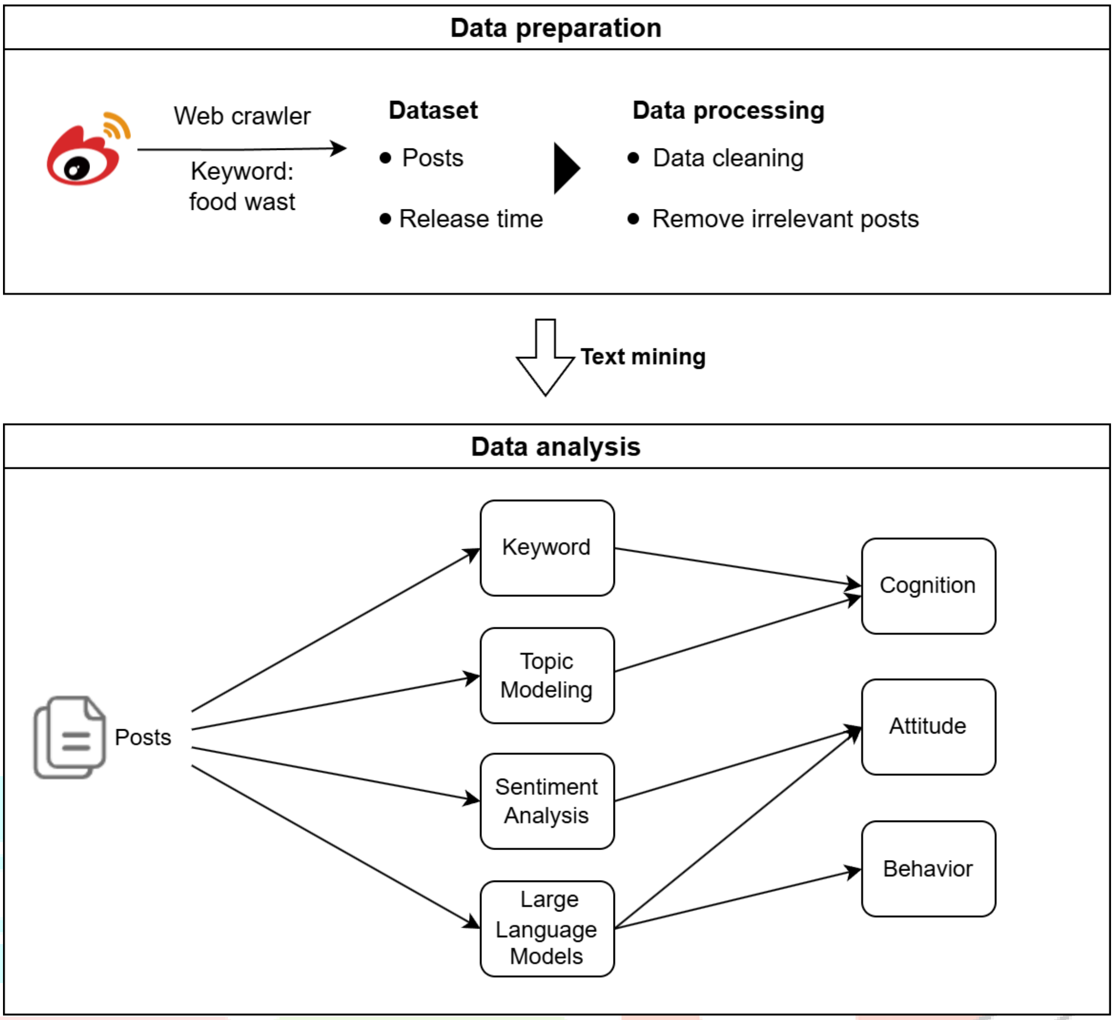

Figure 1. The process of data collection, processing, and analysis.

Method

Keyword analysis

Keyword analysis is an important tool in text mining and information retrieval for identifying representative and important words in a text. As a core method in the field of text mining and information retrieval, the core value of keyword analysis lies in the extraction of core terms with domain characterization significance through semantic weight calculation. In this study, a quantitative analysis method based on word frequency statistics is adopted to screen out the top ten keywords with significant high-frequency features in the text corpus, revealing the core dimensions of the public's concern about food waste. These high-frequency terms reflect the distribution of hotspots in the discussion of the issue and provide data support for the subsequent construction of a cognitive framework of food waste.

