

Article

Understanding Consumer Panic Buying Behaviors during the Strict Lockdown on Omicron Variant: A Risk Perception View

Yaodong Yang ¹, Huaqing Ren ² and Han Zhang ^{3,*}

¹ School of Economics, Anhui University, Hefei 230039, China

² School of Public Affairs, Nanjing University of Science and Technology, Nanjing 210094, China

³ School of Economics and Management, Nanjing University of Science and Technology, Nanjing 210094, China

* Correspondence: njuzhanghan@njust.edu.cn

Abstract: Panic buying has been globally observed, leading to substantial stock-outs and supply chain disruptions, thus inducing additional panic buying. Regarding panic buying behavior as an intuitive over-protective measure during the strict lockdown and seal-off management in China, this study presented a synthetic conceptual model by integrating the protective action decision model (PADM). We examined inductively the relationships among media exposure, cognitive-affective risk perception, stakeholder perception, protective perception, and panic buying behavior using a survey of 517 participants who experienced panic buying during the Omicron epidemic in China. Results suggest that traditional media exposure could attenuate people's affective risk perception, whereas social media exposure increases the degree of cognitive and affective aspects of risk perception. Furthermore, we detect that cognitive and affective risk perceptions positively affect people's panic-buying behaviors. The effects of stakeholder and protective perceptions on panic buying were also examined.



Citation: Yang, Y.; Ren, H.; Zhang, H. Understanding Consumer Panic Buying Behaviors during the Strict Lockdown on Omicron Variant: A Risk Perception View. *Sustainability* **2022**, *14*, 17019. <https://doi.org/10.3390/su142417019>

Academic Editors: Belem Barbosa, Pankaj Deshwal and Sikandar Ali Qalati

Received: 8 November 2022

Accepted: 14 December 2022

Published: 19 December 2022

Publisher's Note: MDPI stays neutral with regard to jurisdictional claims in published maps and institutional affiliations.



Copyright: © 2022 by the authors. Licensee MDPI, Basel, Switzerland. This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license (<https://creativecommons.org/licenses/by/4.0/>).

Keywords: Omicron variant; panic buying; media exposure; cognitive-affective processes; risk perception

1. Introduction

The brand-new SARS-CoV-2 VOC Omicron was initially discovered on 2 November 2021, in South Africa, where it subsequently quickly spread. Compared to Delta VOC, at least 90% of the world's genomes were sequenced in October 2021; it has caused sudden pandemic breakouts across South Africa, Europe, and the rest of the planet [1]. The relevant epidemiology of the Omicron wave in early 2022 has demonstrated that the Omicron variant tends to be more contagious than prior variants, including the Delta variant [2]. The guidance on prevention and control for the Omicron variant infection presented by China's dynamic zero-COVID policy has claimed that a strict lockdown to keep "social distancing" is among the most cost-effective countermeasures to alleviate the transmission of the highly transmissible Omicron variant [3,4]. Furthermore, as early as April 2022, rumors, speculations, and official clarifications about the forthcoming nationwide functional product shortage pervaded from media and word-of-mouth communication when the strict lockdown and seal-off management measures were implemented in Shanghai, China's financial hub. Thus, waves of mass panic buying occurred in several cities in March and April 2022, in response to the forthcoming long-term lockdown or phased closed-off management situation in the Omicron-stricken cities. With a sense of urgency to buy during the Omicron epidemic, not only functional products but also other protective equipment, for instance, face masks, alcohol-based hand sanitizer, N95 respirators, and antiviral drugs, have been subjected to mass panic buying.

Panic buying refers to the collective behavior of numerous people rushing to buy and hoard a certain amount of limited and unique types of products, such as antiviral

drugs, vinegar, salt, oil, rice, and so on [5,6]. This behavior is due to the fear of upcoming environmental, natural, or manufacturing crises or the anticipation of a potential shortage of those products and a possible high price increase [7]. Consumer panic buying behavior has been observed following multiple disasters, including Hurricane Katrina in the U.S. Gulf Coast area in 2005, the nuclear crisis in Japan in 2011, Hurricane Sandy in New York City in 2012, and the global COVID-19 pandemic in 2020. Recently, panic buying was observed globally, particularly for function products panic in Shanghai, Shenzhen, Hongkong, and Italy, due to the rapid spread of the novel Omicron coronavirus [8,9]. For instance, panic buying of medical supplies could easily lead to stock-out situations, which substantially prevents the highly vulnerable people and frontline health workers who need more surgical supplies to fight the pandemic from accessing them [10]. Otherwise, a mass wave of panic buying could further disrupt the supply chains, which commonly lead to price increases [11]. In such a setting, understanding the mechanism of consumer panic buying behavior during the strict lockdown and seal-off management is not only for researchers in consumer behavior and crisis management but also has critical implications for marketing practitioners (e.g., consumers, regulators, and policymakers).

Despite the extensive existence of panic buying, particularly the recent waves of consumer panic buying behaviors triggered by the Omicron variant, studies are limited to understanding the intrinsic mechanism of panic buying. Given the inherent common focus of the Omicron epidemic research, Yuen et al. [6] concluded several antecedents of panic buying, including perception (e.g., perceived threat and scarcity of products), fear of the unknown, coping behavior, and social psychological factors. Additionally, the protective action decision model (PADM) captures information cues and risk perception in shaping the individuals' protective actions in risk situations [12,13]. The PADM was initially presented by Lindell and Perry [14], to analyze respondent perceptions in response to a threatening situation. The framework postulates stages of human responses to various risks or disasters, starting with the interpretation of warning information originated and diffused from multiple channels. Then, Hazard adjustment activities, such as having emergency plans or buying disaster related insurance plans, are also broadly defined as protective actions. However, the extant studies have shed little light on risk-related factors in determining panic buying. Thus, as to this study, we try to address the following issues from a risk perception view: (1) To what extent will the Omicron epidemic information that people derived from information sources (media exposure) affect consumer's risk perception toward panic buying behavior? (2) How do consumers' perception of stakeholders and protective perceptions affect their final panic buying behavior?

Based on the PADM model, we address the first gap by empirically examining the influences of two types of information sources—traditional media (e.g., TV, radio, newspaper) and social media (e.g., WeChat, Weibo). That is, people received epidemic information on their two distinctive patterns of risk perception, namely cognitive and affective risk perceptions. Then, we adopt the dual-process risk perception model to predict the consumer's panic buying behavior. Similarly, based on the PADM, our study addresses the second issue by empirically investigating the influences of stakeholder and protective perceptions on panic buying behavior.

Our study is organized as follows. After the introduction, Section 2 presents the theoretical background, whereas Section 3 develops the hypotheses and a conceptual model for our study. Section 4 depicts the research method, including the data and methodology. Section 5 describes the data analysis and the results from testing hypotheses, whereas Section 6 concludes the discussions and managerial implications for practitioners. Section 7 proposes the limitation and directions for future research.

2. Theoretical Background

2.1. Risk Perception and Its Dimensions: The Cognitive and Affective Scale

Risk perception refers to an individual's subjective judgment toward a specific risk-related situation [15]. Individuals' risk perceptions tend to be conceived as a construct

integrating two components of a potential risk event, namely perceived probability and severity [16–18]. The extant research has investigated the effects of risk perception on multiple behavioral contexts, such as protective behavior from a given hazard [13,19], health-related behavior [20], and evacuation behavior [21]. The decision-making of human risk aversion behavior is assumed to be a simply cognition-driven process. This notion implies that an individual's risk aversion behavior is predominantly driven by the cognitive assessment of the probability and consequences of a given risk situation [22]. However, a burgeoning research stream conducted in disasters preparedness and health behavior context has emphasized that the affective processes involved in the subjective judgments of risk should be accounted for the influence of risk perception in shaping behaviors [20,23–25]. As this stream of research evolved, two unique but complementary dimensions of risk perception have been identified when studying risk perceptions, decisions, and behaviors, namely cognitive and affective risk perception [26].

Specifically, the cognitive process of risk perception refers to the extent of an individual's perceived logical, rational, and analytical control over a given risk situation, which means that this process is slow and laborious [23,26,27]. Driven by knowledge, cognitive risk perception typically comes from accumulated experience that enables a person to assess the risk situations objectively. An example of the cognitive process of a given risk situation is that people believe that the risk would be increasing or that the experts and government could alleviate the risk appropriately. Apparently, "risk-as-analysis" can reflect the primary characteristic of cognitive-based risk perception. Nonetheless, not all risk perceptions toward risk situations produce a deliberate cognitive process but rather through an emotionally driven procedure. Hence, affective risk perception, what is often labeled as "risk-as-feeling", is defined as an automatic, intuitive, fast whisper of emotion or feeling that is produced unconsciously or consciously toward a stimulus [24–26]. In other words, affective risk perception reflects the emotion-driven element of risk construct in contrast to cognitive-based risk perception, which represents the knowledge-driven element. Hence, a bi-directional analysis of risk perception regarding the relationship between cognitive and affective aspects as a dual-process perspective has progressively been adopted by scholars to predict risk behaviors effectively [20,28,29].

