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# Developing a Behavior Change Framework for Pandemic Prevention and Control in Public Spaces in China

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**Abstract:** Preventive behavior, such as hand hygiene, facemask wearing, and social distancing, plays a vital role in containing the spread of viruses during pandemics. However, people in many parts of the world usually encounter difficulties adhering to this behavior due to various causes. Thus, this article aims to develop a research framework and propose design strategies to prompt individuals' behavior change during pandemics. Initially, we integrated a literature review and a structured interview ($n$ = 22) to ascertain the core factors impacting behavior change during pandemics. These factors were categorized into four aspects: perceptional factors (attitudes, subjective norms and perceived behavior control, risk perceptions); social factors (knowledge and information dissemination, governmental regulations); physical factors (tools and facilities and surveillance); and sociocultural factor (cultural contexts). Then, a theoretical framework with antecedents was developed to reveal behavior intention and formation process. After that, an empirical study was carried out to test the research framework through a questionnaire survey ($n$ = 549). The research findings indicated that all derived factors could directly or indirectly affect individuals' preventive behavior during pandemics. This article strives to provide valuable insights for different stakeholders when coping with pandemic situations.

**Keywords:** behavior change; public health; pandemic prevention and control; structural equation modeling; public design



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## 1. Introduction

With globalization and human activities escalating, emerging pandemics that threaten public health, social security, and economies are increasing in frequency [1,2]. Currently, the unfolding COVID-19 pandemic has triggered an unprecedented health crisis that influences all spheres of human life [3]. Besides causing virus transmission, pandemics and corresponding control measures may expose the risk of uneven socioeconomic and political systems [4]. For instance, amidst the COVID-19 pandemic, India has witnessed a massive crisis in female migrant workers, while Romania has seen transnational labor troubles and a rise of nationalism [5–7]. The devastating impacts of pandemics have also been observed in global food systems and agriculture [8,9]. More importantly, although humans have defeated many past pandemics, future pandemics are unpredictable and inevitable [10]. Hence, it is highly significant to develop public health solutions for pandemic prevention and control.

Generally, there is often a long, uncertain pandemic situation before massive vaccination or antiviral medicines' development. During this period, nonpharmaceutical interventions, such as quarantine, social distancing, and hand hygiene, are necessary and

critical choices to limit the spread of viruses [11–14]. Currently, people in many parts of the world are required to follow strict control measures suggested by the World Health Organization (WHO) to contain the COVID-19 pandemic. Similarly, the Chinese Center for Disease Control and Prevention (CDC) have also imposed a series of health interventions for pandemic prevention and control [15]. These public health interventions and social control measures often require rapid, large-scale public behavior change, including wearing face masks; correctly washing hands; avoiding touching the eyes, nose, and mouth with unwashed hands; reducing contacts; and maintaining social distancing [16,17].

Behavior change can play a significant role in pandemic prevention and control [18]. As Perra (2021) posed, pandemics and human behavior are often intertwined [16]. On the one hand, human behavior and interactions can drive the spread of pandemics, while on the other hand, pandemics can lead to public behavior change. Back in 1919, the Science Magazine published a paper that indicated behavior change was related to the 1918 Spain flu and illustrated several negative factors that prevented public behavior change [19]. Betsch (2020) noted that the unfolding COVID-19 pandemic could be contained through large-scale and rapid behavior change [12]. Van Bavel et al. (2020) emphasized that slowing transmission during a pandemic requires dramatic shifts in people's behavior [20]. Additionally, the association between behavior change and pandemic prevention and control has also been verified by practical situations. At this time, COVID-19 is out of control in many parts of the world, and most of us have suffered from several grave waves of this pandemic. One of the main reasons is that many people are unwilling to follow social control measures and change their behavior patterns. On the contrary, the spread of COVID-19 has been widely restricted in China, although there are several disadvantaged factors, such as densely populated urban areas and high population mobility. Some studies attributed this extraordinary success to people's strict compliance with social control measures and behavior change [21,22].

Although the significance of behavior change during pandemics has been recognized, several problems still exist. From the practical view, a genuine and massive behavior change is quite challenging and complicated. Currently, preventive measures and behavior are recommended by authorities worldwide to contain the COVID-19 pandemic, but many people still fail to adhere to these behavior and control measures [23]. Moreover, new knowledge and ideas are urgently needed for the current or future pandemics. Even though we can gain some experience of human behavior from previous pandemics, many things have changed and need to be reassessed, including the virus, information access, social media, and the interaction between authorities and the public [12]. From the theoretical viewpoint, first, few studies have attempted to construct a behavior change framework for pandemic prevention and control, especially under the Chinese context. Second, research integrating design science with behavior science for pandemic prevention and control is relatively scarce.

The present study strives to identify critical determinants of preventive behavior and construct a research framework to facilitate people's behavior change during pandemics. Initially, we integrated the literature review and user interview results to obtain key variables and construct a behavior change framework. Then, we tested the research framework by using the structural equation modeling (SEM) approach. To achieve the research goal, three research questions were posed: First, what factors affect people's behavior change for pandemic prevention and control? Second, how can we construct a behavior change framework for pandemic prevention and control? Third, how can we propose design strategies for prompting people's behavior change during pandemics? This article makes the following knowledge contributions. At the theoretical level, this article explores the potential of integrating public health, behavior science, and design science under a global pandemic context, contributing to the knowledge of "design for behavior change" and "design for pandemic prevention and control". It refines the structure of the original theory of planned behavior (TPB) model by adding extra variables. Meanwhile, this study extends the applicability of the TPB model by exploring it under a pandemic

context. To the best of our knowledge, it is one of the first studies that attempts to construct a behavior change framework for pandemic prevention and control under the Chinese context. At the practical level, it clarifies key influential factors and individuals' behavior change formation processes during pandemics. The research findings can guide different stakeholders in facilitating people's preventive behavior change during pandemics.

## 2. Literature Review

### *2.1. Pandemic-Related Behavior Change*

Behavior change is a construct focusing on helping individuals willingly perform the recommended behavior and systematically understand the changing process. In the context of public health, it refers to people making efforts to change their habits and attitudes and finally achieve a healthy lifestyle to prevent diseases [24]. For example, diabetes patients are supposed to change their eating habits to control their blood sugar. They are often required to avoid the intake of food with high sugar. Meanwhile, they should maintain their weight by participating in more exercise. In this study, the term "behavior change" refers to how people change their behavior patterns and lifestyles to adapt to a pandemic situation.

More specifically, the behavior change in the current research belongs to a type of public health intervention during pandemics. According to Brownson et al. (2010), there are three main levels of public health interventions for addressing pandemic threats, where the downstream level concentrates on individual behavior change and disease management, the midstream level concentrates on interventions affecting communities, and the upstream level concentrates on policies and regulation enactment [25]. We roughly classified these health interventions into two types: The first type is at the governmental level, including isolation, quarantine, lockdown, testing, screening, and tracing. The second is at the individual level, including facemask wearing, hand hygiene, social distancing, and conduct reduction. In this regard, behavior change in our study refers to individual-level health interventions. Even though both types of intervention have been widely applied for pandemic prevention and control, the latter (individual-level interventions) show more advantages and strengths in some situations, which can be attributed to three reasons. First, some governmental-level interventions, such as lockdowns or massive testing, are costly to implement, which may not be applicable in underdeveloped regions. Second, the effects of individual behavior change are much more consistent, as governmental actions usually serve as a post hoc remedy. Third, people can play a more active role in individual-level behavior change than passive compliance with governmental interventions. In other words, individual-level interventions may be smoother and more natural than governmental-level interventions.

