Information, trust and confidence: a framework to understand public risk perceptions after wildfires in China

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ABSTRACT

Wildfires are increasingly frequent and intense due to climate change and human activities. Public risk perceptions after wildfires play a critical role in wildfire management, but there is a lack of specific studies in China. Based on theories such as risk perception, this paper constructs a theoretical model of wildfire risk perception, proposes an explanatory framework of information-trust-confidence, and uses principal component analysis (PCA) to analyze and measure the influencing factors of the subjective construction of perceived risk and the degree of influence of different factors. A study of 408 residents in Bijie, China was conducted to find out how information about fire conditions and economic losses, trust in the government, and confidence in coping with wildfires affect risk perception after a wildfire. The study found a negative correlation between information, trust, confidence, and risk perception.

Keywords

Wildfires, risk perceptions, PCA, pearson correlation coefficient, "information-trust-confidence" framework

INTRODUCTION

As of January 8, 2025, several wildfires erupted in Los Angeles County, California, due to the influence of the "Santa Ana winds". These wildfires led to multiple deaths and necessitated the evacuation of at least 150,000 residents in the county. Over 1.5 million people in Southern California were left without electricity, and the economic losses from the wildfires were estimated to range from $52 billion to $57 billion. Classified as natural disasters, wildfires are ecological catastrophes that have severe repercussions on human societies, ecosystems, and economies (Campos et al. 2024). In China, wildfires are a common occurrence, with a total of 26,383 such incidents from 2012 to 2021, causing cumulative losses exceeding ¥1,245.74 million (Hu et al. 2024). These alarming statistics underscore the detrimental effects of wildfires on people's lives and societal progress. Moreover, the frequent occurrence of wildfires can impose significant psychological stress on residents, potentially leading to panic and undermining social stability (Mamuji and Rozdilsky 2019).

Within this framework, perceptions of risk are pivotal in quelling public anxiety and managing wildfires, influencing decisions and behaviors across a spectrum from broad governmental strategies to minute individual actions. The concept of "risk perceptions" was initially introduced by Bauer in the 1960s, who noted that varying individuals harbor divergent views on identical risks. The Royal Society later characterized risk perceptions as encompassing individuals' beliefs, attitudes, assessments, and emotional responses to dangers and advantages, as well as broader cultural and social inclinations (Pidgeon et al. 1992). This topic has remained a focal point of ongoing interest, with an increasing number of scholars delving into and refining the notion of risk perceptions. Concentrating on wildfire contexts, a multitude of researchers have explored public risk perceptions in wildfire situations across diverse geographical areas.

When exploring the issue of risk perceptions after wildfires, the theoretical framework aspect is an important aspect that cannot be ignored. For the wildfire scenario, Ruggiero et al. (2020) calibrated the Wildfire Decision Model (WDM) using survey data collected after the 2016 Chimney Tops 2 wildfire in Tennessee, USA. The model agreed well with preliminary findings in the wildfire evacuation literature that risk perceptions were influenced by external factors such as warnings and fire cues and internal factors such as education, previous wildfire evacuation experience and time of residency in a property. In other natural disaster fields, Teun (2011) constructed a theoretical framework of emotion, trust and perceived risk, among others, to predict Dutch citizens' flood preparedness intentions, arguing that both cognitive and affective mechanisms affect citizens' preparedness intentions. Zheng et.al (2019) collected information on the impacts of flood preparedness from the residents of two areas hardest hit by the earthquake by collecting completed 629 valid questionnaires, combined with a constructed theoretical framework of the effects of perceived risk, negative emotions, and coping styles on the destruction of place attachment, and found that residents of the more severely affected areas perceived higher risk and more negative emotions, providing theoretical guidance for restoring the place attachment of residents in areas affected by large-scale disasters.

Furthermore, the influencing factors of risk perceptions after wildfires also deserves in-depth exploration. Chloe (2022) investigated the factors influencing wildfire risk perceptions of residents in Hobart, Tasmania, Australia, combining an interdisciplinary approach of resident surveys, focus group discussions, and geospatial fire risk assessment, ultimately finding that providing residents with personalized risk information may be the key to reducing risk perceptions. Mariah et al. (2019) conducted a survey of 614 individuals through in-person interviews across the Boise Metropolitan Area in Idaho and an additional 1,623 Boise State University affiliates via an online questionnaire. Using statistical methods such as Fisher's exact test and Cohen's kappa coefficient, they analyzed correlations and consistency within the datasets to assess the relationship between people's perceptions of wildfire smoke hazards and the smoke-related illnesses they actually experienced.

