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ORIGINAL RESEARCH

Does Fear of the New Coronavirus Lead to Low-Carbon Behaviors: The Moderating Effect of Outcome Framing

Wenlong Liu[1,2]
Wen Shao[3]
Qunwei Wang[2]

[1]School of Management, Fudan University, Shanghai, People's Republic of China; [2]College of Economics and Management, Nanjing University of Aeronautics and Astronautics, Nanjing, Jiangsu, People's Republic of China; [3]School of Economics & Management, Southeast University, Nanjing, Jiangsu, People's Republic of China

Purpose: Air pollution has been found to aggravate the infection and mortality of COVID-19, leading to increasing attention on pro-environmental behaviors. Considering individuals' psychological distance from COVID-19, this research aims to examine the relationship between fear of COVID-19, air pollution concern, and low-carbon behaviors.

Methods: Two survey-based studies were conducted in this research. Study 1 consisted of 323 participants and examined the relationships between psychological distance (PD) from COVID-19, fear of COVID-19, air pollution concern, and low-carbon behaviors. Study 2 identified the moderating effect of outcome framing using an intergroup experiment in which 304 participants were randomly assigned to two groups (gain framing vs loss framing).

Results: The results of Study 1 showed that the closer the PD was, the higher the fear was. Fear of COVID-19 and low-carbon behaviors were positively associated. Additionally, air pollution concern acted as a mediator in their relationship. The results of the moderating effect test in Study 2 showed that fear and air pollution concern led to higher low-carbon behavioral intention within gain framing than within loss framing.

Conclusion: This research revealed that personal fear of public health emergencies will lead to environmental pollution concern and pro-environmental behaviors, and information from the outside plays a moderating role. The results provide implications for policy advocacy of the health and environmental sectors and for guiding people's low-carbon behaviors.

Keywords: COVID-19, psychological distance, fear, air pollution concern, low-carbon behavior, outcome framing

Introduction

According to the World Health Organization (WHO), coronavirus disease 2019 (COVID-19) has caused more than 103.9 million infections worldwide as of February 3, 2021.[1] Current studies show that the spread of viruses is associated with air pollutants that exceed standards.[2–6] Specifically, studies indicate that the degree of air pollution in a city can affect the spread speed and severity of COVID-19.[2,7] As the most polluted regions in Europe, Lombardy and Emilia-Romagna have the highest virus lethality levels in the world.[3] In China, the United States and Italy, the COVID-19 infection rates are markedly high in areas that are seriously affected by carbon monoxide (CO) and nitrogen dioxide (NO_2).[5] Recent studies have further revealed that the number of confirmed COVID-19 cases is positively correlated with the levels of $PM_{2.5}$, PM_{10}, CO, NO_2, and O_3, and even short-term exposure to these air pollutants will increase the risk of COVID-19 infection.[8,9] Specifically, the

Correspondence: Wenlong Liu
Email willenliu@nuaa.edu.cn

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effects of $PM_{2.5}$ and PM_{10} on COVID-19 are more significant in Russia, England, Germany and France, whereas the effects of O_3 and $PM_{2.5}$ were more significant in America and Canada from January 21 to May 20, 2020, and $PM_{2.5}$, PM_{10}, SO_2, NO_2, and O_3 contribute to the increase in newly confirmed cases.[10] Furthermore, mortality is high in areas with high particulate matter, CO and NO_2 levels.[4,11–13] An estimate suggests that a one-unit increase in $PM_{2.5}$ concentration ($\mu g/m^3$) is associated with a 9% increase in COVID-19-related mortality.[14] The inflammation, cell damage and respiratory diseases caused by air pollution may inhibit people's early immune responses to COVID-19 infection and, consequently, make them more vulnerable to infection and death.[3–6]

The COVID-19 outbreak triggered numerous studies on microorganisms, especially on whether the revival of glacial pathogens could cause deadly pandemics. Global warming accelerates the melting of ice layers that have been frozen for millions of years, thereby releasing ancient living microorganisms each year. Some such microorganisms can survive by adapting to new conditions and have been proven to exist.[15–22] Ancient pathogens pose a threat to human beings. Humans have never been exposed directly to such pathogens; thus, the human immune system is not familiar with them. Therefore, fatal epidemics are likely to occur.[21]

The above studies demonstrate the significant connections between the severity of air pollution and the virulence of viruses as well as the release and threat of ancient pathogens. This correlation and threat cannot be ignored and require individual and social intervention and preventive action. The increase in greenhouse gas emissions results in global warming, and excess carbon emissions lead to air pollution.[23–25] Therefore, low-carbon behaviors (LCBs) have become the basic consensus in terms of human responses to global warming and air pollution.[26] Under the threat of epidemics and glacier microorganisms, LCBs are an effective solution at present.