### *2.2. Existing Health Interventions during Pandemics*

During the current pandemic, authorities worldwide have imposed various health interventions, of which phone applications are one of the most popular and preferable choices [16,26]. In China, the QR scanning system serves as a health status monitor and tracking system to deal with COVID-19, distinguishing people according to different infectious risk levels [27]. For example, people with red codes often have a high-risk level of infection, which means that they should be limited as to travel, while green codes indicate a low risk level, meaning that the owners can travel freely. Similarly, India's 'Arogya Setu' app can demonstrate users' exposure levels to viruses [28]. The Hong Kong authority also developed a mobile application called "stay at home" to check whether people leave the allotted quarantine center without permission [29]. In this case, if people under quarantine leave without permission, the app will alert supervisors. Moreover, many such phone applications can also record users' health status and assist them if a need arises. In Singapore, authorities combined different monitoring approaches to ensure people stay at home and follow the quarantine rules. When people are under quarantine, they need to update their geographic locations to official platforms every day. Meanwhile, they may face random phone calls and home visits by health workers and police. In some

regions, Bluetooth technology and smart robotics were applied to help people keep a certain distance [30].

In addition, publicity and information dissemination are also popular interventions during pandemics. As Toppenberg-Pejcic et al. (2019) noted, infectious disease communication is crucial and necessary to public health and safety [31]. Similarly, Oh et al.'s (2020) research also reveals that social media can disseminate messages to improve health behavior outcomes [32]. In effect, various types of media platform have been applied in both previous and current pandemic contexts [21,33]. In China, some mass media platforms, such as "We-chat", "Tencent News", "Toutiao", and "Sina Weibo", have set specialized columns to enable the public to access real-time information during pandemics. In Colombia, researchers used a participatory design and gamification design approach to broadcast pandemic prevention and control information to indigenous communities. The poster design in a gamified form enables indigenous communities to bridge their beliefs between traditional ancestral medicine and official medical recommendations during the COVID-19 pandemic [34]. In India, the government developed the Gok Direct app to avoid misinformation [29]. Based on GPS and big-data technology, the public can even know the daily routes of the suspected or identified patients. However, some mobile applications face criticism concerning privacy infringement and user data theft [29]. Overall, various health intervention measures have been adopted for pandemic prevention and control, which are mainly at the governmental level. Many of them draw attention to monitoring and screening during quarantine periods. These types of health intervention are often short-term and mandatory, while few strive to prompt a long-term and massive individual behavior change during pandemics. Thus, it is necessary to develop a behavior change framework for practical guidance.

### *2.3. The Theory of Planned Behavior*

The theory of planned behavior (TPB) was developed based on the theory of reasoned action (TRA). In 1967, Martin Fishbein and Icek Ajzen proposed TRA to explain the relationship between attitudes and human behavior [35]. TRA implies that human behavior relies on previous attitudes and intentions. In other words, the engagement of individuals' behavior is determined by their expected behavior outcomes. However, TRA received some criticism that can be clustered around three issues: the relationship between attitudes and subjective norms, the sufficiency of indicators, and the limited range of meaning in theory [36]. In this regard, Icek Ajzen proposed TPB, which was an extension and improvement of TRA. Additionally, TPB links beliefs to behavior and implies that human behavior is shaped by three core elements: attitudes, subjective norms, and perceived behavior control [37]. Currently, TPB is one of the most popular models used to predict human behavior or behavior intentions [38]. This model has been widely applied for human behavior research, such as waste-sorting behavior, learning behavior, consumer behavior, and exercise behavior [38–41].

Given that TPB is effective in explaining human behavior, it is appropriate to develop a model based on the original TPB. Nevertheless, TPB has faced some criticism due to the inadequate variables in its construction [38]. Furthermore, Ajzen (1991) also stated that "extra variables can be added to the TPB model if they can capture a significant part of the variance in behavior" [37]. Based on the above illustration, this study attempts to extend the original TPB and develop a new model explaining people's behavior change and formation during a pandemic context.

### *2.4. Research Gap*

After reviewing the previous literature, several research gaps were determined. In design sciences, current research and practices mainly attempt to impose mandatory and short-term interventions to contain virus transmissions, such as tracing, disinfection, screening, isolation, and protection from infection [14,29,42–44]. However, few of these focus on persistently promoting individual behavior change. In behavior sciences, although previous

studies have investigated individual behavior and its influential factors during pandemic situations, few attempt to construct a framework to reveal individuals' preventive behavior change formation processes, especially under the Chinese context [12,20,45–48]. Moreover, rare studies extend and refine the traditional TPB model during pandemics. Lastly, studies integrating the knowledge of behavior science, public health, and design science are relatively scarce. Thus, it is of high significance to address these gaps comprehensively.

## 3. Methodology

This study was constructed of qualitative and quantitative research methods in sequence, constituting three main research steps. First, we reviewed related literature and conducted a user interview to obtain critical determinants of people's behavior change during pandemics. After that, a behavior change framework was constructed to reveal people's behavior change intention and formation processes during pandemics. Second, we conducted an empirical study to test the theoretical framework by using an SEM approach. Third, we discussed the research findings and developed design strategies and policies to foster public behavior change during pandemics.

## 4. Hypotheses Development and Research Framework

We conducted a structured interview to obtain key variables for framework construction, with 22 participants responding, including designers, design researchers, health workers, and administrators in public spaces. Appendix A Table A1 summarizes the detailed demographic profile of interviewees. All respondents had relevant knowledge backgrounds to provide valuable information. The interview protocol contained three parts. First, we gave a brief introduction about the research topic and related terminology, such as "pandemic", "behavior change", and "design intervention". Second, interviewees provided their respective demographic information. Third, interviewees answered a series of research questions related to our research topic, including "what are the key factors influencing people's behavior change during pandemics?"; "how do they influence people's behavior change during pandemics?"; and "are there any gaps between behavior change intentions and behavior change implementations?". Due to the time and distance limitations, the interviews were conducted mainly through social software and phone calls. We employed a smartphone and a laptop to record the interview result. Once the interview data were collected, they were subsequently coded and clustered to generate key themes, with the Nvivo 12.0 Plus software assisting. Notably, we followed a six-step thematic analysis approach proposed by Braun and Clarke (2006) during the data analysis process [49].

After that, we integrated the literature review and user interview results to identify the key variables of behavior change during pandemics and constructed a theoretical framework. Then, we proposed a theoretical framework built by variables and their interactive relationships, revealing people's behavior change formation process, see Figure 1.

### *4.1. Attitudes towards Behavior Change during Pandemics*

"Attitudes" is derived from the TPB model, which denotes people's subjective behavior assessment in a specific circumstance [37]. Individuals with positive attitudes towards a given behavior are more likely to perform it [50]. In the current research, attitudes refer to people's positive and negative feelings about performing the recommended behavior for pandemic prevention and control. Many previous studies have explored the role of attitude in shaping individual behavior. As Goh et al. (2017) stated, personal attitudes could affect noncompliant behavior at national parks among visitors [51]. In the technology acceptance model (TAM), individuals' attitudes towards a new technology can directly result in behavior intentions [52]. The impact of attitudes on behavior has also been verified under a pandemic context. Myers and Goodwin (2012) pointed out the link between people's vaccination intentions during the swine flu pandemic [53]. Similarly, Ang et al. (2021) noted that risk-taking attitude was one of the significant predictors for social distancing

behavior during the COVID-19 pandemic [54]. Generally, individuals who believe that the recommended behavior is valuable and vital in containing pandemics will be more willing to perform it. Hence, people's attitudes are to be included in the research framework. For this purpose, the following hypothesis was formulated.

