mathematics

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Applying the Push-Pull Mooring to Explore Consumers' Shift from Physical to Online Purchases of Face Masks

Sung-Wen Yu [1], Jun-Yan Liu [1], Chien-Liang Lin [2,*] and Yu-Sheng Su [3,*]

[1] Department of Marketing and Distribution Management, National Pingtung University, Pingtung 900, Taiwan
[2] College of Science and Technology, Ningbo University, Cixi 315211, China
[3] Department of Computer Science and Engineering, National Taiwan Ocean University, Keelung 202, Taiwan
* Correspondence: linjianliang@nbu.edu.cn (C.-L.L.); ntoucsiesu@mail.ntou.edu.tw (Y.-S.S.)

Abstract: In response to the emergency management caused by COVID-19, Taiwan began to impose a name-based rationing system for the purchase of face masks by having consumers visit physical stores and preorder them online. By doing so, the risk of face mask shortages caused by panic buying was reduced. To understand consumers' willingness to switch from buying face masks at physical stores to preordering them online, we used a push-pull-mooring (PPM) model to measure related dimensions. We administered an online questionnaire survey and collected 233 valid responses. In the present study, perceived risk (including time risk, psychological risk and social risk) was treated as a second-order formative indicator, while pull effect was measured by the variables of critical mass and alternative attraction. Mooring effect was measured by switching cost. Through structural equation modeling (SEM), perceived risk, as well as critical mass and alternative attraction, had a significant effect on switching intention, while switching cost had no significant relationship with switching intention. This study investigated whether perceived risk (time risk, psychological risk and social risk), critical mass, alternative attraction and switching cost can serve as references for purchase behaviors amid future emergency management, through the prism of population migration theory, and proposed recommendations for their promotion and implementation.

Keywords: push-pull-mooring; face masks; COVID-19; perceived risk

MSC: 62P25

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Citation: Yu, S.-W.; Liu, J.-Y.; Lin, C.-L.; Su, Y.-S. Applying the Push-Pull Mooring to Explore Consumers' Shift from Physical to Online Purchases of Face Masks. *Mathematics* **2022**, *10*, 4761. https://doi.org/10.3390/math10244761

Academic Editors: Chaman Verma, Maria Simona Raboaca and Zoltán Illés

Received: 28 October 2022
Accepted: 12 December 2022
Published: 15 December 2022

1. Introduction

In December 2019, a series of atypical pneumonia cases arose in China and were quickly identified by medical researchers as a new type of coronavirus disease (COVID-19) that spread mainly through droplet transmission. COVID-19 can cause fever, headache, dizziness, lack of strength, vomiting, diarrhea and even death. No medication has proven effective in the treatment of COVID-19. Therefore, countries worldwide have implemented strategies such as social distancing, quarantines for medical observation, mask-wearing, handwashing and reducing physical contact to lower virus droplet transmission [1–5]. Since the COVID-19 outbreak over two years ago, despite the continuation of multiple closures and control, as well as lockdown measures or vaccination, there has never been a specific end time for the eradication of the pandemic and sustainable sound health management has thus become a vital issue [6].

Consumers make impulse purchases out of panic and shock because they are prompted by situations in which they recall a shortage that heightens the necessity of certain products [7]. The rise in demand caused by panic-based impulse purchases creates considerable fluctuations in product quantities and can result in demand for products that exceed supply and products going out of stock. Product shortages caused by excessive demand raise product prices and decrease supply, which can threaten the economy and produce crises. To solve this problem, proper allocation and control measures must be imposed on maximum purchase quantities [1]. In response to mask shortages caused by panic-based impulse purchases, Taiwan began to impose a self-designed, name-based rationing system for purchasing masks. The rolling correction response to the emergency enabled customers to purchase masks by preordering them online, rather than queuing up in front of storefronts [8].

According to studies on consumer purchase behavior, consumers usually develop a plan before making a purchase. For example, the theory of planned behavior (TPB) proposed by Ajzen [9] dictates that consumers' intentions and behaviors are affected by the information available to them, social influences and their perceived behavioral control. During the purchasing process, consumers must consider perceived risks that amount to potential losses incurred before the desired outcomes are achieved [1,10,11]. When consumers are dissatisfied with the information quality of a product or service, they tend to alter their purchasing patterns, making alternative attractiveness a crucial factor that influences their switching intention [12,13]. According to the literature, the concept of critical mass—proposed by Oliver et al. [14]—positively affects switching intention when an innovative or superior product or service is used or given adequate attention. Because alternative attractiveness affects switching intention, if consumers believe that their popularity in social circles will increase by using alternative services or solutions, the impact of alternative attractiveness can increase substantially [13,15–17]. If the services provided by physical stores are limited, online shopping becomes a convenient alternative that increases consumers' intention to switch [18]. During the switching process, consumers primarily consider their money and time [19]. The COVID-19 pandemic prompted consumers to switch their purchase patterns from shopping in physical stores to preordering products online. Thus, migration behavior caused by emergency management policies should be investigated.

By applying the push–pull–mooring (PPM) theory of migration, we uncovered two reasons why consumers switched their mask-purchasing patterns from shopping at physical stores to making purchases online. First, to address the impact of COVID-19, the Taiwan Centers for Disease Control (TCDC), overseen by the Ministry of Health and Welfare (MOHW), began collecting all masks made by domestic manufacturers and controlling the time and quantity of masks distributed. In addition, policies were established to limit the physical distribution of masks to pharmacies contracted by the National Health Insurance (NHI). Subsequently, a mask map was created to provide customers with information such as the remaining number of masks at each pharmacy. Such a model was effective in reducing citizens' panic over not being able to buy face masks at the beginning of the pandemic, thereby stabilizing the situation in the early days of the pandemic [20]. In March 2020, Taiwan expanded mask distribution channels to online orders and convenience store pickups, thereby reducing the risk of infection from waiting in line and social contact, and considerably increasing the rates of successful purchases [8,21,22]. Consumers began pouring into convenience stores to pre-order masks online through ibon (an interactive kiosk) with their NHI cards. Through rolling corrections to policies, an NHI app was launched for consumers to pre-order masks on their smartphones for pickups at convenience stores every two weeks. This switch in purchasing patterns differs from changes documented in other studies on switching intention. The switching of mask purchase channels from in-store shopping to online preordering in response to COVID-19 contrasts with conventional shifts in purchasing habits. The application of the PPM model in this study holds value in the theoretical discussion of migration behavior during the management of emergencies. Second, this study differs from conventional behavioral research in that it applies the main concepts of PPM to interpret migration behavior that occurs in numerous situations in terms of push, pull and mooring [23,24].