2.2. The PADM Theory

This study is mainly structured according to the PADM framework, initially presented by Lindell and Perry [14], to analyze respondent perceptions in response to a threatening situation. The framework postulates stages of human responses to various risks or disasters, starting with the interpretation of warning information originated and diffused from multiple channels. Then, the assessment and formation of personal stakeholder perceptions, threat perceptions, and protective action perceptions are conducted, ultimately resulting in a behavioral protective response [12,13]. As this framework evolved, this conceptual model has been broadly applied to investigate natural, environmental, and man-made hazards, including earthquakes [30], floods [19], hurricanes [31], city smog [32], and product recall crises [33].

Our present study employs the PADM framework to investigate consumer panic buying behaviors, particularly for panic buying of function products, in the context of the Omicron epidemic for the following reasons. First, the guidance on prevention and control for the Omicron infection presented by the Chinese government has simultaneously claimed that the lockdown and seal-off management measure is one of the most cost-effective countermeasures to alleviate the transmission of Omicron variant [3,34,35]. China was the first country to implement a lockdown to curb the spread of the disease across the country. Hence, staying at home can be considered an effective protective action. Second, as a novel coronavirus that was primarily transmitted through respiratory droplets, the Omicron coronavirus has been proven to be highly threatening to the human body because it can be easily transmitted among humans [2]. Since then, people have displayed anxiety-related behaviors, rushing to stores overnight to buy functional products as the forthcoming

nationwide shortage. Consumers who are likely to be subjected to the Omicron epidemic or live near the disease-hit area are more likely to show negative emotions toward the epidemic. Moreover, they displayed anxiety-related over-protective behaviors, for instance, rushing to drugstores overnight to buy masks due to the forthcoming nationwide facemask shortage [36]. Consequently, the PADM framework is appropriate for examining consumer panic buying behaviors during the pandemic.

3. Hypotheses

3.1. Media Exposure and Risk Perception

The existing studies have reinforced the role of mass media in affecting people's risk communication and perception, particularly for those without first-hand experience [37,38]. People are more likely to depend on the mass media to realize what is happening beyond personal access because most do not have direct experience. Prior scholars have claimed that media exposure can exert an extensive impact on public perceptions of risk, particularly in health-related issues, for instance, MERS-CoV [39], Avian flu [40], Smoke haze (versus dengue fever) [41], and H1N1 flu [42]. Based on the social amplification of risk that was initially presented by [37], media exposure can act as a "social amplification station" to affect public risk information processing and thus make people's risk perceptions amplified or attenuated [43]. Otherwise, a different media source could have distinctive effects on risk perception [38,44], indicating that not only the information what is reported, but also how it is spread, and by whom it is reported could affect audiences' risk perceptions.

The source of mass media includes traditional media, such as television, radio, and newspapers, and social media, such as the Internet, microblogs, and WeChat. Traditional media tended to be the most common information source during the pre-Internet era, and presently, the public still uses traditional media to acquire information. In China, all televisions, radio stations, and most newspaper offices are state-owned and aim to provide the latest news to the public and are employed for ideological propaganda purposes [45]. Recently, the study of Li and Zhong [46] found that the frequency of using TV contributes to the generation of positive emotions. Hence, information disseminated from traditional media is inclined to be positive and extensive, which contributes to guiding proper public opinion. Moreover, the central and the local government are considered the most reliable and trustworthy information sources [47]. Consequently, traditional media is likely to deliver authoritative and positive content, which contributes to the alleviation of public panic after the Omicron outbreak. Based on the above arguments, we hypothesize the following:

Hypothesis 1a (H1a). *Great exposure to Omicron information in traditional media is negatively related to consumer's cognitive risk perception toward the epidemic.*

Hypothesis 1b (H1b). *Great exposure to Omicron information in traditional media is negatively related to consumer's affective risk perception toward the epidemic.*

Different from the one-way provider-to-audience communication of traditional media, social media represents a two-way communication between provider and user or user and user, which makes it more obtrusive than the traditional one [42,48]. Notably, the public tends to directly participate in discussing risk topics when traditional media cannot provide enough information. Hence, social media provides an available platform for a better understanding of the risk issue because risk communication would be highly efficient and effective when there is two-way communication [38]. From this view, more involvement in social media would benefit from controlling risk perception. Nonetheless, due to the rapid updating of news, social media also facilitates the spread of rumors and misinformation. Given the inherently fast information diffusion characteristic, the public may easily be subject to information overload problems when it comes to Internet sources, leading to confusion, stress, and even mistakes [49]. In addition, social media's risk information, specifically for epidemic information, is commonly framed in emotional

terms [39]. As to the Omicron situation, the outbreak of the novel coronavirus can easily trigger the public's consistent expression of negative emotions, such as fears, worries, and anxieties, mainly through social media. As Prentice et al. [50] noted, crowd psychology can be amplified through the fast information diffusion in social media, which finally has a significant impact on panic buying behaviors. The study of Li and Zhong [46] also confirms that perceptions of risk seriousness are primarily induced by their frequent adoption of online social media. Hence, the public frequently adopts social media to express emotional concerns and share epidemic information, which could finally amplify the public's risk perceptions. Accordingly, we hypothesize the following:

Hypothesis 2a (H2a). *Great exposure to Omicron information in social media positively relates to consumer's cognitive risk perception toward the epidemic.*

Hypothesis 2b (H2b). *Great exposure to Omicron information in social media positively relates to consumer's affective risk perception toward the epidemic.*

3.2. Risk Perception and Panic Buying Behavior

In the PADM framework, a person's perception of risk or threat determines his or her decision-making process after receiving and interpreting the risk information derived from outside, which thus finally shapes his or her protective response [13]. In this study, we assume that panic buying behavior, such as panic buying of functional products during the epidemic, could be regarded as a person's protective response as hoarding the daily necessities to staying at home and keeping "social distancing" has been identified by the government as a cost-effective way to prevent the transmission of the novel Omicron coronavirus [35]. Several previous studies on multiple risky situations have mostly detected a positive relationship between risk perceptions and the intention to adopt protective actions, including floods [19,51], hurricanes [52,53], earthquakes [54], terrorist attacks [55], product recalls [33], and health-related situations [18,32].

As a dual-process model of risk perception has been proposed, extant research has also empirically examined the cognitive and affective components of risk perceptions in affecting protective responses to various risk situations. For instance, Miceli et al. [56] investigated the effect of perceived flood risk on disaster preparedness. They found that only the affective appraisal of flood risk, measured by the feelings of worry, could positively influence disaster preparedness. Similarly, Terpstra [57] demonstrated that cognitive and affective routes of the perceived flood risk facilitate the residents' preparedness behavior. Altarawneh et al. [23] recently employed the dual-process risk perception model to predict the residents' flood preparedness intentions in Australia. Their findings also confirmed the positive effects of cognitive and affective dimensions of risk perceptions on protective behavioral intentions. Furthermore, Gaube et al. [20] examined the relationship between cognitive and affective aspects of perceived health risk and pro-health actions. They emphasized that arousing risk-related emotions improves health behaviors' effectiveness.

Concerning the Omicron epidemic, the coronavirus has been proven to be highly transmissible with an evident observable physical danger to human bodies [36]. Thus, an individual tends to cognitively assess whether the epidemic is catastrophic, fatal, reducible, and controllable and then decide to take protective behaviors, such as wearing a medical mask and home confinement. Suppose the individual perceives a high likelihood of being infected and susceptibility to being harmed by the coronavirus. In that case, he or she tends to implement "static management" as soon as possible. In addition, the epidemic that evokes negative emotions, for instance, dread, fear, and worries, would lead to an affective response, specifically when the Omicron variant is complex and dreadful. Hence, the cognitive and affective routes of perceived epidemic risks could result in impulsively and obsessively buying behaviors, which encouraged consumers to rush to stores or su-

permarkets overnight to buy products as the strict lockdown and seal-off management. Consequently, we postulate the following:

Hypothesis 3 (H3). *The cognitive risk perception is positively related to consumer's panic buying behavior during the Omicron pandemic.*

Hypothesis 4 (H4). *The affective risk perception is positively related to consumer's panic buying behavior during the Omicron pandemic.*

3.3. Stakeholder Perception and Panic Buying

The existing research has characterized stakeholders of a particular risk or hazard, including authorities such as provincial/local government officials, watchdogs such as media, industry, and households, and professionals such as doctors/health departments [32]. As a core perception in the PADM framework, stakeholders' perception refers to the public perception of expertise, trustworthiness, and protection responsibility [13,58,59]. Specifically, perceived expertise describes the degree of authoritative knowledge about the topic, while perceived trustworthiness reflects the willingness to precisely transmit hazard-related information [60]. Perceived protection responsibility denotes the cognitive evaluation of the extent to which the public believes other community stakeholders have an obligation to protect them from hazards. Hence, stakeholder perception captures how people detect the three attributes of risk information distributed by multiple channels [59].