While existing literature has investigated the factors influencing risk perceptions in wildfire contexts and developed relevant frameworks, the intricate interplay between these factors and risk perceptions remains inadequately elucidated and quantified. This shortfall stems from a lack of in-depth analysis of the factors themselves, thereby hindering a comprehensive grasp and accurate forecasting of individuals' risk perceptions post-wildfires. Although empirical studies have been carried out in various regions, research on public risk perceptions following wildfires in China is predominantly embedded within broader natural disaster studies. To date, no targeted studies specifically focusing on this aspect in the Chinese context have been identified.

Therefore, it is urgent to construct a theoretical framework for wildfire risk perception applicable to China. This study selected Bijie, a city in China with a high frequency of wildfires in recent years, to conduct an empirical study to reveal the current situation of public wildfire risk perceptions in China, and quantitatively explain the complex relationship between risk perceptions after wildfires and different factors by constructing an indicator system for risk perceptions after wildfires. Under this system, the study explores the role of different influencing factors and quantitatively explains the complex relationship between risk perceptions and different factors.

THEORETICAL MODEL CONSTRUCTION

The applicability of the "information-trust-confidence" model to risk perceptions research has been empirically verified. Wang et al. (2020) conducted a study on risk perceptions during the initial phase of the novel coronavirus pneumonia outbreak, thereby validating the efficacy of the "information-trust-confidence" model. Their findings underscored the critical intermediary role of trust, highlighting it as the most pivotal variable in community construction. Yang et al. (2018) adopted the "information-trust-confidence" framework as the foundational logic for their subjective construct model of neighborhood avoidance risk perception. They discovered that information, confidence, and trust exert significant influence throughout the entire developmental trajectory, spanning from the origination of neighborhood risks to the perception of such risks, and further extending to social amplification and collective resistance. Building on wildfire scenarios, this study integrates preliminary research outcomes and expert advice to refine and adapt the "information-trust-confidence" theoretical framework. This adaptation aims to more accurately capture the public's risk perceptions in the aftermath of wildfires.

Information

The sufficiency of information serves as a fundamental prerequisite for individuals to accurately comprehend various matters. The extent to which the public focuses on fire-related information has a direct and significant impact on their perception of associated risks. This is well illustrated by the social amplification theory of risk (Kasperson et al. 1998), which posits that wildfire risk information tends to intensify as it disseminates. When risk events intersect with psychological, social, institutional, and cultural processes, they can either amplify or mitigate the public's risk perceptions and subsequent behaviors. For instance, an individual's level of concern regarding specific details of a fire, such as its precise location and scale, plays a crucial role in shaping their perception of fire risk (Taylor et al. 2007). Moreover, the economic ramifications of fires, particularly the damage to property and infrastructure, constitute a key factor influencing public concern. This heightened concern, in turn, intensifies the public's perception of fire risk. Consequently, in this study, the concern for information pertaining to fire situations and economic losses was chosen as secondary indicators of information adequacy.

Trust

Numerous researchers have identified an inverse relationship between government trust and risk perception (Wang et al. 2022). It has been established that government trust substantially influences the public's perception of risk (Huang et al. 2019). During a crisis, government trust serves as a precursor that shapes the degree of risk perception among the populace. Consequently, this study zeroes in on the trust factor, specifically "government trust". However, there is no consensus among scholars regarding the definition of "government trust". Carnevale (1996) regards government trust as the public's faith in the government's reliability and steadfastness. Grimmelikhuijsen et al. (2014) contends that government trust encompasses the public's evaluation of three facets of government: capability, benevolence, and honesty. For the purpose of this study, Carnevale's classification is adopted to holistically gauge individuals' trust in the government across two dimensions: reliability and dependability.

Confidence

Confidence is a mental state wherein an individual's self-assurance escalates following the successful completion of a specific task (Snyder et al. 2020). For instance, community fire prevention and control initiatives can enhance residents' experience, thereby boosting their confidence in tackling wildfires. Self-confidence is a positive conviction in one's ability to achieve desired outcomes and reflects a subjective assessment of one's knowledge (Zellner et al. 1970). McCaffrey (2015) posits that knowledge significantly influences people's risk tolerance. Zhong et al. (2021) conducted a study that revealed a knowledge gap in disaster communication and prevention, and demonstrated a negative correlation between risk perception and knowledge, thus lending support to McCaffrey's argument. Consequently, in this study, two indicators—disaster prevention and control measures, and subjective perception of knowledge—were identified as the primary sources of confidence.

