



## Article

# Does Internet Use Affect Citizens' Perception of Social Safety? A Cross-Sectional Survey in China

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**Abstract:** Since the advent of the Internet has changed how risk information develops and disseminates, citizens' risk perception alters correspondingly. Although extant studies have explored the impacts of Internet use on citizens, only a few have focused on citizens' perception of social safety exclusively. This study examined the effect of Internet use and Internet use frequency on citizens' perception of social safety with 2017 China Social Survey data. It found that Internet use and Internet use frequency have a significant negative impact on citizens' social safety perception. Compared to non-users, the probability of perceiving society as very safe decreases significantly by 2.3% for Internet users. Subsequently, this study avoided the endogeneity issues by employing the Bioprobit and CMP methods, and the robustness check adopted propensity score matching methods. In general, it supported results in benchmark regression. The heterogeneity analysis indicated that Internet use had a higher negative impact on citizens in the western region, rural household registration, and middle-aged groups. It suggests that the establishment of a comprehensive mechanism to regulate online information involving governments, Internet industrial organizations, and Internet users may improve governance effectiveness. In addition, education targeting Internet literacy is required to enable a more rational citizen participation on the Internet.

**Keywords:** internet use; social safety perception; China; CSS2017

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## 1. Introduction

Safety is closely connected to one's quality of life and happiness, claiming the fundamental needs of human beings. It is also a prerequisite for any social, economic, cultural, and political development. Since the 1980s, human society has been experiencing a profound structural transformation, where a sense of risk and unsafety has prevailed. In 2022, the United Nations Development Programme stated in New Threats to Human Security in the Anthropocene that, despite years of development and growth, there is a growing sense of unsafety. Statistics show that six out of seven people globally are affected somehow by their sense of unsafety [1]. It is undeniable that modern society is full of risks with uncertainties and complexities, where unsafety has become inseparable from daily life. For instance, an Italian survey with 6002 participants revealed that despite a downward trend in crime rates over the last few decades, people are increasingly worried about their safety [2]. Williams et al. [3] also found similar results among public high school students. As an important component of individual safety, social safety includes both objective social safety conditions and subjective social safety perception. Global crises, represented for example by the September 11 attacks, the Fukushima nuclear accident, the Ebola virus disease, and the COVID-19 pandemic have disrupted social safety and the global governance order significantly. These have greatly affected citizens' perception of social safety and left the public anxious. For example, the COVID-19 pandemic has already threatened the lives, health, and safety of hundreds of millions of citizens. Global public

crises clearly affect citizens' perceived social safety and psychological well-being, leaving them in a state of fear and insecurity. Citizens' perception of social safety is critical for social order in an emerging risk society. In addition, it also helps with citizens' satisfaction with government as well as individuals' well-being and social integration [4,5]. Failure in building citizens' perception of social safety will seemingly lead to mass panic and social unrest among citizens. Meanwhile, it affects citizens' trust in government and their social identity, undermines social cohesion and citizen compliance [6], and, thus, leads to social instability. It is highly possible to induce a large number of risks when these negative factors are expanded, which in turn will further disrupt social order and generate a major social crisis. In this sense, how to effectively build a safe environment and increase citizens' perception of social safety have become inescapable globally [7].

Extant research on social safety perception has been closely related to actual situations in human society for quite a long time. Its influencing factors vary across social development stages. In a pre-modern society, religion, traditional culture, kinship, and geography shape the fundamental perception of social safety. Along with the advent of the risk society, studies have shown that risk perception becomes a key factor affecting citizens' perception of social safety [8]. Nowadays, Information and Communication Technologies (ICTs) are prevalent, which have profound impacts on contemporary society [9]. With the rapid development of ICTs and Internet infrastructure as well as the popularity of the Internet worldwide, Internet use has already penetrated individuals' daily lives. According to Internet World Statistics (IWS), the number of Internet users worldwide reached 4.648 billion in May 2020, accounting for 59.6% of the global population, and the average Internet user spends nearly 7 h a day on all terminals. China has the largest population of Internet user since 2008. According to the 50th Statistical Report on Internet Development in China released by the China Internet Network Information Center, in June 2022, the number of Chinese netizens was 1.051 billion, the Internet penetration rate reached 74.4%, and the average Internet user spent 29.5 h online per week [10]. Scholars have extensively studied the impact of the Internet from both personal and social perspectives [11,12]. On the one hand, the Internet provides a social platform for citizens' interaction, information sharing, and social participation, indicating positive effects in terms of individuals' quality of life improvement [13], while, on the other hand, the dark side of the Internet has also been revealed through unexpected risks and high social costs [14]. It is believed that information transmitted via the Internet may have the social amplification effect of risk during crises [15], indicating negative impacts on citizens' risk perceptions, subjective emotions, and coping behaviors [16]. Taking environmental performance as an example, some scholars found that compared to non-Internet users, online media has large volumes of pictures and videos about smog, and this makes Internet users more likely to ignore the government efforts in environmental protection and perceive a low environmental performance [14,17]. Although extant research has suggested that risk perception affects citizens' perception of social safety [18], it does not directly address the question regarding the impact of Internet use on citizens' perception of social safety. To fill this gap, building upon the negative bias theory and social amplification of risk framework, this study explores the impact of Internet use on citizens' perception of social safety using national representative data from the 2017 China Social Survey. This study contributes to the understanding of Internet use and civil society psychology. In addition, considering the potential endogeneity of Internet use [19], this study employs a conditional mixed process (CMP) approach, bivariate ordered probit model (Bioprobit), and propensity score matching (PSM) to estimate the relationship between Internet use and citizens' perception of social safety to improve model robustness.

## 2. Literature Review and Theoretical Hypothesis

Social safety perception is citizen's subjective affective or emotional responses during their evaluation of social risk and social vulnerability [19]. Studies on citizens' perception of social safety can be traced back to criminal sociology. Evidence shows that a poor social safety environment and high crime rates can gradually increase citizens' fear and

anxiety about crime, resulting in a decrease in citizens' perception of social safety. In this sense, a sound community policing system and a strong capacity of community police can increase citizens' perception of safety [20]. Meanwhile, studies have also suggested that neighborhood relations and neighbor trust can predict citizens' perception of social safety. For instance, Johansson-Nogués [21] further argued that the ontological insecurity may contribute to the erosion of basic trust systems among community members. Some other demographical factors, including gender, age, and education, may also affect citizens' social safety perception. For example, Han and Liu [22] found that age and education were significantly correlated with citizens' perception of food safety in social safety, while income, gender, and household size did not predict changes in citizens' perception of food safety. However, Ge and He [23] found a connection between household registration, gender, their wealth, and citizens' perception of social safety. In addition, risk perception is also commonly mentioned as a central element in the analysis of societal reactions to specific risks and actions taken. For example, Miao [24] showed that risk perception significantly and negatively predicted the perception of social safety. Valente and Valera Pertegas [4] affirmed it with a large-scale survey data in Italy.

