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Relationship between Risk Perception, Emotion, and Coping Behavior during Public Health Emergencies: A Systematic Review and Meta-Analysis

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Abstract: Complex mechanisms exist between public risk perception, emotions, and coping behaviors during health emergencies. To unravel the relationship between these three phenomena, a meta-analytic approach was employed in this study. Using Comprehensive Meta-Analysis 3.0, 81 papers were analyzed after selection. The results of the meta-analysis showed that (1) risk perception (perceived severity, perceived susceptibility) and negative emotions (especially fear) are both correlated with coping behaviors; (2) risk perception is strongly correlated with fear and moderately correlated with anxiety; and (3) anxiety predicts the adoption of coping behaviors. The existing research provided an empirical basis for implementing effective coping behavior interventions and implied that management decisionmakers need to consider reasonable interventions through multiple channels to maintain the public's risk perception and emotions within appropriate levels. Finally, future research directions are suggested.

Keywords: meta-analysis; public health emergency; risk perception; emotion; behavior

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1. Introduction

In December 2019, multiple cases of an unknown form of pneumonia were reported, which were later confirmed to be caused by novel coronavirus (COVID-19) infections. COVID-19 has spread to many countries around the world and has been recognized by the World Health Organization as a global pandemic. In addition to the novel coronavirus outbreak, many other public health events have occurred or are occurring in various countries, such as SARS, Ebola, H1N1, and H7N9 outbreaks. Globally, for the period from January 2020 to December 2021, the World Health Organization estimates that there were 14.83 million excess deaths associated with the COVID-19 pandemic [1]. During the 2009 influenza A (H1N1) pandemic, there were an estimated 201,200 deaths worldwide due to respiratory diseases [2]. Illness and death caused by infectious diseases have exerted a huge burden and negative impact on the world.

Epidemics and pandemics pose a threat to public health, and the uncertainty and hazards associated with such events often cause negative emotions such as public panic, anxiety, and nervousness. Excessive public panic and anxiety can lead to irrational snap behavior [3]. Individuals can even develop mental health problems such as stress disorders, depression, and suicidal behavior [4,5]. Risk perception is considered to be the key factor affecting mood. The higher the risk perception of an individual is, the stronger the impact it has on one's mental health, leading to the development of negative emotions such as fear and anxiety [6].

In the face of a public health event, before vaccines and preventive medicines are developed and produced, the public adopts a range of nonpharmaceutical interventions, such as washing hands, using masks, and avoiding public transportation. These protective behaviors are simple, inexpensive, and effective in minimizing the spread and impact of diseases. High levels of public support, participation, and cooperation relating to health-protective behaviors are key to overcoming an epidemic or pandemic [7]. Research on health behaviors suggests that risk perception is central to determining individual preventive behaviors. Risk communication forms the basis of risk perception, which facilitates the formation of accurate knowledge and enables the practice of preventive behaviors [8,9]. In addition, studies have shown that emotions are an important factor in decision-making processes among individuals [10,11]. In the context of a public health event, the public may develop negative emotions such as fear and anxiety, and these negative emotions increase the implementation of preventive behaviors [12,13].

As noted above, individuals' risk perception, emotional states, and coping behaviors are related to their own physical and mental health and then to the normal functioning of society. Coping behavior is directly related to controlling the spread of the outbreak. Individual factors contribute to their correct coping decisions, notably risk perception and emotion [14,15]. Understanding the public's cognitive and perceptual patterns is important for guiding prevention programs and mental health communications. Media exposure, government intervention, etc., affect the psychology, perceptions, and behavior of individuals [16,17]. It is necessary to examine the current state of public perception and identify the gap between it and the actual situation regarding the development of pandemics. For this purpose, many scholars have applied Protection Motivation Theory (PMT); Knowledge, Attitude, and Practice (KAP); Health Belief Model (HBM); and other health behavior change theories to conduct several studies on public risk perception, emotions, and coping behaviors, which provide a basis for national decisionmakers to adopt precise prevention and control strategies, including health education, for the public [18–23]. The research is based on public perceptions of risk, emotions, and coping behaviors. Cross-sectional surveys have been used to understand the performance of the public in terms of risk perception, emotions, and coping behaviors and the relationship between them.

Each survey is independent and decentralized, ranging from targeting a small group of people engaged in a particular career in a city to a nationwide sample of people. Although such studies can provide good guidance in the short term, there are limitations due to their sample size and regional limitations. Inconsistent findings exist in numerous studies. For example, Wang et al. concluded that risk perception inhibits coping behavior [24], whereas Kim et al. found no significant association between the perceived risk of infection and coping behavior in the context of the H1N1 outbreak in 2009 [23]. However, in previous studies, the path of influence between two variables has often been considered or studied for only one variable. Few researchers have explored this issue from the perspective of the internal mechanisms of the three phenomena. However, the existence of linkage effects between these three phenomena may affect the effectiveness of interventions. Therefore, it is necessary to systematically study how they relate to each other. For example, Levkovich et al. examined only the effect of perceived vulnerability on behavior [25]. Shen et al. focused on the role of risk perception in preventive behavior [26]. Yildirim et al. discussed the relationship between risk perception and fear in preventive behavior but lacked consideration of the pathway of risk perception and emotion [12]. Therefore, a systematic study is needed. The strength of the relationship between risk perception, emotion, and behavior also varies considerably across studies. Few studies have been conducted to integrate the results in this area; address the controversies in this area; avoid bias in the results of previous individual studies influenced by sample size, age, and region; and draw more general and accurate conclusions from a macroscopic perspective. The current study aims to integrate and analyze existing research on public health events through meta-analysis and explore future research directions. By estimating the strength of the relationship between public risk perception, negative emotions, and coping behaviors, a critical path is identified. Thus, the current findings will provide a basis for decisionmakers to intervene in risk perception and regulate public emotions and preventive behaviors. By analyzing existing research, we will seek to identify potential research gaps in risk perception, emotions, and behaviors related to public health events and pave the way for future research.

2. Methods

The present study used a meta-analysis technique that describes the outcomes of various empirical studies by using the correlation coefficient as an effect size estimate [27]. Effect size estimates were combined to provide useful insights [19]. A meta-analysis typically involves the identification of studies, the determination of inclusion and exclusion criteria, the coding of studies, statistical analysis, and data analysis. These steps are described below in detail.

2.1. Identification of Studies

Step 1: CNKI (China National Knowledge Internet) is one of the most complete and powerful databases of dissertations and articles in China. It has obvious advantages in terms of the types of journals, the number of citations, and the update cycle. Web of Science is an internationally renowned database with relatively high-quality articles. The CNKI and Web of Science electronic databases were searched using keywords related to public health events, risk perception, emotion, and coping behavior. We identified the keywords to be searched by pre-reading the literature. The search terms used were as follows.

Public health events: "COVID-19"; "SARS-CoV-2"; "novel coronavirus"; "coronavirus disease 2019"; "Ebola"; "H1N1"; "polio"; "poliomyelitis"; "SARS"; "atypical pneumonia"; "Zika"; "H7N9"; "flu"; "influenza"; "grippe".

Risk perception: "Risk Perception".