Fear and worry increased significantly during the COVID-19 outbreak in Europe.[27,28] At the individual level, fear can lead to safety or threat-reducing behaviors (eg, pollution mitigation).[29–32] Given this, our research investigated the impact of individuals' fear of COVID-19 (FC) on their LCBs and this relationship under outcome framing. Specifically, studying whether public health occurrences, such as the COVID-19 pandemic, raise personal concerns about air pollution and trigger LCBs has theoretical significance. Meanwhile, studying individual low-carbon behavioral intention (LCBI) after the different results of LCBs and non-LCBs are realized has practical significance. This paper consists of five sections. Section 1 introduces the research background and significance. Section 2 summarizes existing research and theories and presents the hypotheses. The research design and data analysis results are presented in Section 3, whereas the implications are discussed in Section 4. Finally, conclusions and limitations are summarized.

Literature Review and Hypothesis

Psychological Distance (PD)

Psychological distance (PD) is an individual's perceived distance between a target, a goal, a threat or an event and himself/herself. Specifically, it refers to the distance of oneself from an object hypothetically, temporally, spatially and/or socially. Moreover, PD affects a person's motivation and action preference.[33] Events are considered psychologically remote if they (1) are unlikely to happen, (2) occurred a long time ago or will occur in the future, (3) occur in distant areas, and/or (4) occur in dissimilar individuals.[34–36]

PD affects a person's cognition, attitude and behavior toward an object or event. For instance, if the individual perceives different PDs from an organization, then the violation of morality or responsibility of the organization can affect the attitude and response of the individual on different levels.[34] In the online shopping context, perceived similarity from a poster's profile image, language style and described experience can affect individuals' PD from online reviews and products, thereby affecting their purchase intentions and behaviors.[37] In the climate change context, individuals who perceive a far distance between themselves and global warming tend to show little concern about its consequences and limited support for environmental policies.[38] PD is related to the cognitive style, which, in turn, can change PD. PD is also related to emotions. Individuals with psychological closeness to environmental issues have an intense risk perception of environmental pollution and demonstrate considerable pro-environmental behaviors and environmental policy support.[35,39]

Air Pollution Concern (APC) and Low-Carbon Behaviors (LCBs)

Environmental concern refers to individuals' consciousness and worry about environmental issues and intention to exert effort to solve them.[40] According to Ham and

Han,[41] compared with the view of individuals with low environmental concern, that of individuals with high environmental concern of business green practices has a greater impact on their willingness to purchase. Many other studies have also identified and supported the positive effects of environmental concerns on pro-environmental behaviors.[42–45] One explanation for this relationship is that environmental concerns induce pro-environmental behaviors by engendering individual moral obligations to improve the environment.[42,46]

Studies have also demonstrated the impact of environmental concern on the adoption of specific pro-environmental behaviors, such as energy conservation,[47,48] green purchasing,[49–51] recycling[52,53] and choice of ecological transportation.[52,54] Air pollution and climate change have posed considerable threats to humans and raised public air pollution concerns (APCs).[55] Air pollution is a specific aspect of environmental problems; thus, it is reasonable that individuals' APC may foster environmentally friendly behaviors.

Environmentally friendly behaviors help mitigate ecological damage, preserve natural resources and restore the environment.[56] LCBs are a subset of pro-environment behaviors.[57] Moreover, LCBs, that can be divided into private and public LCBs, can positively affect the usage of resources and help improve the dynamics and structure of the ecosystem.[58] The three types of private LCBs are habitual behaviors (eg, energy-saving and garbage-sorting habits), consumption behaviors (eg, buying energy-efficient appliances and products with less packaging) and resource recycling (eg, recycling paper and cans).[59] Meanwhile, public LCBs exert an indirect impact on the environment by promoting public policies or influencing social members' eco-friendly behaviors (eg, improving and implementing environmental policies and advocating for low-carbon consumption and lifestyles).[60]

Fear of COVID-19 (FC)

Fear is a type of adaptive and subjective emotion in the face of danger and is used to mobilize energy to cope with potential threats. If the threat is uncertain and continuous (eg, COVID-19), then fear may exist over a long period of time.[31] Fear consists of four areas: fear of physical conditions, fear of important people, fear of the unknown, and fear of inaction.[61] COVID-19-related fear has five factors, specifically, danger and pollution, concerns about economic consequences, virus-caused xenophobia, compulsive examination and comfort seeking, and traumatic stress symptoms.[28]

According to European public opinion polls, fear and worry have increased dramatically since the COVID-19 outbreak in Europe.[27,28] From the perspective of PD, the risk perceptions of the public can be linked to the closeness they feel to the virus.[35,39] That is, the COVID-19 outbreak in Europe lessened residents' PD to the virus, thereby leading to high risk perceptions and a sharp increase in fear. At the individual level, fear can enhance fear (eg, pollution concerns and health anxiety) and lead to safety behaviors (eg, hand washing) and threat-reducing behaviors (eg, pollution mitigation).[29–32] As demonstrated by researchers, the spread speed and severity of COVID-19 can be affected by the degree of air pollution.[2] Thus, fear of COVID-19 may arouse individuals' concern about air pollution and intention to adopt LCBs. Therefore, the following hypotheses are presented.