Drawing on these insights, this study employs the "information-trust-confidence" framework to develop an indicator system for assessing risk perceptions following wildfires, as depicted in Figure 1. A total of six secondary indicators were meticulously chosen to form this system: characteristics of the fire, economic impact, government reliability, government dependability, fire prevention efforts, and cognitive awareness, which are detailed in Table 1. The data pertaining to these indicators were exclusively sourced from a comprehensive questionnaire survey.

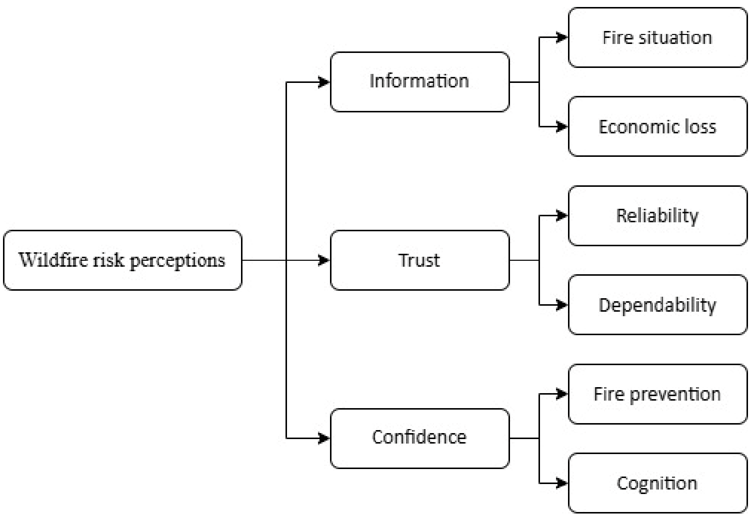


Figure 1. A theoretical framework for risk perceptions after wildfires

Table 1. Risk perceptions of wildfires indicator system for the residents

Level 1 indicators	Level 2 indicators	Measurement questions

Information	fire situation	✧ I am concerned about the information about the causes and influences of fire.
		✧ I am concerned about the safety risks associated with wildfires.
	economic loss	✧ I am concerned about the material damage caused by fires.
Trust	reliability	✧ I feel that the government has sufficient capacity to deal with forest fires.
		✧ I am satisfied with the overall effectiveness of the information obtained from previous forest fires.
		✧ I think village officials will provide enough information about fires.
	dependability	✧ I support the ban on open fires for ancestor worship and smoking in forest areas.
		✧ I will follow the cadres' instructions to evacuate.
		✧ I would like to receive clear instructions from the government on how to act during a fire.
Confidence	fire prevention	✧ My community has fire prevention and control measures.
		✧ I believe that management and technology can be improved to reduce forest fires or put them out in a timely manner.
	cognition	✧ I can accurately judge a forest fire and evacuate safely within five minutes of the fire starting.
		✧ I have experience in dealing with forest fires.
		✧ I know how to use a fire extinguisher.

EMPIRICAL ANALYSIS

Research area

Between February 10th and 21st, 2024, a total of 221 wildfires were documented in Guizhou Province, China, inflicting considerable property damage and casualties among local residents. Bijie, situated in the northwest of Guizhou Province, boasts a high forest coverage and substantial timber reserves. Its terrain and landscape are primarily composed of karst formations, which may complicate the rapid isolation and control of fire sources, thereby escalating the risk of fire propagation. The city experiences a humid subtropical monsoon climate, marked by hot and rainy summers, as well as mild and dry winters—meteorological conditions that heighten the likelihood of forest fires. Particularly during the dry season, reduced precipitation coupled with dried-out vegetation renders the area highly susceptible to ignition.

There are 46 (including unrecognized) ethnic groups living in Bijie: *Han, Yi, Miao, Hui, Buyi, Bai, Mongolia, Zhuang, Dong, Li, Manchu, Yao, Tujia, Hani, Dai, Jingpo, Gelao, Jing, and Uyghur*, with ethnic minority populations accounting for 25.88% of the city's total population. The distinct cultural backgrounds of different ethnic groups will influence the three factors mentioned above. For instance, the Miao ethnic group's "Yilang" tradition (a folk autonomous convention) shapes participatory trust in modern grassroots governance.