Emotion: "emotion"; "sadness"; "anxious"; "anxiety"; "fear".

Coping behavior: "practice"; "behavior"; "coping behavior"; "prevention".

Boolean operators such as "AND" and "OR" were used to combine these search terms. The search was performed from database inception to May 2022. For Chinese studies, the restricted sources were the Peking University Core, Chinese Social Sciences Citation Index (CSSCI), and Chinese Science Citation Database (CSCD). After aggregating the studies and removing duplicates, a total of 8187 publications were found.

Step 2: The inclusion and exclusion criteria (see Section 2.2) were discussed and agreed upon by all authors. These criteria and the relevance of the topic were used as a guide for the initial screening. Two authors individually read the titles, keywords, and abstracts of all 8187 publications to weed out the irrelevant ones. The two authors resolved their differences through discussion. A total of 871 were found to be potentially eligible in this step.

Step 3: For the publications shortlisted in step 2, the two authors further consulted the full text of each study. The studies that could be included in the final meta-analysis were screened according to the criteria in step 2 above. Again, disagreements were resolved by discussions between the two authors. A total of 790 studies were excluded for various reasons, such as unavailability of the original text, irrelevant topics, inconsistent research directions, and nondisclosure of the required data. Ultimately, 81 documents were included in the meta-analysis.

2.2. Inclusion and Exclusion Criteria

The inclusion criteria were as follows: (1) cross-sectional study—there were no restrictions regarding the method of data collection (paper questionnaire, telephone survey, Google Forms, etc.); (2) the survey used Likert scales for quantitative measures as much as possible and reported Pearson correlation coefficients or Spearman correlation coefficients between at least two variables involved in the study model; (3) the sample size was determined; (4) the publication was a journal paper, conference paper, etc., that had been peer-reviewed; (5) the study population included individuals aged 7 years or older; and (6) the behaviors examined in the study involved nonpharmacological intervention behaviors. Coping behaviors included hygienic behaviors (such as washing one's hands, coughing or sneezing into one's hands or a tissue, cleaning surfaces); mask wearing; social distancing (such as avoiding crowds, postponing or canceling large public gatherings, working online); and seeking the advice of a professional or a relative.

The exclusion criteria were as follows (in Figure 1): (1) a systematic review or purely theoretical study; (2) the article only examined the basic performance of the public during the health event; (3) duplicate reports by the same author or based on the same survey; (4) the study examined people under 7 years of age; (5) Pearson correlation coefficients or Spearman correlation coefficients were not reported; (6) the study was too detailed, i.e., classified nonpharmacological interventions for protective behaviors and studied them individually; and (7) the behaviors in the study were presented as pharmacological interventions.

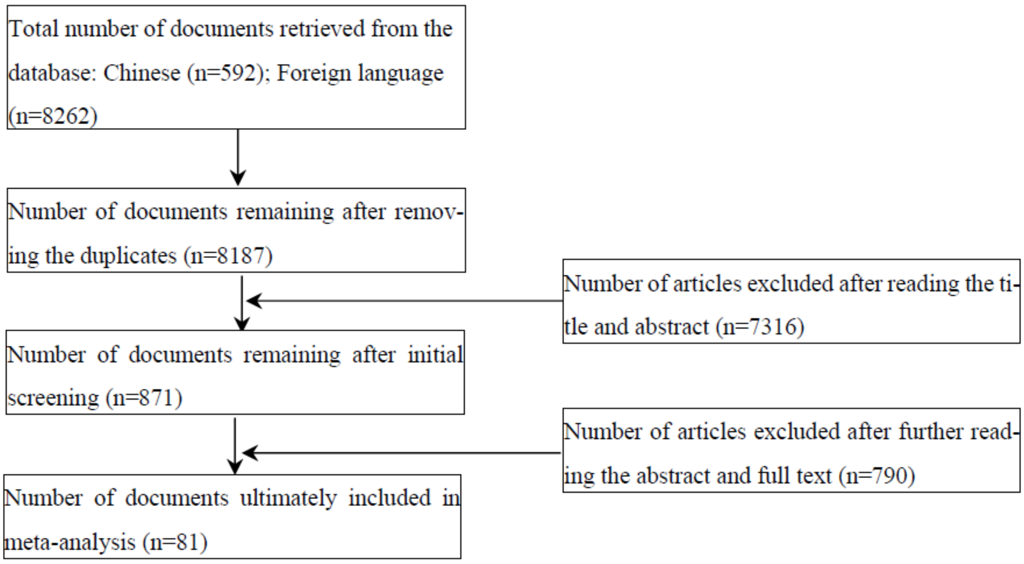

Figure 1. Flowchart of selected articles included in this systematic review and meta-analysis.

2.3. Literature Coding Procedure

Basic information about the included studies was recorded: title, authors, source, year of publication, sample size, correlation coefficient, events involved, and study population.

To perform Spearman's correlation analysis, we transformed the statistical derivation of the two sides of the following equation, in accordance with Rupinski and Dunlap [28]:

$$r = 2 * \sin\left(\frac{\pi}{6} * r_s\right) \quad (1)$$

2.4. Statistical Analysis

The fixed effects model and random effects model are two popular statistical models that have been used for meta-analysis. The fixed effects model assumes that there should be a single effect in the whole population and that the difference between effect sizes is due to variance. The random effects model, on the other hand, assumes that the different effects occur in the aggregate of the extracted sample. This study applied the Q statistic to establish the presence of heterogeneity in the study and used the I2 statistic to estimate the magnitude of heterogeneity [29]. If heterogeneity was significant, the analysis was performed using a random effects model. If there was no significant heterogeneity, a fixed effects model was used.

2.5. Data Analysis Procedures

In this study, Pearson's correlation coefficient (r) was used as the effect value indicator, where $r \leq 0.10$ indicated a low correlation, $0.10 < r < 0.40$ indicated a medium correlation, and $r \geq 0.40$ indicated a high correlation [30]. The effect size provides an estimate of the degree of existence of the phenomenon of the relationship. The higher the value of the effect size, the greater the existence of the phenomenon. Meta-analysis main effects tests and moderating effects tests were performed using the Comprehensive Meta-Analysis Version 3.3 (CMA 3.3) software. In the process of effect value estimation, to ensure the independence of effect values, if more than 2 effect values appeared for a study factor pair, the effect size of the total sample was included if the overall performance of the sample was disclosed, i.e., the overall effect. If the overall performance of the sample was not disclosed, we decided whether all effect values were included separately depending on the situation.

3. Results

3.1. Basic Characteristics of the Included Literature

The literature was searched using the CNKI and Web of Science databases and screened using strict inclusion and exclusion criteria, and 81 papers were included. In total, 5 papers included studies conducted on multiple occasions at different times and in different groups, and, thus, a total of 86 studies were included. The timespan of the studies ranged from 2005 to 2022, and the public health events included ZIKA, SARS, H1N1, H7N9, MERS, influenza, and the current COVID-19 pandemic. The included studies were all journal papers. A total of 63,358 subjects were identified as the general public, university students, medical-related students, medical workers, service industry workers, firefighters, etc. The basic information of the included studies is shown in Table 1.

Table 1. Basic information of the included studies.