Topic modeling

Topic modeling, as a probabilistic generative text mining method, systematically reveals the implicit conceptual structural system in large-scale text sets by constructing the potential semantic space of document-word-topic. Its core mechanism lies in the establishment of a topic mixture distribution (θ) at the document level and a lexical item probability distribution (φ) at the topic level based on the statistical inference of lexical item co-occurrence patterns, so as to realize the multilevel deconstruction of textual semantic units [26]. Among them, Latent Dirichlet Allocation (LDA) dynamically infers the number of topics through a Bayesian nonparametric framework, while Embedded Topic Model (ETM) utilizes the embedding representation of neural networks to capture semantic nonlinear associations, which form a paradigm complementarity between generative and discriminative methods [27].

In the field of food research, topic modeling is used to identify topics related to healthy eating, food fraud detection and policy topic mining. In this study, topic modeling was used to identify popular perceptions of food waste in social media. To overcome the shortcomings of LDA topic models in handling short textual comments—such as information sparseness, topic fragmentation, and inadequate capture of semantic associations—this study employs the fusion of Sentence-BERT and LDA for topic recognition of commentary text, as proposed by Ruan and Huang [28], to analyze topics within the processed dataset of 81,286 Weibo posts through topic modeling.

Sentiment analysis

In order to explore the public's attitudes toward food waste, this study uses the SnowNLP Chinese natural language processing tool to perform sentiment analysis on the collected Weibo data. The sentiment analysis framework of the tool consists of three core processing stages: firstly, the built-in word segmentation algorithm slices the Chinese text into words and parses the continuous statements into independent lexical units; secondly, a simple Bayesian classifier is used for machine learning modeling, and the posterior probability of the text belonging to the positive or negative sentiment category is calculated to achieve the sentiment discrimination; finally, the probability is normalized to the [0,1] interval to generate the sentiment score, which converges to 1 to indicate positive sentiment and 0 to characterize the sentiment of the public. Finally, the probability value is normalized to the interval [0,1] to generate an emotion score, where convergence to 1 indicates positive emotion and convergence to 0 characterizes negative emotion [29]. This technical solution effectively balances the semantic complexity of social media texts with the operability of analysis, and provides a methodological basis for quantitatively interpreting public emotional tendencies.

Quantitative Analysis Using Large Language Models

In order to examine the shift in public attitudes and behaviors toward food waste before and after the release of the Anti-Food Waste Law, this study used the GLM-4 PLUS version of the ChatGLM model to analyze microblog comments. The GLM-4 PLUS version of the ChatGLM model was used to analyze the comments on Weibo, which was ranked among the top on the General List in October 2024 in the Chinese Semantic Comprehension Ability Benchmark SuperCLUE, confirming that it is capable of analyzing Chinese text [30]. With the help of the batch API system provided by ChatGLM, this study quantitatively assessed the public's comments based on the prompt (Table 1) in the following two dimensions, each of which was scored on a 0–10 scale: (1) Attitude, which reflects the public's cognitive and affective tendencies towards anti-food waste; (2) Behavior, which evaluates the public's behavior in real life; The scoring process strictly followed the explicit evidence in the text, especially for extreme scores (0–2 or 8–10), which required sufficient supporting evidence to ensure objectivity and reliability of the scores. Through this method, unstructured textual data are converted into quantifiable statistical indicators, laying the foundation for subsequent statistical analysis.

TABLE 1. SCORING CRITERIA FOR PUBLIC ATTITUDES AND BEHAVIORS TOWARDS ANTI-FOOD WASTE IN MICROBLOG COMMENTS.