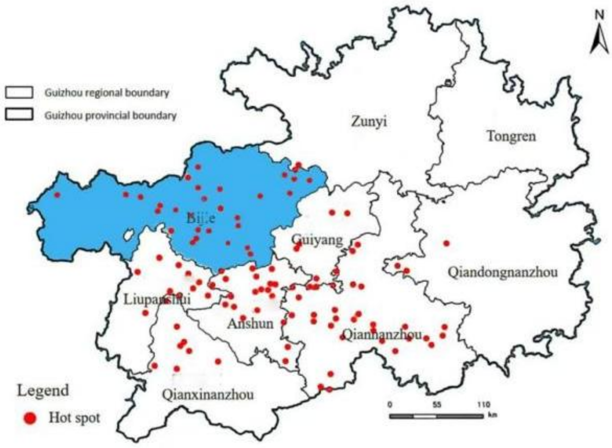


Figure 2. Satellite Remote Sensing Monitoring Map of Fire Points in Guizhou Province 2024-02-20 20:01:00 to 21:00:00

Note: The data are derived from Ecological and Agricultural Meteorological Center of Guizhou Province

Data sources

The data for this study were gathered from an on-site questionnaire survey focusing on wildfire risk perceptions in Bijie. Participant selection was based on preliminary investigations that fully considered diversity across groups, ages, and genders to ensure broad sample representation.

Nevertheless, despite the various measures taken in the design and implementation of this study, it must be acknowledged that it may not be possible to completely avoid the systematic error introduced by the non-randomness of sample selection, which leads to the sample being unrepresentative of the population—this is known as selection bias. For example, some young and middle-aged adults may be unable to participate in the survey due to working away from home, resulting in an under-representation of this group in the sample. Additionally, respondents with lower levels of education may have difficulty understanding and completing the questionnaire, which in turn affects their participation rate. These factors can lead to an imbalanced sample, thereby affecting the generalizability of the research findings.

This study has endeavored to minimize the impact of such biases. Given that the interviewees may have limited knowledge and could find it difficult to understand and respond to the relatively complex Likert scale format, our team ultimately decided to conduct the survey using a structured interview approach. First, the survey team underwent specialized training before the interviews, enabling them to communicate with respondents in a clear and comprehensible manner to ensure accurate information delivery. Second, the structured interview format can better guide respondents in answering questions and reduce comprehension biases caused by differences in knowledge levels through the facilitation of the interviewers.

Overall, although selection bias may still exist to some extent, the measures taken ensure that such bias will not have a significant impact on the research findings. This study is still able to provide valuable insights into the impact of forest fires on different groups.

A total of 500 responses were collected, with 422 deemed valid. Specific interview questions and answer options are detailed in the appendix. In particular, the survey participants were primarily from the vicinity of high forest fire risk zones, encompassing adjacent villages and towns within the administrative boundaries and comprised three main groups: students, local villagers and townspeople, and laborers. The specifics of the respondents are shown in Table 2.

Table 2. Respondent specifics

	Han	Ethnic minorities	Total number
Students	135	60	195
Village residents	86	34	120
Migrant workers	100	7	107
Total number	321	101	422

Reliability test and validity test

Reliability generally denotes the consistency and stability of a measuring tool. A highly reliable instrument exhibits two key features: the coherence of its questions and the reproducibility and steadiness of the questionnaire results. In this research, the Cronbach's α coefficient was employed to assess reliability, a widely recognized measure for evaluating internal consistency. This coefficient's value spans from 0 to 1, with higher figures signifying a stronger correlation among questionnaire items, thereby indicating that the questions collectively more accurately gauge a unified concept. According to Lee J. Cronbach (1951), a coefficient below 0.6 suggests inadequate reliability; a range of 0.7-0.8 implies considerable reliability, while 0.8-0.9 denotes excellent reliability. The findings revealed a Cronbach's α of 0.705 for the questionnaire, reflecting a robust correlation among its items and solid internal consistency. This suggests that the items effectively measured the targeted variables within the study.

High reliability does not imply flawless design; it merely suggests that the questions are consistent and stable in measurement. This leads us to consider "validity". Validity evaluates whether a questionnaire or scale accurately represents what it claims to measure. In this study, validity was assessed via the KMO test and Bartlett's sphericity test. The KMO value gauges whether the correlations among variables are suitable for principal component analysis or factor analysis. A higher KMO value indicates stronger correlations among variables and greater suitability for factor analysis. Kaiser and Rice (1974) suggested that values above 0.5 are acceptable. Bartlett's sphericity test checks whether the correlation matrix among variables is an identity matrix. If the significant p-value of Bartlett's test is below 0.001 (Bartlett 1951), it implies a significant correlation among variables, making factor analysis appropriate. Table 3 presents the results of the KMO test and Bartlett's sphericity test. With a KMO value of 0.715, the data meet the test criteria, signifying sufficient correlation for principal component analysis. The significance p-value of Bartlett's sphericity test is less than 0.001, passing the significance test and indicating significant correlations among variables, suitable for factor analysis. Through these two tests, the study confirms that the data's structural validity is adequate for modeling analyses like principal component analysis, meaning the questionnaire effectively captures the correlations among variables. Thus, further analysis based on the model will be conducted.