**Hypothesis 1 (H1).** *Attitudes towards behavior change positively influence people's behavior change intentions during pandemics.*

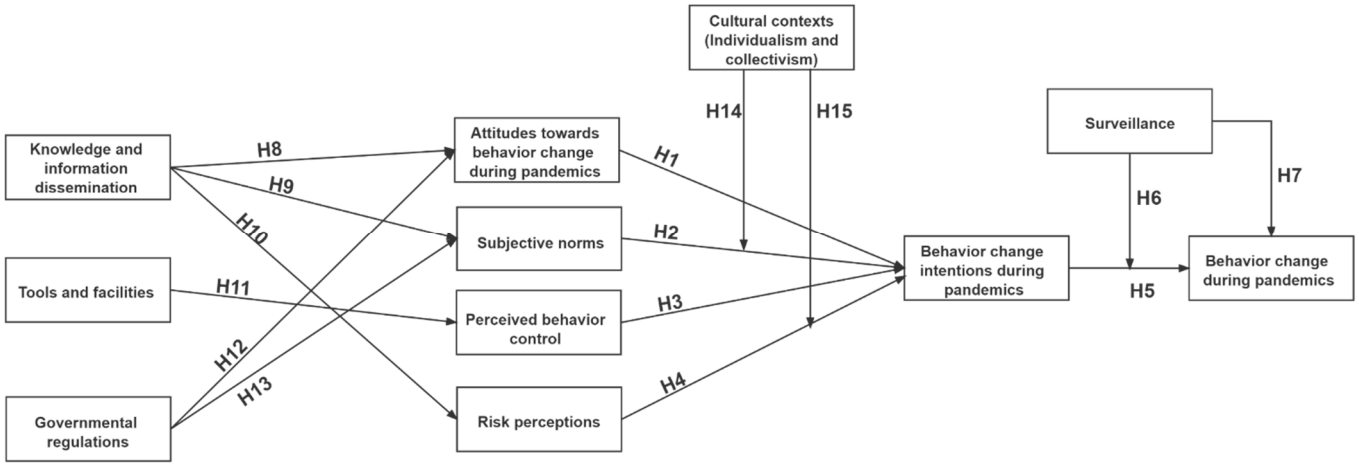


**Figure 1.** Theoretical framework.

### *4.2. Subjective Norms*

Subjective norms are also an essential factor for constructing the TPB model, which emphasize the perceived social pressure from surrounding environments, such as others' opinions, especially for closely related people [37]. Generally, the observation and consultation of other people's behavior are primary sources that construct subjective norms. In other words, if an individual thinks the people surrounding him support him in performing a certain behavior, he is encouraged to act in this way. Previous empirical studies have suggested the significant influence of subjective norms on people's behavior intentions, such as waste sorting and mobile health service adoption [39,55]. In the current study, subjective norms indicate that friends or family members may influence one's willingness to perform the recommended behavior during pandemic situations. This factor has a considerable power to shift human behaviors, especially for those who share common identities [56]. As Bond et al. (2012) illustrated, in many cases, public interventions do not directly affect people who receive the intervention but indirectly affect their surrounding groups, who then deliver this effect through behavior imitation [57]. Additionally, Christakis and Fowler (2013) emphasized that social networks could amplify beneficial and harmful behaviors during a pandemic [58].

In addition, it is worth noting that subjective norms can have particularly significant effects in the Chinese context. The main reason is that collectivism is an important part of Chinese culture, meaning that the Chinese may be easily influenced by social policies and public views [59]. Under the current "nationwide anti-pandemic" circumstance, everyone in China assumes responsibility for following social control measures for pandemic prevention and control. Therefore, subjective norms can be included in the anticipated framework, and the subsequent hypothesis is as follows.

**Hypothesis 2 (H2).** *Subjective norms positively influence people's behavior intentions for pandemic prevention and control.*

### *4.3. Perceived Behavior Control*

Perceived behavior control refers to the extent to which individuals believe in performing certain behavior, reflecting one's perception of the related executive abilities [37]. The element "perceived behavior control" is derived from Bandura's concept of self-efficacy [37]. Fishbein and Cappella (2006) also stated that perceived behavior control is equivalent to the concept of self-efficacy to a certain degree [60]. In this study, perceived behavior control denotes people's confidence and subjective assessments of whether they can adhere to the pandemic-related behavior change. Many prior studies have revealed the significant impact of perceived behavior control on human behavior. For instance, Zhang et al. (2019) pointed out that perceived behavior control can affect users' security perceptions when conducting electronic transactions via mobile payment applications [61]. Regarding the pandemic-related behavior change, Agarwal's (2014) study implied that attitudes, subjective norms, and perceived behavioral control could affect people's A/H1N1 vaccine intentions when entered in the second block [62]. Yu et al.'s (2021) research indicated that perceived behavior control was significantly associated with social and physical distancing measures in Hong Kong [63]. Myers and Goodwin (2012) found that personal attitude, subjective norms, and perceived control were significant predictors of the vaccination intentions of the swine flu pandemic for UK citizens [53].

**Hypothesis 3 (H3).** *Perceived behavior control positively influences people's behavior change intentions during pandemics.*

### *4.4. Risk Perceptions*

The factor "risk perceptions" was extracted from the health belief model (HBM) [64]. In the current research, it refers to people's subjective assessment of diseases and perceived vulnerability. Risk perceptions can be divided into the personal level and social level [65]. The former represents severe impacts on individuals, while the latter focuses on the whole society. Risk perceptions are related to one human emotion, which is fear. Generally speaking, fear is one of the critical emotions and responses of humans during a pandemic, as it can activate humans' defense systems to cope with the pandemic threat. According to Witte and Allen's (2000) study, fear can make people change their behaviors to combat a pandemic if they have a sense of efficacy [66]. In this case, if people feel they are vulnerable when exposed to a pandemic situation without any preventive measure, they will be willing to follow social control measures and change their behavior. On the other hand, when a pandemic situation eases, some people will relax vigilance and be reluctant to perform the recommended behavior. This can partly explain why pandemic situations always last for several waves in many parts of the world but cannot be thoroughly contained. In addition, previous findings also indicated a positive association between risk perceptions and behavior change during pandemics. For example, Leung et al.'s (2003) study revealed that individuals' protective measure adoptions could be affected by the perceptions of risk and the anxiety levels of the public at large during the SARS epidemic [67]. Additionally, Liu et al.'s (2020) research indicated that risk perceptions could predict people's compliance with preventive behavior or vaccination behavior during pandemics [68]. Based on the above discussions, we came up with the following hypothesis.

**Hypothesis 4 (H4).** *Risk perceptions positively influence people's behavior change intentions during pandemics.*

### *4.5. Intention–Behavior Discrepancy and Surveillance*

In practical situations, there may be a discrepancy existing between behavior change intentions and genuine behavior change [39]. In other words, people's actual behavior may not be determined by their behavior intentions in some cases. Thus, bridging this gap is critical for steering people to achieve their final behavior change goals. In this article, surveillance was considered a catalyst that drives behavior change intentions to actual

behavior change for pandemic prevention and control. In Michie's behavior change wheel model, surveillance can act as a type of restriction or constraint to reduce the opportunities for the opposite behavior [50]. Chan et al. (2020) emphasized that challenging surveillance may lead to a failure of preventive measure adherence [23].

Generally, people may feel uncomfortable or inconvenient when performing pandemic-related behavior. For example, wearing face masks prevents a person from breathing freely, and following strict hand-hygiene rules is time-consuming. Due to these unpleasant experiences, people may be reluctant to perform such behaviors even though they have corresponding behavior intentions. Under such circumstances, surveillance may directly determine individuals' behavior performance. Sometimes, people are forced to wear masks when entering public spaces due to the surveillance from workers in these places. Furthermore, some digital solutions, such as phone applications, wearable devices, and smart public facilities can also play a role in real-time monitoring to ensure preventive behavior performance [29,30,69]. For instance, Sathyamoorthy et al. (2020) designed a mobile robot based on "deep enforcement learning" methods, which can detect and warn people who do not keep six feet of physical distance from each other [30]. In this study, we defined surveillance as various approaches aiming to monitor individuals' behavior modification statuses in public spaces. Rather than symptoms, surveillance targets people's preventive behaviors (for example, hand hygiene, social distancing, and mask wearing). We then roughly categorized surveillance into four types: surveillance from wearable devices, surveillance from mobile phone applications, surveillance from public facilities, and surveillance from workers in public spaces. Based on the above elaborations, it can be anticipated that surveillance acts as an external factor that may have a direct and moderate impact on people's behavior change implementations, and the following hypotheses were postulated.

**Hypothesis 5 (H5).** *Behavior change intentions positively influence behavior change implementation during pandemics*.

**Hypothesis 6 (H6).** *Surveillance positively moderates the relationship between behavior change intentions and behavior change implementation during pandemics*.