Unlike the traditional theory of planned behavior (TPB), PPM considers the unique characteristics of each context to determine the push, pull and mooring factors of various topics. Thus, PPM is suitable for exploring the switching of mask purchase channels from offline shopping to preordering online in response to COVID-19. Studies on PPM have mostly used dissatisfaction-related elements as push factors [12,13,25] and alternative attractiveness-related aspects as pull factors [15,26,27], despite that users' switching intention is affected by diverse components [15]. We identified the push, pull and mooring factors that drove consumers to switch from buying masks in physical stores to pre-ordering them online during the COVID-19 pandemic. To pinpoint the factors influencing Taiwanese consumers' switching intention, we constructed a suitable theoretical framework based on the literature. This study aims, through previous literature, to find out the environmental factors that are suitable for the application of the PPM model and can fully explain the application of the PPM model amid emergency management so as to interpret the possibility of applying the PPM model in the issue of emergency management, and to understand the key factors that may affect consumers' switching intention through the shift of face mask purchase mode. Therefore, this study contends that it is necessary to investigate the use of the PPM model in emergency management issues under different contexts. In terms of the content of the study, Section 2 presents a literature review, which includes a review of pandemic-related studies, the introduction of the concepts of PPM, push, pull, and mooring. Section 3 (Research model and hypotheses) primarily presents the research model and hypotheses, construct operationalization and data collection. Section 4 (Results) includes those of measurement model and structural model. Eventually, Section 5 (Discussions and conclusions) includes practical implications, implications for research and limitations, along with future research.

2. Literature Review

2.1. Relevant Studies on Protective Face Masks during the Pandemic

During the pandemic, face masks were worn as a public health approach to constrain the spread of COVID-19. As wearing face masks to avoid virus transmission is a vital topic during a pandemic, the effects of face mask use were disseminated through social media and analysis was conducted in six sub-Saharan African countries. Study findings indicate that dissemination through social media was effective in building public acceptance of the effectiveness of face masks in preventing COVID-19 [28]. Fatfouta & Oganian [29] analyzed whether face masks reduce social interactions and found that interpersonal interactions decreased significantly when face masks were worn in the early days of the pandemic. After a few weeks, however, motivational attributions effectively moderated such a phenomenon and increased the acceptance of face mask wearing as an act of seeking to protect others. Wismans et al. [30] studied the multiple regulations mandating the wearing of face masks imposed by countries to protect citizens' health during the pandemic. Their findings indicated that the effectiveness of various measures over time hinged on citizens' trust in the government and that the stringency of the regulations was also positively correlated with the level of compliance. Meo et al. [31] investigated the level of knowledge, attitudes and actual behaviors regarding face mask use in Saudi Arabia during the COVID-19 pandemic. They concluded that citizens possess above-average knowledge and optimism regarding face mask use and that face masks played a vital dominant role in constraining the spread of SARS-CoV-2. In contrast to previous studies that focused on the effectiveness of face mask wearing in reducing SARS-CoV-2 transmission, Hanna [32] adopted an interview method to understand issues regarding the social aspects arising from face mask wearing, including the stigma or exclusion associated with not wearing face masks. By summarizing the above studies, it can be observed that numerous studies have continued to focus on the effective benefits of mask protection. Succeeding content will address studies related to switching behavior.

2.2. The Migration of Population Theory and Push–Pull–Mooring

Population migration theory was originally proposed to understand human migration [33,34]; it explains why human beings migrate from point A to point B during the occurrence of certain events or factors [35]. Migration can be divided into short- and long-term and can be caused by numerous conditions. Short-term migration involves migrants leaving their hometowns for temporary stays in other places and returning to their hometowns after achieving certain goals. An example of a temporary cause of short-term migration is leaving for work or studying in order to gain access to resources. Long-term migration refers to migrants permanently leaving their hometowns because of external factors [36]. Jackson [36] proposed two types of migration: voluntary and involuntary. Voluntary migration is a decision that an individual makes independently based on his/her situation (e.g., resources and opportunities) without interference from external factors. Involuntary migration refers to forced relocation caused by pronounced interference from external and negative factors (e.g., wars and natural disasters). Lee [33] examined the migration of population theory to describe the push and pull factors of migration. In Lee's push–pull model, push factors—resulting from external, negative causes (e.g., a lack of job opportunities, a lack of resources, or disease)—force individuals to leave their place of residence, whereas pull factors prompt them to willingly leave for another location because of positive reinforcement, such as job prospects and economic incentives.

Moon [34] expanded the push–pull model by adding mooring factors. The PPM model dictates that an individual's decision to migrate is determined by push, pull and mooring factors. Moon [34] reaffirmed that the effects of mooring factors on the migration process are substantial and can be either positive or negative. Mooring factors involve aspects such as personal interests, social values and cultural values, all of which require consideration during the migration process. After the idea of PPM was introduced, experts and scholars from many fields began to discuss it in relation to a myriad of topics. Wu et al. [11] used PPM to explain switching intention for cloud storage services, while Tang and Chen [12] applied PPM to explain the potential factors affecting brand microblog users' switching intention. In the face of the impact of COVID-19, numerous studies have examined the switching behaviors induced by the pandemic, including how the COVID-19 outbreak drove the educational ecosystem to shift toward online education [37]. Yu & Chen [38] investigated the switching behaviors of consumers from traditional cash payments to mobile payments during COVID-19 outbreaks in Taiwan. Owing to the change in lifestyle brought about by the pandemic, researchers have applied the PPM model to explain consumers' shift from physical to non-contact purchase behavior [39]. Among the studies in which PPM has been applied to explain push, pull and mooring factors, the constructs vary depending on the context. Hence, the unique characteristics of a context must be taken into account before PPM can be used as a research framework to identify the push-pull mooring factors in a given situation [13].

2.3. Push Factors

In studies on push factors, risks often entail negative effects and opinions that are crucial to consumers' switching intention. For example, the reliability, safety and accuracy of the services provided by suppliers determine consumers' perceptions of service suitability, which in turn affects their decisions on whether to select alternative information systems. Uncertain information and the environment can put services at risk. The push aspect of the PPM has been widely explored. For example, Wu et al. [11] identified perceived risk as the main push factor influencing users' intention to switch cloud computing services and noted that severe risk factors can create public debate and increase users' switching intention. Cheng et al. [40] investigated users' behavior in switching computing services and observed that risk is a factor driving users to switch from their original service to an alternative, lower-risk service. Perceived risks were first proposed by Jacoby and Kaplan [41] and are classified into five categories: psychological, performance, physical, financial and social. Peter and Tarpey [42] introduced the concept of time risk, which refers to the time required to return, exchange, or adjust a product. Time, social and psychological risks have their own definitions. Peter and Tarpey [42] defined time risk as the need to spend more time satisfying product requirements. Jacoby and Kaplan [41] defined psychological risk as the possibility of purchasing unsuitable products and services, and social risk as the possibility of becoming isolated from others because of product or service errors.

We used three of the risks (i.e., time, psychological and social) proposed by Wu et al. [11] as the main push factors for two reasons. First, the concept of risk resulting from uncertain information quality has rarely been addressed as an aspect of the push construct of the PPM. When masks were only available in physical stores at the beginning of the COVID-19 outbreak in early February 2020, the Taiwanese government designed a map indicating each store's inventory of masks to assist consumers in purchasing them. However, without real-time updates, consumers sometimes received incorrect inventory information, which resulted in masks going out of stock while consumers were in line waiting to purchase them. In such a situation, time risk is the chance that consumers spend time and successfully or unsuccessfully make a purchase according to information quality. The psychological risk of this scenario is consumers rejecting the in-store purchase of masks due to fear of COVID-19. Social risk would consist of the impact of public opinion if a consumer were to catch the virus while purchasing masks in a store.