No.	Study Code No.	Location	Sample Size	Event	Subjects
1	Yildirim 2022 [31]	Turkey	3190	COVID-19	The general public
2	Song 2021 [32]	Republic of Korea	211	COVID-19	The general public
3	Alijanzadeh 2021 [33]	Iran	3652	COVID-19	The general public
4	Wong 2020 [34]	China	352	COVID-19	Hong Kong South Asians
5	Mirakzadeh2021 [35]	Iran	80	COVID-19	Rural tourism operators
6	Wang 2021 [24]	China	429	COVID-19	The general public
7	Levkovich 2021 [25]	Israel	482	COVID-19	The general public
8	Wang 2021 [36]	China	200	COVID-19	The general public
9	Mihelic 2021 [37]	Slovenia	394	COVID-19	The general public
10	Shabu 2021 [38]	Iraq	976	COVID-19	University teachers and students
11	Rayani 2021 [39]	Iran	319	COVID-19	general student population
12	Alagili 2021 [40]	Saudi Arabia	1027	COVID-19	The general public
13	Yazdanpanah 2020 [41]	Iran	305	COVID-19	Rural youth
14	Fathian-Dastgerdi 2021 [42]	Iran	797	COVID-19	Teenagers
15	Iorfa 2020 [43]	Nigeria	890	COVID-19	The general public
16	Iorfa2 2020 [43]	Nigeria	664	COVID-19	The general public
17	Rad 2021 [44]	Iran	2032	COVID-19	The general public
18	Shen 2021 [26]	China	3000	COVID-19	The general public
19	Moghadam 2022 [45]	Iran	305	COVID-19	Rural adults
20	Xie 2020 [46]	China	317	COVID-19	The general public
21	Yildirim2 2021 [12]	Turkey	4536	COVID-19	The general public
22	Pilch 2021 [47]	Poland	397	COVID-19	The general public
23	Jadil 2021 [48]	Morocco	215	COVID-19	The general public
T	Jadil2 2021 [48]	India	229	COVID-19	The general public
25	Rabin 2022 [49]	America	186	COVID-19	The general public
26	Batra 2021 [50]	India	381	COVID-19	Medical students
27	Shi 2021 [51]	China	2830	COVID-19	The general public
28	Karimy 2021 [52]	Iran	1090	COVID-19	The general public
29	Cui 2010 [53]	Republic of Korea	484	H1N1	Medical students
30	Choi 2018 [54]	Republic of Korea	249	ZIKA	Medical students
31	Hu 2020 [55]	China	1063	COVID-19	The general public
32	Tang 2021 [56]	China	627	Public health events	The general public
33	Alhaimer 2022 [57]	Kuwait	746	COVID-19	The general public
34	Mehanna 2021 [58]	Sudan	680	COVID-19	The general public
35	Arceo 2021 [59]	The Philippines	304	COVID-19	The general public
36	Liu 2021 [13]	America	590	COVID-19	The general public
37	Bagherzadeh 2021 [60]	Iran	660	COVID-19	Parents of primary school students
38	Zhang 2021 [61]	Republic of Korea	299	COVID-19	The general public

Table 1. *Cont.*

No.	Study Code No.	Location	Sample Size	Event	Subjects
39	Grano 2022 [62]	Italy	309	COVID-19	The general public
40	Grano2 2022 [62]	Italy	237	COVID-19	The general public
41	Kurnia 2021 [63]	Indonesia	112	COVID-19	Nursing students
42	Kim 2021 [64]	Republic of Korea	186	COVID-19	The general public
43	DeDonno 2022 [65]	America	719	COVID-19	The general public
44	Suk 2021 [66]	Republic of Korea	300	COVID-19	Firemen and marine police
45	Magano 2021 [67]	Portugal	1122	COVID-19	The general public
46	Idrees 2022 [68]	Pakistan	440	COVID-19	The general public
47	Elsayed 2022 [69]	Egypt	582	COVID-19	The general public
48	Feng 2022 [70]	China	632	COVID-19	The general public
49	Zhang2 2021 [71]	China	192	COVID-19	The general public
50	Gungor 2021 [72]	Turkey	1473	COVID-19	The general public
51	Das 2021 [73]	India	550	COVID-19	The general public
52	Jouybari 2018 [74]	Iran	300	influenza	High school students
53	Sadeghi 2018 [75]	Iran	400	H1N1	Pregnant women
54	Zhang3 2020 [76]	China	710	H7N9	The general public
55	Gutierrez-Dona 2012 [77]	Costa Rica	428	H1N1	The general public
56	Gutierrez-Dona2 2012 [77]	Costa Rica	97	H1N1	The general public
57	Wong2 2005 [78]	Hong Kong, China	1537	SARS	The general public
58	Karademas 2013 [79]	Greece	273	H1N1	The general public
59	Karademas2 2013 [79]	Greece	273	H1N1	The general public
60	Li 2022 [80]	China	306	COVID-19	The general public
61	Bults 2014 [81]	Netherlands	1249	Q Fever	The general public
62	Kim2 2016 [82]	Republic of Korea	249	MERS	Nursing students
63	Park 2022 [83]	Republic of Korea	193	respiratory tract infection	Nursing students
64	Borges 2022 [84]	Ireland	364	COVID-19	College students
65	Kwak 2021 [85]	Republic of Korea	159	COVID-19	Nursing students
66	Haejin 2021 [86]	Republic of Korea	291	COVID-19	Nursing students
67	Lee 2021 [87]	Republic of Korea	222	COVID-19	Nursing students
68	Donizzetti 2022 [88]	Italy	1301	COVID-19	Old people
69	Haeran 2020 [89]	Republic of Korea	400	COVID-19	Medically inclined college students
70	Kyung 2021 [90]	Republic of Korea	184	COVID-19	Nursing students
71	Jeon 2021 [91]	Republic of Korea	200	COVID-19	Nurses
72	Zancu 2022 [92]	Romania	634	COVID-19	College students
73	Fu 2022 [93]	China	522	COVID-19	Youths
74	Jeong 2022 [94]	Republic of Korea	187	COVID-19	Nursing students
75	Kim3 2021 [95]	Republic of Korea	500	COVID-19	College students
76	Jeon2 2022 [96]	Republic of Korea	237	COVID-19	Service workers
77	Minjung 2020 [97]	Republic of Korea	412	COVID-19	Adults
78	Park2 2021 [98]	Republic of Korea	241	COVID-19	Nursing students
79	Lee2 2022 [99]	Republic of Korea	371	COVID-19	Aircraft crews
80	Lee 2021 [100]	Republic of Korea	261	COVID-19	College students
81	Li 2021 [101]	China	802	COVID-19	The general public
82	Zhang 2015 [102]	China	2709	H7N9	The general public
83	Ayandele 2021 [103]	Nigeria	172	COVID-19	The general public
84	Janis 2020 [104]	Norway	4338	COVID-19	The general public
85	Li 2020 [105]	China	454	COVID-19	The general public
86	Zeidi 2021 [106]	Iran	340	COVID-19	Dentists

These studies were conducted in a piecemeal fashion rather than in a systematic way. Of the 86 studies included, 5 studies (5.8%) examined the relationship between emotion and behavior, 10 studies (11.6%) examined the relationship between risk perception and emotion, 59 studies (68.6%) examined the relationship between risk and coping behavior, and 8 studies (9.3%) examined the relationship between risk and behavior as well as emotion and behavior. Only four studies (4.7%) examined the relationship between all three phenomena simultaneously. There is a need to conduct systematic and comprehensive research on this subject.