H1: The closer the PD from COVID-19 is, the higher the FC will be.

H2a: Individuals with a deep FC will have high APC.

H2b: Individuals with a deep FC will adopt LCBs positively.

Mediating Role of Air Pollution Concern (APC)

Individual behavior is a result of attitude and behavioral intention.[62] In the environmental field, actual pro-environmental behaviors are closely related to specific knowledge, concern and behavioral intentions.[63] Meanwhile, environmental knowledge is an important predictor of individuals' environmental concerns and pro-environmental behaviors.[57,64] Environmental education, such as raising individuals' awareness of climate change, is an essential approach to strengthen social members' concern and thereby encourage them to adopt LCBs.[57,65] It can be inferred that air pollution, a specific type of environmental problem, can cause public concern and LCBs. Furthermore, prior studies have revealed that the infection rates and mortality of COVID-19 are significantly related to air pollutants, such as CO, NO_2, and $PM_{2.5}$.[2,4,5] This may lead to citizens' high concern about air pollution and thereby strengthen their LCBs. Thus, the following hypotheses are presented.

H2c: Individuals with high APC will adopt LCBs positively.

H2d: Individuals' APC will have a mediating effect on the relationship between their FC and LCBs.

Moderating Role of Outcome Framing

A frame is a mental mode that determines a person's view of a problem and expectation when making a decision. Frames confine people into specific mindsets and limited ideas. Individuals perceive, understand and interpret a frame differently due to their traits or situational factors.[66] Gain framing and loss framing are distinguished to describe the expected positive or negative results of a decision, respectively. Within gain framing, people believe that their decision to adopt a certain act can result in positive outcomes, whereas within loss framing, people believe that their decision to (not) adopt a certain act can lead to negative outcomes.[67] Individuals' behaviors can be predicted according to the degree to which they expect positive results and the degree to which they endeavor to avoid negative results.[68]

Framing is a process by which an issue is communicated and individuals construct a particular conceptualization of a specific issue or reorient their mindset about the issue.[69] Online sources, which spread on social media today, frame the viewpoints of social members on issues by emphasizing certain information, thereby affecting public reactions. These emphases generally pay attention to certain aspects of issues (eg, gains or losses) and aim to influence the behavioral intentions of people by illustrating the potential positive or negative results of their attitudes and decisions.[70]

Manipulating message frames may elicit individuals' different risk perceptions and sense-making.[70] A transportation decision-related investigation found that framing the positive results (gains) of eliminating air pollution has a more significant impact on individuals' intention to use public transportation than framing the negative results (losses).[66] All other variables being controlled, emphasizing the benefits of mitigation efforts, rather than focusing on the potential losses of not taking actions, can lead to additional positive responses when communicating climate change mitigation.[71] In contrast, investigations also find that individuals are more sensitive to losses than to gains and highly evaluate risks when making decisions.[72–75] However, loss framing, as a moderator, is more effective in influencing individuals' waste recycling behaviors when paired with concrete mindsets, whereas gain framing is more efficacious when paired with abstract mindsets.[68] Compared with concrete personal gains or losses, the environmental pollution issue involves relatively abstract and public interests. Given the above literature, this research suggests that gain framing significantly interacts with other factors in influencing individuals' low-carbon behaviors and proposes the following hypotheses.

H3a: The influence of individuals' FC on their LCBI is more significant within gain framing than within loss framing.

H3b: The influence of individuals' APC on their LCBI is more significant within gain framing than within loss framing.

Materials, Methods, and Results

Measures

This research consisted of two studies. Study 1 examined the relationships among PD from COVID-19, FC, APC, and LCBs. Study 2 explored the moderating role of outcome framing on the influences of FC and APC on LCBI. On the basis of the widely used measurement of PD in prior studies,[38,71] this research developed four items to measure individuals' hypothetical, temporal, spatial and social PD from COVID-19.

At the earlier stage of the COVID-19 pandemic, an FCV-19S scale was developed by Ahorsu et al to measure the symptoms of fear of COVID-19 from the perspective of psychiatry, including sweating and insomnia.[76] This scale was later adopted by Chang et al and Chi et al in their psychometric evaluation of people in the COVID-19 pandemic.[77,78] During the same period, another fear of the COVID-19 questionnaire (FCQ) was developed by Mertens et al, consisting of the dimensions of both subjective worry and safety behaviors.[31,79] Considering that FC is a risk perception as well as relevant behaviors induced by the new coronavirus pandemic, this study adopted the FCQ to measure FC.