Dimension	Score Range	Description
Attitude Dimension	0–2	Strongly opposed to anti-food waste (the lower the score, the stronger the opposition)
Attitude Dimension	3–4	Tendency to oppose, but with some understanding
Attitude Dimension	5	Neutral attitude, no clear expression of support or opposition
Attitude Dimension	6–7	Tendency to support, with reservations
Attitude Dimension	8–10	Strongly supports anti-food waste (the higher the score, the stronger the support)
Behavior Dimension	0–2	Severe food waste behavior
Behavior Dimension	3–4	Slight food waste behavior
Behavior Dimension	5	Neutral behavior, neither wasteful nor particularly frugal
Behavior Dimension	6–7	Slight behavior to reduce food waste
Behavior Dimension	8–10	No food waste at all

In order to dynamically track the policy effects, the study adopts multiple time window comparative analysis: taking the time of legislation release as the reference point, seven time periods of 7/14/30/90/180/270/360 days are set to compare the differences between before and after the implementation of the policy within each time window through the t-test of independent samples. Specific analytical indicators include three dimensions: attitude score, behavior score, and overall support. For each dimension, this study calculated the following statistics: (1) the difference between the sample means before and after policy implementation; (2) the t-statistic and its significance level (p-value); and (3) Cohen's d effect size. Interpretation of the effect sizes was based on Cohen's (1988) categorization criteria: d = 0.2 for a small effect, d = 0.5 for a medium effect, and d = 0.8 for a large effect[31].

III. RESULTS AND DISCUSSION

Keyword analysis

After word segmentation and removal of stop words for Weibo data about food waste, we counted the number of occurrences of each word and obtained the following results (Table 2):

TABLE 2. KEYWORD OCCURRENCE COUNTS AND WEIGHTS.

Keyword	Weight	Count
Waste	0.15	173080
Food	0.11	152155
Weibo	0.02	17790
Clean Plate	0.02	20304
Grain	0.02	31979
Video	0.02	24049
Reduce	0.02	31924
Catering	0.02	17133
Health	0.02	22578

The results revealed distinct patterns in public discourse around food waste. The two most prominent terms were "waste" and "food", collectively accounting for approximately 26% of the total weighted frequency. The significant presence of policy-related terms such as "Clean Plate" and "grain" reflects the influence of government initiatives like the "Clean Plate Campaign" on public discourse. Additionally, the high frequency of platform-specific terms like "Weibo" and "video" highlights the significant role of social media in facilitating public discussion of food waste issues. This finding underscores the importance of social media platforms as channels for policy communication and public engagement in food waste reduction initiatives.

Textual analysis of the Weibo sample

Overall Topic Modeling

After performing topic modeling analysis on the preprocessed 81,286 microblog data, this study used topic consistency and perplexity as evaluation indicators. By comprehensively analyzing the changing trends of the two (as shown in Figure 2 and Figure 3), we finally determined that the optimal number of topics was 13. Based on this, we obtained the topic modeling results shown in Table 3.

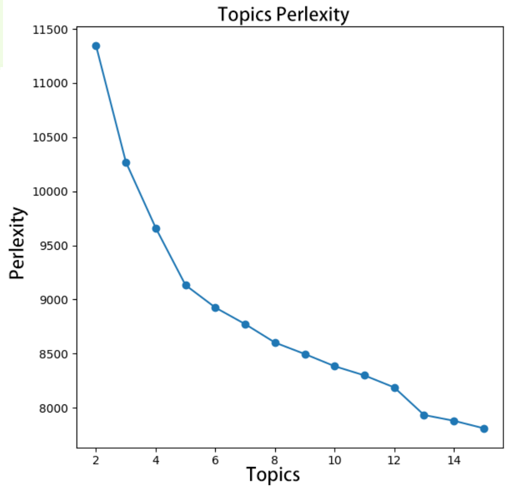

Figure 2. Trends of Topic Perplexity in Weibo Sample Textual Analysis.

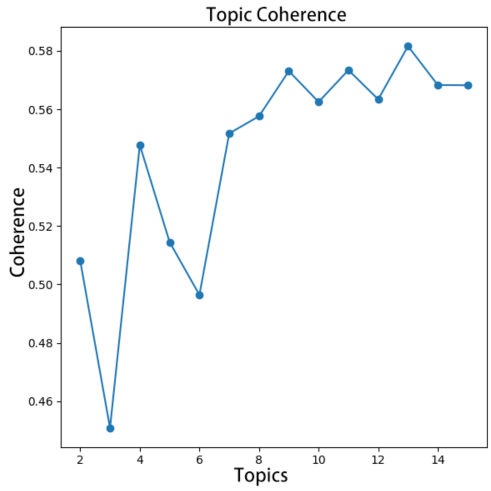

Figure 3. Trends of Topic Coherence in Weibo Sample Textual Analysis.