With the advent of information society, the Internet rapidly penetrated into citizens' social interactions and gradually replaced traditional media outlets. As one of the most important channels for people to obtain information, the Internet has greatly reduced information exchange cost and improved the efficiency of information dissemination. It makes it more convenient for individuals to access the information needed through cell phones, computers, and other terminals. However, the Internet does not always have a positive impact on citizens. The Internet is a double-edge sword depending on how it is used. During public emergencies, information retrieval and interactive services carried on the Internet may mislead citizens' social perception and behaviors. The adoption of any modern technology can have unintended negative effects, as Gkeredakis et al. [25] stated. Although digital technologies accelerate social innovation for quick responses to the COVID-19 pandemic, it also poses many risks and moral dilemmas ahead. As for negative effects of the Internet, most extant scholarly work builds upon the social amplification of risk framework. Kaspersen et al. [26] first proposed the social amplification of risk framework (SARF) and argued that the interactions between risk events and psychological, social, and cultural aspects can strengthen or weaken public perceptions of risk and related risk behaviors. It emphasizes that once the risk events are experienced by some social actors, the risk information exchange is systematically disseminated through heterogeneous actors in amplification stations [27]. Most individuals' perception of risk events or risk information depends on the information system, and the new media powered by the Internet has become one of the most important information sources. Kaspersen et al. [26] pointed out that risk information is processed by individual and social amplification stations, including scientists, news media, cultural groups, and interpersonal networks. Similarly, Guo and Li [28] emphasized that networked media communication is an important bridge for risk perception transmission and an amplification station for social risks. Online and social media environments add complexity to the risk amplification process and are more powerful than traditional media in amplifying risk [29]. The risk information spread and amplified through the Internet not only affects public risk perception, but also directly affects the public perception of social safety. Building upon this, Chung [14] discussed the social amplification of risk in the Internet environment in Korea, and argued that the Internet acts as a social amplification station, allowing risk information to reach a wider range of the population in minutes. The Internet exacerbates the public perception of social risks and leads to a sense of unsafety in the society. A survey on food safety in China shows that information flow on the Internet has a greater impact on public perception than factual experience [30]. With the spread of COVID-19 around the world, much attention has been garnered on the social amplification effect of risks in the context of the Internet and new media [31]. The negative impact of Internet use on public safety perception has also been confirmed. For example, Hopfer et al. [32] showed that risk information about

the COVID-19 pandemic on Twitter has generated much more public risk perception than objective and reasonable risks. This finding is further explored in a study by Lee et al. [33] on the dissemination of risk information. In addition, negative impacts in other domains were also demonstrated, including unwillingness to participate in health promotion and disease prevention [34], associated increase of attitude and emotional risk of anti-political power [35].

Recent studies have also shown that high exposure and wide dissemination of COVID-19 related information on new media has significantly increased public anxiety and fear of COVID-19. This effect is stronger for those who are susceptible to emotional contagion, leading to more concerns about the safety of the society in which they live [36]. In such cases, the lack of a sense of safety is likely to affect citizens' self-decision-making and corresponding behaviors. Some studies have found that individual's decision-making and behaviors are greatly affected by online misinformation. For example, the false information about vaccine safety on social media may make the public feel unsafe about vaccination, thus presenting their resistance and hesitation to vaccines [37]. To sum up, in the social amplification of risk framework, online media and social tools enabled by the Internet play the function of a risk amplification station. It is critical in the formation, generalization, and diffusion of public risk perception. The negative effects brought by Internet use may further affect public social safety through risk perception since risk perception is an important predictor of social safety [38]. Thereby, we propose that,

**Hypothesis 1.** *Compared to non-use of the Internet, Internet use diminishes citizens' perception of social safety.*

The negative bias theory provides another theoretical perspective other than merely technology to understand the relationship between Internet use and citizens' society safety perception. Negative bias refers to the fact that negative events are likely to exert greater impacts on individuals' mental state and decision-making process than neutral or positive events [39]. The negative bias theory suggests that dangers attract much attention in order to stay alert, and it is human nature to pay more attention to negative alarming signals [40,41]. Rozin and Royzman [42] further divided negative bias into four aspects, including negative potency, negative gradient, negative advantage, and negative differentiation. Among them, negative potency means that negative information has a greater influence on individual behaviors compared to positive information, while the negative gradient emphasizes that negative information spreads faster than positive information. The negative advantage is a combination of positive and negative information that creates a greater negative impression. Negative differentiation mainly emphasizes that negative information is more likely to promote diverse behaviors [39]. Scholars have widely applied the negative bias theory to explore negative memory bias, risk decision bias, and public organization behavior bias [43]. Recently, with the advancement of ICTs, some have applied the negative bias theory to analyze information dissemination via the Internet. Primack et al. [44] confirmed that negative information on social media generates more attention than positive information. Positive experience is likely to create pleasant memories for a short time, while negative experiences may in turn leave individuals with lasting traumatic memories.

Compared with traditional media outlets, the Internet is massive, personalized, decentralized, autonomous, and self-organized. All these have gradually decreased the information supervision. Besides, the sources and contents of social risk information online vary significantly, such as false information and hard-to-tell rumors. The Internet makes individuals are at a higher risk of being exposed to negative or inaccurate risk information [45], leading towards more anxiety and panic about social risks. Under the framework of negative bias theory, this may also lead to a sense of unsafety. As Sikder et al. [46] pointed out, online social networks achieve large-scale confirmation bias by empowering individuals to choose the narratives they want to engage with. Building on this, Abdul Ghani et al. [47] empirically found that low-quality crime messages widely disseminated

on social media exacerbated Malaysians' perceptions and fears of crime risk, and directly contributed to a decrease in social safety perception. Thereby, we propose that,

**Hypothesis 2.** *If citizens access information more often via the Internet, their perception of social safety decreases.*

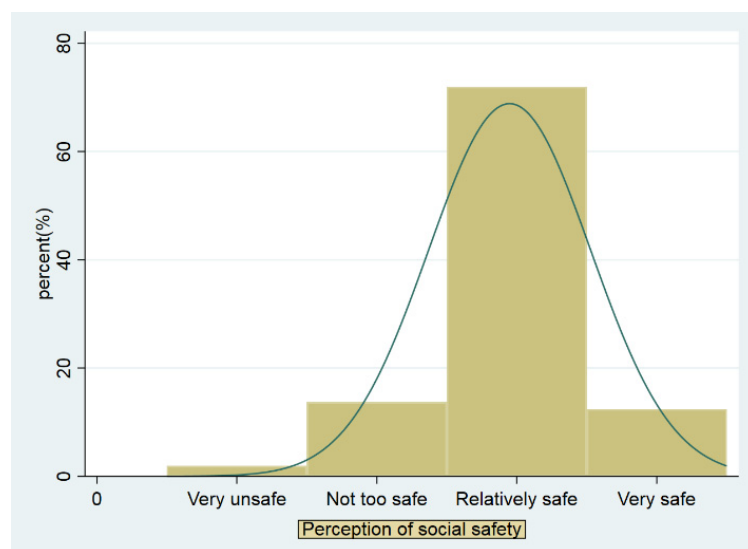
### 3. Method

#### 3.1. Data Sources

The data is from the 2017 China Social Survey (CSS), a biannual longitudinal sample survey initiated by the Institute of Sociology of the Chinese Academy of Social Sciences (CASS) in 2005. The survey focuses on citizens' perception of property, information, labor, medical care, transportation, and social safety, covering 31 provinces/autonomous regions/municipalities, involving 151 districts and 604 villages/residential committees. In this sense, the collected data are representative and reliable. We obtained a valid sample containing 10,143 observations by eliminating the missing and invalid values of variables.