Table 3. KMO and Bartlett's test

KMO Quantity of Sample Suitability		0.715
Bartlett's test of sphericity	approximate chi-square (math.)	852.213
	(number of) degrees of freedom (physics)	91
	significance	< 0.001

Principal component analysis (PCA)

Standardization of raw data

Principal component analysis (PCA) was first introduced by Karl Pearson in 1901 (Pearson 1901) as a method for data analysis and mathematical model construction. PCA is commonly utilized to reduce the dimensionality of high-dimensional datasets. When a particular feature of the data has an exceptionally large value, it tends to carry significant weight in the overall error computation. To avoid disproportionately emphasizing such high-value features, it is necessary to normalize each feature. This ensures that all features fall within a uniform range of magnitudes prior to conducting PCA.

Suppose that there are m indicator variables for principal component analysis, namely $x_1, x_2, \cdots, x_m$, there are n evaluation variables, and the i -th indicator of the j -th evaluation object is x_{ij}. The value of each indicator x_{ij} is transformed into the standard indicator $\tilde{x}_{ij}$.

$$\tilde{x}_{ij} = \frac{x_{ij} - \bar{x}_j}{s_j}, (i = 1,2,\cdots,n; j = 1,2,\cdots,m)$$

Among them, $\bar{x}_j = \frac{1}{n}\sum_{i=1}^{n} x_{ij}$, $s_j = \frac{1}{n-1}\sum_{i=1}^{n}(x_{ij} - \bar{x}_j)^2$, $(j = 1,2,\cdots,m)$, i.e. $\bar{x}_j, s_j$ are the sample mean and sample standard deviation of the j -th indicator; $\tilde{x}_i = \frac{x_i - \bar{x}_i}{s_i}, (i = 1,2,\cdots,m)$ is the standardized indicator variable.

Create a matrix of correlation coefficients between variables R

$$R = (r_{ij})_{m\times m},\ r_{ij} = \frac{\sum_{k=1}^{n} \tilde{x}_{ki} \cdot \tilde{x}_{kj}}{n-1}, (i, j = 1,2,\cdots,m)$$

Where $r_{ii} = 1, r_{ij} = r_{ji}, r_{ij}$ is the correlation coefficient between the i -th indicator and the j -th indicator.

Calculate the eigenvalues and eigenvectors of the correlation coefficient matrix R

Calculate the eigenvalues $\lambda_1 \geq \lambda_2 \geq \cdots \lambda_m \geq 0$ of the correlation coefficient matrix R and the corresponding eigenvectors $\mu_1, \mu_2, \cdots, \mu_m$, where $\mu_j = (\mu_{1j}, \mu_{2j},, \cdots, \mu_{nj})^T$, from the eigenvariables to form m new indicator variables.

$$\begin{cases} y_1 = (\mu_{11}\tilde{x}_1 + \mu_{21}\tilde{x}_2 + \cdots + \mu_{n1}\tilde{x}_n) \\ y_2 = (\mu_{12}\tilde{x}_1 + \mu_{22}\tilde{x}_2 + \cdots + \mu_{n2}\tilde{x}_n) \\ \cdots \\ y_m = (\mu_{1m}\tilde{x}_1 + \mu_{2m}\tilde{x}_2 + \cdots + \mu_{nm}\tilde{x}_n) \end{cases}$$

where y_1 is the 1st principal component, y_2 is the 2nd principal component, ... , y_m is the m -th principal component.

Calculation of composite score

①Calculate the information contribution rate and cumulative contribution rate of eigenvalue $\lambda_j (j = 1,2,\cdots,m)$.

Information contribution of principal component $y_j : b_j = \frac{\lambda_j}{\sum_{k=1}^{m} \lambda_k} (j = 1,2,\cdots,m)$

Cumulative contribution of principal component $y_p : a_p = \frac{\sum_{k=1}^{p} \lambda_k}{\sum_{k=1}^{m} \lambda_k}$

The cumulative contribution rate reflects the degree to which all extracted factors account for the total variance of the variables in the dataset, serving as a key metric for assessing the model's explanatory capacity. As per Prof. Wu, a distinguished authority on quantitative research methodologies, in the realm of social sciences, a cumulative contribution rate of 60% or above signifies the reliability of principal components (Wu 2010). In this study, the results indicate that when eight principal components are extracted, the cumulative contribution rate amounts to 75.64%. This suggests that the extracted principal components possess substantial explanatory power, effectively representing the structure of the original variables. Consequently, the model exhibits a high level of fit, enabling a more precise reflection of the underlying relationships within the data.