TABLE 3. TOPIC MODELING RESULTS.

Category	No.	Topic Number and Label	Top 1 – 10 Keywords
Social Governance Category	1	Global Food Waste and Food Crisis	Hunger, Tip of the Tongue, Food, Cherish, Global, World, Reject, Clear Your Plate, Waste, Grain
Social Governance Category	3	Campus Canteen Waste	Stop, Activity, Canteen, Dining, Saving, Student, Waste, Civilization, Clear Your Plate, Catering
Social Governance Category	4	Exposure of Waste Phenomena	Netizen, Fan, CCTV, Really, Eating Broadcast, Super Topic, Weibo, Video, Food Waste
Social Governance Category	6	Artists' Publicity Against Waste	Waste, Idol (referring to an admired celebrity), Santa (a person's name), Disposable, Energy, Wild, Support, Earth, Reduce, Wang Yibo
Behavioral Practice Category	2	Daily Catering Waste	China, Super Topic, Life, Foodstuff, Reading, Nutrition, Refrigerator, Health, Waste, Food
Behavioral Practice Category	7	Online Catering Chaos	Anchor, Foodstuff, Live Broadcast, Video, Food, CCTV, Wang Eating Broadcast (a specific person's eating broadcast), Waste,

			Big Stomach, Eating Broadcast
Behavioral Practice Category	11	Dining Behavior Habits	Eat, Don't Want, Thing, Tastes Bad, Feel, Tastes Good, Like, Really, Food, Waste
Behavioral Practice Category	5	Disposal of Surplus Food	Health, Life, Reduce, Garbage, Weibo, Grain, Video, Foodstuff, Food, Waste
Value Cognition Category	8	Rational Diet Culture	Nutrition, Feel, Time, Diet, Exercise, Health, Lose Weight, Body, Waste, Food
Value Cognition Category	10	Emotion of Cherishing Food	Love, Grain, Life, Weight, Delicious, Thing, Beautiful, Food, Clear Your Plate, Waste
Value Cognition Category	12	Moral Value Judgment	A Lot, Life, Thing, Like, Others, Life, Time, Life, Food, Waste
Value Cognition Category	13	Healthy and Thrifty Life	Super Topic, Weibo, Health, A Lot, Life, Really, Time, Like, Waste, Food
Experience and Perception Category	9	Dietary Experience and Perception	Feel, Like, Tastes Bad, Eat, Tastes Good, Don't Want, Thing, Really, Food, Waste

Based on the analysis results of SBERT-LDA topic modeling, this study divides the public's perception of food waste into four categories: social governance, behavioral practice, value perception, and experience. The first three dimensions show a significant correspondence with the relevant provisions of the Anti-Food Waste Law.

In the social governance dimension, the theme of "campus canteen waste" closely echoes the provisions of Article 9 of the Anti-Food Waste Law on school catering service management and Article 21 on the responsibilities of education administrative departments [10]. At the same time, social activities such as "waste exposure" and "artists' anti-waste propaganda" are in line with the clear requirements of Article 22 of the law on the responsibilities of news media [10]. These correspondences illustrate the role of legal provisions in guiding public opinion and regulating the behavior of education departments.

In the behavioral practice dimension, the study focuses on specific topics such as daily eating behavior, online dining, personal dining habits, and leftovers. These topics effectively echo the provisions of Article 14 of the Anti-Food Waste Law on personal food conservation [10]. It is particularly noteworthy that the discussion on the chaos of online catering in Topic 7, especially the collective boycott of "big stomach king" programs, is a typical case of the law changing public cognition. This phenomenon is directly derived from the strict prohibition of promoting wasteful eating behaviors in Article 22 of the Anti-Food Waste Law, which reflects the role of the law in regulating media content and shaping public cognition [10].