#### 3.2. Variable Selection

**Perception of Social Safety.** The independent variable is the perception of social safety. Social safety perception is defined as the subjective affective or emotional reactions of the public in the process of assessing social risk and social vulnerability [19]. Regarding the measurement, scholars have mainly used questionnaire surveys to obtain citizens' subjective feelings and psychological evaluations of social safety conditions [48,49]. Similarly, the perception of social safety in the 2017 CSS survey is measured by asking respondents the following question, *how do you feel about the current social safety situation in society in general?* The respondents have five options including very unsafe, not too safe, relatively safe, very safe, and hard to say. However, very few people ( $N = 64$ ) answered hard to say, and, thus, we removed them. Figure 1 describes the distribution of citizens' perception of social safety, and most of the participants showed a relatively safe feeling. The average social safety perception of participants surveyed is 2.949, close to relatively safe.



**Figure 1.** The distribution of social safety perception.

**Internet Use.** For measurement of Internet use, this study took two approaches based on CSS2017 data. The first one is about use of the Internet, and the assessment question is as follows, *do you usually go online?* This study constructed a dichotomous variable based on whether respondents use the Internet, assigning use to 1 and non-use to 0. The second one is Internet use frequency with the following assessment question, *how often*



do you usually go online for the following activities? The options are browsing political news, entertainment news, seeking information, making friends, and participating in discussions and other. The Cronbach's alpha for the Internet use frequency is 0.9153, indicating a high internal consistency. Based on empirical practices [50], this study constructed the variable of Internet use frequency in the category of information access by taking the mean value for the above five entries.

### 3.3. Control Variables

Previous studies showed that citizens' perception of social safety is influenced by both demographic-economic variables along with psychosocial factors [23,51,52]. Following this, we included two types of control variables. For demographic variables, we chose gender, age, education level, household registration, marital status, and socioeconomic status. Specifically, gender is assigned as a dummy variable, in which male = 1 and female = 0. Age is the actual age of the respondent in 2017. Marital status is a dummy variable, in which married = 1 and otherwise is 0. Education level was divided into not attending school, primary school, junior high school, high school/technical secondary school/vocational high school, and college and above, which were assigned a score of 1–5, respectively. Socioeconomic status is an overall measure of individual or family-based factors, such as income, education, and occupation. Extant studies pointed out that socioeconomic status is an important predictive variable affecting citizens' perception of social safety [53]. In the CSS2017 questionnaire, one question asked the respondents to choose the corresponding social status they belong to in society. We measured their socioeconomic status for the five available groups, and assigned a value of 1 to 5 accordingly, including lower, lower-middle, middle, upper-middle, and upper. For psychosocial factors, we included police trust, neighbor trust, party and government officials trust, life satisfaction, awareness of public safety issues, and social safety maintenance satisfaction [20,54]. Regarding the awareness of public safety issues, the CSS2017 questionnaire asks respondents whether they believe that social safety is the most important social problem in China today, with No = 0 and Yes = 1. Regarding social safety maintenance satisfaction, the CSS2017 questionnaire asked respondents to rate their satisfaction with the local government's efforts to combat crime and maintain social safety. Responses included four options, very good, relatively good, not very good, and very bad. Referring to existing experience, we combined very bad and not very good into low satisfaction and the two better groups into high satisfaction, respectively assigned to 0 and 1. The definitions of each variable and the results of statistical analysis are shown in Table 1.

**Table 1.** Variable definition and descriptive statistics.

Variable	Coding Scheme for the Response	Mean	SD
Perception of social safety	Fourth categories: 1 = very unsafe and 4 = very safe	2.949	0.579
Internet use	Uses the Internet = 1, otherwise = 0	NA	NA
Internet use frequency	Never = 0, Several times a year = 1, At least once a month = 2, At least once a week = 3, Many times a week = 4, Almost every day = 5	1.200	1.641
Gender	Male = 1, female = 0	NA	NA
Age	Age in 2017	46.654	14.223
Household registration	Rural = 1, urban = 0	NA	NA
Educational level	Not attending school = 1, primary school = 2, junior high school = 3, high school/technical secondary school/vocational high school = 4, college and above = 5	3.024	1.205
Marital status	Unmarried/Divorce or widowed = 0, Married/Cohabiting = 1	NA	NA
Police trust	Self-reported police trust by an individual citizen (from 1 = totally distrusted to 4 = very trusting)	3.014	0.825
Neighbor trust	Self-reported neighbor trust by an individual citizen (from 1 = totally distrusted to 4 = very trusting)	3.004	0.681
Party and government Officials trust	Self-reported party and government officials trust by an individual citizen (from 1 = totally distrusted to 4 = very trusting)	2.753	0.869

**Table 1.** Cont.

Variable	Coding Scheme for the Response	Mean	SD
Socioeconomic status	Self-reported socioeconomic status by an individual citizen (from 1 = lower to 5 = upper)	2.021	0.895
Life satisfaction	Self-reported life satisfaction by an individual citizen (from 1 = strongly unsatisfied to 10 = strongly satisfied)	6.718	2.1990
Awareness of public safety issues	Yes = 1, no = 0	NA	NA
Social safety maintenance satisfaction	High satisfaction = 1, low satisfaction = 0	NA	NA
IV—communication expenditure <sup>a</sup>	Log of communication expenditures in 2016	7.061	1.427

<sup>a</sup> Instrumental variables in endogeneity analysis.

### 3.4. Analytical Model

The explanatory variable is the perception of social safety, which is a discrete variable with assigned values 1–4. Since ordinary least squares (OLS) and ordered probit models (Oprobit) have been widely used to measure discrete variables [55], this study used both OLS and ordered probit models to analyze the factors influencing citizens’ perception of social safety. Among them, the ordinary least squares regression model is as follows.

$$y_i = \gamma + X_i\alpha + Z_i\beta + \varepsilon_i \tag{1}$$

In Equation (1),  $y_i$  represents perception of social safety;  $X_i$  represents Internet use;  $\alpha$  is the related coefficient estimated;  $Z_i$  represents control variables that affect citizens’ perception of social safety;  $\beta$  is the related coefficient estimated;  $\varepsilon_i$  is the random disturbance term;  $i$  represents the  $i$  th citizen;  $\gamma$  is a constant.

Meanwhile, considering that the perception of social safety is a four-category variable, the ordered probit model is as follows.

$$y_i^* = \gamma_1 + X_i\alpha_1 + Z_i\beta_1 + \varepsilon_i \tag{2}$$

$$y_i = \begin{cases} 1, y_i^* \leq C1 \\ 2, C1 < y_i^* \leq C2 \\ 3, C2 < y_i^* \leq C3 \\ 4, C3 < y_i^* \end{cases} \tag{3}$$

In Equation (2),  $y_i^*$  is the latent variable for the  $i$ -th investigator’s perception of social safety,  $X_i$  represents Internet use;  $Z_i$  represents control variables that affect citizens’ perception of social safety;  $\varepsilon_i$  is the random disturbance;  $\alpha_1$  represents the regression coefficients of citizens’ Internet use;  $\beta_1$  denotes the regression coefficients of the control variables;  $\gamma_1$  is a constant. In Equation (3),  $C1$ – $C3$  are the coefficients estimated. When below the threshold  $C1$ , citizens feel very unsafe ( $y_i = 1$ ); when above  $C1$  but below  $C2$ , citizens feel not very safe ( $y_i = 2$ ). In this sense, when higher than  $C3$ , it means that the citizens feel very safe ( $y_i = 4$ ).