We reviewed the full text of the 81 included studies. They were relatively uniform in the way they measured variables such as fear, anxiety, risk perception, and coping behavior. All had multiple items set, scored on a scale, and responses were summed to obtain a total score, with the level of the score representing the level of the variable. Fear was measured using the FCV-19S or other self-administered scales. Anxiety was measured using the SAS Anxiety Self-Rating scale, the GAD-7 scale, the POMS scale, the Brunel Mood scale, etc.

Risk perception was measured by items such as the PRQ scale, with questions such as "I have a high risk of infection...", etc. Perceived susceptibility was measured by items such as "I have a high risk of infection with novel coronavirus". For perceived severity, items such as "I think this novel coronavirus is very serious" were used. Coping behavior was measured using preventive protective behaviors recommended by health agencies. The factors of the included studies are shown in Table 2.

Table 2. The factors included in the studies.

Variable		Example of Measurement Items
Fear		"It makes me uncomfortable to think about coronavirus-19", "I am afraid that someone in my family may get sick from the coronavirus", "I am frightened because of COVID-19", "I feel fearful about COVID-19", etc.
Anxiety		"I feel calm and can sit still easily", "I feel that everything is all right and nothing bad will happen", etc.
Risk Perception	Perceived Severity	"I think this new coronavirus is very serious", "I think the new coronavirus poses a serious threat to public health"," I think this new coronavirus is very powerful", etc.
	Perceived Susceptibility	"I am at risk for novel coronavirus", "My family/friends are likely to have novel coronavirus", "People around me are likely to have novel coronavirus", etc.
Coping Behavior		"I avoided going to places outside the home where there were other people", "Regularly and thoroughly clean your hands with an alcohol-based hand rub or wash them with soap and water", "How often do you perform the following preventive measures?", etc.

3.2. Main Effects Test

The corresponding pooled and transformed effect sizes (Pearson's correlation coefficient r and sample size n) under each of the relationships were imported into CMA 3.3 for heterogeneity test. The results show that the Q statistic was significant for each relationship, indicating the existence of different effects in the population from which the sample was extracted, which does not support the hypothesis of homogeneity. The I2 was greater than 50% for all relationships, indicating a high degree of heterogeneity; therefore, the random effects model was chosen to ensure the stability of effect values.

The results of this study are shown in Table 3. The corresponding forest diagrams are shown in Figures 2–8. The results show that the combined correlation coefficient between risk perception and coping behavior was 0.189 [95% CI (0.121, 0.256)]; the combined correlation coefficient between perceived susceptibility and coping behavior was 0.207 [95% CI (0.133, 0.279)]; the combined correlation coefficient between perceived severity and coping behavior was 0.296 [95% CI (0.237, 0.354)]; the combined correlation coefficient between risk perception and fear level was 0.481 [95% CI (0.327, 0.610)]; the combined correlation coefficient between risk perception and anxiety level was 0.338 [95% CI (0.208, 0.457)]; the combined correlation coefficient between fear and coping behavior was 0.239 [95% CI (0.089, 0.377)]; and the combined correlation coefficient between anxiety and coping behaviors was 0.122 [95% CI (−0.088, 0.321)].

The results indicate that risk perception, perceived susceptibility, perceived severity, and fear were significant predictors of coping behavior. The effect sizes of anxiety and coping behavior were not statistically significant. Perceived severity had the strongest relationship with coping behavior, followed by perceived susceptibility and risk perception. For emotion, risk perception was significantly and positively associated with fear and anxiety. Risk perception had the strongest relationship with fear, followed by anxiety.

Table 3. Main effects test results.

Relationships	Number of Studies	Sample Size	Overall Effect	p-Value	Heterogeneity Test			I2 (%)	95% CI	
					Q_B	df	P		Lower Limit	Upper Limit
Risk Perception–Behavior	28	20,273	0.189	0.000	636.986	27	0.000	95.8	0.121	0.256
Perceived Susceptibility–Behavior	41	25,951	0.207	0.000	1475.235	40	0.000	97.3	0.133	0.279
Perceived Severity–Behavior	34	19,395	0.296	0.000	643.657	33	0.000	94.9	0.237	0.354
Risk Perception–Fear	8	11,384	0.481	0.000	643.961	7	0.000	98.9	0.327	0.610
Risk Perception–Anxiety	10	8897	0.338	0.000	388.233	9	0.000	97.7	0.208	0.457
Fear–Behavior	11	19,711	0.239	0.002	1083.559	10	0.000	99.1	0.089	0.377
Anxiety–Behavior	9	6086	0.122	0.254	456.461	8	0.000	98.3	−0.088	0.321

Study name	Correlation	Lower limit	Upper limit	Z-Value	p-Value
Alijanzadeh 2021 [33]	0.091	0.059	0.123	5.512	0.000
Wong 2020 [34]	0.235	0.134	0.331	4.474	0.000
Wang 2021 [24]	-0.332	-0.414	-0.245	-7.122	0.000
Shabu 2021 [38]	0.206	0.145	0.265	6.519	0.000
Iorfa 2020 [43]	0.250	0.187	0.311	7.607	0.000
Iorfa2 2020 [43]	0.230	0.157	0.301	6.021	0.000
Shen 2021 [26]	-0.110	-0.145	-0.075	-6.046	0.000
Xie 2020 [46]	0.370	0.271	0.461	6.883	0.000
Batra 2021 [50]	-0.030	-0.130	0.071	-0.583	0.560
Choi 2018 [54]	0.020	-0.105	0.144	0.314	0.754
Elsayed 2022 [69]	0.183	0.103	0.260	4.454	0.000
Zhang2 2021 [71]	0.013	-0.129	0.154	0.179	0.858
Wong2 2005 [78]	0.230	0.182	0.277	9.172	0.000
Kim2 2016 [82]	0.290	0.172	0.400	4.683	0.000
Borges 2022 [84]	0.320	0.225	0.409	6.301	0.000
Kwak 2021 [85]	0.390	0.249	0.514	5.143	0.000
Haejin 2021 [86]	0.174	0.060	0.283	2.983	0.003
Lee 2021 [87]	0.180	0.050	0.304	2.693	0.007
Haeran 2020 [89]	0.130	0.032	0.225	2.605	0.009
Kyung 2021 [90]	0.130	-0.015	0.270	1.759	0.079
Jeon 2021 [91]	0.300	0.168	0.421	4.344	0.000
Jeong 2022 [94]	0.230	0.089	0.362	3.177	0.001
Minjung 2020 [97]	0.343	0.255	0.426	7.230	0.000
Park2 2021 [98]	0.229	0.106	0.345	3.597	0.000
Lee2 2022 [99]	0.410	0.322	0.491	8.356	0.000
Lee 2021 [100]	0.250	0.133	0.360	4.103	0.000
Li 2021 [101]	0.127	0.058	0.195	3.609	0.000
Zhang 2015 [102]	0.375	0.342	0.407	20.495	0.000
	0.189	0.121	0.256	5.335	0.000