Table 3. Eigenvalues and their variance contribution

Principal component	Percentage variance	Cumulative %
1	21.982	21.982
2	10.247	32.23
3	9.319	41.549
4	8.732	50.281
5	7.383	57.664
6	6.45	64.115
7	6.063	70.177
8	5.463	75.64

② Calculate the composite score

Composite score calculation formula: $Z = \sum_{j=1}^{p} b_j y_j$, where b_j is the information contribution of the j-th principal component.

Based on the above analysis, when calculating the composite score of information, trust, confidence and risk perception level, the specific calculation process of step (3) is as follows in turn.

$$\begin{cases} y_1 = (\mu_{q,1}\tilde{x}_q + \mu_{q+1,1}\tilde{x}_{q+1} + \cdots + \mu_{q+n,1}\tilde{x}_{q+n}) \\ y_2 = (\mu_{q,2}\tilde{x}_q + \mu_{q+1,2}\tilde{x}_{q+1} + \cdots + \mu_{q+n,2}\tilde{x}_{q+n}) \\ \cdots \\ y_8 = (\mu_{q,8}\tilde{x}_q + \mu_{q+1,8}\tilde{x}_{q+1} + \cdots + \mu_{q+n,8}\tilde{x}_{q+n}) \end{cases}$$

Composite score calculation formula of Information: $Z_1 = \sum_{j=1}^{p} b_j y_j (p = 8, q = 1, n = 2)$

Composite score calculation formula of Trust: $Z_2 = \sum_{j=1}^{p} b_j y_j (p = 8, q = 4, n = 5)$

Composite score calculation formula of Confidence: $Z_3 = \sum_{j=1}^{p} b_j y_j (p = 8, q = 10, n = 4)$

Composite score calculation formula of Risk Perceptions: $Z_4 = \sum_{j=1}^{p} b_j y_j (p = 8, q = 1, n = 14)$

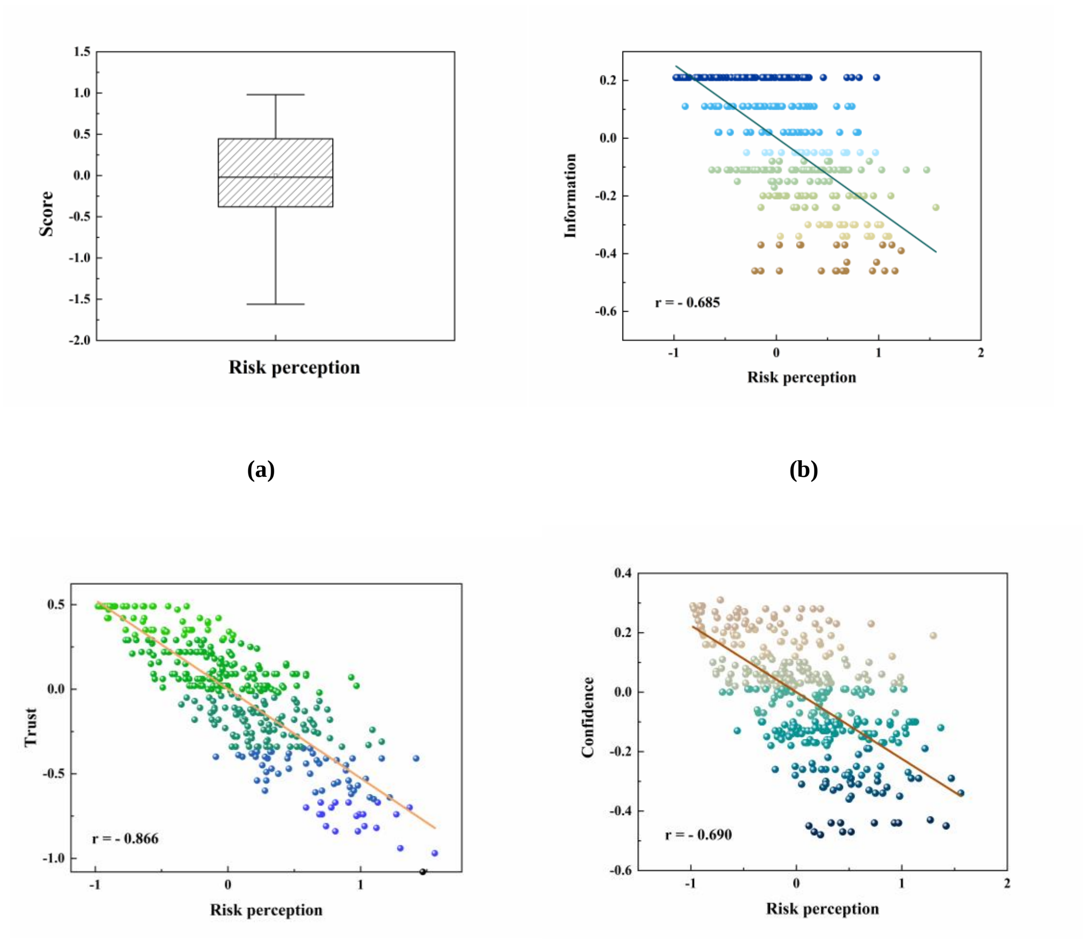
Finally, combined with the formula for calculating the composite score, the information composite score, trust composite score, confidence composite score and risk perception composite score are derived respectively. For ease of understanding, in the following calculations and data analysis, they are referred to as Information, Trust, Confidence and Risk Perceptions.