**Hypothesis 7 (H7).** *Surveillance positively influences behavior change implementation during pandemics*.

### *4.6. Information and Knowledge Dissemination*

In the present study, this factor refers to spreading messages related to pandemic prevention by using various publicity approaches. These messages may contain the number of infections, death tolls and cure rates, public policies, social control measures, the development of antiviral medicines and vaccines, and so on. Information and knowledge dissemination are crucial determinants of people's behavior change during pandemics [70]. As Zhao et al. (2015) noted, the information individual gather is a critical factor affecting how they react to disease transmission [71]. In the health belief model (HBM), knowledge and information about a given disease can affect individual behaviors [64]. Lin et al. (2017) stated that if people lack the scientific recognition and knowledge of pandemics, such as pathogenicity, transmission approaches, severity, and perniciousness, they will not take adequate preventive measures or change their behavior to protect themselves [72]. In contrast, having a systematic understanding of pandemics can facilitate positive preventive measures. For example, if people know that an infectious disease, such as COVID-19, is transmissible via droplets through coughing, sneezing, or intimate contact, they will cover their mouths when coughing or sneezing and reduce unnecessary contact. Wright et al. (2019) highlighted that intervention information and messages concerning breast cancer can impact people's preventive behavior [73]. During a public health crisis, various media platforms are the primary point of access to knowledge and information for the public.

This information is essential for constructing the risk perception and facilitating preventive responses [74]. Moreover, we cannot ignore the negative impacts of fake news or rumors about pandemics, as they sometimes can result in public panic or misperception [75]. Based on this, it is thus reasonable to include information and knowledge dissemination in the framework, and the following hypotheses were built.

**Hypothesis 8 (H8).** *Information and knowledge dissemination positively influence attitudes towards behavior change during pandemics.*

**Hypothesis 9 (H9).** *Information and knowledge dissemination positively influence subjective norms during pandemics.*

**Hypothesis 10 (H10).** *Information and knowledge dissemination positively influence risk perceptions during pandemics.*

### *4.7. Tools and Facilities*

Individuals often interact with various tools and facilities when they perform protective behavior during pandemics. In the current research, tools and facilities include face coverings; hand-hygiene facilities; wash basins; vending machines (offering face coverings and hand sanitizers); and some auxiliary facilities. For instance, during the mask-wearing process, face masks act as a product, while wearing behavior is regarded as an interaction between users and products. In this regard, facemask design can directly affect people's wearing experiences, thereby determining their behavioral intentions. The role of tools and facilities was also mentioned in previous behavior studies [61,76]. For instance, Verbeek (2005) used a microwave oven to demonstrate how tool design can mediate particular behavior via improving user experiences [77]. To prevent users from leaving their cards after using ATMs, Lockton et al. (2010) forwarded several improved schemes for ATM design, such as providing feedback and making key elements more prominent. [78]. Overall, well-designed tools and facilities can make it easier and more convenient for people to perform the recommended behavior. In other words, people's self-efficacy and confidence in behavior change may increase with the assistance of usable tools and facilities. Hence, the hypothesis was as follows.

**Hypothesis 11 (H11).** *Tools and facilities positively influence perceived behavior control during pandemics.*

### *4.8. Governmental Regulations*

Governmental regulations were proposed as another external factor that indirectly affects people's behavior change during a pandemic. Since the outbreak of COVID-19, Chinese authorities have launched a series of regulations to contain the spread of viruses. These regulations require citizens to perform various recommended behaviors, including wearing facemasks; correctly washing hands; avoiding touching the eyes, nose, and mouth with unwashed hands; reducing contacts; and maintaining social distancing [15]. Moreover, domestic regions were categorized into three types in China based on their pandemic risk levels, including high-risk, medium-risk, and low-risk levels. The behavior change requirement of areas with different risk levels varies. The interview results also suggested that authorities' policies can impose incentive or punitive measures to facilitate behavior modifications. In this regard, practical situations in China have suggested the dominant role of governmental regulation in shaping public behavior during pandemics. On the other hand, previous researchers have also emphasized the effects of government regulations on behavior change. As Yu et al. (2021) noted, successful social distancing needs combined efforts from governmental measures and personal responses [63]. Ibuka et al. (2010) stated that a high emphasis should be given to the role of health authorities in facilitating the public's performance of protective behavior [79]. Regarding people's attitudes, governmental

regulations can make people value the importance of pandemic-related behavior change. As for subjective norms, governmental regulations are often characterized by their official and authoritative features, which can act on people's cognition of subjective norms. In this regard, two hypotheses could be forwarded.

**Hypothesis 12 (H12).** *Governmental regulations positively influence attitudes towards behavior change during pandemics.*

**Hypothesis 13 (H13).** *Governmental regulations positively influence subjective norms during pandemics.*

*4.9. Cultural Context (Individualism/Collectivism)*

Cultural context is a vital factor that shapes individual behavior intentions. In the sociocultural theory, individuals' interactions with their cultures stress how cultural beliefs and attitudes affect people's thoughts and actions [80]. Human behavior and cultural context are often intertwined with each other. On the one hand, an individual's internal dispositions and tendencies can be shaped and generated by cultural and social experiences [81]. On the other hand, the way people think and act can, in turn, affect wider cultural circumstances [82]. Notably, considering a global pandemic circumstance, this study mainly focuses on one aspect of cultural context: individualism/collectivism. According to Eckhardt (2002), the terminology individualism/collectivism (IC) refers to how individuals are integrated into groups [83]. People in an individualistic circumstance concentrate on their willingness and goals more than the groups' regulations and orders they belong to. On the other hand, people in a collectivistic society focus more on group success and benefits than their own achievements [84]. Individualism/collectivism can affect people's behavior change process. Some researchers have argued that individualism/collectivism could moderate the relationship between subjective norms and behavior change intentions [84,85]. As we know, people may care about others' views more in a collectivist culture. During the current COVID-19 pandemic, there is a significant discrepancy between citizens in East Asia and Western countries concerning their protective behavior implementations. This discrepancy can reflect cultural differences between East Asia's collectivism and Western individualism. As Van Bavel et al. (2020) illustrated, people in Asian regions often prioritize following social regulations rather than their own desires [20]. Meanwhile, Asians may be more likely to recognize unobservable situational influences of pandemics, like herd immunity, suggesting the impact of individualism/collectivism on risk perceptions [20]. Based on the above analysis, the inclusion of cultural context was recommended in the conceptual framework, and the following hypothesis could be postulated.

**Hypothesis 14 (H14).** *Cultural context (individualism/collectivism) positively moderates the relationship between subjective norms and behavior change intentions for pandemic prevention and control.*

**Hypothesis 15 (H15).** *Cultural context (individualism/collectivism) positively moderates the relationship between risk perception and behavior change intentions for pandemic prevention and control.*

## 5. Empirical Examination

*5.1. Measurement Development*

The research framework consisted of 11 latent variables, including 5 exogenous variables (knowledge and information dissemination, tools and facilities, governmental regulations, cultural context, and surveillance) and 6 endogenous variables (attitudes, subjective norms, perceived behavior control, risk perceptions, behavior change intentions, and behavior change implementations). These variables were measured by three to four items

employing a five-point Likert scale, 1 denoting "strongly disagree" and 5 "strongly agree." All of the measurement items were adapted and developed from prior literature, considering the information and contents they represent in this study, see Appendix A Table A2.

### *5.2. Questionnaire Design and Pilot Test*

After measurement items were developed, we conducted an empirical study based on a questionnaire survey to test the research framework. All questionnaires were translated into Chinese for distribution, as the sampling population in this investigation was Chinese. The questionnaire contained two sections: The first section was designed to obtain participants' demographic information, including gender, age group, income level, educational level, subjective health condition, and vaccination status (COVID-19). The second section was designed to identify people's evaluation of the latent variables that influence behavior change for pandemic prevention and control. Before the formal survey, a pilot test was carried out to judge whether the measurement items were appropriate, during which 50 questionnaires were distributed. On the basis of the feedback and comments, we adjusted the ambiguous and improper wordings of measurement items to ensure that respondents could clearly understand the contents and information provided by the questionnaire.