In the dimension of value perception, the public shows a positive and rational recognition of dietary culture and generally pursues a healthy and frugal lifestyle. This value orientation is also consistent with the reasonable, green and healthy dining concept advocated by Article 14 of the Anti-Food Waste Law, reflecting the influence of the law in guiding social values [10].

In terms of experience, personalized subjective expressions such as "making food unpalatable is the biggest waste" reveal the important influence of dietary experience and emotional factors in food waste behavior.

We can find that public topics are highly consistent with the relevant provisions of the Anti-Food Waste Law, indicating that the formulation of the Anti-Food Waste Law is consistent with the common expectations of the public, and also reflects the influence of the law on public cognition.

Sentiment analysis

Comprehensive analysis

After sentiment classification of all 81826 microblogs, texts with positive sentiment values were marked as 1, and texts with negative sentiment values were marked as 0. According to statistics, there were 42737 posts with positive sentiment, accounting for 54.58% of the collected data, and 4060 posts with neutral sentiment, accounting for 4.99%. There were 34489 negative posts, accounting for42.43%. We found that the public's comments on online food safety were generally neutral and tended to be positive.

In posts with relatively positive emotions, there are more contents advocating against food waste, food conservation, and the "Clean Plate" campaign, such as "Start a green life at the table with Wang Yibo, who is full of positive energy, refuse to use disposable tableware, do not waste food, and travel in a low-carbon and environmentally friendly way". In posts with negative emotions, there are more self-condemnation of one's own food waste behavior. For example: "I have wasted too much food recently, sorry sorry please forgive me".

Content analysis of sentiment-classified posts revealed a complex relationship between emotional polarity and attitudes toward food waste. Quantitative analysis of keyword frequencies in positive posts (sentiment score > 0.6) demonstrated a high occurrence of terms associated with food conservation advocacy and the "Clean Plate" campaign. The most frequent keywords in positive posts included "waste", "food", and collective action-oriented terms such as "we" and "together".

Conversely, many posts classified as negative (sentiment score < 0.4) exhibited expressions of self-reflection and critical discourse. Keyword frequency analysis showed that terms related to personal reflection (such as "self") and restrictive phrases (such as "don't") appeared more frequently in these posts. Notably, the term "waste" appeared with even higher frequency in negative posts, suggesting increased awareness and concern about the issue rather than opposition to waste reduction measures.

Emotional time analysis

As shown in Figure 4, this section counts the percentage of public sentiment towards food waste from 2019 to 2023. Overall, positive sentiments· remained dominant throughout the period, always accounting for more than 50% of the total number of posts.

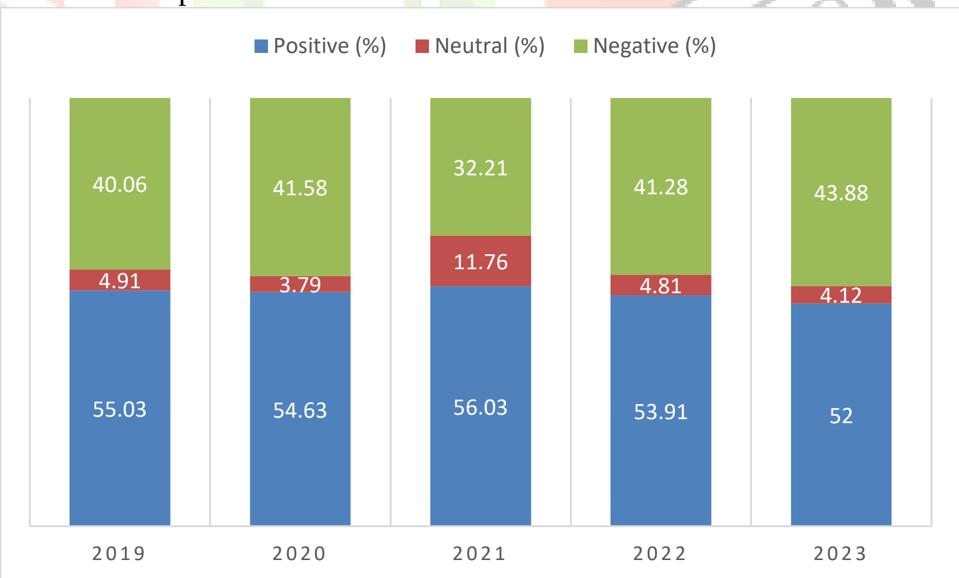

Figure 4. Percentage of Public Sentiments (Positive, Neutral, Negative) towards Food Waste from 2019 – 2023.