APC measures were adapted from Coelho et al and Pu et al.[43,55] Given that LCBs are a subset of pro-environmental behaviors, the current pro-environment behavior scale can be used to measure specific LCBs.[63,80,81] The existing LCBI scale is relatively simple, and its description is broad and general.[80,82–84] The LCBI scale used in this study was slightly modified based on the pro-environment behavior scale. As LCBI is a prerequisite of LCBs, LCBs can be understood as a result of an individual's LCBI.[85] In summary, Study 1 measured LCBs by examining behaviors that had occurred, whereas Study 2 investigated intentions to engage in low-carbon

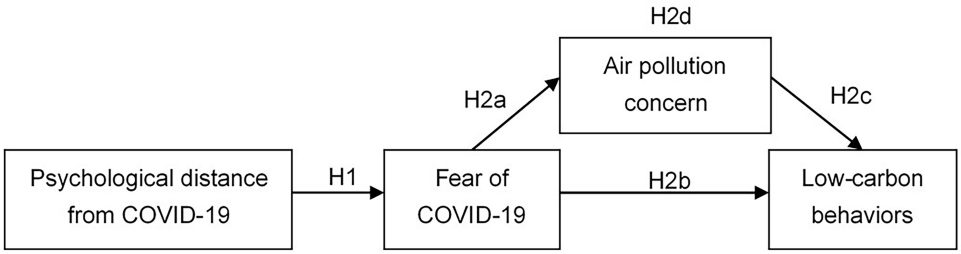

Figure 1 Conceptual model of Study 1.

practices. The items of all constructs are shown in Appendices 1 and 2 in the Supplementary Materials.

Design of Study 1

Study 1 was designed to test H1, H2a, H2b, H2c and H2d, which are presented in the conceptual model (Figure 1), specifically, 1) the relationship between PD and FC and 2) the relationship between FC and LCBs and the mediating effect of APC.

Study 1 solved the research problem with an online survey questionnaire consisting of five parts. Part 1 measured PD from COVID-19, and the question item was the expression of close PD. The larger the measured value is, the closer the PD is. Part 2 measures FC, and Part 3 measures APC. Part 4 measures LCBs that have occurred, and Part 5 collects demographic information. A 7-point Likert scale (1= totally disagree, 7 = totally agree) was employed in this study (see Appendix 1 in the Supplementary Materials).

Results of Study 1

Descriptive Statistics

The data collection for Study 1 took place online from April 15 to May 10, 2020, targeting netizens aged above 18. A written informed consent form was provided within the web-based questionnaire. All the participants were told that their answers would only be used for academic research and that no other individual or organization could access the data. The participants were allowed to move to the next step only after clicking the "Accept" button below the written informed consent form. By understanding our research purpose, a total of 412 volunteers participated in this investigation. After deleting those questionnaires in which more than 10 consecutive questions were answered with the same value, a total of 323 usable responses were analyzed. The distribution of the demographic characteristics of the samples is shown in Table 1.

Reliability and Validity Test

Considering that most items were adopted and modified from prior studies, exploratory factor analysis (EFA) was performed using SPSS 25, and the results are presented in Table 2. Four components were extracted from the scales through EFA. After rotation, all the items fell below the preconceived variables. The Cronbach's α values of all

Table 1 Distribution of Demographic Information of Samples (N = 323)

Demographic Characteristics		N	Percent
Gender	Male	156	48.3%
	Female	167	51.2%
Age	Below 20 years	72	22.3%
	21–35 years	181	56.0%
	Above 35 years	70	21.7%
Region	East China	72	22.3
	North China	34	10.5%
	Northeast China	29	9.0%
	Central China	27	8.3%
	South China	52	16.1%
	Southwest China	50	15.5%
	Northwest China	50	15.5%
	Overseas	9	2.8%
Occupation	Full-time student	112	34.7%
	Production personnel	57	17.6%
	Sales staff	48	14.9%
	Marketing/public relations staff	52	16.1%
	Service personnel	29	9.0%
	Others	25	7.7%
Educational background	High school or below	200	61.9%
	Bachelor degree	87	26.9%
	Master or Ph.D degree	36	11.2%
Income (monthly)	Less than 5000 yuan	172	53.3%
	5000–8000 yuan	132	40.9%
	More than 8000 yuan	19	5.8%

Abbreviation: N, number of valid participants.

Table 2 Factor Loadings of the Exploratory Factor Analysis and Internal Consistency (Cronbach's α)

Items	PD	FC	APC	LCBs	Cronbach's α
PD1	0.793				0.849
PD2	0.783				
PD3	0.783				
PD4	0.788				
FC1		0.665			0.909
FC2		0.722			
FC3		0.676			
FC4		0.726			
FC5		0.731			
FC6		0.748			
FC7		0.783			
FC8		0.806			
APC1			0.730		0.784
APC2			0.773		
APC3			0.814		
LCB1				0.733	0.921
LCB2				0.784	
LCB3				0.750	
LCB4				0.759	
LCB5				0.748	
LCB6				0.760	
LCB7				0.772	
LCB8				0.815	

Abbreviations: PD, psychological distance; FC, fear of COVID-19; APC, air pollution concern; LCBs, low-carbon behaviors. These abbreviations are also used in the subsequent tables and figures.