The perception of stakeholders has been viewed as a critical determinant of compliance with the recommended protective actions [32,53,59]. Individuals receive hazard information or warnings through a variety of channels and sources, according to the PADM. This is especially important given the advent of social media and the abundance of outlets providing risk and hazard information. People tend to adopt the recommended protective actions when they detect that the hazard-related information has a high level of expertise, trustworthiness, and protection responsibility. Hazard adjustment activities, such as making emergency preparations and purchasing catastrophe insurance, are also widely classified as protective acts. From the perspective of the behavior of panic buying, consensus on the appearance of functional products shortage has not been identified at the initial stage of the Omicron pandemic. Since the "strict lockdown" policy in many cities in China leads to consumers engaging in panic buying products they don't need or hoarding much more than they need, performing impulsively buying behaviors has not been regarded as protective actions or viewed as over-protective behaviors [5], which the governments have persistently prohibited. In this regard, we assume that the probability that the public will engage in panic buying would be attenuated when they perceive a high level of expertise, trustworthiness, and protection responsibility from the stakeholders. Based on the above arguments, we hypothesize that:

Hypothesis 5 (H5). *Stakeholder perception is negatively related to consumer's panic buying behavior during the Omicron pandemic.*

3.4. Protective Perception and Panic Buying

Protective perception has been typically used to capture the perceived efficacies and beliefs that protective behavior is effective in alleviating the risk and that one can successfully act [13]. According to the PADM, two subcategories of protective perception, hazard-related and resource-related attributes, are identified when evaluating an individual's willingness to implement protective actions [12]. Hazard-related attributes emphasize the extent of people's perceived effectiveness of performing protective behaviors could mitigate the hazard, underlining the relationship between the hazard itself and hazard adjustment [14]. Hence, hazard-related attributes reflect people's perceived utility of hazard adjustment in protecting them from hazards. Different from hazard-related attributes that highlight the hazard itself, the notion of resource-related attributes is defined as people's perceived effort,

cost and knowledge requested to perform a protective action, emphasizing the relationship between required resources and the mitigation behaviors [57].

Both hazard-related attributes and resource-related attributes have been proven to be highly predictive of hazard adjustments [32,50]. People tend to have more confidence in taking actual protective behaviors when they detect a high level of hazard-related attributes [19]. Likewise, when people estimate a high level of resource demand, such as time, money, and exceptional knowledge, required to adopt hazard adjustments, they are more likely to express unwillingness to take actual protective behaviors. As to our study, considering panic buying after the outbreak of the Omicron pandemic can be regarded as an over-protective behavior, we assume that perceived hazard-related attributes contribute to the formation of panic buying intentions and actual behaviors. Furthermore, although the PADM depicts that resource-related attributes generally tend to be negatively associated with performing protective behaviors, we propose that a higher level of resource demand could result in more panic-buying behaviors because panic buying is typically characterized as impulsive purchasing or herding goods that are predictive of stock-out situations [6].

For instance, meat and vegetables were subjected to panic buying in China on May 2022. Meat prices have increased because supermarkets quickly ran out of meat and vegetables after the outbreak of the Omicron epidemic. However, consumers still could afford the increased retail price of meat, whereas the shortage was not a severe problem at the initial stage of the pandemic. In this regard, we assume that the probability that consumers will engage in panic buying, particularly for daily necessities, is dependent upon what they believe to be barriers preventing them from performing. Thus, we hypothesize that:

Hypothesis 6 (H6). *Protective perception is positively related to consumer's panic buying behavior during the Omicron pandemic.*

We summarize these hypotheses in Figure 1.

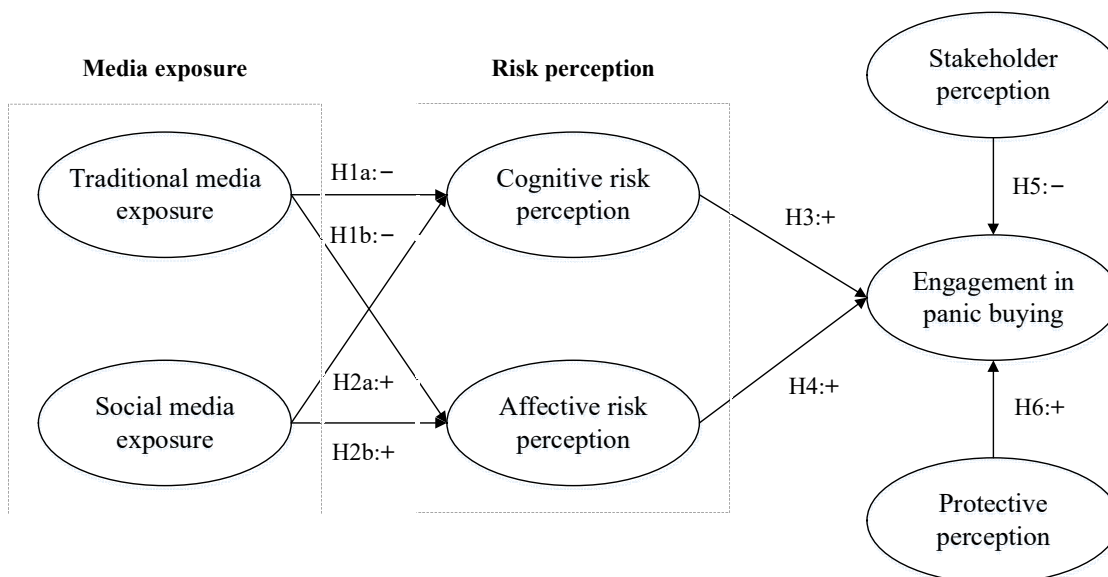


Figure 1. Conceptual Model.

4. Data and Methods

4.1. Sample and Data Collection

In response to the outbreak of the Omicron epidemic, the National Health Commission of China and the local governments have ordered a nationwide mobility restriction as an emergency measure to slow down the spread of the novel coronavirus. Conducting an offline survey to address our research questions due to the strict home confinement policy is infeasible. Hence, an online questionnaire survey was formally conducted by employing Wenjuanxing, the largest online questionnaire platform in China, to investigate

public panic buying status during the Omicron epidemic period in the east of China, including Anhui Province, Jiangsu Province, Shanghai City, and Zhejiang Province. We choose the Omicron epidemic in China as our research context for two reasons. First, China was initially subjected to the 2022 novel Omicron coronavirus disease, considering that some original Omicron cases were discovered and reported in Hongkong and Shanghai in February 2022. Then, cases were gradually reported in other provinces, including Shanghai, Guangdong, Hunan, Jiangsu, and Henan. In mid-June 2022, the reported incidence of the novel Omicron coronavirus disease cases in Shanghai exceeded 58,000 (<https://www.cn-healthcare.com/articlewm/20220623/content-1388631.html> accessed on 25 June 2022). Second, to prevent social contact and reduce Omicron transmissions, China has implemented unparalleled strict lockdown and seal-off management measures, such as closing restaurants and bars, shops, entertainment centers, and gymnasiums; prohibiting public gatherings, and advocating or imposing working from home. China was the first country to implement a lockdown to curb the spread of the Omicron disease across the country. On 29 March 2022, China's central government imposed a staggering seal-off lockdown in Shanghai city to quarantine the center of the Omicron outbreak. Hence, the complex and dreadful epidemic forces the residents, particularly those in areas with severe outbreaks, to rush to stores overnight to buy functional products due to the forthcoming nationwide shortage. Given this setting, China presents an ideal context for investigating the effect of media exposure and risk perception on panic buying behaviors.

A four-part online questionnaire was employed to collect data: (1) a brief introduction of our research and an appreciation to the respondents for their participation; (2) detailed items that are employed to capture the different scales of our key constructs; (3) additional questions that aim to obtain the demographics of the participants, for instance, age, education, work, household income, and the number of the confirmed case in the local place; (4) online lottery to thank for the respondents' participation. Then, we conducted our online survey from 1 May 2022 to 15 September 2022. We mainly focused on respondents who experienced panic buying products, such as meat, vegetables, functional products, basic cleaning products, and others. After the outbreak of the Omicron epidemic, those who had not experienced any panic buying activities were excluded according to their responses. In addition, we highlighted the academic uniqueness to eliminate the potential impacts of the online platform to strengthen the quality of the online survey.