Assuming  $\varepsilon_i$  obeys the logistic distribution,  $\mu$  denotes all explanatory variables, and  $\delta(\cdot)$  denotes the cumulative distribution function,  $y_i$  can be expressed as:

$$P(y_i = 1) = \delta(C1 - \mu\alpha) \tag{4}$$

$$P(y_i = 2) = \delta(C2 - \mu\alpha) - \delta(C1 - \mu\alpha) \tag{5}$$

$$P(y_i = 3) = \delta(C3 - \mu\alpha) - \delta(C2 - \mu\alpha) \tag{6}$$

$$P(y_i = 4) = 1 - \delta(C3 - \mu\alpha) \tag{7}$$

Further, since the coefficients estimated from the ordered probit model are not intuitive, they fail to provide sufficient information in terms of significance and parameter meaning. Therefore, we report the marginal effect of each explanatory variable regarding on the impact of perceived social safety.

In addition, whether to use the Internet is a choice individuals make based on their own circumstances, and there are differences in the Internet use across age groups. For example, younger people tend to be more likely to use the Internet than older people. Considering whether Chinese citizens use the Internet may not satisfy the requirement of random sampling, i.e., that citizens who use the Internet and those who do not differ systematically at the level of their own characteristics, direct regressions may be selectively biased. To this end, this study uses propensity score matching (PSM) to construct a counterfactual framework and correct for potential sample selectivity bias [56] to ensure the robustness of the text study findings. The propensity score matching model avoids the effect of confounding variables by dividing the sample into treatment and control groups and conducting a staged analysis. The model is as follows.

$$y_i = y_{0i} + (y_{1i} - y_{0i})D_i \tag{8}$$

$$ATT = E(y_{1i} - y_{0i})D_i = 1 \tag{9}$$

In Equation (8),  $D_i$  refers to the treatment variables including 1 and 0. When  $D_i = 1$ , the individual enters the treatment group; when  $D_i = 0$ , the individual enters the control group. In this study, the core independent variables are divided into two categories, namely, the treatment group of citizens who use the Internet and the control group of citizens who do not use the Internet.  $y_{1i}$ ,  $y_{0i}$  represent the estimated results for the treatment and control groups, respectively. Equation (9) represents the Average Treatment Effect on Treated (ATT) for the treatment group. All data processing and analysis were performed using STATA16. Figure 2 shows the technical research framework adopted.

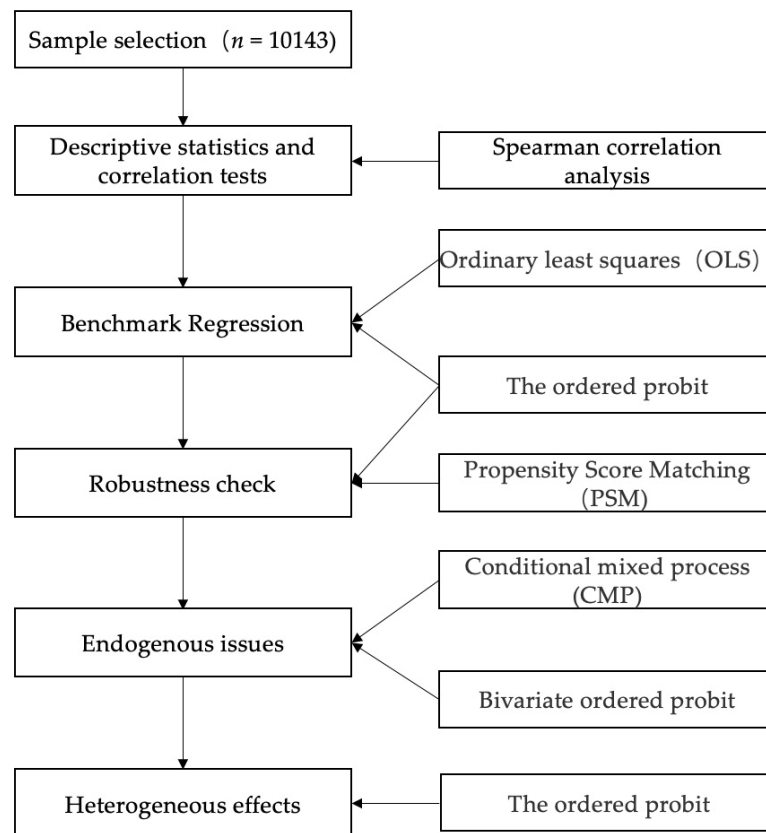


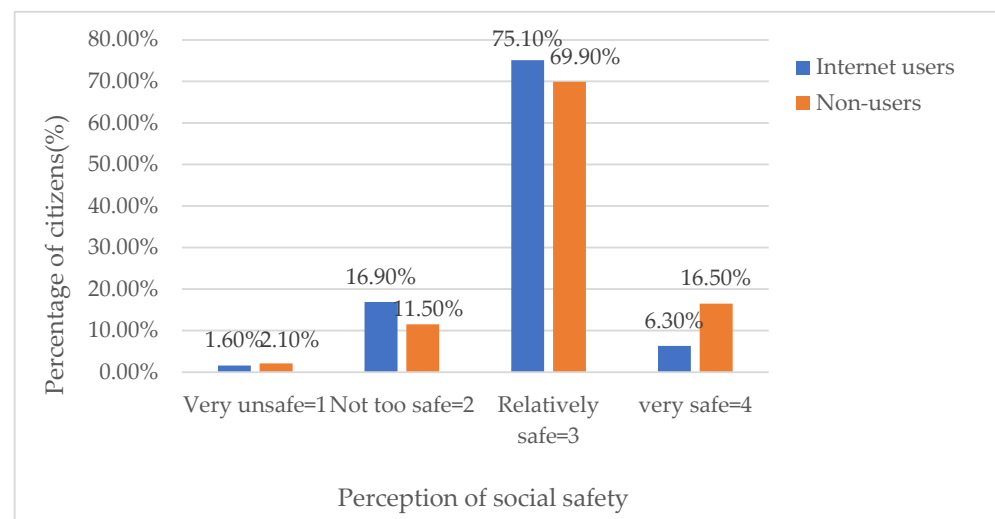
Figure 2. Technical framework.



## 4. Results

### 4.1. Descriptive Analysis

In total, this study included 4069 Internet users accounting for 40.12%, and 6074 non-Internet users with average perception of social safety amounted to 2.949. It shows that the total percentage of citizens who do not use the Internet choosing very unsafe and not very safe is 13.6%, which is lower than the 18.5% of citizens who use the Internet. The total percentage of citizens who do not use the Internet choosing relatively safe and very safe is 86.4%, which is significantly higher than that of citizens who use the Internet (81.5%). Figure 3 provides the details. In addition, the average social safety perception of Internet users is 2.86, while the average social safety perception of non-Internet users is 3.01. This means that the social safety perception of citizens who do not use the Internet is slightly higher than that of Internet users.