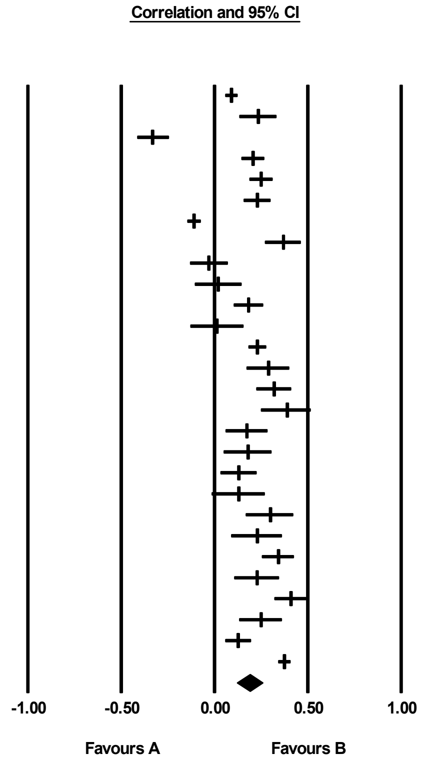

Figure 2. The correlation between risk perception and coping behavior. The columns of the figure as labeled above in the figure represent the following: study, correlation, upper limit, lower limit, Z-value, p-value, correlation, and 95% CI. Favors A indicates the degree of negative correlation between the two factors. Favors B indicates the degree of positive correlation.

Study name	Correlation	Lower limit	Upper limit	Z-Value	p-Value
Yildirim 2022 [31]	0.220	0.187	0.253	12.626	0.000
Song 2021 [32]	0.055	-0.081	0.189	0.794	0.427
Mirakzadeh 2021 [35]	0.444	0.249	0.605	4.187	0.000
Mihelic 2021 [37]	0.630	0.566	0.686	14.661	0.000
Rayani 2021 [39]	0.224	0.117	0.326	4.051	0.000
Alagili 2021 [40]	0.050	-0.011	0.111	1.601	0.109
Yazdanpanah 2020 [41]	0.380	0.280	0.472	6.952	0.000
Fathian-Dastgerdi 2021 [42]	0.140	0.071	0.207	3.971	0.000
Rad 2021 [44]	0.092	0.049	0.135	4.156	0.000
Moghadam 2022 [45]	0.370	0.269	0.463	6.750	0.000
Pilch 2021 [47]	0.540	0.466	0.606	11.992	0.000
Jadil 2021 [48]	0.360	0.238	0.471	5.488	0.000
Jadil2 2021 [48]	0.420	0.307	0.521	6.730	0.000
Rabin 2022 [49]	0.410	0.283	0.523	5.893	0.000
Karimy 2021 [52]	0.210	0.153	0.266	7.028	0.000
Cui 2010 [53]	-0.002	-0.091	0.087	-0.044	0.965
Alhaimer 2022 [57]	0.620	0.574	0.662	19.762	0.000
Mehanna 2021 [58]	0.317	0.248	0.383	8.542	0.000
Arceo 2021 [59]	0.008	-0.105	0.120	0.139	0.890
Bagherzadeh 2021 [60]	0.294	0.223	0.362	7.765	0.000
Zhang 2021 [61]	0.275	0.167	0.377	4.856	0.000
Grano 2022 [62]	0.423	0.327	0.510	7.895	0.000
Grano2 2022 [62]	0.516	0.416	0.604	8.733	0.000
Kurnia 2021 [63]	0.010	-0.176	0.195	0.104	0.917
Kim 2021 [64]	0.057	-0.088	0.199	0.772	0.440
DeDonno 2022 [65]	0.472	0.413	0.527	13.717	0.000
Suk 2021 [66]	0.390	0.290	0.482	7.097	0.000
Jouybari 2018 [74]	0.161	0.049	0.269	2.799	0.005
Sadeghi 2018 [75]	0.423	0.339	0.500	8.993	0.000
Li 2022 [80]	0.290	0.184	0.389	5.197	0.000
Bults 2014 [81]	0.200	0.146	0.253	7.156	0.000
Park 2022 [83]	0.314	0.181	0.436	4.479	0.000
Zancu 2022 [92]	0.280	0.207	0.350	7.226	0.000
Kim3 2021 [95]	0.150	0.063	0.235	3.369	0.001
	0.296	0.237	0.354	9.284	0.000

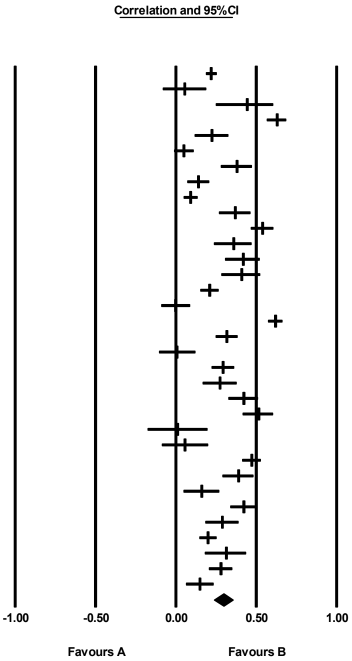

Figure 3. The correlation between perceived severity and coping behavior. The columns of the figure as labeled above in the figure represent the following: study, correlation, upper limit, lower limit, Z-value, *p*-value, correlation, and 95% CI. Favors A indicates the degree of negative correlation between the two factors. Favors B indicates the degree of positive correlation.