variables were above 0.7, thereby demonstrating the acceptable reliability of the scales.[86] A confirmatory factor analysis (CFA) in SmartPLS 3.0 was adopted to further confirm the validity and reliability of the scales. The results (see Table 3) showed that all the values of average variance extracted (AVE) were above the benchmark value of 0.5.[87] In addition, all the factor loading values were above the threshold of 0.7 (see Table 4). Therefore, the convergent validity of all the constructs in this study was confirmed. The square roots of AVEs on the diagonal of Table 3 were greater than the correlation coefficient values between each construct and all the other constructs.[87] In addition, the loadings of all constructs on their corresponding factors were considerably greater than their cross-loading values on other factors (see Table 4). Therefore, the discriminant validity of all constructs in the research model was confirmed.[88] Moreover, the composite reliability (CR) values in Table 3 were above the recommended value of 0.7, thus confirming the reliability of the scales.[88]

Furthermore, Harman's one-factor test was used to examine the common method bias that might exist due to the self-reported data.[89] The result showed that the first and largest extracted component accounted for 39.49% (< 50%) of the variance, indicating that common method bias was not a serious concern in this study.

Regression Analysis

SPSS 25 regression analysis was used to examine H1, H2a, H2b and H2c. First, the control variables, including the respondents' gender, age, region, occupation, education, and income, were inputted into the regression model (see Table 5). The results in Model 2 demonstrated that close PD was positively related to FC ($\beta = 0.454$, $p < 0.001$); therefore, H1 was supported. Moreover, Model 4 showed that fear was positively related to APC ($\beta = 0.443$, $p< 0.001$); therefore, H2a was supported. As shown in Model 6, fear was also positively related to LCBs ($\beta = 0.468$, $p < 0.001$); therefore, H2b was supported. As shown in Model 7, there also existed a positive relationship between APCs and LCBs ($\beta = 0.275$, $p < 0.001$; H2c was supported). A SmartPLS 3.0-based structural model test confirmed the above results.

Mediating Effect of APC

To examine the mediating effect of APC between FC and LCBs, a bootstrapping analysis was performed using the PROCESS package in SPSS 25. The resample size of bootstrapping was set as 5000, and the confidence interval was set as 95%. As shown in

Table 3 Mean, Standard Deviation (SD), Composite Reliability (CR) and Discriminant Validity

Variables	Mean	SD	CR	AVE	PD	FC	APC	LCBs
PD	5.040	1.119	0.899	0.689	**0.830**			
FC	5.107	1.081	0.927	0.614	0.484	**0.784**		
APC	5.159	1.079	0.874	0.698	0.315	0.462	**0.835**	
LCBs	5.202	1.103	0.936	0.646	0.342	0.496	0.457	**0.804**

Note: The bolded values on the diagonal line are the square roots of AVEs.

Table 4 Cross Loadings of Factors

Items	PD	FC	APC	LCBs
PD1	0.846	0.422	0.296	0.281
PD2	0.816	0.381	0.254	0.297
PD3	0.836	0.405	0.290	0.318
PD4	0.822	0.398	0.203	0.239
FC1	0.325	0.738	0.425	0.377
FC2	0.391	0.775	0.350	0.389
FC3	0.371	0.741	0.374	0.373
FC4	0.374	0.783	0.378	0.395
FC5	0.376	0.789	0.348	0.424
FC6	0.398	0.774	0.293	0.355
FC7	0.390	0.827	0.361	0.419
FC8	0.410	0.835	0.363	0.374
APC1	0.294	0.442	0.856	0.419
APC2	0.281	0.377	0.839	0.370
APC3	0.206	0.328	0.811	0.349
LCB1	0.261	0.413	0.348	0.779
LCB2	0.298	0.396	0.352	0.817
LCB3	0.257	0.406	0.414	0.808
LCB4	0.226	0.313	0.322	0.755
LCB5	0.264	0.441	0.379	0.808
LCB6	0.280	0.444	0.343	0.808
LCB7	0.312	0.395	0.414	0.822
LCB8	0.294	0.364	0.354	0.832

Table 6, air pollution concerns had a partial mediating effect, as the confidence intervals of the direct and indirect effects did not include 0; that is, both were significant (H2d was supported).

Design of Study 2

Study 2 was designed to examine H3a and H3b, which are presented in the conceptual model (Figure 2), specifically, 1) how outcome framing moderates the influence of FC on LCBI and 2) how it moderates the influence of APC on LCBI.

An intergroup experiment according to outcome framing (gain framing vs loss framing) was conducted in this study, and an online survey investigation was employed to collect data. Two questionnaires were designed for each group regarding the different outcome framings. Both questionnaires contained five parts. Parts 1 and 2 measure FC and APC, respectively. The narratives of the different outcome framings (see Appendix 3) and manipulation test items are provided in Part 3. Part 4 measures LCBI, and Part 5 collects demographic information. A 7-point Likert scale (1= totally disagree, 7 = totally agree) was employed in Study 2 (see Appendix 2 in the Supplementary Materials).