### *5.3. Data Collection and Sampling*

In this research, we did not impose any limitations on the sampling population, because nearly all Chinese people have undergone much suffering from the current COVID-19 pandemic. Still, we preferred to survey people with adequate knowledge and experiences in the related fields, including design science, behavior science, epidemiology, and public health. Generally, the statistical power and accuracy of SEM are mainly determined by sample sizes [86]. To identify a suitable sample size, we referred to several traditional rules of thumb in SEM. First, the ratio of the number of cases ($n$) to the number of measured variables ($p$) is a crucial rule for sample determination, and 10:1 is a commonly suggested ratio [87]. Moreover, researchers should also consider the potential of adjusting sample sizes moderately, based on the following factors: model complexity, normality of data, measured variables per latent variable number, and so on [86,88]. Based on this, we argued that a sample size between 500 and 650 was suitable for our study, and a total of 750 revised questionnaires were distributed both online and offline in China. The online questionnaires were given out through "wenjuanxing", an online survey platform, while the paper questionnaires were given out in some public spaces in Hefei. Finally, we received 549 valid answers for further analysis.

### *5.4. Data Analysis*

The data analysis plan of this research consisted of three steps. Initially, SPSS 25.0 software was employed to conduct a descriptive analysis and reliability analysis. Second, the researcher carried out confirmatory factor analysis to check the validity and model fit of the measurement model, during which MPLUS 7.4 software was used. Third, path analysis and moderation effect analysis were conducted for hypothesis testing with the assistance of MPLUS 7.4 software.

### *5.5. Results*

#### 5.5.1. Participants

The demographic information of the participants in the questionnaire survey is listed in Appendix A Table A3. Of the 549 participants, 288 were males and 261 were females. The age groups of under 20, 21–30, 30–40, 40–50, and above 50 contained 58 people, 138 people, 173 people, 141 people, and 39 people, respectively. Regarding the educational level, 93 respondents were under junior high school level, 94 respondents were in high school, 124 respondents had a diploma degree, 173 respondents had a bachelor's degree, and 39 respondents had a master's degree or above. As for their income level, the groups of

monthly earnings under RMB 2500, RMB 2500–5000, RMB 5000–7500, RMB 7500–10000, and above RMB 10,000 contained 34, 222, 137, 107, and 49 people, respectively. Moreover, 34 respondents felt they were in very poor health condition, 48 respondents felt they were in poor health condition, 108 respondents felt they were moderately healthy, 207 respondents felt they were in good health condition, and 152 respondents felt they were in very good health condition. Regarding the COVID-19 vaccination situation, 19 respondents were not vaccinated, 131 respondents were vaccinated but had not complete their vaccinations, and 399 respondents had completed their vaccinations.

#### 5.5.2. Reliability, Validity, and Fit Index of the Measurement Model

Table 1 summarizes several main indexes that served for reliability and validity testing. As shown in Table 1, all Cronbach's alphas of the latent variables were over 0.7, suggesting an excellent internal consistency in the latent variables [89]. Moreover, these latent variables also had good reliability, as all of the composite reliability (CR) scores exceeded the recommended value (0.7) [90]. Regarding validity, the convergent validity can be reflected in the value of average variance extracted (AVE) and standardized factor loadings [91]. These two values for all the latent variables were above 0.5 and 0.7, indicating the measurement model had adequate convergent validity. In addition, the model's discriminant validity was examined by comparing the latent variables' square root of the AVE and coefficient [83]. As demonstrated in Table 2, all latent variables' square roots of the AVE were above their coefficients, which indicated good discriminant validity.

**Table 1.** Reliability and unidimensionality.

| Latent Variable | Cronbach's Alpha | Observable Variable | Standardized Factor Loading | AVE | Composite Reliability |
|---|---|---|---|---|---|
| KID | 0.895 | KID1<br>KID2<br>KID3<br>KID4 | 0.818<br>0.834<br>0.817<br>0.832 | 0.681 | 0.895 |
| TF | 0.861 | TF1<br>TF2<br>TF3<br>TF4 | 0.78<br>0.782<br>0.792<br>0.763 | 0.607 | 0.861 |
| GR | 0.842 | GR1<br>GR2<br>GR3 | 0.805<br>0.854<br>0.743 | 0.643 | 0.843 |
| ATT | 0.848 | ATT1<br>ATT2<br>ATT3<br>ATT4 | 0.777<br>0.796<br>0.736<br>0.746 | 0.584 | 0.849 |
| SN | 0.876 | SN1<br>SN2<br>SN3<br>SN4 | 0.819<br>0.825<br>0.768<br>0.783 | 0.639 | 0.876 |
| PBC | 0.845 | PBC1<br>PBC2<br>PBC3 | 0.828<br>0.834<br>0.749 | 0.647 | 0.846 |
| RP | 0.877 | RP1<br>RP2<br>RP3<br>RP4 | 0.808<br>0.843<br>0.784<br>0.767 | 0.642 | 0.877 |

**Table 1.** *Cont.*

| Latent Variable | Cronbach's Alpha | Observable Variable | Standardized Factor Loading | AVE | Composite Reliability |
|---|---|---|---|---|---|
| BCI | 0.898 | BCI1 | 0.829 | 0.689 | 0.899 |
| | | BCI2 | 0.855 | | |
| | | BCI3 | 0.837 | | |
| | | BCI4 | 0.798 | | |
| BCIP | 0.872 | BCIP1 | 0.818 | 0.631 | 0.872 |
| | | BCIP2 | 0.787 | | |
| | | BCIP3 | 0.776 | | |
| | | BCIP4 | 0.795 | | |
| CC | 0.859 | CC1 | 0.728 | 0.607 | 0.860 |
| | | CC2 | 0.859 | | |
| | | CC3 | 0.777 | | |
| | | CC4 | 0.746 | | |
| SV | 0.881 | SV1 | 0.798 | 0.650 | 0.881 |
| | | SV2 | 0.842 | | |
| | | SV3 | 0.786 | | |
| | | SV4 | 0.798 | | |

Note: Square roots of AVE are on diagonal; AVE = averaged variance extracted.

**Table 2.** Correlation matrix of the measurements.

| Construct | AVE | KID | TF | GR | ATT | SN | PBC | RP | BCI | CC | SV | BCIP |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| KID | 0.681 | (0.825) | | | | | | | | | | |
| TF | 0.607 | 0.279 *** | (0.779) | | | | | | | | | |
| GR | 0.643 | 0.206 *** | 0.27 *** | (0.802) | | | | | | | | |
| ATT | 0.584 | 0.33 *** | 0.213 *** | 0.264 *** | (0.764) | | | | | | | |
| SN | 0.639 | 0.134 ** | 0.205 *** | 0.229 *** | 0.246 *** | (0.799) | | | | | | |
| PBC | 0.647 | 0.208 *** | 0.191 *** | 0.098 * | 0.218 *** | 0.110 * | (0.804) | | | | | |
| RP | 0.642 | 0.217 ** | 0.230 *** | 0.174 *** | 0.271 *** | 0.222 *** | 0.117 * | (0.801) | | | | |
| BCI | 0.689 | 0.194 *** | 0.173 *** | 0.199 *** | 0.334 *** | 0.184 *** | 0.213 *** | 0.195 *** | (0.830) | | | |
| CC | 0.607 | 0.109 * | 0.07 | 0.114 * | 0.099 * | 0.104 * | −0.054 | 0.127 ** | 0.13 ** | (0.779) | | |
| SV | 0.650 | 0.016 | −0.039 | 0.011 | 0.015 | 0.094 | 0.019 | 0.032 | −0.034 | 0.045 | (0.806) | |
| BCIP | 0.631 | 0.147 ** | 0.244 *** | 0.202 *** | 0.231 *** | 0.167 *** | 0.146 ** | 0.241 *** | 0.256 *** | 0.004 | 0.170 *** | (0.794) |

Note: * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$; square root of AVE is on diagonal.