To summarize the literature, time, social and psychological risks are the primary concepts discussed in relation to the push construct of PPM.

2.4. Pull Factors

Migration from point A to point B is caused by pull factors [33]. In the literature on PPM, alternative attractiveness is a pull factor that explains consumers' switching intention [12,13,15,25–27]. Studies have also reported that consumers tend to seek feasible alternatives when physical stores fail to meet their needs. Alternative attractiveness is a chief factor that affects consumers' decision to switch services. When the expected quality of an alternative service is superior to that of the original one, consumers' intention to switch to the alternative service increases [41]. Several studies have explored the concept of critical mass, which is also known as "network externality". Critical mass has affected numerous technologies and has been used to explain the rise in the value of a given technology as its user base increases [43]. According to Wu et al. [11], when a critical mass occurs, consumers tend to be more drawn to alternative services, which increases their trust in the alternative services recommended by other users.

In response to the COVID-19 pandemic, TCDC implemented comprehensive mask expropriation emergency management measures. As a result, consumers are now forced to queue at pharmacies to purchase masks in stores or pre-order them online [8]. The switch from in-store purchases to preordering online to avoid the risk of infection constitutes a type of migration. In sum, alternative attractiveness and critical mass are the chief concepts discussed in relation to the pull construct of PPM.

2.5. The Mooring Factor

According to the literature, mooring factors are personal or social aspects that may prompt residents to leave or stay in certain locations [34]. Based on this concept, we defined the mooring factors of the online pre-order model as factors that drive consumers to give up or continue in-store shopping. Most studies have identified the cost of switching as the central factor affecting the mooring construct of PPM [11,13,25,26,40]. Studies have found that consumers evaluate the cost of switching in terms of time, performance and financial and psychological factors. However, the cost of switching varies across situations [26,40]. The cost of switching could be tangible monetary costs, intangible perceptive costs, or a combination of both (e.g., educational and emotional costs) (Chang et al., 2017) [25]. Chang et al. [26] also noted that excessive energy and time costs hinder consumers' switching processes. Exposure to an alternative service that requires lower switching costs can increase consumers' switching intention [11]. Consumers' acceptance of the cost of switching during the management of the COVID-19 pandemic must be assessed. Accordingly, we used switching cost as the chief mooring factor.

3. Research Model and Hypotheses

3.1. Research Model

Based on the literature on the PPM model, we developed a research model to investigate Taiwanese consumers' switching behavior in response to COVID-19. We also defined the potential push-pull mooring constructs in the context of the online pre-order model. We identified three primary constructs of the PPM model: push factors, which include time risk, psychological risk, social risk and dissatisfaction; pull factors, which encompass alternative attractiveness and critical mass; and the mooring factor of switching cost. The following figure presents the relationships between the model's constructs (see Figure 1).

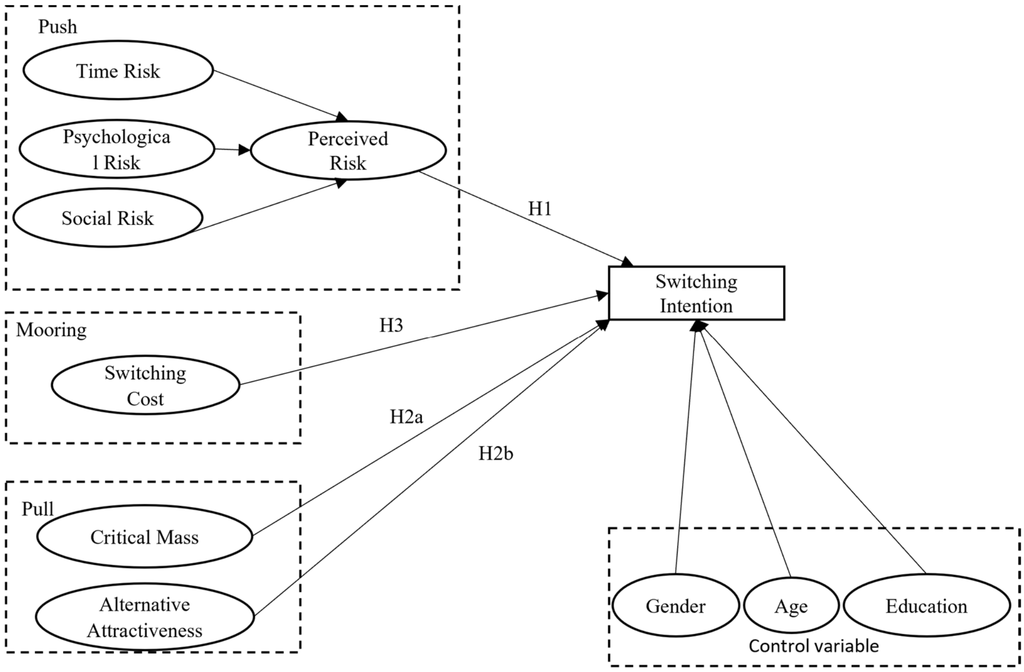

Figure 1. Research model.

3.2. Hypotheses

3.2.1. Push Factors

Migration from offline physical stores to online preordering during the COVID-19 pandemic was caused by environmental uncertainty. The push construct of the PPM model usually refers to consumers' dissatisfaction with services due to negative factors (e.g., risks) that cause them to switch from the original service model to an alternative one that satisfies their needs. Perceived risk denotes consumers' anxiety about the risks they are aware of, which drives them to seek solutions that reduce risks to a tolerable level. They may even pursue completely risk-free solutions [41]. The main causes of perceived risks are the uncertainty and adverse consequences that consumers experience when purchasing products or services [11,44,45]. The risk of being infected with COVID-19 from the physical purchase during the pandemic can also lead to consumers' perceived risk of purchasing a product, which in turn leads to consumers' switch to non-contact transactions [37]. The uncertainty caused by the COVID-19 outbreak is closely tied to perceived risks. Exposure to excessive risks can not only cause death, but also creates unbearable psychological conditions among consumers, produces psychological risks, triggers public opinion in society or on social media and generates social risks [46].

Because risks strongly affect consumers' decisions in the context of COVID-19, we highlighted potential risks affecting consumer decision-making and the uncertainty involved in in-store shopping. We pinpointed time, psychological, and social risks as potential perceived risks. We excluded physical, performance, and financial risks from the study because the Taiwanese government dominates the offline mask distribution channel. Although this service is dominated by the government, in-store shoppers still face the uncertainty of being informed that masks are out of stock halfway through a queue and end up wasting their time (time risk), the possibility of finding in-store purchases of masks unsuitable due to fear of becoming infected with COVID-19 (psychological risk) and potential exposure to negative public opinion upon becoming infected with the virus (social risk). Informational and environmental uncertainty during COVID-19 can impose various risks on consumers; we defined such uncertainty as perceived risk. The push construct of the PPM model was mostly interpreted as a negative reason that leads consumers to seek alternative services. According to Wu et al. [11], time, psychological and social risks are the negative factors that produce push effects. Therefore, we defined these three variables as push factors affecting consumers' switching intention in the context of COVID-19. Thus, we developed the following hypothesis:

H1. *The higher the perceived time, psychological and social risks, the greater consumers' switching intention from offline shopping to preordering online*.