Results of Study 2

Descriptive Statistics

A total of 304 valid responses (ie, 155 in the gain framing group and 149 in the loss framing group) were received via an online experimental survey from May 15 to June 30, 2020, targeting netizens aged above 18. In the online survey, the respondents were randomly assigned to either the gain framing group or the loss framing group after they accessed the survey link. Written informed

Table 5 Results of Study 1

Variables	FC		APC		LCBs		
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
Gender	0.195***	0.118*	0.167**	0.081	0.137*	0.046	0.023
Age	0.141*	0.064	0.108	0.046	0.194**	0.128*	0.115*
Occupation	−0.055	−0.027	−0.148*	−0.124*	−0.054	−0.028	0.006
Education	0.025	−0.023	0.149**	0.137**	0.104	0.092	0.054
Income	0.021	0.016	−0.014	−0.024	−0.023	−0.033	−0.026
Region	0.074	0.083	−0.034	−0.067	−0.010	−0.044	−0.026
PD		0.454***					
FC				0.443***		0.468***	0.346***
APC							0.275***
R2	0.070	0.261	0.069	0.235	0.065	0.269	0.326
ΔR2	0.070	0.191	0.069	0.183	0.065	0.204	0.057
F	3.935	15.865	3.909	15.163	3.691	16.592	18.989
ΔF	3.935	81.437	3.909	77.045	3.691	87.905	26.405

Note: *p<0.05, **p<0.01, ***p<0.001.

Table 6 Mediating Effect of APC

	Coefficient (β)	S.E.	LLCI	ULCI
Direct effect	0.368	0.053	0.263	0.473
Indirect effect	0.135	0.038	0.064	0.212
Total effect	0.503	0.050	0.406	0.601

Abbreviations: S.E., standard error; LLCI, lower limit of confidence interval; ULCI, upper limit of confidence interval.

consent was acquired from each respondent using the same approach as that used in Study 1. The results of demographic distribution analysis showed that 54.9% of the respondents were male, and 71.7% of the respondents were younger than 35 years old (see Table 7). The respondents from North and South China accounted for 35.5% of the total number of respondents. Furthermore, 42.5% of the respondents possessed a bachelor's degree or higher. In terms of income, 89.5% of the participants earned less than 8000 Yuan a month.

Outcome Framing Manipulation Test

Independent sample t-tests in SPSS 25 were conducted to examine the manipulation of outcome framing. Loss framing was coded as 0, whereas gain framing was coded as 1. T1, T2, T3 and T4 (four questions for the manipulation of outcome framing; see questions 20–23 in Appendix 2 in the Supplementary Materials) were used as the test variables. Table 8 demonstrates that the manipulation was successful.

Moderating Effect Test of Outcome Framing

A hierarchical regression analysis in SPSS 25 was performed to examine H3a and H3b. The four variables, namely, FC, APC, the interaction item of fear and outcome framing and the interaction item of air pollution concern and outcome framing, were inputted into the regression model (see Table 9). The results showed that the standardized coefficients of the interaction items were positive ($p < 0.001$), thereby indicating that both FC and APC had a more significant influence on LCBI under gain outcome framing than under loss outcome framing. Figure 3A shows the influence of FC on LCBI under gain and loss framing (H3a was supported). Figure 3B illustrates the influence of APC on LCBI under gain and loss framing (H3b was supported).

Discussion

This research explored how social members' fear of the new coronavirus is reshaping their pro-environmental behavior. The results of Study 1 indicated that PD from COVID-19 is significantly related to FC. Specifically, the closer the PD is, the deeper the fear is. This confirmed the proposition of prior studies that the fear of social members is associated with the closeness they perceive to the risk.[35] This can also explain why Europeans felt increased fear and worry after the COVID-19 outbreak in Europe.[27,28] The results also showed that APC partially mediates the relationship between FC and LCBs. Specifically, the deeper the FC is, the higher the APC and the more LCBs there are. The significant relationship between the infection rates and mortality of COVID-19 and the air pollutants revealed in prior investigations makes individuals who perceive a high level of FC more concerned about air pollution and, thus, reinforce their LCBs.[2,4,5] In short, people's fear induces pollution concerns and pollution mitigation actions.