Finally, 645 questionnaires were collected from the three provinces and one municipality located in the east of China. A total of 128 questionnaires were invalid because of the missing data and outliers, thereby leading to a response rate of approximately 80.2%. Table 1 presents the demographic information of the participants.

4.2. Measures

Manifold items originating from the existing research were adopted and slightly modified to match the Omicron variant context, as shown in the Appendix A. We measured each item using a five-point Likert scale (1 denotes strongly disagree and 5 denotes strongly agree). We adapted eight items from Lee [55] and Ng et al. [41] to measure the two types of media exposure. The traditional media exposure was captured by the degree to which the participants received the epidemic information from televisions, radio, and newspapers. Similarly, social media exposure was captured by the degree to which the participants received, commented, and transmitted the epidemic information through social media, such as WeChat, Weibo, Tencent, and so on. The criteria of Demuth et al. [61] and Trumbo [29] were employed to measure cognitive and affective risk perception. Cognitive risk perception included five items and was measured by asking the participants the extent to which they objectively evaluate the risk situations. Affective risk perception was adapted and measured by six items. The respondents were asked how much the epidemic makes them feel dreadful, fearful, worried, sad, anxious, and angry. In addition, stakeholder and protective perceptions were adapted from Liu et al. [32] and Wang et al. [59]. These measurements include three items for stakeholder perception and six for protective perception.

They were measured by asking the respondents to depict the extent to which they perceived that the other stakeholders (e.g., government officials, hospital doctors, experts) would protect them from the pandemic and which they can take action. Finally, the engagement in panic buying was measured by six items from impulsive buying and obsessive-compulsive buying that were adapted from Islam et al. [5] and Ridgway et al. [62].

Considering the potential impacts of the demographics of the respondents on their response strategies, we incorporated the respondent age, gender, income, and education in our SEM analysis to account for possible alternative explanations.

Table 1. Demographic profile of respondents.

	Variables	N	Percentage (%)
Age	Less Than 21	67	13.0%
	21~30	177	34.2%
	31~40	181	35.0%
	41~50	61	11.8%
	More Than 50	31	6.0%
Gender	Female	252	48.7%
	Male	265	51.3%
Income	Less Than ¥30,000	43	8.3%
	¥30,000–¥70,000	133	25.7%
	¥70,000–¥120,000	143	27.7%
	¥120,000–¥200,000	152	29.4%
	Over ¥200,000	46	8.9%
Education	Less Than High School	46	8.9%
	High School	124	24.0%
	Vocational School	96	18.6%
	College Graduate	183	35.4%
	Master or PhD	68	13.2%

5. Results

5.1. Reliability and Validity

A confirmatory factor analysis was performed by using AMOS to include all the scales in the model to assess measurement quality. The factor loading of all the scales is between 0.739 and 0.902, indicating an acceptable fit. The normed χ^2 (χ^2 to df, $\chi^2 = 786.379$, df = 610) is 1.289, lower than the benchmark value of 3.0. Furthermore, the SRMR scale is 0.028, lower than the benchmark value of 0.1. RMSEA scale is 0.024, lower than 0.08, thus displaying a suitable fit. Otherwise, both NFI = 0.941 and CFI = 0.986 are greater than 0.90. Common method bias was controlled through comparing the fit between the one-factor and measurement models, where the one-factor model yielded a worse fit than measurement model (χ^2 to df = 18.43, $\chi^2 = 6532.109$, df = 355, SRMR = 0.154, RMSEA = 0.212, NFI = 0.321, CFI = 0.221).

Construct validity in this study was tested using the average variance extracted (AVE), ranging from 0.675 to 0.808. All the AVE scores are above the desired value of 0.50. Thus, convergent validity is reached. As a result, we can postulate that our measurement model fits the data appropriately. Moreover, testing is also necessary for discriminant validity. We first use the constrained phi technique with confirmatory factor analysis (CFA) to evaluate the discriminant validity. Using this technique, two components are first successively limited to 1.0 (constrained CFA model) and then released (unconstrained CFA model). The research model's construct pairings are then tested against each other. The two models differ significantly in terms of Model Chi-squared statistics (χ^2), which suggests that the two constructs should be distinct. The Chi-squared statistics (χ^2) difference values for every conceivable pairing of constructs are shown in Table 2, which means that the discriminant validity of our study is good. In addition, the square roots of all the AVE scores for each construct are likewise calculated, and we discover that each of them is bigger than the correlations between all the constructs' absolute values (see Table 3).

Table 2. Assessment of discriminant validity.

Models	Constrained Model (Corr. = 1)		Unconstrained Model (Corr. = Free)		Chi-Square Difference ($\Delta\chi^2$)
	χ^2	df	χ^2	df	
TME-SME	1459.279	612	1122.829	611	336.450
TME-CP	1229.607	612	1007.993	611	221.614
TME-AP	1501.533	612	1143.956	611	357.577
TME-SP	1113.771	612	950.075	611	163.696
TME-PP	1413.497	612	1099.938	611	313.559
TME-EPB	1464.987	612	1125.683	611	339.304
SME-CP	1212.283	612	999.331	611	212.952
SME-AP	1163.939	612	975.159	611	188.780
SME-SP	1399.405	612	1092.892	611	306.513
SME-PP	1150.808	612	968.593	611	182.215
SME-EPB	1115.217	612	950.798	611	164.419
CP-SP	1263.497	612	1024.938	611	238.559
CP-AP	1210.595	612	998.487	611	212.108
CP-PP	1174.967	612	980.673	611	194.294
CP-EPB	1160.509	612	973.444	611	187.065
AP-SP	1457.307	612	1121.843	611	335.464
AP-PP	1210.085	612	998.232	611	211.853
AP-EPB	1182.963	612	984.671	611	198.292
SP-PP	1382.491	612	1084.435	611	298.056
SP-EPB	1438.895	612	1112.637	611	326.258
PP-EPB	1189.873	612	988.126	611	201.747

Notes: (1) TME: Traditional media exposure; SME: Social media exposure; CRP: Cognitive risk perception; ARP: Affective risk perception; EPB: Engagement in panic buying; SP: Stakeholder perception; PBC: Protective perception. (2) All $\Delta\chi^2$ tests are significant at $p < 0.001$ (critical χ^2 for 1 degree freedom at $p = 0.001$ is 3.84).

Furthermore, Table 3 demonstrates the descriptive statistics and the Pearson correlation coefficients among traditional media exposure, social media exposure, cognitive risk perception, affective risk perception, engagement in panic buying, subjective norm, and perceived behavior control. The results display low inter-correlations among these constructs, which suggests that multicollinearity is not a concern (Table 3).

5.2. Hypotheses Testing

Figure 2 displays the parameter estimates of the structural model analysis. SEM estimates were generated using AMOS, and the final results are shown in Table 4. The fitting indicators in our empirical model fit well (TLI = 0.978, CFI = 0.981, RMSEA = 0.028, SRMR = 0.060). The relationships among variables in the model were calculated and illustrated in Figure 2.

Table 3. Means, standard deviation and correlations.

Variables	Means	S.D.	1	2	3	4	5	6	7	8	9	10
1. Traditional media exposure	3.053	1.069	0.892									
2. Social media exposure	3.088	0.874	−0.237 **	0.851								
3. Cognitive risk perception	3.192	0.821	−0.021	0.126 **	0.822							
4. Affective risk perception	3.044	0.825	−0.216 **	0.294 **	0.215 **	0.822						
5. Engagement in panic buying	3.133	0.932	0.069	−0.138 **	−0.005	−0.137 **	0.833					
6. Stakeholder perception	2.992	0.834	−0.145 **	0.302 **	0.253 **	0.302 **	−0.063	0.899				
7. Protective perception	3.064	3.064	−0.222 **	0.303 **	0.222 **	0.299 **	−0.164 **	0.278 **	0.832			
8. Respondent age	2.636	2.636	0.028	−0.092 *	0.044	−0.027	−0.023	−0.054	0.047	NA		
9. Respondent gender	0.513	0.513	0.039	−0.049	−0.042	−0.072	0.063	−0.051	−0.056	0.020	NA	
10. Respondent income	3.048	3.048	−0.077	0.049	0.176 **	0.021	−0.093 *	0.034	0.070	0.054	−0.013	NA
11. Respondent education	3.199	3.199	0.067	0.019	0.062	−0.055	0.035	−0.002	−0.007	0.015	−0.003	0.064

Note: N = 517; Diagonal elements in bold represent the square root of AVE (average variance extracted) for each construct; * $p < 0.05$, ** $p < 0.01$.