Table 3 demonstrates the goodness of fit of the research models, which can be reflected in the following indexes: chi-square, df, chi-square/df, the root mean square residual (SRMR), the root mean square error of approximation (RMSEA), normed-fit Tucker–Lewis Index (TLI), and comparative-fit index (CFI) [92,93]. Therefore, it can be derived that both the measurement model (chi-square/df = 1.180, SRMR = 0.028, RMSEA = 0.018, TLI = 0.987, and CFI = 0.988) and structural model (chi-square/df = 1.315, SRMR = 0.062, RMSEA = 0.024, TLI = 0.979, and CFI = 0.977) had good model fit.

**Table 3.** Goodness-of-fit of model.

| Research Model | Chi-Square | df | Chi-Square/df | TFI | CFI | RMSEA | SRMR |
|---|---|---|---|---|---|---|---|
| Benchmark value | / | / | 1–5 | >0.9 | >0.9 | <0.08 | <0.08 |
| Measurement model | 901.798 | 764 | 1.180 | 0.987 | 0.988 | 0.018 | 0.028 |
| Structural model | 1047.779 | 797 | 1.315 | 0.979 | 0.977 | 0.024 | 0.062 |

#### 5.5.3. Hypothesis Testing

The results of the hypothesis testing are summarized in Table 4. Behavior change intentions were positively impacted by attitudes ($p < 0.001$, $t = 5.707$), subjective norms ($p < 0.05$, $t = 2.067$), perceived behavior control ($p < 0.01$, $t = 3.114$), and risk perceptions

($p < 0.05$, $t = 2.168$), indicating that H1, H2, H3, and H4 are supported. Both surveillance ($p < 0.001$, $t = 6.059$) and behavior change intentions ($p < 0.001$, $t = 3.848$) could positively influence behavior change implementations, so H5 and H7 are supported. Moreover, knowledge and information dissemination was positively and significantly associated with attitudes ($p < 0.001$, $t = 6.542$), subjective norms ($p < 0.05$, $t = 2.123$), and risk perceptions ($p < 0.001$, $t = 5.086$). Hence, H8, H9, and H10 are accepted. Tools and facilities had a positive influence on perceived behavior control ($p < 0.001$, $t = 4.160$); thus, H11 is supported. Governmental regulations could positively influence both attitudes ($p < 0.001$, $t = 4.531$) and subjective norms ($p < 0.001$, $t = 4.553$), supporting H12 and H13, respectively.

**Table 4.** The results of path analysis.

| Hypothesis | Path Direction | Standardized Coefficient | Standard Error | CR (*t* Value) | *p* Value | Result |
|---|---|---|---|---|---|---|
| H1 | ATT → BCI | 0.274 | 0.048 | 5.707 | 0.000 | Accepted |
| H2 | SN → BCI | 0.098 | 0.047 | 2.067 | 0.039 | Accepted |
| H3 | PBC → BCI | 0.147 | 0.047 | 3.114 | 0.002 | Accepted |
| H4 | RP → BCI | 0.103 | 0.048 | 2.168 | 0.030 | Accepted |
| H5 | BCI → BCIP | 0.266 | 0.044 | 6.059 | 0.000 | Accepted |
| H7 | SV → BCIP | 0.177 | 0.046 | 3.848 | 0.000 | Accepted |
| H8 | KID → ATT | 0.297 | 0.045 | 6.542 | 0.000 | Accepted |
| H9 | KID → SN | 0.102 | 0.048 | 2.123 | 0.034 | Accepted |
| H10 | KID → RP | 0.233 | 0.046 | 5.086 | 0.000 | Accepted |
| H11 | TF → PBC | 0.200 | 0.048 | 4.160 | 0.000 | Accepted |
| H12 | GR → ATT | 0.215 | 0.047 | 4.531 | 0.000 | Accepted |
| H13 | GR → SN | 0.221 | 0.049 | 4.553 | 0.000 | Accepted |

To further examine whether the moderating effects of cultural context and surveillance exist, we conducted a moderation effect test by using the "Latent Moderated Structural Equations" (LMS) approach [94]. We referred to Su et al.'s (2019) MPLUS code for moderating effect testing [95]. As demonstrated in Table 5, cultural context could positively moderate the relationship between subjective norms and behavior change intentions. Thus, H6 is confirmed. In other words, when the value of cultural context is high, subjective norms and behavior change intentions have a more positive relationship. Moreover, the moderating effects of risk perceptions ($p > 0.05$, $t = 1.680$) and surveillance ($p > 0.05$, $t = -1.785$) were not significant, so H14 and H15 are rejected. Figure 2 shows the final results of the proposed research framework.

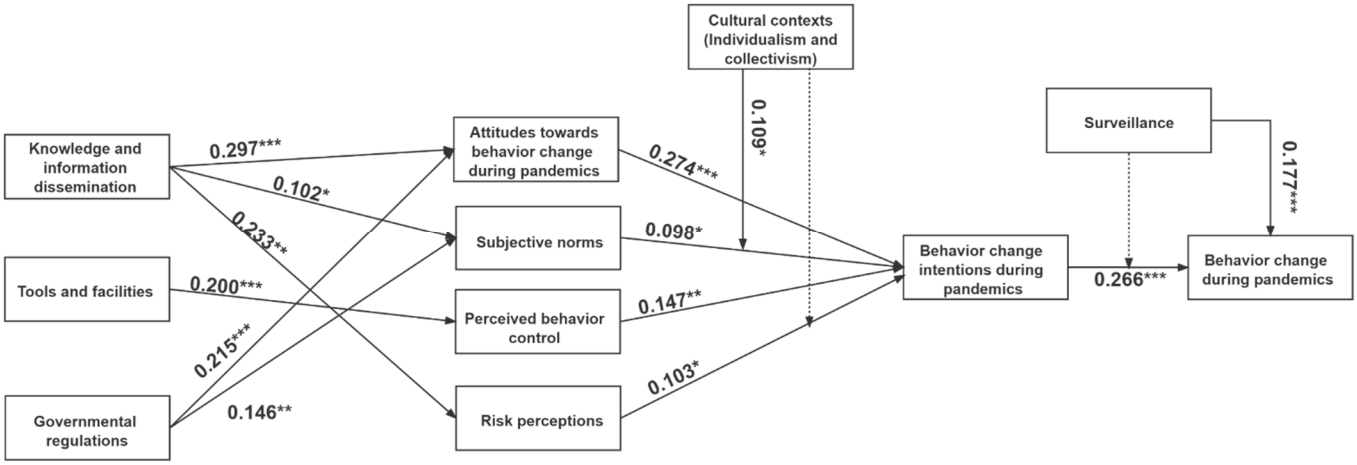


**Figure 2.** The results of the proposed framework. Note: * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$.

**Table 5.** The results of moderating effect testing.

| Hypothesis | Path Direction | Standardized Coefficient | Standard Error | CR (*t* Value) | *p* Value | Result |
|---|---|---|---|---|---|---|
| H6 | BCI × SV → BCIP | −0.155 | 0.087 | −1.785 | 0.074 | Rejected |
| H14 | CC × SN → BCI | 0.109 | 0.049 | 2.247 | 0.025 | Accepted |
| H15 | CC × RP → BCI | 0.101 | 0.060 | 1.680 | 0.093 | Rejected |

## 6. Discussions and Implications

This research aimed to examine the critical determinants of pandemic-related behavior change and develop a theoretical framework to reveal the structural relationship. As illustrated in the TPB model, attitudes, subjective norms, and perceived behavior control can help people form strong behavior change intentions during pandemics. This finding echoes Yu et al. (2021), Gibson et al. (2021), and Hagger et al.'s (2020) studies during the current COVID-19 pandemic [63,96,97]. Moreover, research on the previous A/H1N1 and swine flu pandemic also demonstrated similar results [71,74]. In addition, we need to focus on the extra factors added to the original TPB model. First, we proved a positive and significant association between risk perceptions and behavior change intentions, which is consistent with Liu et al.'s (2020) research [68]. Similarly, Karasneh et al.'s (2021) study also suggested that the risk perception of pandemics could predict people's compliance with preventive measures during the COVID-19 pandemic [98]. Van der Weerd et al. (2011) stated that a high level of risk perception was positively linked to an intention to adopt protective measures during the influenza A pandemic [99]. Hence, our findings explain why people's compliance with social control measures differs when pandemic situations change. When pandemic situations are eased, authorities should take measures to prevent people from relaxing their vigilance.