**Figure 3.** Internet use/SSP relation for Internet users versus non-users.

Appendix A Table A1 presents the results of the Spearman correlation analysis of Internet use, frequency of Internet use, and related control variables with civil social safety perception. According to the results, both Internet use ( $-0.144, p < 0.01$ ) and Internet use frequency ( $-0.143, p < 0.01$ ) significantly negatively predict civil social safety perception. In terms of control variables, gender ( $0.062, p < 0.01$ ), age ( $0.159, p < 0.01$ ), house registration ( $0.064, p < 0.01$ ), police trust ( $0.239, p < 0.01$ ), neighbor trust ( $0.205, p < 0.01$ ), party and government officials trust ( $0.259, p < 0.01$ ), life satisfaction ( $0.168, p < 0.01$ ), and social safety maintenance satisfaction ( $0.151, p < 0.01$ ) are positively correlated with the civil social safety perception. However, educational level ( $-0.126, p < 0.01$ ) and awareness of public safety issues ( $-0.031, p < 0.01$ ) have a significant negative correlation with civil social safety perception. The results provide a preliminary positive conclusion of the research hypothesis, indicating the necessity of subsequent regression analysis.

### 4.2. Benchmark Regression

#### 4.2.1. The Impact of Internet use and Internet use Frequency on Perception of Social Safety

We performed OLS and ordered probit regressions to analyze the relationship between Internet use and perception of social safety. The results showed estimated coefficients of  $-0.051$  ( $p < 0.01$ ) and  $-0.023$  ( $p < 0.01$ ), indicating that the effect of Internet use on citizens' perception of social safety was statistically significant and negatively correlated. This means Hypothesis 1 is supported. The results further revealed that probability of perceiving society as very safe decreases significantly by 2.3% for Internet users compared to non-users. Meanwhile, the result of the relationship between Internet use frequency and citizens' perception of social safety showed that the regression coefficients were  $-0.015$  ( $p < 0.01$ ) and  $-0.007$  ( $p < 0.01$ ), respectively, indicating that the effect of Internet use

on citizens' perception of social safety was statistically significant and negatively correlated. This means Hypothesis 2 is supported. Table 2 presents the details.

**Table 2.** Internet use, Internet use frequency, and perception of social safety.

Variables	OLS		Ordered Probit	
	(1)	(2)	(1)	(2)
Internet use	−0.051 *** (0.016)		−0.023 *** (0.007)	
Internet use frequency		−0.015 *** (0.005)		−0.007 *** (0.002)
Gender	0.069 *** (0.013)	0.069 *** (0.013)	0.030 *** (0.006)	0.029 *** (0.006)
Age	0.003 *** (0.001)	0.003 *** (0.001)	0.001 *** (0.000)	0.001 *** (0.000)
Household registration	0.025 * (0.014)	0.025 * (0.014)	0.011 * (0.006)	0.011 * (0.006)
Educational level				
Primary school	−0.037 (0.027)	−0.038 (0.027)	−0.018 (0.013)	−0.019 (0.013)
Junior high school	−0.029 (0.027)	−0.031 (0.027)	−0.018 (0.013)	−0.019 (0.013)
High school/technical secondary school/vocational high school	−0.064 ** (0.030)	−0.067 ** (0.030)	−0.033 ** (0.013)	−0.034 ** (0.013)
College and above	−0.088 *** (0.033)	−0.086 ** (0.034)	−0.042 *** (0.014)	−0.041 *** (0.014)
Marital status	−0.033 ** (0.017)	−0.035 ** (0.017)	−0.013 * (0.007)	−0.014 * (0.007)
Police trust	0.049 *** (0.010)	0.048 *** (0.010)	0.020 *** (0.004)	0.020 *** (0.004)
Neighbor trust	0.071 ** (0.011)	0.071 ** (0.011)	0.029 *** (0.005)	0.029 *** (0.005)
Party and government officials trust	0.048 *** (0.010)	0.090 *** (0.010)	0.037 *** (0.004)	0.037 *** (0.004)
Socioeconomic status	−0.001 (0.008)	−0.001 (0.008)	−0.001 (0.003)	−0.001 (0.003)
Life satisfaction	0.034 *** (0.003)	0.034 *** (0.003)	0.014 *** (0.001)	0.014 *** (0.001)
Awareness of public safety issues	−0.069 ** (0.032)	−0.069 ** (0.032)	−0.030 ** (0.013)	−0.030 ** (0.013)
Social safety maintenance satisfaction	0.122 *** (0.016)	0.123 *** (0.016)	0.045 *** (0.006)	0.046 *** (0.006)
Province	YES	YES	YES	YES
Constant	1.882 *** (0.089)	1.881 *** (0.089)	—	—
R-squared/Pseudo R2	0.1304	0.1304	0.0835	0.0836
Observations	8246	8224	8246	8224

Robust standard errors are in parentheses. \*  $p < 0.1$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$  (same as below).

#### 4.2.2. The Impact of Control Variables on Perception of Social Safety

In addition, most control variables were significantly correlated with citizens' perception of social safety. For example, gender ( $r = 0.069$ ,  $p < 0.01$ ), age ( $r = 0.003$ ,  $p < 0.01$ ), household registration ( $r = 0.025$ ,  $p < 0.1$ ), police trust ( $r = 0.049$ ,  $p < 0.01$ ), neighbor trust ( $r = 0.071$ ,  $p < 0.01$ ), party and government officials trust ( $r = 0.048$ ,  $p < 0.01$ ), life satisfaction ( $r = 0.034$ ,  $p < 0.01$ ), and social safety maintenance satisfaction ( $r = 0.122$ ,  $p < 0.01$ ) showed a significant positive correlation with perception of social safety. The marital status ( $r = -0.033$ ,  $p < 0.05$ ) and awareness of public safety issues ( $r = -0.069$ ,  $p < 0.05$ ) showed a significant negative correlation with perception of social safety. As for educational level, high school ( $r = -0.064$ ,  $p < 0.05$ ), college and above ( $r = -0.088$ ,  $p < 0.01$ ) have a negative effect on the perception of social safety. However, it is noteworthy that socioeconomic status does not have a significant effect on citizens' perception of social safety.

### 4.3. Robustness Check

To check the robustness of the results, we made the independent variable social safety perception the dummy variable. Specifically, respondents were assigned 1 if they answered very safe or relatively safe and 0 if they answered very unsafe or not too safe. Figure 4 presents the details. After that, we used the same analytical methods, and the results showed that Internet use and Internet use frequency are negatively correlated with perception of social safety. In addition, we also applied an alternative analytical method by replacing the ordered probit model to the ordered logit model, for robustness check by changing the form of data distribution. The results also revealed that Internet use and Internet use frequency are correlated significantly and negatively with social safety perception. The ordered logit results are congruent with the baseline regression results. Table 3 presents the details.