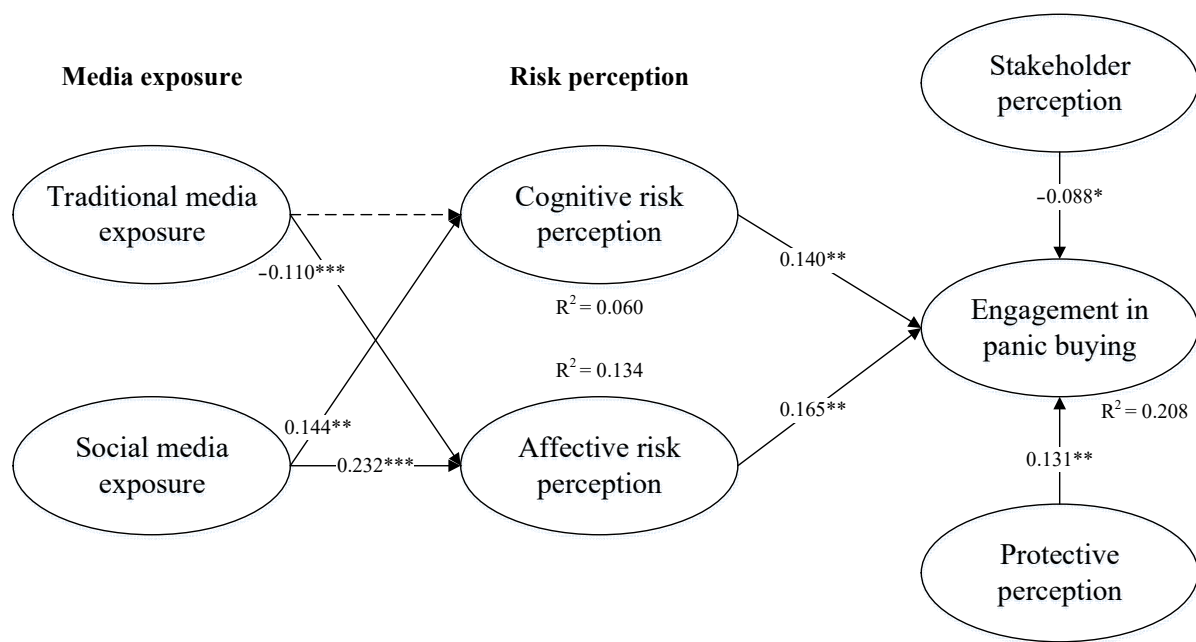


Figure 2. Structural equation model analysis results; Dotted lines indicate insignificant paths; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 4. Confirmatory factor analysis results.

Items	Factor Loading	S.E.	C.R.	<i>p</i>	Cronbach's Alpha	Composite Reliability	AVE
TME1	0.892	0.043	24.092	***	0.899	0.921	0.795
TME2	0.894	0.041	23.820	***			
TME3	0.888	-	-	-			
SME1	0.840	0.045	22.514	***	0.929	0.929	0.725
SME2	0.885	0.044	24.415	***			
SME3	0.854	0.044	24.415	***			
SME4	0.849	0.043	23.419	***			
SME5	0.827	-	-	-			
CP1	0.843	-	-	-	0.893	0.913	0.676
CP2	0.811	0.051	19.047	***			
CP3	0.838	0.049	19.560	***			
CP4	0.823	0.049	19.758	***			
CP5	0.796	0.049	18.217	***			
AP1	0.823	0.066	17.639	***	0.922	0.925	0.675
AP2	0.806	0.061	17.656	***			
AP3	0.851	0.065	18.734	***			
AP4	0.853	0.066	18.741	***			
AP5	0.850	0.066	18.281	***			
AP6	0.739	-	-	-			
SP1	0.902	-	-	-	0.893	0.927	0.808
SP2	0.901	0.039	23.271	***			
SP3	0.894	0.041	23.352	***			
PP1	0.822	0.063	18.956	***	0.929	0.931	0.693
PP2	0.836	0.059	19.320	***			
PP3	0.851	0.059	19.633	***			
PP4	0.866	0.061	19.262	***			
PP5	0.838	0.048	21.693	***			
PP6	0.779	-	-	-			

Table 4. Cont.

Items	Factor Loading	S.E.	C.R.	<i>p</i>	Cronbach's Alpha	Composite Reliability	AVE
EPB1	0.826	-	-	-			
EPB2	0.836	0.042	25.289	***			
EPB3	0.851	0.048	22.027	***	0.933	0.932	0.694
EPB4	0.866	0.049	22.691	***			
EPB5	0.838	0.049	21.101	***			
EPB6	0.779	0.050	18.114	***			

Notes: (1) TME: Traditional media exposure; SME: Social media exposure; CRP: Cognitive risk perception; ARP: Affective risk perception; EPB: Engagement in panic buying; SP: Stakeholder perception; PBC: Protective perception. (2) *** $p < 0.001$.

Inconsistent with H1a, traditional media exposure has a nonsignificant influence on cognitive risk perception but has expected a significantly negative effect on affective risk perception ($\beta = -0.110, p < 0.001$). Consistent with H2a and H2b, social media exposure has a significant positive impact on cognitive and affective aspects of risk perception, and the influence of social media exposure on affective risk perception ($\beta = 0.232, p < 0.001$) is larger than that on cognitive risk perception ($\beta = 0.144, p < 0.01$). Hence, our findings support H1b, H2a, and H2b but reject H1a. The results also show that both cognitive and affective dimensions of risk perceptions positively and directly affect engagement in panic buying, which are consistent with H3 and H4. We can also detect that affective risk perception ($\beta = 0.165, p < 0.01$) would be more strongly correlated with engagement in panic buying than cognitive risk perception ($\beta = 0.140, p < 0.01$) according to the regression coefficients. Therefore, H3 and H4 are strongly supported. Considering the significant negative effect of the stakeholder perception ($\beta = -0.088, p < 0.05$) and the significant positive effect of protective perception on consumer panic buying behaviors ($\beta = 0.131, p < 0.01$), H5 and H6 are both supported.

6. Discussion and Conclusions

6.1. Discussion

This study aims to examine the factors that motivate individuals to take radical protective actions by engaging in mass panic buying during the Omicron pandemic. The proposed PADM framework can be viewed as a decision-making process, which makes our model comprised of four parts: (1) external information cues (traditional and social media exposure), (2) individual's psychology appraisal of the threats (cognitive and affective risk perception), (3) antecedents of behavioral intentions (stakeholder perception and protective perception), and (4) engagement in panic buying behavior.

Media exposure describes how individuals acquire epidemic information from multiple channels and have been proven to be of great significance for understanding people's risk perceptions [38,44]. As demonstrated by the structural relationship analysis, our study argues that two channels of media exposure shape consumers' risk perceptions toward the Omicron epidemic. Nonetheless, the effects of these information channels on risk perceptions are different. Specifically, our findings reveal that traditional media exposure significantly negatively affected affective risk perception, but its impact on cognitive risk perception was not significant. Given that the governments primarily operate traditional media for ideological propaganda, the governments constantly emphasize the official rhetoric of "Omicron being under control" through the traditional media to sustain socioeconomic stability. Hence, traditional media helped break down the level of adverse public emotions by disseminating such positive information to alleviate people's panic psychology. Meanwhile, the ideological propaganda characteristic of traditional media in China could not decrease public cognitive-based risk perception toward the Omicron pandemic, given that seldom negative information would be released via TV, radio, and newspaper. Hence, the effect of traditional media exposure on the cognitive aspect of risk perception is insignificant.

Our study concludes that exposure to epidemic information on social media increases Chinese people's cognitive and affective aspects of risk perception toward the Omicron epidemic, which keeps consistent with the existing studies [39,63]. Notably, social media exposure exerts more effect on the affective dimension than on the cognitive scale of risk perception. The Omicron pandemic is a highly transmissible, visible, and harmful pandemic, making it readily discussed and shared immediately on the social network. In this regard, social media acts as a platform for people to socialize and for individuals and public organizations to exchange epidemic information [4]. For example, the famous expert Wenhong Zhang holds Weibo accounts to communicate health knowledge and epidemic information with the public. Chinese consumers who are involved in the social network are likely to have an increased awareness of epidemic prevention and intervention strategies by communicating and commenting on the epidemic information. This event contributes to their improved cognitive and affective assessment of epidemic risk. In addition, our findings also confirm that social media could act as an underlying driver of negative emotions, for instance, worry, fear, sadness, and anger, due to the rapid spread of misinformation and rumor via the social network.