Information and knowledge dissemination are significantly associated with three perceptional factors, attitudes, subjective norms, and risk perceptions, which are crucial stimulants for people's behavior intentions and implementations during pandemics. This finding echoes Zhao et al. (2015) and Reynolds et al.'s (2005) research on behavior change during pandemics [71,74]. Other studies also demonstrated a strong but indirect association between information and knowledge dissemination and individual behavior change. For instance, Van Bavel et al. (2020) highlighted that information or messages that provide in-group models are effective for spreading protective behavior [20]. During pandemics, many people cannot realize the influential role of behavior change for pandemic prevention or the devastating impacts of pandemics, because they do not have sufficient knowledge or correct information [72]. What is more, people are often misled by fake news or misinformation in the current information explosion era. Hence, access to authorized and specialized information about pandemic situations is necessary. This specialized information access can be integrated with mass media, such as news phone applications or TV programs. Moreover, policymakers should consider educating the public regarding knowledge about pandemic-related behavior.

During pandemics, tools and facilities can positively influence people's perceived behavior control, promoting people's behavior change intentions and vice versa. As Stosic et al. (2021) noted, if face coverings are not well-designed, they may bring discomfort or inconvenient experiences to users and minimize users' behavior willingness [100]. Therefore, designers should consider how to advance the existing products or design new products to make it easier and more convenient for people to change their behavior. According to Dr. Norman's emotional design theory, tools and facilities can be designed from three facets: the visceral level, behavioral level, and reflective level [101]. At the visceral level, products' materials, appearance, sizes, colors, and structures should be considered. For instance, designers can consider face coverings that adapt to different face shapes or features. Different styles of face coverings can be designed to fit each age group. At the behavioral level, designers should consider reducing the difficulty of behavior change by

improving current designs or developing new designs. Just as the WHO's recent report mentioned, an effective way to achieve this is to make new habits of protection behaviors less costly [102]. Generally, people interact with products or environments when they perform the recommended protective behaviors during pandemics. In this regard, we suggest developing new interactive modes between humans and products to provide guidance or support to address this issue. For instance, new control modes, such as voice control, phone application control, and other distance control methods, can be used to replace the traditional keyboard control of machine operation. In this case, people do not need to pay attention to the behavior change rules. Instead, they just need to behave normally. At the reflective level, designers can emphasize the value and significance of behavior change for pandemic preventive control via hints or empathy.

Furthermore, although the TPB model indicates that behaviors can only result from people's intentions, this research found a discrepancy between behavior change intentions and behavior change implementations. This finding is consistent with Gibson et al. (2021) and Hagger et al.'s (2020) studies [96,97]. As demonstrated in our framework, surveillance can be a vital factor contributing to pandemic-related behavior change in addition to people's intentions. In other words, surveillance can act on people who may not be willing to perform the recommended behavior during pandemics. Indeed, there are some pandemic situations during which people may not be willing to change their behavior. For example, people may not have behavior change intentions for a short period, especially at the early stages of pandemics. Additionally, when pandemics last for a long time, "pandemic fatigue" may emerge and minimize people's willingness to change behavior [103]. In this case, governmental agencies should strengthen the role of surveillance to foster behavior change. Multiple approaches can be employed for surveillance, including phone applications, manual work, and facilities.

In the current research, it was found that governmental regulations can positively influence two factors, attitudes and subjective norms, thereby indirectly promoting people's behavior change during pandemics. This finding echoes Ibuka et al.'s (2010) argument [79]. For policymakers, it is crucial to emphasize the different roles of governmental regulations, such as constraint, motivation, and punishment. Designers can attempt to strengthen the power of governmental regulations through design. For example, policy slogans can be integrated with urban furniture design to improve the visibility and accessibility of these slogans. In addition, designers can create a public image based on pandemic-related policies.

Cultural context (mainly referring to collectivism/individualism in this article) does not directly affect pandemic-related behavior change but does moderate the relationship between subjective norms and behavior change intentions. This finding partly mirrors Van Bavel et al.'s (2021) view, which attributes differences in response to the pandemic to cultural context (collectivism vs. individualism) [20]. As we know, people living in collectivist circumstances value group benefits more than personal benefits, and they have more willingness to be accepted by groups. In this case, subjective norms, including families' views, friends' views, and supervisors' views, can show more influence on people. Hence, policymakers should consider their respective cultural context when imposing public health interventions. For example, in a collectivist cultural context (such as East Asian regions), governmental agencies should emphasize the association between pandemic-related behaviors and national benefits to motivate behavior change. Some public slogans that emphasize group benefits can be delivered, such as "wearing face coverings protects not only ourselves but also protects people around us". Additionally, celebrities should be good role models to guide the public in behavior change during a pandemic. Designers can develop a data visualization platform to highlight the people who are performing the recommended behavior for pandemic prevention, thereby encouraging more people to follow these behaviors.

## 7. Conclusions

In modern society, humans may inevitably suffer from various infectious diseases triggered by pandemic situations. Under such backgrounds, preventive behavior change, as a nonpharmaceutical intervention, is an effective treatment for pandemic prevention and control. Thus, it is essential to understand the factors that affect the public's compliance with preventive behavior during pandemics. This article attempted to construct a research framework to reveal individuals' preventive behavior formation and influential factors during pandemic situations. We identified several key influential factors of pandemic-related behavior change through a literature review and a user interview. These factors contain various facets, including perceptional factors (attitudes, subjective norms, perceived behavior control, and risk perceptions); social factors (governmental regulations and knowledge and information dissemination); physical factors (tools and facilities and surveillance); and sociocultural factors (cultural contexts). Then, we constructed a theoretical framework based on the interactive correlations among these factors. The research framework was subsequently tested and proved to be effective based on an empirical study. The research findings suggest that all derived factors directly or indirectly impact individuals' behavior change during pandemics. In addition, we discussed corresponding design strategies for pandemic-related behavior change from both policy makers' and designers' viewpoints. Based on the above elaboration, this study is a typical endeavor that provides public health solutions by integrating the knowledge of behavioral sciences and design sciences, which has the following knowledge contributions.

From the theoretical viewpoint, this study is one of the first studies integrating behavior science, design science, and public health in pandemic situations. It validates the effectiveness of the TPB model in human behavior research through an empirical study. Moreover, it refines the original TPB model in a global pandemic context by adding several exogenous variables. In this regard, our research framework is an extension and improvement of the original TPB model.

From the practical viewpoint, this article enables researchers to have a comprehensive understanding of individuals' behavior change formation process during pandemics. By understanding the role of different factors (perceptional, social, physical, and sociocultural), stakeholders can impose more effective interventions to cope with pandemic situations. For instance, governmental authorities can enact more targeted policies while designers can develop valuable products to promote pandemic-related behavior change. In this regard, this article can help us contain the spread of viruses and minimize the devastating impacts of pandemics.

However, it is undeniable that there are several limitations to the current research. First, our research scope was narrow due to the dynamic pandemic situation. This research was conducted in 2021, when China was facing a normalized pandemic prevention situation. In this case, our study only explored people's behavior intentions and implementations under a normalized pandemic circumstance, which may not be suitable for all pandemic phases. Thus, future studies are recommended to span all pandemic stages, including early, middle, and later pandemic situations. Second, our research scope was limited to China. Generally, people's behavior change intentions or implementations are affected by many sociocultural factors, such as lifestyles, culture, customs, and living circumstances. Hence, our research findings may not fit other regions worldwide, especially in Western culture. Future studies are recommended to compare people's behavior change willingness and influential factors under different cultural contexts. Third, the influential factors we investigated in this article may not be comprehensive. For example, several previous studies have pointed out the association between behavior change and demographic factors, for example, ages, employment statuses, nationalities, educational levels, and income levels [45,47,96]. However, we did not consider this potential factor in the present study. In this regard, future studies are recommended to explore the impact of various demographic factors on individuals' behavior change during pandemics in China. Lastly, we did not consider examining other relationships among the variables in the framework.