**Table 3.** Robustness check.

Variables	Change the Variable Encoding Method		Change the Model Setting Form	
	(1)	(2)	(3)	(4)
Internet use	−0.092 ** (0.047)		−0.023 *** (0.007)	
Internet use frequency		−0.027 * (0.015)		−0.007 *** (0.002)
Gender	0.221 *** (0.041)	0.220 *** (0.041)	0.031 *** (0.006)	0.031 *** (0.006)
Age	0.009 *** (0.002)	0.009 *** (0.002)	0.001 *** (0.000)	0.001 *** (0.000)
Household registration	0.002 (0.043)	0.002 (0.043)	0.012** (0.006)	0.012 ** (0.006)
Educational level				
Primary school	0.019 (0.070)	0.016 (0.070)	−0.023 * (0.013)	−0.024 * (0.013)
Junior high school	0.103 (0.072)	0.100 (0.071)	−0.025 * (0.013)	−0.026 ** (0.013)
High school/technical secondary school/vocational high school	0.092 (0.081)	0.088 (0.081)	−0.040 *** (0.014)	−0.041 *** (0.014)
College and above	0.029 (0.091)	0.036 (0.092)	−0.049 *** (0.014)	−0.047 *** (0.015)
Marital status	−0.137 *** (0.050)	−0.140 *** (0.050)	−0.015 ** (0.007)	−0.016 ** (0.007)
Police trust	0.045 * (0.026)	0.045 * (0.026)	0.021 *** (0.004)	0.021 *** (0.004)
Neighbor trust	0.110 *** (0.028)	0.107 *** (0.028)	0.031 *** (0.005)	0.031 *** (0.005)
Party and government officials trust	0.186 *** (0.026)	0.187 *** (0.026)	0.039 *** (0.004)	0.039 *** (0.004)
Socioeconomic status	0.037 * (0.022)	0.037 * (0.022)	−0.001 (0.003)	−0.001 (0.003)
Life satisfaction	0.070 *** (0.009)	0.070 *** (0.009)	0.001 *** (0.000)	0.014 *** (0.001)
Awareness of public safety issues	−0.153 * (0.087)	−0.156 * (0.088)	−0.029 ** (0.013)	−0.029 ** (0.013)
Social safety maintenance satisfaction	0.380 *** (0.039)	0.381 *** (0.039)	0.048 *** (0.007)	0.049 *** (0.007)
Province	YES	YES	YES	YES
Constant	−1.245 *** (0.265)	−1.243 *** (0.265)	—	—
R-squared/Pseudo R <sup>2</sup>	0.0900	0.0899	0.0878	0.0879
Observations	8246	8224	8246	8246

Robust standard errors are in parentheses. \* $p < 0.1$ , \*\* $p < 0.05$ , \*\*\* $p < 0.01$  (same as below).

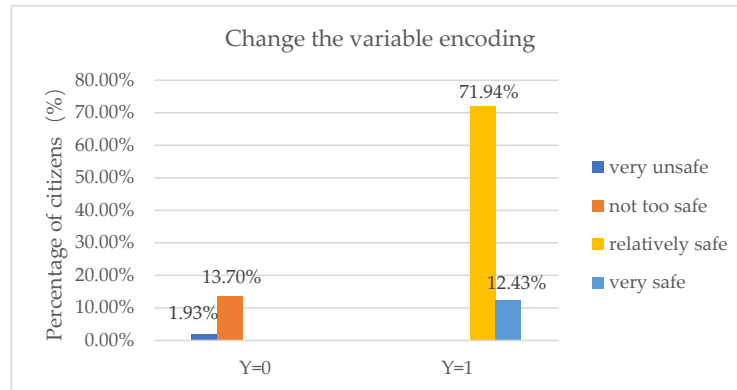


Figure 4. Change the variable encoding.

Considering the self-selection bias problem, we further constructed a counterfactual framework by adopting the propensity score matching model and performing a robustness check on the baseline regression results. Specifically, we used the K-nearest neighbor matching to set up the treatment and reference groups, and matched logit regression and balance tests. As shown in Table 4, the standardized deviations of all covariates were less than 10%, while the two paired samples’ *t*-tests had companion probability values above 0.1, which satisfied the requirement of the balance test. The K-nearest neighbor matching was further applied to calculate the Average Treatment Effect on Treated (ATT) for the treatment group, and the results showed that the estimated coefficient of ATT was  $-0.056$ , and the absolute value of the *t*-test was 2.01. It showed that after the adoption of propensity score matching to correct for selection bias and eliminate systematic differences between variables, the net effect of Internet use on citizens’ perception of social safety remained negative, which was congruent with the previous baseline regression results and fully confirmed the robustness of the results.

Table 4. Balance test.

Variable	U/M	Mean		Bias (%)	Reduce Bias (%)	<i>t</i> -Test	
		Treated	Control			<i>t</i>	<i>p</i>
Gender	U	0.4759	0.4535	4.5	1.7	2.03	0.043
	M	0.4753	0.4973	−4.4		−1.45	0.164
Age	U	36.567	52.815	−136.8	97.6	−62.17	0.000
	M	36.606	36.213	3.3		1.30	0.194
Household registration	U	0.5519	0.7787	−49.5	99.1	−22.63	0.000
	M	0.5532	0.5553	−0.5		−0.18	0.857
Educational level	U	3.8726	2.5064	136.9	97.5	61.82	0.000
	M	3.8700	3.8365	3.4		1.43	0.154
Marital status	U	0.7182	0.8732	−39.2	94.0	−18.07	0.000
	M	0.7200	0.7106	2.3		0.86	0.391
Police trust	U	2.8715	3.1160	−30.1	94.8	−13.46	0.000
	M	2.8720	2.8848	−1.6		−0.67	0.506
Neighbor trust	U	2.8976	3.0756	−26.7	80.2	−11.92	0.000
	M	2.8987	2.9340	−5.3		−1.61	0.107
Party and government officials trust	U	2.6530	2.8314	−21.1	65.3	−9.41	0.000
	M	2.6539	2.7157	−7.3		1.47	0.142
Socioeconomic status	U	2.2256	1.9088	36.2	93.0	16.28	0.000
	M	2.2224	2.2445	−2.5		−1.06	0.290
Life satisfaction	U	6.9554	6.5944	16.8	74.1	7.48	0.000
	M	6.9531	7.0465	−4.3		−1.61	0.107
Awareness of public safety issues	U	0.0332	0.0402	−3.7	61.3	−1.66	0.096
	M	0.0333	0.0360	−1.4		−0.62	0.536
Social safety maintenance satisfaction	U	0.7761	0.7816	−1.3	−84.0	−0.60	0.551
	M	0.7756	0.7655	2.4		1.01	0.314

Due to the length of the article, this paper only reports the balance test results after k-nearest neighbor matching. Among them, the parameter of k-nearest neighbor matching is set to  $k = 2$ .

#### 4.4. Endogenous Issues

To avoid the endogeneity, we used the log form of household communication expenditure in 2016 option in the CSS2017 questionnaire as an instrumental variable for Internet use, defined as communication expenditure. Therefore, we re-estimated the impact relationship between Internet use, communication expenditures, and perception of social safety using the conditional mixed process approach (CMP) and bivariate ordered probit model (Bioprobit).