People's risk perception of the epidemic is critical to predicting their protective behaviors. As expected, we detect that cognitive (severity, likelihood) and affective (anticipated negative emotions) appraisals of individuals' perceived Omicron epidemic risk lead to decisions regarding panic buying behaviors. Similarly, we also find that affective risk perception tends to have a more substantial predictive power than cognitive appraisal. These findings are not only in line with prior studies that repeatedly emphasize a dual-process approach to risk perception [23–25] but are also consistent with studies demonstrating that affective component of risk perception matters in predicting health-related behaviors [20,41]. Notably, we focus on people's panic buying behavior, particularly for functional products, where the entire country is subjected to the Omicron pandemic. This event also means panic buying behavior can be regarded as excessively protective. As aforementioned, our results support the argument that Omicron epidemic information dissemination through social media channels overwhelms individuals' cognitive assessment of the actual epidemic risk, thus resulting in an uncontrollable amount of negative emotions, for instance, fear, sadness, worry, and among others. The widespread of the novel coronavirus, which is characteristic of "out of control" in the initial stage, could have stimulated individuals to process the epidemic information more heuristically rather than cognitively evaluating the risk. Thus, affective risk perception is likely to lead to engagement in panic buying.

Stakeholder perception can be viewed as a reflection of trustworthiness, expertise, and protection responsibility about information sources in which individuals are confident to adjust their behaviors. Although the PADM and echo the results of the existing research [32,53] have demonstrated that perceived trustworthiness, expertise, and protective responsibility are significantly predictive of protective behaviors, our results suggest that perception of stakeholder contributes to the alleviation of panic travels during the pandemic. A plausible explanation is that trustworthiness, expertise, and protective responsibility have become extremely important due to the widespread horrific epidemic. The accuracy and reliability of governmental sources could weaken panic behaviors. Hence, building the perception of trustworthiness, expertise, and responsibility on the central/local government officials and health department experts may expressively reduce people's readiness to panic buy or hoard products.

Furthermore, our research also illustrates a positive effect of protective perception on panic buying behavior. Chinese residents have begun to realize the horrible transmission speed of the virus after the pandemic outbreak, and there is a growing awareness that self-protective consciousness will contribute to buying impulsively and obsessively. Hence, hazard-related attributes of the Omicron pandemic seem to lead consumers to panic buying behaviors that they might mistake as protective actions. The peer pressure through word-of-mouth derived from significant referents likely contributes to the conformance in the stockpile of products, thus stimulating them to rush to stores overnight to buy.

Likewise, consumers' panic buying behaviors are also influenced by resource-related attributes. Different from the past research that claimed a negative impact of resource-related attributes on behaviors, required efforts or costs associated with hoarding functional products, for example, increased purchasing price, long waiting time, and uncertainties related to outside activities appear to not be barriers for panic buying behaviors in the context of Omicron pandemic.

6.2. Contributions and Implications

Our study extends research on panic buying behaviors and risk analysis of the Omicron epidemic in several ways. First, in responding to the call for additional attention on the COVID-19 variant and risk analysis [64], our research on panic buying behavior that was globally witnessed after the outbreak of the epidemic contributes to the risk analysis studies. As a comparatively unexplored area in consumer behavior study, consumer panic buying behavior tends to be explained with traditional behavioral theories. However, it might not be appropriate to apply in the Omicron epidemic context. Consequently, based on risk perceptions, we are among the first to examine the antecedents of panic purchasing decisions during the Omicron epidemic. Second, we expand the existing risk perception study that has focused on the cognitive aspect (e.g., likelihood, perceived severity). Prior to our study, the early risk perception research featured an affective component of risk perception by shedding light on individuals' feelings of risk, which has received limited attention. The existing research has emphasized the role of emotions in shaping the effectiveness of risk perception in predicting the adoption of protective behaviors [24–26]. Therefore, our study answers the call for risk perception study as a dual-process model in multiple risk situations. Remarkably, our results imply that affective risk perception considerably influences consumers' panic buying behavior during the epidemic, thus contributing to this literature by providing a comprehensive view of risk perception during the epidemic. Third, our study lends support to the PADM as a valid theoretical framework in explaining a new but "problematic" behavioral category (e.g., panic buying) in a dreaded, novel, unfamiliar context (e.g., the Omicron pandemic). The PADM illustrates its explanatory utility in the novel coronavirus epidemic context, whereas it also displays its application in predicting radical protective behaviors in the epidemic context, albeit the stakeholder perception is a negative and significant predictor. The application of PADM in impulsively and obsessively buying is noteworthy because the Omicron epidemic remains understudied from the risk communication and behavioral perspectives.

Practically, as an excessive protective behavior toward the Omicron epidemic, the status of panic buying behavior (e.g., foods, basic cleansing products) could be alleviated by adjusting consumers' risk perception and risk communication. Accordingly, a better understanding of how consumers' perceived epidemic risk has been amplified or attenuated by multiple external factors, including traditional and social media exposure, enables policymakers to precisely manage public risk perception and thus, protective actions. Our results suggest that triggering Omicron-related emotions can increase public intentions to engage in panic buying. Moreover, the usage of traditional media (or other media channels that mainly transmit trustworthy messages or news regarding the Omicron epidemic in other contexts) to release epidemic information is an effective way to alleviate negative emotions in China. Therefore, more pandemic-related scientific information should be primarily disseminated through the authoritative media, for instance, TV, radio, and newspaper as the traditional media in the Chinese context, to correct public misperceptions, enhance public confidence in "Omicron being under control," and normative belief of self-protective actions. Moreover, as social media is likely to be inundated with misinformation and rumors, campaigns should be implemented to help the public identify inaccurate information through deliberating thinking, adequate epidemic information seeking, and processing. As such, governments and public medical and health organizations should take responsibility for improving the epidemic information accuracy and decreasing the rumors, which thus contributes to enhancing risk communication effects.

7. Limitations and Research Prospect

This research also has several limitations, which may open avenues for future research. First, we have elaborately surveyed media exposure and people's cognitive and affective risk perception toward the Omicron epidemic and have investigated the influence of stakeholder perception and protective perception on the panic buying phenomenon. However, we have not examined the perceived scarcity of such products in such a situation. As perceived scarcity is a strong predictor of panic buying [6], perceived scarcity does not appear in our research model because our analysis is primarily based on the PADM framework. Hence, the incorporation of perceived scarcity should be meticulously investigated in future research. Second, although we take cross-sectional data to examine the proposed conceptual model, multi-wave survey data with time lags tend to be more acceptable for the specific context because the impact of media exposure on risk perception requires gradual processes. Finally, although China has initially been subjected to the Omicron pandemic, our empirical context is focused on the Chinese context, which might limit the universality of the findings. Our findings should be expanded to other economies that have also witnessed a similar influx of the Omicron pandemic (e.g., the United States, Spain, and Italy). Thus, future research may examine the robustness of our conclusions in other countries.

Author Contributions: Writing—original draft, Y.Y.; Writing—review & editing, H.R.; Supervision, H.Z. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by the National Natural Science Foundation of China grants (#72002102), Fundamental Research Funds for the Central Universities (#30920010017), Initial Research Funds for Young Teachers of Nanjing University of Science and Technology (#JGQN2004), and the Postgraduate Research & Practice Innovation Program of Jiangsu Province, Grant Numbers: KYCX22_0567.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: Not applicable.

Conflicts of Interest: The authors declare no conflict of interest.

Appendix A. Measurement Items

Traditional media exposure

TME1. After the outbreak of Omicron, I received information about the epidemic mainly through television news.

TME2. After the outbreak of Omicron, I received information about the epidemic mainly through the radio.

TME3. After the outbreak of Omicron, I received information about the epidemic mainly through newspapers.

Social media exposure

SME1. After the outbreak of Omicron, I saw many pictures regarding the epidemic being shared on my social media, such as WeChat, Weibo, Tencent, etc.

SME2. After the outbreak of Omicron, many people on my online social network frequently posted status updates about the epidemic on their Wechat, Weibo, Tencent, etc.

SME3. After the outbreak of Omicron, I saw many posts that related to health information about the epidemic that people shared on my social network.

SME4. After the outbreak of Omicron, I saw many people commenting on others' status updates about the epidemic.

SME5. After the outbreak of Omicron, many people on my online social network shared links that were related to the epidemic on their Wechat, Weibo, Tencent, etc.

Cognitive risk perception

CRP1. It is likely that the Omicron variant will bring about widespread health problems.

CRP2. If I do not quarantine, I will likely be personally affected by the Omicron variant.

CRP3. I do not currently think the Omicron variant presents any threat to me (reverse scored).

CRP4. I believe that the danger posed by the Omicron variant is considerable.

CRP5. I think the potential impact of the Omicron variant is significant.

Affective risk perception

ARP1. In thinking about the widespread Omicron variant, I feel dread.

ARP2. In thinking about the widespread Omicron variant, I feel fearful.

ARP3. In thinking about the widespread Omicron variant, I feel worried.

ARP4. In thinking about the widespread Omicron variant, I feel sad.