In the present study, we attempted to construct a behavior change framework by clarifying the causal effects and moderating effects among variables. However, there may be other types of relationships in addition to this. For instance, Zhang's (2016) study suggested a nonlinear effect of crime on bus ridership, while Zhang et al.'s (2020) study indicated a similar effect between built environment factors and car ownership [104,105]. Hence, future studies are recommended to consider this possibility, for example, the exogenous influence of built environment features on behavior change mechanisms.

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## Appendix A

**Table A1.** Demographic profile of informants in the interview.

| Informant | Age | Gender | Educational Level | Occupation |
|---|---|---|---|---|
| Informant 1 | 46 | Male | PhD | Associate professor of design |
| Informant 2 | 43 | Male | PhD | Professor of design |
| Informant 3 | 31 | Male | Master | Senior lecture in design |
| Informant 4 | 31 | Female | Master | Senior lecture in design |
| Informant 5 | 37 | Female | Master | Senior lecture in design |
| Informant 6 | 29 | Female | PhD | PhD candidate in design |
| Informant 7 | 28 | Male | Master | Interactive designer |
| Informant 8 | 30 | Male | Master | Urban designer |
| Informant 9 | 29 | Male | Master | Design manager |
| Informant 10 | 29 | Female | Master | Industrial designer |
| Informant 11 | 28 | Male | Bachelor | Government servant in pandemic prevention and control sector |
| Informant 12 | 28 | Male | Bachelor | Government servant |
| Informant 13 | 28 | Female | Master | Health worker |
| Informant 14 | 29 | Female | Bachelor | Health worker |
| Informant 15 | 23 | Female | Bachelor | Health worker |
| Informant 16 | 30 | Male | Master | Health worker |
| Informant 17 | 29 | Male | Master | Health worker |
| Informant 18 | 53 | Female | Middle school | Community worker |
| Informant 19 | 22 | Female | Diploma | Hotel worker |
| Informant 20 | 29 | Female | Master | Administrative assistant at university |
| Informant 21 | 29 | Female | Bachelor | Kindergarten manager |
| Informant 22 | 34 | Male | PhD | Computer Engineer |

**Table A2.** Latent variables and measurement items.

| Latent Variables | Measurement Item | Reference |
| --- | --- | --- |
| Attitudes (ATT) | ATT1: I think behavior change is significant during pandemics.<br>ATT2: I think behavior change is an effective solution during pandemics.<br>ATT3: I think behavior change can curb the spread of viruses during pandemics.<br>ATT4: I think behavior change can improve public security and health during pandemics. | [37] |
| Subjective norms (SN) | SN1: I will perform the recommended behaviors during pandemics if my family members think I should do so.<br>SN2: I will perform the recommended behaviors during pandemics if my close friends think I should do so.<br>SN3: I will perform the recommended behaviors during pandemics if the people I value think I should do so.<br>SN4: I will perform the recommended behaviors during pandemics if the general public around me performs them. | [37,59] |
| Perceived behavior control (PBC) | PBC1: I have the skills and abilities to perform the recommended behavior for pandemic prevention and control.<br>PBC2: It is up to me to perform the recommended behavior for pandemic prevention and control.<br>PBC3: It is easy and convenient for me to perform the recommended behavior for pandemic prevention and control. | [37,61] |
| Risk perception (RP) | RP1: I am vulnerable if exposed to pandemic circumstances.<br>RP2: If I am infected by viruses during pandemics, I will not be unable to manage my daily activities.<br>RP3: If I am infected by viruses during pandemics, it will be risky.<br>RP4: I could easily develop severe symptoms if infected during pandemics. | [68] |
| Behavior change intentions (BCI) | BCI1: I have intentions to wear facemasks when visiting public places or taking public transport during pandemics.<br>BCI2: I have intentions to keep a certain physical distance from others and avoid crowded public places during pandemics.<br>BCI3: I have intentions to keep hands clean and correctly wash hands during pandemics.<br>BCI4: I have intentions to reduce contact with objects in public places during pandemics. | [106] |
| Behavior change implementations (BCIP) | BCIP1: I always wear facemasks when visiting public places or taking public transport during pandemics.<br>BCIP2: I always keep a certain physical distance from others and avoid crowded public places during pandemics.<br>BCIP3: I always keep my hands clean and correctly wash my hands during pandemics.<br>BCIP4: I always reduce contact with objects in public places. | [68,106] |
| Knowledge and information dissemination (KID) | KID1: I have sufficient knowledge about the virus transmission method during pandemics.<br>KID2: I know how to adopt correct preventive measures for pandemic prevention and control.<br>KID3: I can receive real-time information about pandemic situations.<br>KID4: I can distinguish fake news and misinformation during pandemics. | [39] |
| Cultural context (individualism/collectivism) (CC) | CC1: I think being accepted as a member of a group is more important than having autonomy and independence.<br>CC2: I think group success is more important than individual success.<br>CC3: I think being loyal to a group is more important than individual gain.<br>CC4: Individuals should stick with the group even through difficulties. | [77] |

**Table A2.** *Cont.*

| Latent Variables | Measurement Item | Reference |
| --- | --- | --- |
| Tools and facilities (TF) | TF1: I have access to tools and facilities (e.g., wash basins, face coverings, hand sanitizers, wearable devices, mobile applications) during pandemics.<br>TF2: The tools and facilities are well-designed.<br>TF3: The tools and facilities are useful for behavior change during pandemics.<br>TF4: The tools and facilities can assist me in performing the recommended behavior during pandemics. | [107] |
| Governmental regulations (GR) | GR1: The incentive regulations from governments encourage me to perform the recommended behavior during pandemics.<br>GR2: The punitive regulations from governments encourage me to perform the recommended behavior during pandemics.<br>GR3: The epidemic prevention regulations from governments encourage me to perform the recommended behavior during pandemics. | [108,109] |
| Surveillance (SV) | SV1: Wearable devices can monitor whether I perform the recommended behavior during pandemics.<br>SV2: Mobile applications can monitor whether I perform the recommended behavior during pandemics.<br>SV3: Smart facilities can monitor whether I perform the recommended behavior during pandemics.<br>SV4: Workers in public spaces can monitor whether I perform the recommended behavior during pandemics. | [29,30,69] |

**Table A3.** Demographic information and partial contents of the questionnaire survey.

| Attribute | Value | Frequency | Percent |
| --- | --- | --- | --- |
| Gender | Male | 288 | 52.5% |
| | Female | 261 | 47.5% |
| Age | Under 20 | 58 | 10.4% |
| | 21–30 | 138 | 24.8% |
| | 31–40 | 173 | 31.1% |
| | 41–50 | 141 | 25.4% |
| | Above 50 | 39 | 7.0% |
| Educational level | Under Junior high school | 93 | 16.9% |
| | High school | 94 | 17.1% |
| | Diploma | 124 | 22.6% |
| | Bachelor's degree | 173 | 31.5% |
| | Master's degree and above | 65 | 11.8% |
| Monthly income (RMB) | <2500 | 34 | 6.2% |
| | 2500–5000 | 222 | 40.4% |
| | 5000–7500 | 137 | 25.0% |
| | 7500–10,000 | 107 | 19.5% |
| | >10,000 | 49 | 8.9% |
| Subjective health condition | Very poor | 34 | 6.2% |
| | Poor | 48 | 8.7% |
| | Moderate | 108 | 19.7% |
| | Good | 207 | 37.7% |
| | Very good | 152 | 27.7% |
| Vaccination status | Not vaccinated | 19 | 3.5% |
| | Vaccinated but not fully | 131 | 23.9% |
| | Fully vaccinated | 399 | 72.7% |

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