3.2.2. Pull Factors

The concept of critical mass was introduced by Oliver et al. [14] and refers to the desire to engage in collective action. In the context of technological services, the higher the degree of consumer participation or usage, the greater the value of a given technology [43]. Critical mass is often influenced by sociology and economics. When a critical mass forms, sociologists argue that the intention to use an information system is influenced by information and regulations, whereas economists maintain that the adoption of information technology (IT) and its innovations depends on network externalities [46]. The shift in consumers' mask-purchasing patterns to preordering masks online during the outbreak of COVID-19 can be evaluated from both sociological and economic angles. The Taiwanese government's policies and regulations have allowed consumers to buy masks online through a smartphone app and *ibon* at convenience stores. When the effects of COVID-19 changed policies and increased the number of service options, consumers who had not used the online preordering service were subject to the effect of critical mass; that is, their intention to switch to the online service was impacted by their peers, ccolleague and family members who used the service, thereby increasing demand for it.

Alternative attractiveness is a crucial factor in research on PPM. When services fail to meet consumers' needs, they seek other services as feasible alternatives to the original service model [12]. Environment-induced uncertainty can entail risk factors that consumers reduce or eliminate by selecting potential alternatives [41]. When more attractive alternative services become available, consumers are likely to stop using the original ones. However, when consumers are unaware of attractive alternative services or find them unappealing, consumers tend to continue using the original services even if they are dissatisfied with them [25]. Consumers can discover attractive alternative services through a myriad of information channels including ads, social media and word of mouth. When the expected quality of an alternative service is superior to the quality of the original one, consumers' intention to switch to an alternative service increases [26]. Thus, the construct of alternative attractiveness is applicable to the effects of COVID-19 for two reasons. First, the risk factors involved in offline shopping services may motivate consumers to pursue alternative low-risk services. Second, the online pre-order model, created through a series of policy improvements, constitutes a service with alternative attractiveness, which considerably reduces risk and increases switching intention.

In PPM, the pull and push constructs exert opposite effects. Studies have investigated the potential pull factors that contribute to migration from service A to service B, as well as the characteristics that render service B more attractive to consumers and lead to their switching behavior [13]. We designated critical mass and alternative attractiveness as the pull factors influencing consumers' switching intention in the context of COVID-19 and developed the following hypotheses:

H2a. *The more influential the critical mass, the higher consumers' switching intention from offline shopping to preordering products online.*

H2b. *The more influential the alternative attractiveness, the greater consumers' switching intention from offline shopping to preordering online.*

3.2.3. The Mooring Factor

Switching costs are incurred when switching from one service to an alternative. These costs can be tangible (e.g., monetary), intangible (e.g., psychological and perceptive), or a mix of both and vary depending on the situation [26]. According to Chen and Keng [47], the mooring effects of switching costs (e.g., psychological, time and ability-related factors) are key aspects affecting consumers' choice to switch from an alternative service back to the original one. Excessively high switching costs reduce switching intention and cause consumers to continue using the original service even if they are dissatisfied with it [25]. Reasonable switching costs increase consumers' switching intention [11]. Based on the literature, we explored switching costs for two reasons. First, switching from an offline mask purchase service to the online preordering model during the COVID-19 outbreak increased switching costs. In-store shopping involves queuing to purchase masks directly from service personnel, whereas online shopping requires consumers to pre-order masks on their own, which represents an increase in switching costs to first-time users. Second, when customers pre-order masks online, they must pay an additional shipping fee, which is not required for offline shopping. This also means that consumers who pre-order masks online must wait for them to be delivered. Hence, we formulated the following hypothesis:

H3. *The higher the switching cost, the lower consumers' intention to switch from offline shopping to preordering online.*

3.3. Construct Operationalization

We investigated Taiwanese consumers' intention to switch from offline shopping to preordering masks online during the COVID-19 outbreak. We invited two professors specializing in information and marketing management to review and modify the questionnaire. They evaluated the reasonableness of its items, revised the content, added more items relevant to the research objectives to ensure the questionnaire's content validity and responded to the questionnaire using a 7-point Likert-type scale. To ensure the questionnaire's quality, the items from the original English scale were translated and reviewed by two professors who confirmed the appropriateness, accuracy and relevance of the translations. The original English scale was translated into Chinese so that the questionnaire could be distributed to the Taiwanese population and the items were modified to suit the research context. These adjustments allowed the respondents to fully understand the items and to complete the questionnaire without any problems. The questionnaire contained: two questions each for time risk (TR), psychological risk (PR), and social risk (SR) according to Wu et al. [11]; three questions developed by Tang and Chen [12] about alternative attractiveness; three questions developed by Wang et al. [48] about critical mass; and three questions created by Chen and Keng [49] about switching costs and switching intention.

3.4. Data Collection

After testing, we distributed the questionnaire. We recruited consumers who had experience with both offline shopping and online preordering of masks during the COVID-19 pandemic as respondents. We created the questionnaire using Google Forms and distributed it online to simplify data collection and generate fast responses, high efficiency and a high participation rate. We distributed the questionnaire on the Academic Questionnaire Board of the PTT Bulletin Board System and on Facebook communities for purchasing masks. We primarily surveyed Taiwanese consumers who had experience preordering masks online during COVID-19. We conducted the survey from mid-July to early August 2020 and collected 487 responses. In terms of sample collection, the present study applied a single cross-sectional research method, which aimed to obtain specific characteristics and meanings describing the group at a single point in time. Moreover, sampling can effectively reflect the current state of research. To ensure their quality and validity, we established four indicators and countermeasures: (1) By checking the respondents' answers, we ensured they had experience with both purchasing masks in physical stores and also preordering them online during the COVID-19 pandemic. We deemed responses indicating a lack of experience with either form of purchasing to be invalid. (2) We considered cases with the same answers (all 1s or 7s) throughout the questionnaire to be invalid. (3) We added a negatively worded question to the questionnaire as a reversal mechanism to identify respondents who randomly responded to the questions. (4) To complete the questionnaire, the respondents had to log in to their Gmail accounts; the system prevented users from making multiple submissions. After excluding invalid responses, 233 valid questionnaires remained, 168 (72.1%) of which were completed by women. Among the respondents for valid questionnaires, 59.2% had an undergraduate degree. Since this study was conducted on a voluntary basis, the respondents were predominantly females whose educational background is largely at university level. In particular, previous studies have indicated that basic information such as gender, age and experience affects users' intentions [43,50]. Therefore, we selected education, gender and age as control variables for switching behavior so as to avoid the impact of gender and education.