The moderating effect analysis in Study 2 revealed that the regression coefficient between fear and LCBI changed significantly under gain framing compared to under loss framing. The regression coefficient between APC and LCBI also changed considerably under gain framing compared to under loss framing. The result is contradictory to statements that claim that individuals are more sensitive to losses than to gains.[72–75] However, it is consistent with the findings of a prior study, which concluded that communicating the benefits of mitigation efforts, rather than the potential negative consequences of not taking actions, can result in more positive responses from citizens.[71] Similarly, positive outcome framing can strengthen

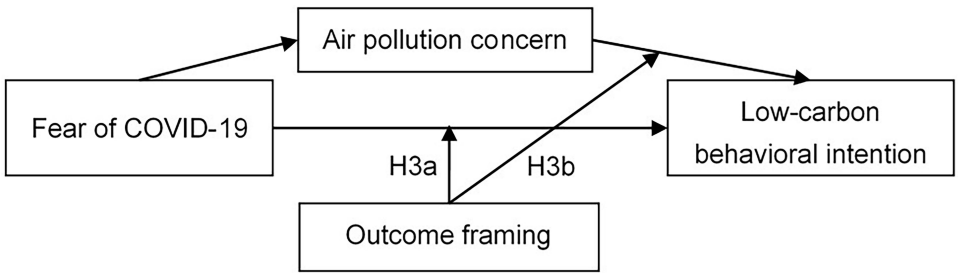

Figure 2 Conceptual model of Study 2.

Table 7 Distribution of Demographic Information of Samples (N = 304)

Demographic Characteristics		N	Percent
Gender	Male	167	54.9%
	Female	137	45.1%
Age	Below 20 years	67	22.0%
	21–35 years	151	49.7%
	Above 35 years	86	28.3%
Region	East China	39	12.8%
	North China	52	17.1%
	Northeast China	34	11.2%
	Central China	32	10.5%
	South China	56	18.4%
	Southwest China	38	12.5%
	Northwest China	44	14.5%
	Overseas	9	3.0%
Educational background	High school or below	175	57.6%
	Bachelor degree	102	33.6%
	Master or Ph.D degree	27	8.9%
Income (monthly)	Less than 5000 yuan	71	23.4%
	5000–8000 yuan	201	66.1%
	More than 8000 yuan	32	10.5%

Abbreviation: N, number of valid participants.

Table 8 Manipulation Test Results of Outcome Framing

Test Variable	Group	N	Mean	SD	t-Value
T1	1	155	6.08	0.707	37.733***
	0	149	2.31	1.013	
T3	1	155	6.04	0.701	31.985***
	0	149	2.83	1.023	
T2	1	155	3.62	1.447	−15.785***
	0	149	5.68	0.689	
T4	1	155	4.13	1.079	−14.887***
	0	149	5.70	0.714	

Note: ***p<0.001.
Abbreviations: N, number of valid participants; SD, standard deviation.

the influences of individuals' FC and APC on their pro-environmental behavioral intention. Based on the above results, the following specific implications were generated.

Theoretical Implications

First, this research enriches the framework to understand individuals' fear of coronavirus from the PD perspective. PD is related to emotions, and individuals with PD close to risks or events have high risk perceptions.[35,39] Fear arises when an individual encounters danger or a threat and is an adaptive subjective emotion.[31] As an emotion, fear can be assumed to be related to PD. This assumption was confirmed by the results of Study 1, which demonstrated that the closer the PD was, the deeper the fear of coronavirus was. That is, an individual's FC is, to some extent, determined by his or her perceived PD from COVID-19.

Table 9 Interaction Effect

Variables	LCBI	
	Model 1	Model 2
FC	0.299***	0.602***
APC	0.386***	0.411***
OF×FC		0.294***
OF×APC		0.272***
R^2	0.358	0.498
ΔR^2	0.358	0.140
F	83.976***	74.115***
ΔF		41.601***

Note: ***p<0.001.

Second, this research theoretically links individuals' fear of coronavirus with their attitude and behaviors toward the environment. When an individual encounters danger or threats that might be caused by environmental issues, fear triggers his or her pollution concerns and pollution mitigation actions.[29–32] Environmental concerns may directly lead to pro-environmental behaviors (including LCBs).[42–45] Considering the examined relevance between the spread of COVID-19 and air pollution,[2,4,5] this study verified the relationship between FC, APC and LCBs from the perspective of specific air pollution issues. The results illustrated that FC can both directly result in LCBs and indirectly lead to LCBs by raising APC.

Third, this research introduces outcome framing into the framework to understand how individuals' LCBI triggered by FC can be enhanced. Outcome framing-related prior works have stated that individuals' perspectives can be formed by providing specific messages.[70] In most cases, including air pollution, gain framing is more effective in encouraging individuals to adopt certain behavior than loss framing.[68] The results of the moderating effect analysis in Study 2 confirmed the proposition of prior research and suggest that specific messages can shape a person's perception of certain issues. Specifically, the relationships between fear and LCBI and between APC and LCBI are more significant when gain framing is provided than when loss framing is provided.