The proportion of positive sentiments peaked in 2021 (56.03%), coinciding with the implementation of the Anti-Food Waste Law. This peak was accompanied by a sharp drop in negative sentiments, which fell to the lowest point in the five-year period (32.21%). This shift suggests that the introduction of formal legislation may help the public make a more positive or balanced evaluation of the issue of food waste.

However, in the following years (2022–2023), the sentiment distribution gradually returned to the pre-2021 pattern. The proportion of positive sentiments showed a slight downward trend, while negative sentiments increased. This trend may indicate that after the initial impact, the Anti-Food Waste Law has insufficient subsequent influence to have a long-term effect on public discourse.

Neutral sentiment remained relatively stable throughout most of the period, at around 4–5%, with the notable exception of 2021 (11.76%). This stability in neutral sentiment suggests that public opinion on food waste tends to be polarized, with most users expressing positive or negative views rather than a neutral stance.

Quantitative Analysis Using Large Language Models on Weibo Texts

After the independent samples t-test, the following results were obtained, and Table 4 and Table 5 represent the test results of attitude scores and the test results of behavioral scores.

TABLE 4. INDEPENDENT SAMPLES T - TEST RESULTS OF ATTITUDE SCORES ACROSS DIFFERENT TIME WINDOWS

Time Window	Mean (Before)	Mean (After)	Sample Size (Before)	Sample Size (After)	t	p	Cohen's d
7	6.79	7.34	938	785	5.09	0	0.25
14	6.7	7.11	1750	2148	5.76	0	0.19
30	6.79	7.47	3854	5659	15.02	0	0.31
60	6.73	7.39	7698	6713	18.07	0	0.3
90	6.82	7.27	11090	7567	13.75	0	0.21
180	6.78	7.03	20986	10470	9.29	0	0.11
270	7.1	6.84	38791	13563	-11.88	0	-0.12
360	7.02	6.74	43484	16922	-13.93	0	-0.13

TABLE 5. INDEPENDENT SAMPLES T - TEST RESULTS OF BEHAVIORAL SCORES ACROSS DIFFERENT TIME WINDOWS

Time Window	Mean (Before)	Mean (After)	Sample Size (Before)	Sample Size (After)	t	p	Cohen's d
7	5.97	5.62	938	785	-3.53	0	-0.17
14	5.86	5.38	1750	2148	-6.94	0	-0.22
30	5.83	6.04	3854	5659	4.77	0	0.1
60	5.77	6.03	7698	6713	7.24	0	0.12
90	5.86	5.96	11090	7567	3	0	0.04
180	5.86	5.83	20986	10470	-0.93	0.35	-0.01
270	5.98	5.71	38791	13563	-12.78	0	-0.13
360	5.93	5.65	43484	16922	-14.95	0	-0.14

Based on the results of the time window t-test, the intervention effect of the "Anti-Food Waste Law" shows significant but different effect characteristics across two dimensions: attitude and behavior.

In the attitude dimension, the policy intervention elicited the most positive and rapid response. Within a 7-day window, the public attitude score significantly increased from 6.79 to 7.34 ($d = 0.25$, $p<.001$), indicating that the policy quickly enhanced public recognition of anti-food waste in the short term. This positive effect peaked in the 30-day window, with the average score rising to 7.47 ($d = 0.31$), showing a significant impact on attitudes. Although the effect weakened in the mid-term (60–180 days), it remained positive, indicating a certain persistence in the policy's influence on public attitudes. However, after 270 days, there was a reversal in attitude, with the score dropping to 6.84 ($d = -0.12$), and this downward trend continued in the 360-day window ($d = -0.13$). This phenomenon needs to be understood from two dimensions: first, from the perspective of policy transmission, public sensitivity to the policy naturally diminishes over time, and attention to policy issues gradually disperses; second, as the observation window extends, the sample includes more non-policy factors, such as changes in social hotspots and public opinion environments, whose cumulative effects may obscure the original policy effects. Therefore, the attitude reversal in the long-term window is more likely to reflect the relative weakening of policy effects amid complex social factors, rather than a simple decline in the policy's effectiveness.