Study name	Correlation	Lower limit	Upper limit	Z-Value	p-Value
Song 2021 [32]	0.420	0.302	0.525	6.457	0.000
Mirakzadeh 2021 [35]	0.657	0.511	0.766	6.910	0.000
Levkovich 2021 [25]	0.080	-0.009	0.168	1.755	0.079
Wang2 2021 [36]	0.128	-0.011	0.262	1.806	0.071
Mihelic 2021 [37]	0.310	0.218	0.397	6.338	0.000
Shabu 2021 [38]	0.190	0.129	0.250	6.000	0.000
Rayani 2021 [39]	0.221	0.114	0.323	3.994	0.000
Alagili 2021 [40]	0.037	-0.024	0.098	1.185	0.236
Fathian-Dastgerdi 2021 [42]	0.110	0.041	0.178	3.112	0.002
Rad 2021 [44]	0.192	0.150	0.234	8.757	0.000
Moghadam 2022 [45]	0.290	0.184	0.390	5.189	0.000
Yildirim2 2021 [12]	0.440	0.416	0.463	31.794	0.000
Pilch 2021 [47]	0.230	0.135	0.321	4.649	0.000
Jadil 2021 [48]	0.380	0.259	0.489	5.825	0.000
Jadil2 2021 [48]	0.480	0.374	0.574	7.862	0.000
Rabin 2022 [49]	0.280	0.142	0.407	3.892	0.000
Shi 2021 [51]	-0.249	-0.283	-0.214	-13.523	0.000
Karimy 2021 [52]	0.040	-0.019	0.099	1.319	0.187
Alhaimer 2022 [57]	0.680	0.639	0.717	22.600	0.000
Mehanna 2021 [58]	0.229	0.157	0.299	6.066	0.000
Arceo 2021 [59]	-0.051	-0.163	0.062	-0.886	0.376
Bagherzadeh 2021 [60]	0.037	-0.039	0.113	0.949	0.343
Zhang 2021 [61]	0.276	0.168	0.378	4.875	0.000
Grano 2022 [62]	0.205	0.096	0.309	3.638	0.000
Grano2 2022 [62]	0.133	0.006	0.256	2.047	0.041
Kurnia 2021 [63]	-0.088	-0.269	0.099	-0.921	0.357
Kim 2021 [64]	0.148	0.004	0.286	2.017	0.044
DeDonno 2022 [65]	0.272	0.203	0.338	7.466	0.000
Suk 2021 [66]	0.310	0.204	0.409	5.524	0.000
Idrees 2022 [68]	0.170	0.078	0.259	3.589	0.000
Jouybari 2018 [74]	0.210	0.099	0.316	3.674	0.000
Sadeghi 2018 [75]	0.214	0.118	0.306	4.331	0.000
Gutierrez-Dona 2012 [77]	0.090	-0.005	0.183	1.860	0.063
Gutierrez-Dona2 2012 [77]	-0.020	-0.219	0.180	-0.194	0.846
Karademas 2013 [79]	0.040	-0.079	0.158	0.658	0.511
Karademas2 2013 [79]	0.260	0.146	0.367	4.373	0.000
Li 2022 [80]	0.360	0.258	0.454	6.560	0.000
Bults 2014 [81]	0.210	0.156	0.262	7.525	0.000
Park 2022 [83]	0.069	-0.073	0.208	0.953	0.341
Zancu 2022 [92]	0.170	0.093	0.245	4.312	0.000
Kim3 2021 [95]	0.000	-0.088	0.088	0.000	1.000
	0.207	0.133	0.279	5.377	0.000

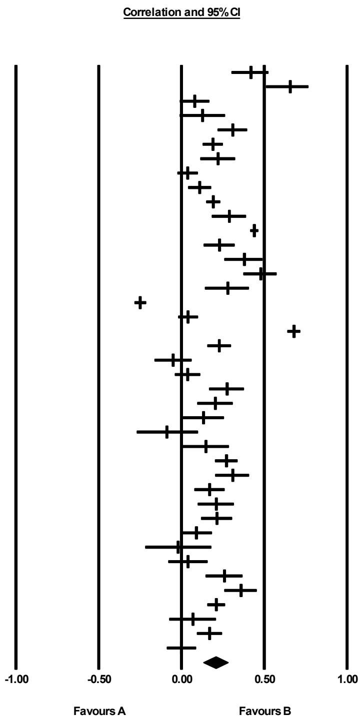

Figure 4. The correlation between perceived susceptibility and coping behavior. The columns of the figure as labeled above in the figure represent the following: study, correlation, upper limit, lower limit, Z-value, *p*-value, correlation, and 95% CI. Favors A indicates the degree of negative correlation between the two factors. Favors B indicates the degree of positive correlation.

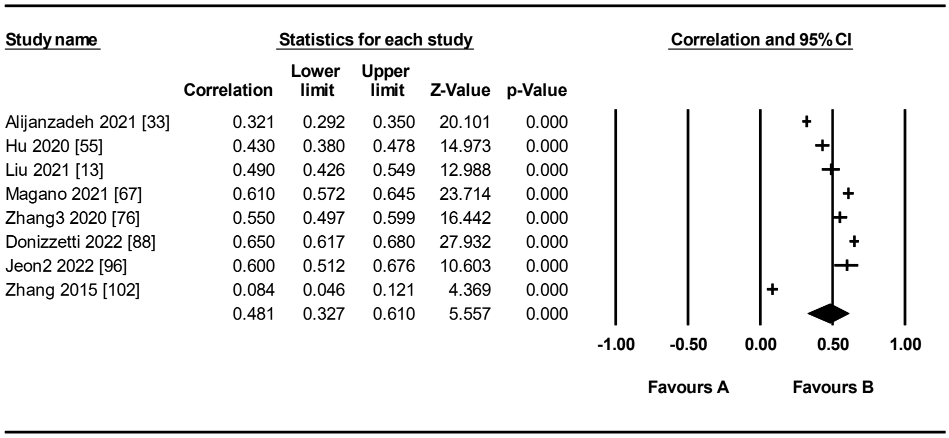

Figure 5. The correlation between risk perception and fear. The columns of the figure as labeled above in the figure represent the following: study, correlation, upper limit, lower limit, Z-value, *p*-value, correlation, and 95% CI. Favors A indicates the degree of negative correlation between the two factors. Favors B indicates the degree of positive correlation.

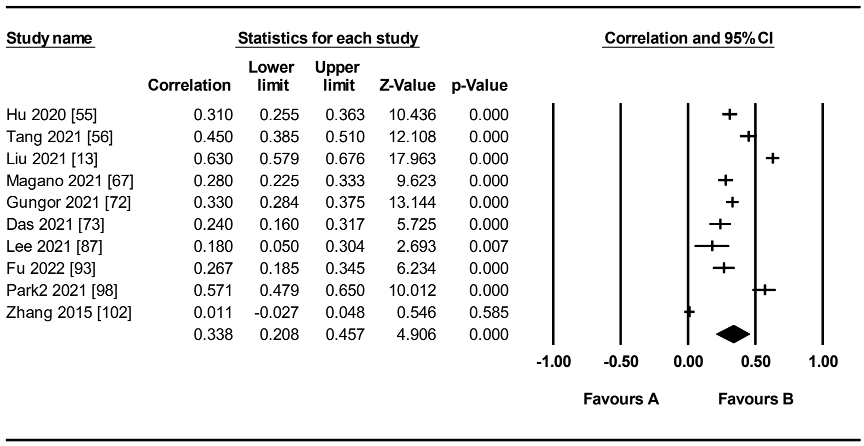

Figure 6. The correlation between risk perception and anxiety. The columns of the figure as labeled above in the figure represent the following: study, correlation, upper limit, lower limit, Z-value, *p*-value, correlation, and 95% CI. Favors A indicates the degree of negative correlation between the two factors. Favors B indicates the degree of positive correlation.

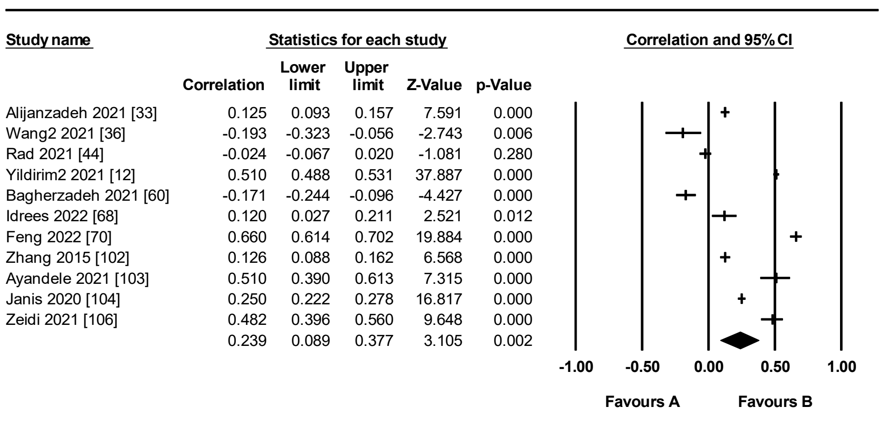

Figure 7. The correlation between fear and coping behavior. The columns of the figure as labeled above in the figure represent the following: study, correlation, upper limit, lower limit, Z-value, *p*-value, correlation, and 95% CI. Favors A indicates the degree of negative correlation between the two factors. Favors B indicates the degree of positive correlation.