Result

The median of public risk perceptions lies near both the upper and lower quartiles, suggesting that there is considerable variation in public risk perception, with notable structural disparities. The distribution of public risk perceptions adheres to a “more in the middle and less at the ends” pattern, indicating that the majority of respondents in Bijie exhibit a moderate level of risk perception.

Figure 3 also reveals that as risk perceptions rise, trust correspondingly declines markedly, indicating an inverse relationship between trust and risk perceptions. While the fluctuations in information and confidence relative to risk perceptions are less dramatic than those of trust, it is still evident that there are overall negative correlations.

To identify the key factors influencing residents' risk perceptions, Pearson correlation analysis was employed to examine the relationships among information, trust, confidence, and risk perceptions. Introduced by statistician Carl Pearson, this method quantifies the degree of linear correlation between variables by computing the ratio of covariance to the product of standard deviations for independent variables X and Y (with Y being the dependent variable P), yielding a P-value ranging from -1 to 1 (Pearson 1895).



(a) (b)

(c) (d)

Figure 3. Residents' risk perception, information, trust and confidence

The analysis found Pearson correlation coefficients of -0.685 between information and risk perceptions, -0.866 between trust and risk perceptions, and -0.690 between confidence and risk perceptions. The coefficient of -0.685 for information and risk perceptions signifies a strong negative correlation, suggesting that as residents receive more relevant information, their risk perceptions tend to decrease. The coefficient of -0.690 for confidence and risk perceptions also indicates a significant negative relationship. The strongest correlation was observed between trust and risk perceptions, with a coefficient of -0.866, highlighting a very robust inverse relationship between these two variables.

CONCLUSION

This study constructs a theoretical framework of "information-trust-confidence" to explore the factors influencing public risk perceptions after wildfires in China. The empirical analysis, conducted in Bijie City, a region with a high frequency of wildfires and a diverse ethnic population, provides valuable insights into the complex interplay between information, trust, confidence, and risk perceptions. The findings are particularly relevant in light of recent wildfires in the United States, which have also highlighted the critical role of public perception in disaster management.

The results of the principal component analysis (PCA) and Pearson correlation analysis reveal significant negative correlations between information, trust, confidence, and risk perceptions. Specifically, trust in the government emerges as the most critical factor, with a strong inverse relationship to risk perceptions. This finding underscores the pivotal role of government trust in shaping public responses to wildfire risks. As trust in government increases, public risk perceptions tend to decrease, suggesting that enhancing government transparency and credibility could be an effective strategy for managing public anxiety and promoting adaptive behaviors in the aftermath of wildfires. In the context of the recent wildfires in the United States, similar patterns have been observed. Areas where the government has been perceived as more responsive and transparent have shown lower levels of public anxiety and better compliance with evacuation orders and other safety measures. This highlights the universal importance of trust in effective disaster management.

Moreover, this study also highlights the importance of information sufficiency in influencing risk perceptions. Although its impact is less pronounced than that of trust, it still plays a significant role in modulating public reactions and can help alleviate public concerns. Therefore, in crisis response and management information systems, accurate fire-related information, including fire progression, rescue operations, and safety tips, should be disseminated in a timely manner through multiple channels such as social media and official media. This transparent communication can enhance the public's trust in the government and rescue agencies, thereby reducing perceived risks.