In the behavior dimension, the policy intervention of the "Anti-Food Waste Law" exhibited a unique "lag-rebound-attenuation " pattern. In the early stages of policy implementation, due to the stronger inertia resistance of behavior change compared to attitude adjustment, there was a brief negative effect: within the 7-day window, the score dropped from 5.97 to 5.62 (d = -0.17, p<.001), and further decreased to 5.38 in the 14-day window (d = -0.22). This initial negative reaction aligns with the characteristics of the behavior dimension, indicating that the public needs time to adjust existing behavior patterns. Subsequently, the policy effect began to gradually manifest: a significant rebound occurred in the 30-day window, with the score rising to 6.04 (d = 0.10, p<.001), reaching a peak of 6.03 in the 60-day window (d = 0.12). This trajectory reveals the gradual process from attitude change to behavior transformation, where the public, after cognitively accepting the policy, needs time to internalize it into concrete actions. The mid-term (90–180 days) effect showed a gradual decline, with changes no longer statistically significant by the 180-day window (p = .35), reflecting the challenge of sustaining behavior change. In the long-term window, behavior scores showed a downward trend, with effect sizes of -0.13 and -0.14 in the 270-day and 360-day windows, respectively. This apparent "negative effect" needs to be interpreted in the context of the window period: on one hand, the behavior dimension itself requires continuous policy guidance and institutional constraints to be maintained; on the other hand, the long-term window includes too many non-policy factors, making it difficult for the measurement results to truly reflect the policy effect.

The phased implementation effect of the "Anti-Food Waste Law" clearly reveals the complex dimensionality of the policy intervention mechanism. Studies have shown that the public's response to the policy presents significant stratification characteristics: the attitude dimension can achieve a rapid leap within 7 days, while the behavior dimension needs to go through a 30-day lag period before showing a positive effect. This gap between cognitive acceptance and behavioral transformation confirms the dilemma of the "intention-action gap" in behavioral economics. What is more noteworthy is that the policy effect shows a systematic decay over time—the attitude score falls back to the baseline level (6.84) after 270 days, and the behavioral change loses statistical significance after 180 days. This double decay phenomenon highlights the limitations of relying solely on cognitive guidance to achieve behavioral change.

IV. Conclusion and Managerial Implications

This study systematically evaluated the policy effects of China's Anti-Food Waste Law by integrating text mining. The research results revealed the following key findings:

Government initiatives and social media platforms played a critical role in the dissemination of anti-food waste policies and public participation. The high frequency of policy-related terms such as "Clean Plate Campaign," as well as the prevalence of platform-specific terms like "Weibo" and "video," indicate that government initiatives have been effectively disseminated through social media and have triggered widespread public discussion. Social media platforms have become important channels for policy communication and public engagement in food waste governance. Second bullet;

Topic model analysis reveals that the public's perception of food waste is multidimensional, closely aligning with the provisions of the Anti-Food Waste Law. The public's understanding of food waste can be distilled into four dimensions: social governance, behavioral practices, value cognition, and experiential perception. These dimensions broadly align with the principles and specific provisions outlined in the Anti-Food Waste Law, finding resonance within key articles such as 7, 8, 14, 20, 21, and 22, which address various aspects of governance, behavior, values, and public awareness related to food waste. This not only demonstrates that the formulation of the Anti-Food Waste Law aligns with widespread public expectations but also underscores its critical role in guiding and shaping public awareness.