Study name	Correlation	Lower limit	Upper limit	Z-Value	p-Value
Wang2 2021 [36]	-0.055	-0.192	0.084	-0.773	0.440
Kim 2021 [64]	-0.156	-0.293	-0.012	-2.128	0.033
Feng 2022 [70]	0.660	0.614	0.702	19.884	0.000
Bults 2014 [81]	0.380	0.332	0.426	14.122	0.000
Park 2022 [83]	-0.217	-0.348	-0.078	-3.039	0.002
Lee 2021 [87]	0.210	0.081	0.332	3.155	0.002
Park2 2021 [98]	0.211	0.087	0.329	3.305	0.001
Zhang 2015 [102]	0.052	0.015	0.090	2.728	0.006
Li 2020 [105]	-0.162	-0.250	-0.071	-3.471	0.001
	0.122	-0.088	0.321	1.141	0.254

Statistics for each study

Correlation and 95% CI

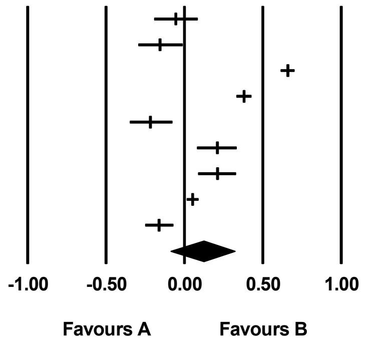

Figure 8. The correlation between anxiety and coping behavior. The columns of the figure as labeled above in the figure represent the following: study, correlation, upper limit, lower limit, Z-value, *p*-value, correlation, and 95% CI. Favors A indicates the degree of negative correlation between the two factors. Favors B indicates the degree of positive correlation.

3.3. Publication Bias Test

Review studies based on empirical results are often prone to publication bias because the effect values of meta-analyses are determined and influenced by the data included in the study. For publication, authors and journal editors may prefer studies that are statistically significant, resulting in the omission of studies that have smaller effect sizes, which is why publication bias exists. In this study, quantitative tests for publication bias were conducted using the fail-safe number, Begg's test, and Egger's test.

For a meta-analysis process under a certain relationship, if the meta-analysis process includes the study data of X, the number of fail-safes must be much greater than 5X to indicate that there is no publication bias [107]. Egger's test is the most commonly used test for publication bias. When the intercept term of Egger's regression is not significant, it indicates that there is no publication bias [108]. Begg's test determines the existence of publication bias by testing the correlation between the effect and sample size [109].

The number of insecurities under the meta-analysis process for each relationship in this study is shown in the table below, all of which satisfy this condition, indicating that there is no publication bias. The results of Begg's test were not significant, with *p*-values greater than 0.05, indicating that the results show no publication bias; the intercept terms of the Egger regressions under all relationships except for risk perception–anxiety and negative emotion–behavior were not significant, and the intercepts and 95% confidence intervals are shown in Table 4, further supporting the absence of publication bias in these studies. Due to the small number of included studies, the results of the meta-analysis studies of the risk perception–anxiety relationship under Egger regression were significant with a *p*-value of less than 0.05; publication bias was present, but the results did not change significantly in the follow-up sensitivity test, indicating that publication bias did not have a significant effect on the results.

3.4. Sensitivity Analyses

The samples used in the meta-analysis were individual studies, and outliers may occur. Sensitivity analysis was performed using the leave-one-out method [110] to observe changes in effect sizes and 95% confidence intervals. One study was removed at a time, and a meta-analysis of the remaining studies yielded multiple combined effect sizes with the intervals shown in Table 5. None of the total effect estimates after removing a study exceeded the upper and lower 95% confidence interval limits of all study estimates, indicating that the results were robust.

Table 4. Publication bias test.

Relationships	k	Fail-Safe Number	Begg's Test			Egger's Test			
			Tau	Z	P	Intercept	SE	95% CI	P
Risk Perception–Behavior	28	3626	0.000	0.000	1.000	1.987	1.935	[−1.991, 5.965]	0.314
Perceived Susceptibility–Behavior	41	8805	0.141	1.303	0.193	0.220	2.110	[−4.048, 4.487]	0.918
Perceived Severity–Behavior	34	2049	0.094	0.786	0.432	3.198	1.810	[−0.489, 6.886]	0.087
Risk Perception–Fear	8	4468	0.107	0.371	0.711	15.377	7.803	[−3.717, 34.471]	0.096
Risk Perception–Anxiety	10	2029	0.044	0.179	0.858	11.154	4.817	[0.047, 22.262]	0.049
Fear–Behavior	11	2592	0.000	0.000	1.000	−2.067	6.830	[−17.517, 13.382]	0.769
Anxiety–Behavior	9	289	−0.139	0.521	0.602	−1.389	5.616	[−14.667, 11.890]	0.812

Table 5. Sensitivity analysis.

Relationships	Main Effect	95% CI		Leave-One-Out	
		Lower Limit	Upper Limit	Min	Max
Risk Perception–Behavior	0.192	0.121	0.256	0.180	0.208
Perceived Susceptibility–Behavior	0.207	0.133	0.279	0.191	0.218
Perceived Severity–Behavior	0.296	0.237	0.354	0.284	0.305
Risk Perception–Fear	0.481	0.327	0.610	0.452	0.528
Risk Perception–Anxiety	0.338	0.208	0.457	0.299	0.372
Fear–Behavior	0.239	0.089	0.377	0.186	0.278
Anxiety–Behavior	0.122	−0.088	0.321	0.039	0.163

4. Discussion

To examine the relationship between risk perception, emotion, and behavior in the context of public health events, this meta-analysis quantitatively synthesized the results of 86 relevant studies. The results of the random effects model showed positive correlations between risk perception, perceived severity, perceived susceptibility, fear, and coping behavior. These results were highly statistically significant. Only the combined correlation coefficient between anxiety and coping behavior was statistically insignificant. The following findings can be confirmed. The higher the individual's risk perception of a public health event, the more actively the individual takes precautions with non-pharmacological interventions. Risk perception, as the primary evaluation of a public health emergency, is a key factor in the emotional response and determines the individual's emotional feelings. Fear can increase alertness and trigger coping behaviors. We performed a quantitative test for publication bias and found no significant publication bias. Sensitivity analysis was used to test the robustness of the results. This study also provides various theoretical and practical implications that can provide suggestions for future research and government interventions.