According to Table 5, the first stage regressions of both the Bioprobit and the CMP showed that communication expenditures were significantly positively related to Internet use at the 1% level, satisfying the instrumental variable correlation condition. In addition, the endogeneity test parameters *athrho* and *atanrho\_12* of the Bioprobit and the CMP were significant at the 10% and 1% statistical levels, respectively. Both indicated that Internet use was an endogenous variable, while the second-stage regression results of the Bioprobit and the CMP showed that Internet use still had a significant negative effect on citizens' perception of social safety after correcting for possible endogeneity bias, further confirming the negative effect of Internet use on citizens' perception of social safety.

**Table 5.** Endogenous test.

Variables	Bioprobit		CMP	
	Phase 1 (1)	Phase 2 (2)	Phase 1 (3)	Phase 2 (4)
Internet use		−0.394 *** (0.168)		−0.257 *** (0.096)
Communications expenditure	0.338 *** (0.014)		0.023 *** (0.003)	
<i>athrho</i>	0.177 * (0.107)			
<i>atanrho_12</i>			0.438 *** (0.166)	
Control variables	YES	YES	YES	YES
Province	YES	YES	YES	YES
Wald test	1046.38 ***		9733.00 ***	
Observations	8074		8074	

Robust standard errors are in parentheses. \*  $p < 0.1$ , \*\*\*  $p < 0.01$ .

#### 4.5. Heterogeneous Effects of Internet use on Social Safety Perception

The imbalance in regional economic power, especially at the level of Internet development, and the variability among social groups lead to possible heterogeneity in the impact of Internet use on citizens' perception of social safety. We tried to develop the heterogeneity analysis of the impact of Internet use on citizens' perception of social safety at three levels: region, household registration, and age, and the regression results are shown in Table 6.

**Table 6.** Heterogeneous test.

Variables	Region			Age			Household Registration	
	Eastern	Central	Western	Young	Middle	Old	Rural	Urban
Internet use	−0.017 (0.010)	−0.022 ** (0.011)	−0.031 ** (0.013)	−0.018 *** (0.007)	−0.028 ** (0.011)	−0.037 (0.024)	−0.025 *** (0.010)	−0.015 * (0.009)
Control variables	YES	YES	YES	YES	YES	YES	YES	YES
Province	YES	YES	YES	YES	YES	YES	YES	YES
Pseudo R2	0.0842	0.0681	0.0992	0.0795	0.0750	0.0791	0.0869	0.0802
Observations	3373	2626	2247	3541	2903	1802	5634	2612

Robust standard errors are in parentheses. \*  $p < 0.1$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$ ; Age\_young ( $\leq 44$  years); Age\_middle (45–59 years); Age\_old ( $\geq 60$  years).

There are significant regional differences in citizens' Internet use due to differences in ICT infrastructure development as well as demographic and regional characteristics. In terms of regional division, there are 10 provinces in the eastern region, 8 provinces in the central region,



and 11 provinces in the western region. Figure 5 presents the details. A sub-sample regression of regions found that Internet use was significantly and negatively associated with citizens' perception of social safety in both central and western regions at the 5% statistical level, with estimated coefficients of  $-0.022$  ( $p < 0.05$ ) and  $-0.031$  ( $p < 0.05$ ), respectively. In addition, we also found no significant correlation between Internet use and citizen's perception of social safety in the eastern region.

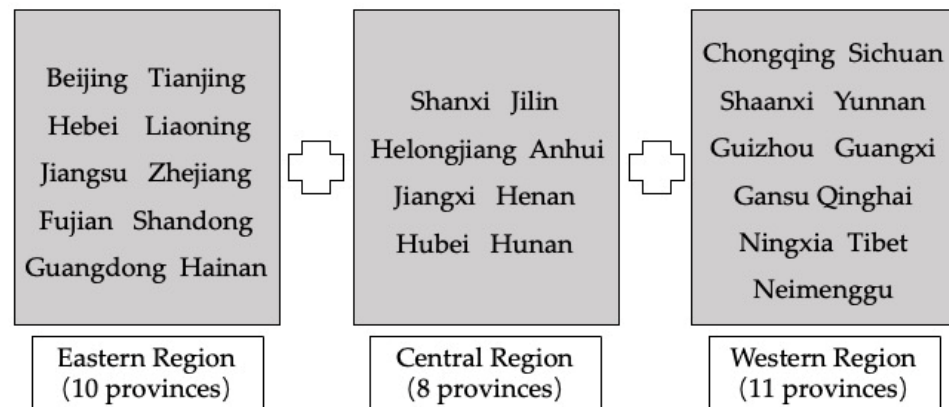


Figure 5. Regional grouping.

Internet use was negatively associated with the perception of social safety in young people ( $r = -0.018$ ,  $p < 0.01$ ) and middle-aged people ( $r = -0.028$ ,  $p < 0.05$ ) at the 1% and 5%, respectively. However, we did not find a significant effect of Internet use on the perceived social safety of older adults. In terms of household registration, the negative impact of Internet use on the perceived social safety of rural citizens ( $r = -0.025$ ,  $p < 0.01$ ) was higher than that of urban citizens ( $r = -0.015$ ,  $p < 0.1$ ).

## 5. Discussion

Nowadays, social risks have been reshaping citizen's social safety perception. How to effectively eliminate the unsafe factors and enhance citizens' social safety perception is critical to improve the quality of life and happiness of citizens. With the rise of emerging Internet-based technologies, their impact on the human social psychological perception is salient. Although the complex relationship between Internet use and citizens' risk perception has been explored extensively, and risk perception has been regarded as one of the antecedents of citizens' social safety perception, will Internet use be able to influence citizens' social safety perception in an increasing digitalized risk society? Our empirical study not only helps the government to formulate proper Internet development strategies, but also sheds lights on social safety governance capabilities.

First, the baseline regression results showed that Internet use, Internet use frequency, and citizens' perception of social safety had negative correlations. After robustness and endogeneity checks, the effect persisted. According to the social amplification of risk framework and negative bias theory, these may attribute to the nature of the Internet, which have greatly enhanced the speed and breadth of information dissemination, exposing citizens to the flood of risk information. On the one hand, this reinforces the symbolic experience of risk and stimulates citizens' perception of social unsafety [17]. The newly emerged social media platforms provide a vehicle for citizens to access COVID-19 stressors and perceive negative emotions in disaster situations, and those who spent more time on social media reported more mental health problems [57]. On the other hand, unlike traditional media outlets that are subject to strict censorship, the Internet helps the dissemination of unverified information, making instant regulations almost impossible. This makes the information quality on the Internet hard to guarantee and increases the social amplification of risk effect. For example, a two-day analysis of Twitter tweets about the COVID-19 pandemic found that there were more tweets with false information than those that were

scientifically proven or fact-checked [58]. This can easily exacerbate citizens' anxiety and perception of social unsafety and affect their coping strategies in a bad way [59]. In addition, excessive mobile Internet use triggers a negative information attention bias, and negative risk information becomes more powerful on the Internet. The longer citizens are exposed to negative social risk information on the Internet, the more likely they are to be disturbed and develop a sense of unsafety.