4. Results

We performed structural equation modeling (SEM) in two steps. First, we assessed the measurement model's reliability and validity using Cronbach's α, convergent validity and discriminant validity. We employed the partial least squares (PLS) method to evaluate the model. Because this study entailed theory-based, exploratory research, subsequent examination of latent variables was required; thus, we used PLS-SEM to perform the analysis [39]. We defined the push factor as a formative second-order construct. The push construct of the model comprises three reflective concepts: TR, SR and PR. PLS-SEM is suitable for testing the formative second-order model, whereas linear structural relations and AMOS are not suitable for testing the reflective and formative second-order models [51,52]. Hence, we utilized PLS to scrutinize the proposed model. We harnessed SmartPLS (version 3.2.8, SmartPLS GmbH, Oststeinbek, Germany) to verify the hypotheses because common method variance is related to a method of measurement, rather than the constructs represented by the measured items and measurement errors may occur. We applied two approaches to reduce common method variance. First, we deliberately designed the questionnaire to have multiple pages to allow respondents to take short breaks between pages, thereby reducing the common method variance resulting from exposure to continuous measurement on the same scale. Second, we performed Harman's single-factor test for common method variance. By looking at the model's main constructs, we eliminated latent variables that may have led to common method variance. Because no construct had total variance over the acceptable level of 50%, common method variance was not a substantial concern [53].

4.1. Measurement Model

We assessed the model's reliability and validity in terms of factor loading, composite reliability (CR), convergent validity and discriminant validity. We used Cronbach's α and factor loadings to evaluate each item's reliability. We determined acceptable factor loading using the level recommended by Hair et al. [54]. The factor loadings for all constructs and items were greater than 0.7. Cronbach's α for all constructs was above 0.7, as recommended by Hair et al. [55]. The CR for all constructs was above the 0.7 level recommended by Hair et al. [56]. All average variance extracted (AVE) values were above the 0.5 level as recommended by Fornell and Larcker [57]. Since the results were all above the level recommended in the literature and the measurement model exhibited satisfactory consistency and convergence. The statistical results are presented in Table 1.

Table 1. Results of reliability and convergent validity of measurement model.

Construct	Factor Loading	α	roh_A	CR	AVE	VIF
Time risk (TR)	0.928 *** 0.923 *** 0.919 ***	0.914	0.915	0.946	0.853	1.775
Psychological risk (PR)	0.770 *** 0.777 *** 0.840 ***	0.712	0.713	0.839	0.634	2.089
Social risk (SR)	0.909 *** 0.915 *** 0.938 ***	0.911	0.931	0.944	0.848	1.239
Alternative attractiveness (AA)	0.987 *** 0.938 *** 0.948 ***	0.911	0.918	0.944	0.850	1.547
Critical mass (CM)	0.844 *** 0.897 *** 0.905 ***	0.858	0.864	0.913	0.778	1.379
Switching cost (SC)	0.914 *** 0.944 *** 0.913 ***	0.914	0.920	0.946	0.853	1.228
Switching intention (SI)	0.941 *** 0.932 *** 0.953 ***	0.936	0.937	0.959	0.887	DV

Notes: $p < 0.01$, ***; Composite reliability (CR); Variance inflation factor (VIF); Dependent variable (DV); Average variance extracted (AVE); significant at $p < 0.01$.

To assess the structure's discriminant validity, we applied the method proposed by Fornell and Larcker [57] and the heterotrait-monotrait (HTMT) ratio of correlations recommended by Henseler et al. [58]. The square roots of the AVE values were greater than the correlation coefficients of all constructs, confirming the satisfactory discriminant validity of the values [57]. The results are presented in Table 2.

Table 2. Construct reliability and validity.

	AA	CM	PR	SR	SC	SI	TR
AA	**0.922**						
CM	0.497	**0.882**					
PR	−0.221	−0.314	**0.796**				
SR	−0.136	−0.145	0.420	**0.921**			
SC	−0.318	−0.130	−0.125	−0.139	**0.924**		
SI	0.551	0.485	−0.247	−0.173	−0.436	**0.942**	
TR	−0.144	−0.171	0.652	0.175	−0.241	−0.059	**0.924**

In this study, discriminant validity was assessed using the heterotrait-monotrait ratio of correlations proposed by Henseler et al. [59]. HTMT reflects the ratio of the mean value of correlations of measures between different latent variables relative to that of correlations of measures of the same latent variable. Consequently, the HTMT of the constructs ξ_i and ξ_j with, respectively, K_i and K_j indicators can be formulated as follows (See Figure 2):

$$\underbrace{\mathrm{HTMT}_{ij} = \frac{1}{K_i K_j}\sum_{g=1}^{K_i}\sum_{h=1}^{K_j} r_{ig,jh}}_{\text{average heterotrait}-\text{heteromethod}} \div \underbrace{\left(\frac{2}{K_i(K_i-1)}\cdot\sum_{g=1}^{K_i-1}\sum_{h=g+1}^{K_i} r_{ig,ih}\cdot\frac{2}{K_j(K_j-1)}\cdot\sum_{g=1}^{K_j-1}\sum_{h=g+1}^{K_j} r_{jg,jh}\right)^{\frac{1}{2}}}_{\substack{\textit{geometric mean of the average monotrait}-\textit{heteromethod} \\ \textit{correlation of construct } \xi_i \textit{ and the average} \\ \textit{monotrait}-\textit{heteromethod correlation of construct } \xi_j}}.$$

Figure 2. Equation for HTMT method.

Henseler et al. [58] suggested that the threshold value for HTMT be below 0.9, and that HTMT values above 0.9 indicate insufficient discriminant validity. The HTMT values obtained in this study ranged from 0.155 to 0.595 (Table 3). All constructs in the model demonstrated acceptable and effective discriminant and convergent validity by the recommended levels in the literature (see Tables 2 and 3).

Table 3. Heterotrait-monotrait ratio (HTMT).

	AA	CM	SR	SC	SI	TR
AA						
CM	0.557					
SR	0.155	0.164				
SC	0.348	0.136	0.150			
SI	0.595	0.534	0.189	0.467		
TR	0.161	0.199	0.184	0.261	0.065	

Table 1 presents the statistical significance of the second-order constructs ($p < 0.05$) for evaluating the formative second-order indicators and their corresponding second-order contributions. TR, PR and SR in the push construct demonstrated statistical significance and adequate explanatory power, even in the second order (Table 4). Thus, we applied the verification and testing methods described in the literature to assess the sample in this study. The results support the idea of a perceived risk as a formative second-order construct.

Table 4. Second-order constructs.

Construct	Sub-Construct	Weights
	Time risk (TR)	0.487 ***
Perceived risk	Psychological risk (PR)	0.399 ***
	Social risk (SR)	0.393 ***

Notes: *** $p < 0.05$.

4.2. Structural Model

As shown in Figure 3, after validation by SmartPLS 3.2.8, the hypotheses can be judged in their validity based on the findings. Therefore, the findings of this study will be interpreted by classifying the hypotheses as valid or invalid. The results of the structural model analysis were verified by the resampling of the Bootstrapping method, with a sample of 5000 as the data processing criterion. According to the results of statistical analysis, the path coefficient of H3 is −0.305 ($p < 0.05$), implying that the hypothesis H3 is invalid. The path coefficient of H1 (Perceived risk) is −0.130 ($p < 0.05$), that of H2a (Critical mass) is 0.257 ($p < 0.05$) and that of H2b (Alternative attractiveness) is 0.258 ($p < 0.05$), indicating that the hypotheses H1, H2a, and H2b are valid. Finally, in terms of the results of control variables, gender ($\beta = 0.022$, $p = 0.657$), age ($\beta = -0.030$, $p = 0.547$) and education ($\beta = 0.074$, $p = 0.274$) have no significant effects on switching intention, indicating no differences in statistical results among different groups.