ARP5. In thinking about the widespread Omicron variant, I feel angry.

ARP6. In thinking about the widespread Omicron variant, I feel anxious.

Stakeholder perception

SP1. Local community doctors/local city or state hospital doctors/local health department personnel/provincial or national public health department personnel/local government officials are knowledgeable about the Omicron pandemic.

SP2. Local community doctors/local city or state hospital doctors/local health department personnel/provincial or national public health department personnel/local government officials are willing to provide me with accurate information on the Omicron pandemic.

SP3. Local community doctors/local city or state hospital doctors/local health department personnel/provincial or national public health department personnel/local government officials are responsible for protecting me from the Omicron pandemic.

Protective perception

PP1. To what extent you would think panic buying or hoarding daily necessities help me reduce the Omicron pandemic risk?

PP2. To what extent would you think panic buying or hoarding daily necessities be helpful in protecting me from the Omicron pandemic?

PP3. To what extent you would think panic buying or hoarding daily necessities would cost a lot of money?

PP4. To what extent you would think panic buying or hoarding daily necessities would require a lot of effort or time?

PP5. To what extent you would think panic buying or hoarding daily necessities would require specialized knowledge?

PP6. To what extent you would think panic buying or hoarding daily necessities would require a lot of cooperation from others?

Engagement in panic buying

EPB1. My home has enough daily necessities and medical supplies.

EPB2. Others might consider me a “shopaholic”.

EPB3. Much of my life centers around buying things.

EPB4. After the outbreak of Omicron, I buy things I don’t need regarding epidemic prevention and control.

EPB5. After the outbreak of Omicron, I bought things I did not plan to buy regarding epidemic prevention and control.

EPB6. After the outbreak of Omicron, I consider myself an impulse purchaser regarding epidemic prevention and control.

References

1. Grabowski, F.; Kocharczyk, M.; Lipniacki, T. The spread of SARS-CoV-2 variant Omicron with a doubling time of 2.0–3.3 days can be explained by immune evasion. *Viruses* **2022**, *14*, 294. [CrossRef] [PubMed]
2. Mefsin, Y.; Chen, D.; Bond, H.S.; Lin, Y.; Cheung, J.K.; Wong, J.Y.; Ali, S.T.; Lau, E.H.Y.; Wu, P.; Leung, G.M.; et al. Epidemiology of infections with SARS-CoV-2 Omicron BA. 2 variant in Hong Kong, January–March 2022. *Emerg. Infect. Dis.* **2022**, *28*, 1856–1858. [CrossRef] [PubMed]
3. People’s Daily Online. China’s Quest for New Ways to Handle Omicron. Available online: <http://en.people.cn/n3/2022/0329/c90000-10077212.html> (accessed on 7 May 2022).

4. Yang, Q.C.; Yang, F.; Zhou, C. What health-related information flows through you every day? A content analysis of microblog messages on air pollution. *Health Educ.* **2015**, *115*, 438–454. [\[CrossRef\]](#)
5. Islam, T.; Pitaifi, A.H.; Arya, V.; Wang, Y.; Akhtar, N.; Mubarik, S.; Xiaobei, L. Panic buying in the COVID-19 pandemic: A multi-country examination. *J. Retail. Consum. Serv.* **2021**, *59*, 102357.
6. Yuen, K.F.; Wang, X.; Ma, F.; Li, K.X. The Psychological Causes of Panic Buying Following a Health Crisis. *Int. J. Environ. Res. Public Health* **2020**, *17*, 3513. [\[CrossRef\]](#)
7. Ding, H. Rhetorics of alternative media in an emerging epidemic: SARS, censorship, and extra-institutional risk communication. *Tech. Commun. Q.* **2009**, *18*, 327–350. [\[CrossRef\]](#)
8. Leung, C.C.; Lam, T.H.; Cheng, K.K. Mass masking in the COVID-19 epidemic: People need guidance. *Lancet* **2020**, *395*, 945. [\[CrossRef\]](#)
9. Omicron Makes Hong Kong's 'COVID-Zero' Unworkable. Available online: <https://dailybrief.oxan.com/Analysis/DB267975/Omicron-makes-Hong-Kongs-COVID-zero-unworkable> (accessed on 16 March 2022).
10. Wesseler, J. Storage policies: Stockpiling versus immediate release. *J. Agric. Food Ind. Organ.* **2020**, *18*, 20190055. [\[CrossRef\]](#)
11. Zheng, R.; Shou, B.; Yang, J. Supply disruption management under consumer panic buying and social learning effects. *Omega* **2020**, *101*, 102238. [\[CrossRef\]](#)
12. Lindell, M.K.; Perry, R.W. *Communicating Environmental Risk in Multiethnic Communities*; Sage Publications: London, UK, 2003; Volume 7.
13. Lindell, M.K.; Perry, R.W. The protective action decision model: Theoretical modifications and additional evidence. *Risk Anal. Int. J.* **2012**, *32*, 616–632. [\[CrossRef\]](#)
14. Lindell, M.K.; Perry, R.W. *Behavioral Foundations of Community Emergency Planning*; Hemisphere Publishing Corp: Washington, DC, USA, 1992.
15. Trumbo, C.W. Communicating the significance of risk. In *Communication and Engagement with Science and Technology: Issues and Dilemmas*; Gilbert, J.K., Stocklmayer, Routledge, S.M., Eds.; Taylor & Francis Group: New York, NY, USA, 2013.
16. Birkholz, S.; Muro, M.; Jeffrey, P.; Smith, H.M. Rethinking the relationship between flood risk perception and flood management. *Sci. Total Environ.* **2014**, *478*, 12–20. [\[CrossRef\]](#)
17. Brewer, N.T.; Chapman, G.B.; Gibbons, F.X.; Gerrard, M.; McCaul, K.D.; Weinstein, N.D. Meta-analysis of the relationship between risk perception and health behavior: The example of vaccination. *Health Psychol.* **2007**, *26*, 136. [\[CrossRef\]](#)
18. Meyer, R.; Broad, K.; Orlove, B.; Petrovic, N. Dynamic simulation as an approach to understanding hurricane risk response: Insights from the Stormview lab. *Risk Anal.* **2013**, *33*, 1532–1552. [\[CrossRef\]](#)
19. Terpstra, T.; Lindell, M.K. Citizens' perceptions of flood hazard adjustments: An application of the protective action decision model. *Environ. Behav.* **2013**, *45*, 993–1018. [\[CrossRef\]](#)
20. Gaube, S.; Lerner, E.; Fischer, P. The concept of risk perception in health-related behavior theory and behavior change. In *Perceived Safety*; Springer: Cham, Switzerland, 2019; pp. 101–118.
21. Horney, J.A.; MacDonald, P.D.; Van Willigen, M.; Berke, P.R.; Kaufman, J.S. Individual actual or perceived property flood risk: Did it predict evacuation from Hurricane Isabel in North Carolina, 2003? *Risk Anal. Int. J.* **2010**, *30*, 501–511. [\[CrossRef\]](#)
22. Loewenstein, G.F.; Weber, E.U.; Hsee, C.K.; Welch, N. Risk as feelings. *Psychol. Bull.* **2001**, *127*, 267. [\[CrossRef\]](#)
23. Altarawneh, L.; Mackee, J.; Gajendran, T. The influence of cognitive and affective risk perceptions on flood preparedness intentions: A dual-process approach. *Procedia Eng.* **2018**, *212*, 1203–1210. [\[CrossRef\]](#)
24. Slovic, P.; Finucane, M.L.; Peters, E.; MacGregor, D.G. Risk as analysis and risk as feelings: Some thoughts about affect, reason, risk, and rationality. *Risk Anal. Int. J.* **2004**, *24*, 311–322. [\[CrossRef\]](#)
25. Van der Linden, S. On the relationship between personal experience, affect and risk perception: The case of climate change. *Eur. J. Soc. Psychol.* **2014**, *44*, 430–440. [\[CrossRef\]](#)
26. Trumbo, C.W.; Peek, L.; Meyer, M.A.; Marlatt, H.L.; Grunfest, E.; McNoldy, B.D.; Schubert, W.H. A cognitive-affective scale for hurricane risk perception. *Risk Anal.* **2016**, *36*, 2233–2246. [\[CrossRef\]](#)
27. Epstein, S. Integration of the cognitive and the psychodynamic unconscious. *Am. Psychol.* **1994**, *49*, 709. [\[CrossRef\]](#)
28. Nerb, J.; Spada, H. Evaluation of environmental problems: A coherence model of cognition and emotion. *Cogn. Emot.* **2001**, *15*, 521–551. [\[CrossRef\]](#)
29. Trumbo, C.W. Influence of risk perception on attitudes and norms regarding electronic cigarettes. *Risk Anal.* **2018**, *38*, 906–916. [\[CrossRef\]](#) [\[PubMed\]](#)
30. Becker, J.S.; Paton, D.; Johnston, D.M.; Ronan, K.R. Salient beliefs about earthquake hazards and household preparedness. *Risk Anal.* **2013**, *33*, 1710–1727. [\[CrossRef\]](#) [\[PubMed\]](#)
31. Lazo, J.K.; Bostrom, A.; Morss, R.E.; Demuth, J.L.; Lazrus, H. Factors affecting hurricane evacuation intentions. *Risk Anal.* **2015**, *35*, 1837–1857. [\[CrossRef\]](#) [\[PubMed\]](#)
32. Liu, Y.; Ouyang, Z.; Cheng, P. Predicting consumers' adoption of electric vehicles during the city smog crisis: An application of the protective action decision model. *J. Environ. Psychol.* **2019**, *64*, 30–38. [\[CrossRef\]](#)
33. Wei, J.; Zhao, M.; Wang, F.; Cheng, P.; Zhao, D. An empirical study of the Volkswagen crisis in China: Customers' information processing and behavioral intentions. *Risk Anal.* **2016**, *36*, 114–129. [\[CrossRef\]](#)
34. World Health Organization. *Infection Prevention and Control during Health Care When Novel Coronavirus (nCoV) Infection is Suspected: Interim Guidance*, 25 January 2020; World Health Organization: Geneva, Switzerland, 2020.