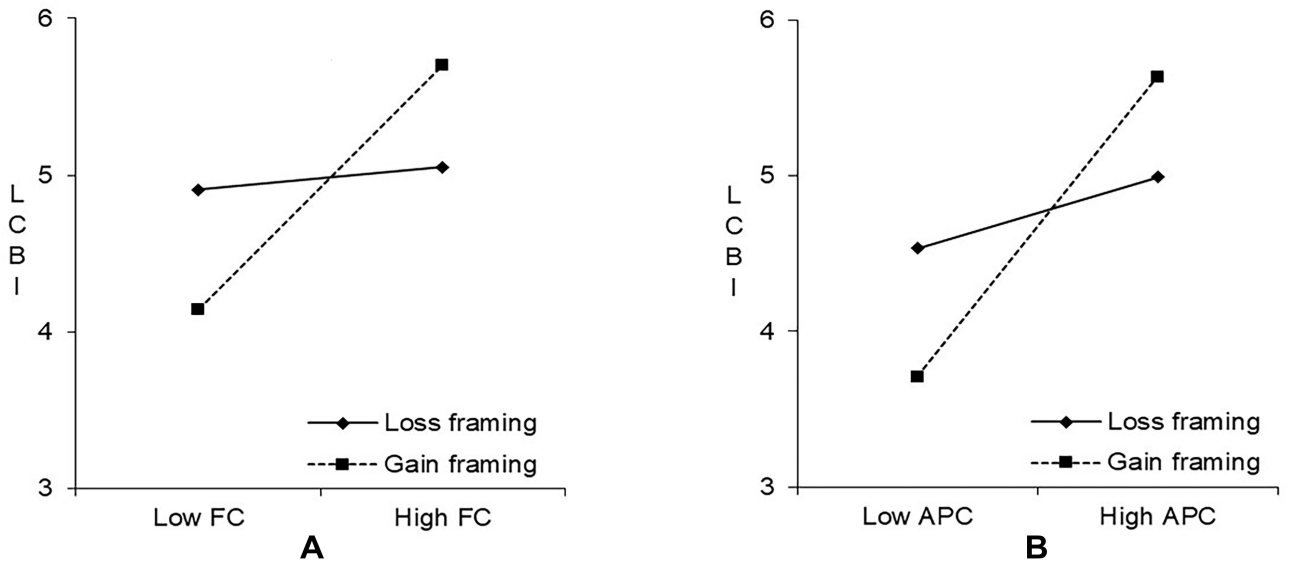

Figure 3 Moderating effects of outcome framing between fear of COVID-19 (FC) and low-carbon behavioral intention (LCBI) (**A**) and between air pollution concern (APC) and LCBI (**B**).

Practical Implications

First, a clear understanding of the psychological mechanism through which social members' pro-environment behaviors can be evoked or enhanced is critical to the promotion of environmental protection. The closer the PD is to COVID-19, the greater the virus threat encountered by an individual and the more concern he or she will invest in environmental pollution. Thus, responsible media and authorities should educate social members about the impact of air pollution on the spread of the virus, appeal to their attention to virus-related events or information and thereby, arouse their low-carbon and other pro-environment behaviors.

Second, the results suggested that individuals are more likely to perform certain behaviors when they learn that their behaviors will generate good results for others or the environment. Health and environmental policies are feasible ways to raise social members' APC and increase their LCBI by lessening PD toward viruses and public emergencies. Using the stimulus of gain framing to convey that engaging in LCBs generates satisfactory results for the environment and epidemics is an effective way to increase LCBI. Given the significant role of gain framing, health and environmental policies could state that adopting LCBs has a positive impact on addressing air pollution and climate change. Specifically, when an individual's risk perception of viruses remains unchanged, the better the outcomes, the stronger the LCBI he or she will generate. Therefore, when gain framing is applied to policy advocacy, individuals with a strong risk perception of viruses and epidemics will respond positively. In addition, gain framing could be used to promote pro-environment behaviors in public environmental education.

Conclusion

By conducting two surveys, this research examined the relationship between individuals' fear of COVID-19 and their low-carbon behaviors. Study 1, which involved 323 participants, revealed that the closer the PD was to COVID-19, the higher the fear of it was. Furthermore, FC positively contributes to low-carbon behaviors, and air pollution concerns act as a mediator in their relationship. Study 2, which involved 304 participants, revealed that fear and air pollution concerns lead to higher low-carbon behavioral intention within gain framing than within loss framing.

Along with the implications generated from this research, limitations and future works are discussed. In our investigation, the relationship between PD and fear was verified. However, the four dimensions of PD were integrated as a whole, and the different influences of each of the four dimensions on fear are expected to be examined in future work. Moreover, Study 2 was unable to track and investigate the actual LCBs of the participants after the stimulus of outcome framing was applied. Although LCBI is a prerequisite of LCBs, it does not necessarily lead to actual LCBs. Therefore, research on the moderating effect of outcome framing by tracking participants' actual behaviors is necessary in the future.

Data Sharing Statement

Data supporting the findings presented in the current work will be available from the corresponding author upon request.

Ethic Statement

Our research was conducted in accordance with the Declaration of Helsinki and approved by the Ethics Committee of the College of Economics and Management of Nanjing University of Aeronautics and Astronautics and did not involve any human clinical trials or animal experiments. The survey participants were told that this research adopted the principle of voluntary participation and their answers would be strictly kept confidential. All participants understood the purpose of this research and agreed to participate voluntarily.

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Disclosure

The authors report no conflicts of interest in this work.

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