Sentiment analysis indicates that public discourse on food waste generally exhibits a neutral to positive attitude, but the long-term influence of the policy requires improvement. Although public positive sentiment increased during the initial implementation of the Anti-Food Waste Law, over the long term, the policy's subsequent influence was insufficient to sustain a lasting effect on public discourse. Sentiment time series analysis shows that the distribution of public sentiment gradually reverted to the pre-implementation pattern, suggesting potential challenges to the policy's long-term effectiveness.

Policy intervention at the behavioral level exhibits a complex "lag-rebound-attenuation" pattern, and the long-term maintenance of behavioral change requires sustained policy guidance and institutional constraints. The study found that behavioral change exhibits greater inertia resistance than attitude change, even showing a brief negative effect initially. However, as the policy is gradually internalized, behavioral scores rebound significantly in the short term, indicating that the transformation of public behavior requires time. Yet, the mid-term effect gradually weakens, and in the long term, behavioral scores trend downward, suggesting that transforming food waste behavior still necessitates stronger policy guidance and institutional constraints.

Based on the above research findings, the following targeted policy recommendations are put forward:

The high frequency of platform-related terms like "Weibo" and "video" in public discussions (Table 2), along with the sustained popularity of policy labels such as "Clean Plate Campaign," highlights the pivotal role of social media in shaping public perception. The government should further leverage social media platforms like Weibo to conduct diverse awareness campaigns. For example, collaborating with well-known influencers to regularly publish data and case studies on food waste (such as annual greenhouse gas emissions caused by food waste and the potential for food savings) can enhance public understanding of the issue. The government could also monitor trending topics on social platforms in real-time (e.g., "leftover disposal," "mukbang excesses") and disseminate this information to local governments, catering associations, and public welfare organizations to support targeted interventions. Additionally, the government can utilize social media platforms for interactive activities, such as a "Clean Plate Challenge," encouraging users to share their own food-saving experiences and fostering a positive social atmosphere.

The research indicates that while public attitudes towards anti-food waste policies improved significantly in the short term, they tended to revert towards baseline levels in the long-term window (270–360 days). This suggests insufficient long-term policy influence. Therefore, the government should establish a long-term policy feedback mechanism to regularly collect and analyze public opinions and suggestions regarding the policy. For instance, quarterly public satisfaction surveys on food waste could be conducted, focusing specifically on the actual effects following the implementation of the Anti-Food Waste Law and changes in public behavior. Based on these findings, policy content and communication strategies should be adjusted promptly to ensure the policy's sustained effectiveness.

The observed lag and rebound in public behavioral change indicate that cognitive guidance alone is insufficient for achieving lasting behavioral modification. The government should further strengthen both supportive and restrictive policy measures. For example, regarding catering businesses, in addition to existing fines, incentive mechanisms could be introduced, offering tax breaks or financial rewards to establishments that actively promote smaller portion sizes or encourage customers to take home leftovers. Furthermore, the government could collaborate with schools and communities to conduct long-term educational activities on food waste. Establishing roles such as "Food Waste Supervisors" could strengthen the monitoring and guidance of public behavior, helping individuals gradually cultivate food-saving habits.

V. RESEARCH LIMITATIONS

This study has the following limitations: Firstly, the data source is primarily limited to the Sina Weibo platform, which may not comprehensively represent the perspectives of all population groups, particularly those not active on social media. The Weibo user base may differ from the overall population in terms of age, education, and socioeconomic status, potentially leading to sampling bias. Secondly, although this study employed different time windows to analyze policy effects, it is difficult to entirely rule out interference from other social events or trends. Particularly in the long-term windows (270–360 days), the sample incorporates more non-policy factors, such as shifts in social hotspots and public opinion environments, whose cumulative effects may obscure the original policy impact. Thirdly, our findings highlight an important methodological limitation in that sentiment scores may not directly correspond to attitudes toward waste reduction, as negative sentiment often indicates support for anti-waste measures, expressed through critical reflection or criticism of waste, rather than opposition. This complexity requires more nuanced analytical approaches that can distinguish between sentiment polarity and underlying attitudes toward food waste policies to accurately assess public responses. Lastly, while large language models demonstrate advantages in text analysis, their scoring process may be influenced by the training data and inherent biases of the model. Although this study established strict scoring criteria, it remains challenging to completely eliminate the possibility of subjective interpretation.

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