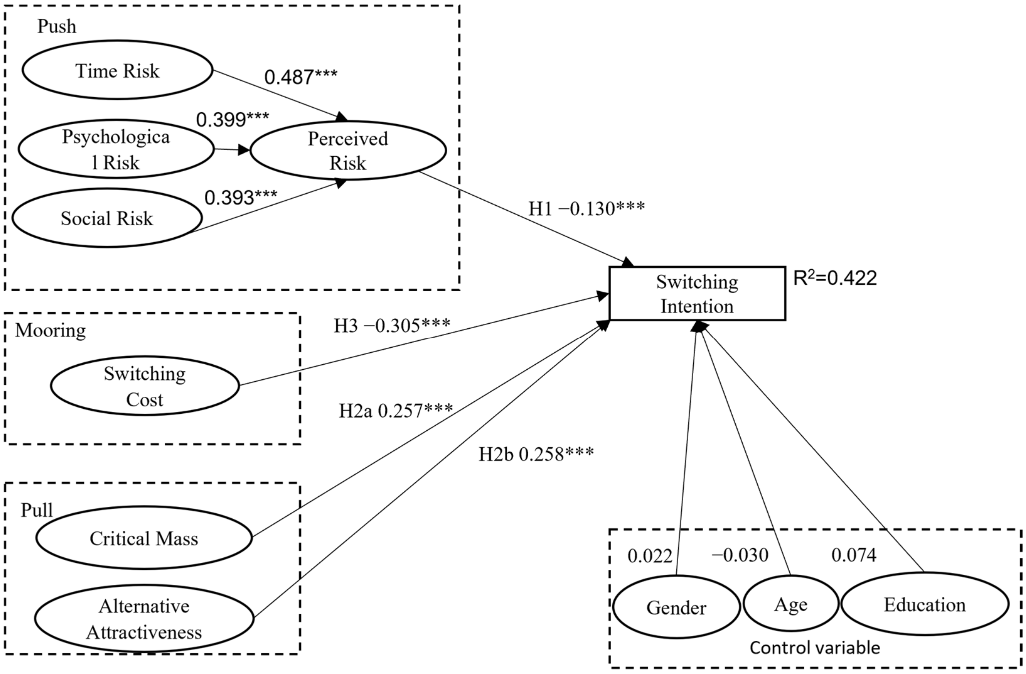

Figure 3. PLS results of the research model. *** $p < 0.05$.

5. Discussions and Conclusions

According to the results, the push factors represented a negative motivation contributing to consumers' switch from offline shopping to preordering masks online. The uncertainties arising from the COVID-19 outbreak caused consumers to perceive TR, PR and SR in shopping at physical stores. These risks drive consumers to select alternative services to avoid the risks caused by excessive uncertainty [11]. The findings imply that push factors in PPM encourage consumers who are dissatisfied with a service to switch to other services [40]. Among the push factors, TR exerted the strongest effect, followed by PR and SR. Our outcomes support the findings of Wu et al. [11], who demonstrated that risks affect consumers' perceptions of services. The push factors exerted a negative influence because consumers dislike services that come with risk. For example, they dislike services that waste time, fail to meet their needs, or arouse negative public opinion. Therefore, perceived risks amid the outbreak of COVID-19 became push factors that increased consumers' switching intention.

We designated critical mass and alternative attractiveness as the major pull factors that affect consumers' switching intention. According to the results, the pull factors were positive motivations contributing to consumers' switch from in-store shopping to preordering masks online. The pull construct of the proposed model (i.e., the attractiveness prompting consumers to adopt a certain behavior) positively affected their migration conduct, which supports the findings of Lee [33], who revealed the positive effect of the push construct in PPM. This outcome suggests that alternative attractiveness and critical mass both achieved satisfactory statistical significance, supporting the results of Wu et al. [11] in relation to the construct of alternative attractiveness and those of Tang and Chen [12] in relation to the construct of critical mass. Consumers who reject uncertain services tend to choose attractive alternatives [12,25]. Subsequently, consumers who do not use new services are affected by critical mass when their friends and family members begin using new services. Critical mass increases switching intention and leads consumers to use new services [11]. Fear of COVID-19 pushed consumers to seek alternative attractive services. Critical mass occurred when consumers' friends and family members began switching to new services, affecting their decision to use such services and increasing their intention to switch services; thus, pull factors were established.

We used switching cost as the mooring factor. Switching costs negatively affect consumers' intention to switch. The results support the findings of Wu et al. [11], who indicated that low switching costs are positively associated with switching intention. Low switching costs positively affect users' service-switching behavior [25]. We discovered that switching costs negatively affected switching intention, denoting that consumers considered switching costs to be affordable. That is, consumers deemed the time, money, and energy required in switching from offline shopping to buying masks online during COVID-19 acceptable. Therefore, we derived the following conclusion regarding mooring factors: Affordable switching costs can increase consumers' intention to switch to the online pre-order service model.

5.1. Practical Implications

We explored consumers' intention to switch from offline shopping to preordering masks online. The rise of mobile commerce has made internet- and smartphone-based consumption patterns the norm [26]. The panic-based rise in demand for masks during a national emergency represents an opportunity to understand consumers' decisions to use offline or online services. In terms of push factors, more factors related to the offline shopping of masks during the COVID-19 outbreak should be considered. Although risks represent possible situations that might not necessarily occur, lack of control concerns consumers and leads to a considerable and unavoidable wave of switching behavior [11]. In-store shopping—which is the only channel through which masks can be purchased for immediate use—involves the uncertainty caused by risks. Thus, lowering such risks is key to ensuring that consumers continue to purchase masks in stores. In terms of pull factors, determining whether the alternative attractiveness of online services can be effectively utilized to replace offline services or to compensate for consumers' dissatisfaction with offline shopping is crucial to increasing consumers' switching intention. Additionally, consumers who are hesitant to switch services are affected by the critical mass created by their peers, colleagues, and family members. Social media must be effectively utilized to promote the attractiveness of new services and to facilitate consumer interaction. For example, inviting YouTubers to promote online services can popularize services and convince consumers that preordering masks online is a common practice. Thus, alternative attractiveness and critical mass can increase consumers' switching intention. In terms of mooring factors, switching cost (high or low) determines consumers' intention to switch to online services. High switching costs decrease switching intention, whereas affordable switching costs increase it [25]. Hence, affordable switching costs increase consumers' intention to switch from offline to online preordering. To increase switching intention, services must be deemed acceptable and easy to use by the public. Reducing switching costs can effectively increase consumers' switching intention.