4.1. Theoretical and Practical Implications

This study offers multiple theoretical implications. First, it synthesizes the results of 86 studies to reveal the link between risk perception, emotions, and behaviors in the context of public health events. These included cross-sectional studies that looked at people's performance across dimensions and the relationships that existed between them. The relationship between the two or the three phenomena is explored in depth. However, research into combining them to gain in-depth knowledge is limited. These studies were conducted in a piecemeal fashion rather than in a systematic way. This meta-analysis provides strong support for the relationship between risk perception, emotion, and behavior. This meta-analysis provides strong support for the relationship between risk perception, emotion, and behavior, and provides a theoretical tool for studying individuals' coping behaviors in the face of a pandemic. Second, by combing and analyzing previous studies, we have identified some research gaps, which will help provide scholars with ideas for conducting subsequent studies. In the studies we have included, the regions covered are biased toward Asia, followed by European countries, with relatively few studies in Africa, the Americas, etc. This may be due to the different research hotspots preferred by scholars in different countries because of their different cultural backgrounds. Different cultural backgrounds do have an impact on the associations between risk perception, emotions, and coping behaviors [111,112]. The moderating role of cultural elements such as individualism and collectivism could be studied in the future. Third, religious beliefs deserve to be taken into account in future research. Different countries have different dominant religious beliefs. Religious beliefs have been associated with emotional well-being and healthy behaviors [113]. Religious beliefs can also be added as a moderating factor. Fourth, we are in the post-pandemic era as the pandemic progresses and policies change. Psychological mechanisms may change across different time periods. Anderson et al. found that fear of COVID-19 did not appear to predict COVID-19 prevention behavior 6 months after initial measurement [114]. Future studies should rigorously test these associations longitudinally and should consider alternative approaches to long-term public health prevention campaigns.

This study also provides key insights from a practical perspective that will help in the development of practical applications. Increased risk perception will motivate people to adopt coping behaviors. The government needs to adjust the public's risk perception in comparison to the actual disease risk. However, it is worth noting that risk perception is related to populations, individuals, geography, and time [115]. In China, people tend to trust the government's advice more and obey the government's guidance. In contrast, in countries where government trust is low, the public tends to be less motivated to adopt coping behaviors because of other factors. In our study, perceived severity plays a greater role in promoting the adoption of health behaviors. However, this can lead to negative emotions such as fear and anxiety. Negative emotions such as fear will motivate people to take precautionary measures, but excessive negative emotions will lead to irrational behavior [3]. Thus, the intervention has to be adapted to the local context and also consider the gap between perceptions and the actual situation. Different governments should assess the gap between individual perception and actual disease severity, as well as the current emotional state. By considering different focuses for risk communication, governments can reasonably intervene in the public's perception of disease severity to promote the adoption of self-protective behaviors.

For intervention, the direction of entry is the monitoring and adjustment of information sources. The public's risk perception and emotions are greatly influenced by the sources of information to which individuals are exposed [116,117]. The media is the main channel of information dissemination and should report the development of events objectively and positively so that the public can form reasonable risk judgments and thus establish a correct risk perception. The use of social media influences users' risk perception through negative sentiment mediation [118]. At high risk perception levels, the public will seek more emotional support from social support systems and vent their emotions in multiple ways [119]. Currently, technologies such as artificial intelligence and big data have become important forces in the field of public management. In response to the public's emotional expression through social media such as Twitter and Facebook, natural language processing tools for artificial intelligence and text mining technology can be used to build a monitoring system to understand the public's current situation and response to intervention strategies. Management can develop better public policy strategies based on the public's identified level of risk perception and changes in sentiment. Inefficient prevention behaviors should be avoided to prevent too low negative emotions and risk perception as well as too high negative sentiment, which can influence larger public opinion. In addition, rumors on social media influence public sentiment through emotional infection, leading to irrational behavior. Managers can use big data technology and specific artificial intelligence algorithms to establish a rumor assessment and graded warning system [120]. By performing rapid response actions to address rumors, their spread can be curbed. Effective risk information communication is essential for establishing correct risk perception and reducing the generation and spread of panic and anxiety. Timely and accurate information disclosure is particularly important for effective risk communication [121]. Managers can use blockchain technology and big data technology for information disclosure platform development to accurately, openly, and transparently release epidemic/pandemic information and respond to public concerns.

4.2. Strengths

To the best of our knowledge, this is the first study to conduct a quantitative meta-analysis of the relationship between risk perception, negative emotions, and coping behaviors based on the context of a public health event. Wang et al. and Teasdale et al. conducted a qualitative systematic evaluation [15,122], but they lacked comprehensive data results to support their findings. Brewer et al. conducted a meta-analysis of the relationship between risk perception and health behavior in the context of vaccination, a pharmacological intervention [123]. This was not conducted for non-pharmacological preventive behaviors. Our study is novel and complements quantitative meta-analyses of the relationship between risk, emotion, and coping behavior in the context of public health events.

In addition, this study proposed future research directions from the perspectives of culture, religion, and time. Further research could focus on a meta-analysis of these possible behavioral determinants or moderators for a more comprehensive understanding of public health protective behaviors during a pandemic. We also suggest practical applications based on our findings, including risk communication and emotion monitoring through big data algorithms or artificial intelligence.

4.3. Limitations

In this study, when searching for studies in major popular electronic databases, the keywords used may not reach all of the relevant literature, and some relevant studies may be missed as a result. In addition, studies in other electronic databases may have been overlooked. Since journals tend to publish studies with significant findings, some studies with insignificant results may be omitted. Thus, we tried to discover whether there was any publication bias in our study. No significant publication bias was found to exist among the included studies.

Pre-published papers were not taken into account considering the quality of the study. Additionally, some relevant studies may have been missed due to limited key search terms. These factors resulted in the relatively low number of studies we included. As such relevant studies accumulate, future reviews should include more research to further validate the results. The advent of the post-pandemic era and changes in policy may lead to changes in the strength of these linkage effects. More comprehensive studies are needed.

5. Conclusions

This study used meta-analysis to evaluate the correlation between risk perception, negative emotions, and coping behaviors in the context of the current COVID-19 pandemic and other public health events. Individual risk perception, especially perceived severity, can prompt people to perform coping actions. High risk perception will lead to negative emotions such as fear and anxiety. Fear predicts the adoption of coping behaviors. This provides a theoretical reference for practical health behavior interventions. The magnitude and direction of effects between relationships may vary across cultures, religions, and time periods. For future research, the moderating role of these factors should be considered.

Author Contributions: Study conception and design: W.Z. and Y.Z. (Yanchun Zhu); data acquisition: Y.Z. (Yuxia Zhao) and Y.J.; data analysis and/or interpretation: Y.Z. (Yuxia Zhao), manuscript drafting: Y.Z. (Yuxia Zhao), W.Z. and Y.Z. (Yanchun Zhu); critical manuscript revision for important intellectual content: W.Z., Y.Z. (Yuxia Zhao), Y.Z. (Yanchun Zhu) and Y.J. All authors have read and agreed to the published version of the manuscript.

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Informed Consent Statement: Not applicable.

Data Availability Statement: The extracted data used to support the findings of this study are available from the corresponding author upon request.

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

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