35. Yang, H.; Nie, H.; Zhou, D.; Wang, Y.; Zuo, W. The effect of strict lockdown on Omicron SARS-CoV-2 variant transmission in Shanghai. *Vaccines* **2022**, *10*, 1392. [\[CrossRef\]](#)
36. Wu, J.T.; Leung, K.; Leung, G.M. Nowcasting and forecasting the potential domestic and international spread of the 2019-nCoV outbreak originating in Wuhan, China: A modelling study. *Lancet* **2020**, *395*, 689–697. [\[CrossRef\]](#)
37. Kasperson, R.E.; Renn, O.; Slovic, P.; Brown, H.S.; Emel, J.; Goble, R.; Ratick, S. The social amplification of risk: A conceptual framework. *Risk Anal.* **1988**, *8*, 177–187. [\[CrossRef\]](#)
38. Vyncke, B.; Perko, T.; Van Gorp, B. Information sources as explanatory variables for the Belgian health-related risk perception of the Fukushima nuclear accident. *Risk Anal.* **2017**, *37*, 570–582. [\[CrossRef\]](#)
39. Oh, S.H.; Lee, S.Y.; Han, C. The effects of social media use on preventive behaviors during infectious disease outbreaks: The mediating role of self-relevant emotions and public risk perception. *Health Commun.* **2021**, *36*, 972–981. [\[CrossRef\]](#)
40. Fung, T.K.; Namkoong, K.; Brossard, D. Media, social proximity, and risk: A comparative analysis of newspaper coverage of avian flu in Hong Kong and in the United States. *J. Health Commun.* **2011**, *16*, 889–907. [\[CrossRef\]](#)
41. Ng, Y.J.; Yang, Z.J.; Vishwanath, A. To fear or not to fear? Applying the social amplification of risk framework on two environmental health risks in Singapore. *J. Risk Res.* **2018**, *21*, 1487–1501. [\[CrossRef\]](#)
42. Han, G.; Zhang, J.; Chu, K.; Shen, G. Self-other differences in H1N1 flu risk perception in a global context: A comparative study between the United States and China. *Health Commun.* **2014**, *29*, 109–123. [\[CrossRef\]](#)
43. Niu, C.; Jiang, Z.; Liu, H.; Yang, K.; Song, X.; Li, Z. The influence of media consumption on public risk perception: A meta-analysis. *J. Risk Res.* **2022**, *25*, 21–47. [\[CrossRef\]](#)
44. Koné, D.; Mullet, E. Societal risk perception and media coverage. *Risk Anal.* **1994**, *14*, 21–24. [\[CrossRef\]](#)
45. Heilmann, S. (Ed.) *China's Political System*; Rowman & Littlefield: Washington, DC, USA, 2016.
46. Li, P.P.; Zhong, F. A Study on the Correlation Between Media Usage Frequency and Audiences' Risk Perception, Emotion and Behavior. *Front. Psychol.* **2021**, *12*, 822300. [\[CrossRef\]](#)
47. Chen, Y.; Ji, H.; Chen, L.J.; Jiang, R.; Wu, Y.N. Food safety knowledge, attitudes and behavior among dairy plant workers in Beijing, northern China. *Int. J. Environ. Res. Public Health* **2018**, *15*, 63. [\[CrossRef\]](#)
48. Kolbitsch, J.; Maurer, H.A. The transformation of the Web: How emerging communities shape the information we consume. *J. UCS* **2006**, *12*, 187–213.
49. Cheng, P.; Ouyang, Z.; Liu, Y. The effect of information overload on the intention of consumers to adopt electric vehicles. *Transportation* **2020**, *47*, 2067–2086. [\[CrossRef\]](#)
50. Prentice, C.; Quach, S.; Thaichon, P. Antecedents and consequences of panic buying: The case of COVID-19. *Int. J. Consum. Stud.* **2022**, *46*, 132–146. [\[CrossRef\]](#)
51. Scovell, M.; McShane, C.; Swinbourne, A.; Smith, D. Applying the Protective Action Decision Model to Explain Cyclone Shelter Installation Behavior. *Nat. Hazards Rev.* **2020**, *22*, 04020043. [\[CrossRef\]](#)
52. Huang, S.K.; Lindell, M.K.; Prater, C.S. Multistage model of hurricane evacuation decision: Empirical study of Hurricanes Katrina and Rita. *Nat. Hazards Rev.* **2017**, *18*, 05016008. [\[CrossRef\]](#)
53. Wachinger, G.; Renn, O.; Begg, C.; Kuhlicke, C. The risk perception paradox—Implications for governance and communication of natural hazards. *Risk Anal.* **2013**, *33*, 1049–1065. [\[CrossRef\]](#) [\[PubMed\]](#)
54. Lindell, M.K.; Whitney, D.J. Correlates of household seismic hazard adjustment adoption. *Risk Anal.* **2000**, *20*, 13–26. [\[CrossRef\]](#) [\[PubMed\]](#)
55. Lee, J.E.; Lemyre, L. A social-cognitive perspective of terrorism risk perception and individual response in Canada. *Risk Anal. Int. J.* **2009**, *29*, 1265–1280. [\[CrossRef\]](#)
56. Miceli, R.; Sotgiu, I.; Settanni, M. Disaster preparedness and perception of flood risk: A study in an alpine valley in Italy. *J. Environ. Psychol.* **2008**, *28*, 164–173. [\[CrossRef\]](#)
57. Terpstra, T. Emotions, trust, and perceived risk: Affective and cognitive routes to flood preparedness behavior. *Risk Anal. Int. J.* **2011**, *31*, 1658–1675. [\[CrossRef\]](#)
58. Siegrist, M.; Gutscher, H. Flooding risks: A comparison of lay people's perceptions and expert's assessments in Switzerland. *Risk Anal.* **2006**, *26*, 971–979. [\[CrossRef\]](#)
59. Wang, F.; Wei, J.; Shi, X. Compliance with recommended protective actions during an H7N9 emergency: A risk perception perspective. *Disasters* **2018**, *42*, 207–232. [\[CrossRef\]](#)
60. Kruglanski, A.W.; Stroebe, W. The Influence of Beliefs and Goals on Attitudes: Issues of Structure, Function, and Dynamics. In *The Handbook of Attitudes*; Albarracín, D., Johnson, B.T., Zanna, M.P., Eds.; Erlbaum: Mahwah, NJ, USA, 2005; pp. 323–368.
61. Demuth, J.L.; Morss, R.E.; Lazo, J.K.; Trumbo, C. The effects of past hurricane experiences on evacuation intentions through risk perception and efficacy beliefs: A mediation analysis. *Weather Clim. Soc.* **2016**, *8*, 327–344. [\[CrossRef\]](#)
62. Ridgway, N.M.; Kukar-Kinney, M.; Monroe, K.B. An expanded conceptualization and a new measure of compulsive buying. *J. Consum. Res.* **2008**, *35*, 622–639. [\[CrossRef\]](#)
63. Choi, D.H.; Yoo, W.; Noh, G.Y.; Park, K. The impact of social media on risk perceptions during the MERS outbreak in South Korea. *Comput. Hum. Behav.* **2017**, *72*, 422–431. [\[CrossRef\]](#)
64. Haas, C. Coronavirus and risk analysis. *Risk Anal.* **2020**, *40*, 660. [\[CrossRef\]](#)