5.2. Implications for Research

The participants in this empirical study were consumers who had experience with both offline shopping and online preordering of masks during the COVID-19 pandemic. We applied the explanatory power of PPM to the management of the COVID-19 emergency and made several contributions to the present study. First, although migration from offline services to IT services has gained considerable attention, studies on PPM have rarely investigated panic-based demand, especially in emergency situations. Second, most studies have examined topics related to long-term migration, such as the migration of younger generations from Facebook to Instagram [15] and migration from certain cloud computing services to attractive alternatives out of dissatisfaction [11]. We explored Taiwan's management of the COVID-19 emergency and analyzed consumers' intention to switch from offline to online services to purchase masks. In terms of push factors, most studies on risk using PPM have been related to IT [11,40]. Our study differs in that we identified the risks of offline services and demonstrated the superiority of online services. In terms of pull factors, studies have reported that a construct's alternative attractiveness can cause the pull effect to become stronger than the push effect in the process of switching from offline to online shopping [15]. Other potential pull factors must be considered in relation to alternative attractiveness to confirm their effects [15]. We used critical mass as a pull factor because COVID-19 is a social issue that depends on the interconnections between family members and friends. Their opinions play a crucial role in determining consumers' switching intention; this phenomenon is relevant to the PPM model of migration theory. A critical mass occurs when a majority of the population is willing to switch services. Hence, analyzing this phenomenon along with alternative attractiveness sheds light on the switching behavior of mask purchasing during the COVID-19 pandemic.

5.3. Limitations and Future Research

To collect data, we distributed a questionnaire through snowball and convenience sampling, which may have limited the viability of demographic variables. For example, the data are not representative of all age groups and regions in Taiwan. As such, researchers should conduct regional investigations to identify the unique effects of regional differences. Our results can only explain switching intention during emergency medical situations and may therefore not be completely generalizable to other types of emergencies. Our results can be used to explain certain emergency management measures. We explored consumers' switching intention from in-store shopping to online mask preordering in response to the emergency management measures of COVID-19 through the framework of PPM. Researchers should employ the PPM as a framework to examine other emergency management situations and to pinpoint potential differences in factors across various regions and contexts. Eventually, this present study primarily adopted a cross-sectional data collection approach. Since data was collected at a single point in time, the findings are also referred to as limitations, particularly because the pandemic has occurred for over two years and consumers in Taiwan have gradually grown accustomed to online face mask purchases. Therefore, subsequent researchers can investigate from the perspective of a longitudinal study and examine data from different time points to understand the shift in consumer behaviors toward online face mask purchases in the post-pandemic era.

Author Contributions: This work was the result of a collaboration between C.-L.L., S.-W.Y., J.-Y.L. and Y.-S.S. All the authors contributed equally in the review and improvement of the manuscript. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by the K. C. Wong Magna Fund at Ningbo University (RC190015, RC202220), Zhejiang Provincial Philosophy and Social Science Planning Project (23NDJC349YB) and the Zhejiang Province Educational Science Planning Project (Y202146358). This study was supported by the Ministry of Science and Technology, Taiwan, under grants MOST 111-2410-H-019-006-MY3 and MOST 111-2622-H-019-001.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: Some or all of the data and models that support the findings of this study are available from the corresponding authors upon reasonable request.

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

References

1. Addo, P.C.; Fang, J.; Kulbo, N.B.; Li, L. COVID-19: Fear appeal favoring purchase behavior towards personal protective equipment. *Serv. Ind. J.* **2020**, *40*, 471–490. [CrossRef]
2. De Vos, J. The effect of COVID-19 and subsequent social distancing on travel behavior. *Transp. Res. Interdiscip. Perspect.* **2020**, *5*, 100121. [CrossRef] [PubMed]
3. Chin, T.; Wang, S.; Rowley, C. Polychronic knowledge creation in cross-border business models: A sea-like heuristic metaphor. *J. Knowl. Manag.* **2021**, *25*, 1–22. [CrossRef]
4. Wang, S.; Chin, T. A stratified system of knowledge and knowledge icebergs in cross-cultural business models: Synthesising ontological and epistemological views. *J. Int. Manag.* **2020**, *26*, 100780. [CrossRef]