Second, social safety perception is influenced by both individual subjective characteristics and objective social environment. With the rapid growth of the number of Internet users and the Internet penetration rate worldwide, the Internet has greatly reduced the cost of information, allowing people to learn about any risk information in a short time. The cyberspace associated with individual Internet use has undoubtedly affected the public's perception of social safety significantly. Based on the national representative data, this study found that Internet use frequency has a significant negative effect on the public's social safety perception. It is consistent with the work of Zhang et al. [40]. Using China's survey data, Zhang et al. [40] revealed that higher frequency of Internet use to browse news, search information, and browse microblogs was associated with lower citizen perception of food safety. Another study also showed that college students who regularly use the Internet and social networks have a higher risk perception of social environment and health [60]. For the online information provision, if not well-supervised, online information providers are likely to report certain crises exaggeratedly to attract public attention. However, it may result in widespread rumors threatening social safety. For individual Internet users, due to the influence of negative bias, higher use frequently means a higher risk of being exposed to negative news and rumors, which in return increases their anxiety and panic. Although many studies indicated the positive effects brought by the Internet, including self-rated health [61], economic growth [62], and personal well-being [63], the dark side of the Internet is worth noting. Future studies can further discuss the impact of the frequency of Internet popularity on citizens' perception of social safety across different cultures.

Third, there is significant heterogeneity in the impact of Internet use on citizens' perception of social safety at the regional, age, and household registration levels. At the regional level, the negative impact of Internet use on citizens' perception of social safety is higher in the western region than in the central region, while it does not have a significant impact on citizens in the eastern region. This difference may be because the eastern, the developed region, of China has high-quality material life security and emergency management capabilities. This makes their citizens have better Internet resilience and social risk resilience to resist the social risk information on the Internet. On the contrary, the underdeveloped region, the western region, still has a large gap in the construction of living facilities, social security level, and social risk management ability compared with the eastern and central-western regions. This makes citizens in the western region more likely to be influenced by social risk information amplified by the Internet and generate more worries and anxieties about their safety. As regards age, Internet use has a higher negative impact on the perceived social safety of middle-aged people than young people, while it does not have a significant effect on older people. This finding is consistent with previous studies [64,65]. A possible explanation is the comparatively lower acceptance and demand for the Internet among older adults. As calculated by the China Family Panel (CFPS), about three-quarters of Chinese 15–44 year-olds used the Internet in 2016, while less than one sixth of those over 45 used the Internet [66]. In addition, as digital natives, young people can easily learn and master social media and other Internet-based communication technologies. However, their limited social experience and cognitive ability make them more vulnerable to the risk information transmitted and processed via the Internet, and this results in a strong sense of distrust and unsafety. Middle-aged people are mostly digital immigrants and have a different ability to adapt to and handle the Internet than young people. As for the middle-aged groups, their family pressure of supporting the elderly and raising young children makes the middle-aged more sensitive to social risk information and more concerned about the negative impact of social risks on their

families. Furthermore, for the middle-aged who cannot quickly acquire Internet skills, the likelihood of unemployment increases, which in return causes a stronger sense of insecurity. At the household registration level, Internet use has a greater negative impact on the perceived social perception of citizens with agricultural household registration than urban citizens do. Possible reasons include the worse living conditions (health care services, scarce educational resources) and surrounding environments in rural areas [55]. In addition, because of the rural population's low level of education and to them having less access to communication technologies, these factors lead to a decrease in the perception of social safety as rural citizens are more susceptible to misinformation and adverse risk information on the Internet.

Fourth, this study also explored other influencing factors of citizens' social safety perception. It found that gender, age, household registration, police trust, neighbor trust, party and government officials trust, life satisfaction, and social safety maintenance satisfaction all showed significant positive correlations with citizens' perception of social safety. These findings are consistent with extant studies [67,68]. We also found that education, marital status, and awareness of public safety issues showed significant negative correlations with citizens' perception of social safety. In terms of the negative relationship between education and perception of social safety, this may contribute to the fact that citizens with higher education are more concerned and sensitive to social risk information, and desire to pursue a more secured living environment. A recent empirical study found that men with higher education had a higher level of concern about the COVID-19 pandemic compared to less educated men in Germany, while many less educated groups considered the risk of contracting COVID-19 to be low and were less infectious relative to the general population. They are more optimistic towards their health and safety in face of COVID-19 [69]. In addition, this study found that socioeconomic status was not significantly correlated with citizens' perception of social safety. This is somewhat different from previous studies. Mowen and Freng [70] concluded that citizens with higher socioeconomic status also reported higher levels of perceived safety. This discrepancy may be because of the population surveyed. Their research focused on the relationship between school safety and the perceived safety of parents and students in the United States, and they focused on schools rather than the society as a whole, while our study featured on a representative group in China to examine their social safety perception in general.

## 6. Conclusions

### 6.1. Major Findings

Based on 2017 CSS data, this study explores the impact of Internet use on citizens' perception of social safety using least squares, ordered probit model, PSM, and other analytical methods. First, Internet use and Internet use frequency have a significant negative impact on citizens' perception of social safety. The probability of perceiving society as very safe decreases by 2.3% for citizens who use the Internet compared to those who do not use the Internet. This finding still works after the subsequent testing by PSM, CMP, and Bioprobit. Second, the heterogeneity analysis reveals that the impact of Internet use on citizens' perception of social safety is significantly different at the regional, age, and household registration levels. Among them, Internet use has a higher negative impact on social safety perception in the western region than in the central region, while it has no significant impact on the eastern region. In terms of age, Internet use does not have a significant impact on the perception of social safety of older adults, but the negative impact on the perception of social safety of middle-aged adults is stronger than that of young adults. In terms of household registration, the negative impact of Internet use on the perceived social safety of rural citizens was higher than that of urban citizens.

### 6.2. Policy Implications

For the digital governance, we should never overlook the risk amplification effect and negative bias effect attached to the Internet. First, the government can accelerate the



Table A1. Cont.

Variables	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
Marital status	0.025	−0.194 ***	−0.236 ***	−0.067 ***	0.299 ***	0.057 ***	−0.221 ***	1							
Police trust	0.239 ***	−0.165 ***	−0.152 ***	−0.067 ***	0.166 ***	0.082 ***	−0.169 ***	0.006	1						
Neighbor trust	0.205 ***	−0.144 ***	−0.147 ***	0.049 ***	0.182 ***	0.096 ***	−0.155 ***	0.071 ***	0.314 ***	1					
Party trust	0.259 ***	−0.115 ***	−0.103 ***	−0.030 ***	0.132 ***	0.029 ***	−0.088 ***	−0.004	0.562 ***	0.311 ***	1				
Socioeconomic status	0.023	0.178 ***	0.190 ***	−0.030 ***	−0.073 ***	−0.158 ***	0.213 ***	0.008	0.021	0.001	0.070 ***	1			
Life satisfaction	0.168 ***	0.079 ***	0.102 ***	0.015	−0.037 ***	−0.074 ***	0.124 ***	−0.039 ***	0.182 ***	0.128 ***	0.210 ***	0.318 ***	1		
Awareness of public safety issues	−0.031 ***	−0.021	−0.017	−0.012	0.016	0.008	−0.013	−0.010	−0.027	−0.020	−0.002	0.024	0.008	1	
Social safety maintenance satisfaction	0.151 ***	−0.007	−0.005	0.007	0.048 ***	−0.035 ***	0.021	0.013	0.191 ***	0.077 ***	0.204 ***	0.036 ***	0.123 ***	−0.065 ***	1

\*\*\*  $p < 0.01$ ; 1–15 represent the variables in the first row on the left respectively.

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