In conclusion, this study contributes to the existing body of literature on risk perceptions by providing a nuanced understanding of the factors influencing public responses to wildfires in a Chinese context. The "information-trust-confidence" framework offers a useful tool for policymakers and practitioners to develop targeted interventions aimed at reducing public anxiety and enhancing resilience in the face of wildfire disasters. The parallels with the experiences in the United States further validate the universal applicability of this framework. Future research could further explore the transformation of the "information-trust-confidence" framework into functional modules of information systems, and deeply integrate principles such as community participation, cultural adaptation, and emotion-driven approaches. This would help achieve a paradigm shift in risk communication from a one-way warning to a two-way empowerment model.

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APPENDIX.

Structured Interview Guide: risk perceptions after wildfires assessment

Part I: Information

1. Fire Situation

①Closed-ended question: Do you actively seek information about the causes or influence related to forest fires?

○ Yes ○ No

Follow-up (if "Yes"): What channels do you typically use to obtain this information? (e.g., village cadres and government personnel, specialist and scholar, network social media, relatives and friends, television, SMS)

Follow-up (if "No"): What factors do you think contribute to your lack of attention to this type of information?

②Scale question: On a scale of 1 ("Not worried at all") to 5 ("Extremely worried"), how concerned are you about the threat of forest fires to personal safety?

○1 ○2 ○3 ○4 ○5

Follow-up: Have you had any direct or indirect experiences with safety threats caused by wildfires? Please provide examples.

2. Economic Loss

Scale question: How concerned are you about potential damage to your property (e.g., homes, belongings) from wildfires? (1-5)

○1 ○2 ○3 ○4 ○5

Follow-up: Have you taken specific measures to protect your property from fire risks? (e.g., purchasing insurance, reinforcing structures)

Part II: Trust

1. Reliability

①Scale question: How would you rate the government's capacity in wildfire prevention, emergency response, and post-disaster recovery? (1 = "Very inadequate", 5 = "Very sufficient")

○1 ○2 ○3 ○4 ○5

Follow-up: Can you provide specific examples of the government's performance? (e.g., rescue efficiency, information transparency during past fires)

②Scale question: How satisfied are you with the information provided by the government or community during past wildfires (e.g., warnings, evacuation guidance)? (1-5)

○1 ○2 ○3 ○4 ○5

Follow-up: What types of information were most critical? What improvements are needed?

③Closed-ended question: Do you believe village cadres or community staff provide timely and sufficient wildfire risk information?

○ Yes ○ No

Follow-up: Describe an experience where you received or failed to receive critical information.

2. Dependability

①Scale question: To what extent do you support banning open flames for rituals (e.g., ancestor worship) and smoking in forested areas? (1 = "Strongly oppose", 5 = "Strongly support")

○1 ○2 ○3 ○4 ○5

Follow-up: What challenges do you think hinder the enforcement of such bans?

②Closed-ended question: If the government orders an immediate evacuation during a wildfire, would you comply?

○ Yes ○ No

Follow-up: What factors might influence your decision? (e.g., trust in authorities, property concerns, clarity of evacuation routes)

③Closed-ended question: Do you want the government to provide clearer wildfire emergency guidelines (e.g., escape routes, shelter locations)?

○ Yes ○ No

Follow-up: How would you prefer to receive these guidelines? (e.g., SMS alerts, community broadcasts, printed materials)

Part III: Confidence

1. Fire prevention

①Multiple-choice question: Which of the following wildfire prevention measures has your community implemented? (Select all that apply)

□ Cadres conduct fire prevention education campaigns

□ Safety warning signs are installed at forest entrances

□ Community-organized fire drills or evacuation training

□ No specific measures in place

Follow-up: Which measure do you find most effective? What additional actions should the community take?

②Scale question: How confident are you that technological solutions (e.g., monitoring systems, firefighting equipment) can effectively reduce or control wildfires? (1-5)

○1 ○2 ○3 ○4 ○5

Follow-up: Have you encountered any such technologies? (e.g., drone patrols, smart fire detection systems)

2. Cognition

①Scale question: How confident are you in your ability to assess wildfire risks and evacuate safely within 5 minutes of a fire starting? (1-5)

○1 ○2 ○3 ○4 ○5

Follow-up: Have you received relevant training? If not, what skills would you like to learn?

②Scale question: How much experience do you have in directly responding to wildfires (e.g., firefighting, evacuation)? (1 = “No experience”, 5 = “Extensive experience”)

○1 ○2 ○3 ○4 ○5

Follow-up: Describe a personal experience and lessons learned.

③Closed-ended question: use a fire extinguisher?

○ Yes ○ No