5. Chin, T.; Meng, J.; Wang, S.; Shi, Y.; Zhang, J. Cross-cultural metacognition as a prior for humanitarian knowledge: When cultures collide in global health emergencies. *J. Knowl. Manag.* **2021**, *26*, 88–101. [CrossRef]
6. Srivastava, S.; Khokhar, F.; Madhav, A.; Pembroke, B.; Shetty, V.; Mutreja, A. COVID-19 Lessons for Climate Change and Sustainable Health. *Energies* **2021**, *14*, 5938. [CrossRef]
7. Foroughi, A.; Buang, N.A.; Senik, Z.C.; Hajmisadeghi, R.S. Impulse buying behavior and moderating role of gender among Iranian shoppers. *J. Basic Appl. Sci. Res.* **2013**, *3*, 760–769.
8. Su, V.-Y.F.; Yen, Y.F.; Yang, K.Y.; Su, W.J.; Chou, K.T.; Chen, Y.M.; Perng, D.W. Masks and medical care: Two keys to Taiwan's success in preventing COVID-19 spread. *Travel Med. Infect. Dis.* **2020**, *38*, 101780.
9. Ajzen, I. From intentions to actions: A theory of planned behavior. In *Action Control*; Springer: Berlin/Heidelberg, Germany, 1985; pp. 11–39.
10. Wu, K.; Vassileva, J.; Noorian, Z.; Zhao, Y. How do you feel when you see a list of prices? The interplay among price dispersion, perceived risk and initial trust in Chinese C2C market. *J. Retail. Consum. Serv.* **2015**, *25*, 36–46. [CrossRef]
11. Wu, K.; Vassileva, J.; Zhao, Y. Understanding users' intention to switch personal cloud storage services: Evidence from the Chinese market. *Comput. Hum. Behav.* **2017**, *68*, 300–314. [CrossRef]
12. Tang, Z.; Chen, L. An empirical study of brand microblog users' unfollowing motivations: The perspective of push-pull-mooring model. *Int. J. Inf. Manag.* **2020**, *52*, 102066. [CrossRef]
13. Xu, Y.C.; Yang, Y.; Cheng, Z.; Lim, J. Retaining and attracting users in social networking services: An empirical investigation of cyber migration. *J. Strateg. Inf. Syst.* **2014**, *23*, 239–253. [CrossRef]
14. Oliver, P.; Marwell, G.; Teixeira, R. A theory of the critical mass. I. Interdependence, group heterogeneity, and the production of collective action. *Am. J. Sociol.* **1985**, *91*, 522–556. [CrossRef]
15. Hou, A.C.; Shiau, W.-L. Understanding Facebook to Instagram migration: A push-pull migration model perspective. *Inf. Technol. People* **2019**, *33*, 272–295. [CrossRef]
16. Hou, A.C.; Chern, C.-C.; Chen, H.-G.; Chen, Y.-C. 'Migrating to a new virtual world': Exploring MMORPG switching through human migration theory. *Comput. Hum. Behav.* **2011**, *27*, 1892–1903. [CrossRef]
17. Lai, J.Y.; Debbarma, S.; Ulhas, K.R. An empirical study of consumer switching behaviour towards mobile shopping: A Push-Pull-Mooring model. *Int. J. Mob. Commun.* **2012**, *10*, 386–404. [CrossRef]
18. Anderson, W.P.; Chatterjee, L.; Lakshmanan, T.R. E-commerce, transportation, and economic geography. *Growth Chang.* **2003**, *34*, 415–432. [CrossRef]
19. Haq, M.; Abbasi, S. Indirect Impact of Hedonic Consumption and Emotions on Impulse Purchase Behavior: A Double Mediation Model. *J. Manag. Sci.* **2016**, *3*, 108–122. [CrossRef]
20. Shibuya, Y.; Lai, C.-M.; Hamm, A.; Takagi, S.; Sekimoto, Y. Do open data impact citizens' behavior? Assessing face mask panic buying behaviors during the COVID-19 pandemic. *Sci. Rep.* **2022**, *12*, 17607. [CrossRef]
21. Tsou, T.-P.; Chen, W.-C.; Huang, A.S.-E.; Chang, S.-C.; Su, C.-P.; Lee, P.-H.; Chan, P.-C.; Wu, H.-H.; Huang, S.-T.; Su, W.-J.; et al. Epidemiology of the first 100 cases of COVID-19 in Taiwan and its implications on outbreak control. *J. Formos. Med. Assoc.* **2020**, *119*, 1601–1607. [CrossRef]
22. Lin, C.Y.; Wang, W.H.; Urbina, A.N.; Tseng, S.P.; Lu, P.L.; Chen, Y.H.; Yu, M.L.; Wang, S.F. Importation of SARS-CoV-2 infection leads to major COVID-19 epidemic in Taiwan. *Int. J. Infect. Dis.* **2020**, *97*, 240–244. [CrossRef] [PubMed]
23. Handarkho, Y.D.; Harjoseputro, Y. Intention to adopt mobile payment in physical stores. *J. Enterp. Inf. Manag.* **2019**, *33*, 285–308. [CrossRef]
24. Yan, R.; Zhang, K.Z.; Yu, Y. Switching from hotels to peer-to-peer accommodation: An empirical study. *Inf. Technol. People* **2019**, *32*, 1657–1678. [CrossRef]
25. Chang, I.-C.; Liu, C.-C.; Chen, K. The push, pull and mooring effects in virtual migration for social networking sites. *Inf. Syst. J.* **2014**, *24*, 323–346. [CrossRef]
26. Chang, H.H.; Wong, K.H.; Li, S.Y. Applying push-pull-mooring to investigate channel switching behaviors: M-shopping self-efficacy and switching costs as moderators. *Electron. Commer. Res. Appl.* **2017**, *24*, 50–67. [CrossRef]
27. Hou, A.C.; Shang, R.A.; Huang, C.C.; Wu, K.L. The effects of Push-pull-mooring on the Switching Model for Social Network sites Migration. In Proceedings of the PACIS, Chengdu, China, 24–28 June 2014; p. 64.
28. Iyamu, I.; Apantaku, G.; Yesufu, Z.; Oladele, E.A.; Eboreime, E.; Afirima, B.; Okechukwu, E.; Kibombwe, G.I.; Oladele, T.; Tafuma, T.; et al. Is social media, as a main source of information on COVID-19, associated with perceived effectiveness of face mask use? Findings from six sub-Saharan African countries. *Glob. Health Promot.* **2022**, *29*, 86–96. [CrossRef] [PubMed]
29. Fatfouta, R.; Oganian, Y. Face masks drive increased rational decision-making. *Curr. Psychol.* **2022**, *4*, 1–10. [CrossRef]
30. Wismans, A.; van der Zwan, P.; Wennberg, K.; Franken, I.; Mukerjee, J.; Baptista, R.; Marín, J.B.; Burke, A.; Dejardin, M.; Janssen, F.; et al. Face mask use during the COVID-19 pandemic: How risk perception, experience with COVID-19, and attitude towards government interact with country-wide policy stringency. *BMC Public Health* **2022**, *22*, 1622. [CrossRef]
31. Meo, S.A.; Alqahtani, S.A.; Aljedaie, G.M.; Binmeather, F.S.; AlRasheed, R.A.; Albarrak, R.M. Face Masks Use and Its Role in Restraining the Spread of COVID-19 Pandemic in Saudi Arabia: Knowledge, Attitude, and Practices Based Cross-Sectional Study. *Front. Public Health* **2022**, *9*, 818520. [CrossRef]
32. Hanna, E.; Martin, G.; Campbell, A.; Connolly, P.; Fearon, K.; Markham, S. Experiences of face mask use during the COVID-19 pandemic: A qualitative study. *Sociol. Health Illn.* **2022**, *44*, 1481–1499. [CrossRef]

33. Lee, E.S. A theory of migration. *Demography* **1966**, *3*, 47–57. [CrossRef]
34. Moon, B. Paradigms in migration research: Exploring 'moorings' as a schema. *Prog. Hum. Geogr.* **1995**, *19*, 504–524. [CrossRef] [PubMed]
35. Boyle, P.; Halfacree, K. *Migration into Rural Areas: Theories and Issues*; John Wiley and Sons Ltd.: New York, NY, USA, 1998.
36. Maslach, C.; Jackson, S.E.; Leiter, M.P.; Schaufeli, W.B.; Schwab, R.L. *Maslach Burnout Inventory*; Consulting Psychologists Press: Palo Alto, CA, USA, 1986; Volume 21, pp. 3463–3464.
37. Nayak, B.; Bhattacharyya, S.S.; Goswami, S.; Thakre, S. Adoption of online education channel during the COVID-19 pandemic and associated economic lockdown: An empirical study from push–pull-mooring framework. *J. Comput. Educ.* **2022**, *9*, 1–23. [CrossRef]
38. Yu, S.-Y.; Chen, D.C. Consumers' Switching from Cash to Mobile Payment under the Fear of COVID-19 in Taiwan. *Sustainability* **2022**, *14*, 8489. [CrossRef]
39. Jeong, D.; Ko, E.; Taylor, C.R. Don't touch the Merchandise! Factors associated with consumer preference for contact free shopping. *J. Bus. Res.* **2023**, *154*, 113261. [CrossRef]
40. Cheng, S.; Lee, S.-J.; Choi, B. An empirical investigation of users' voluntary switching intention for mobile personal cloud storage services based on the push-pull-mooring framework. *Comput. Hum. Behav.* **2019**, *92*, 198–215. [CrossRef]
41. Jacoby, J.; Kaplan, L.B. The components of perceived risk. In Proceedings of the Annual Conference of the Association for Consumer Research, Chicago, IL, USA, 3–5 November 1972.
42. Peter, J.P.; Tarpey Sr, L.X. A comparative analysis of three consumer decision strategies. *J. Consum. Res.* **1975**, *2*, 29–37. [CrossRef]
43. Hsu, C.L.; Lu, H.P. Why do people play on-line games? An extended TAM with social influences and flow experience. *Inf. Manag.* **2004**, *41*, 853–868. [CrossRef]
44. Lin, C.L.; Jin, Y.Q.; Zhao, Q.; Yu, S.W.; Su, Y.S. Factors influence students' switching behavior to online learning under COVID-19 pandemic: A push–pull–mooring model perspective. *Asia-Pac. Educ. Res.* **2021**, *30*, 229–245. [CrossRef]
45. Jin, Y.Q.; Lin, C.L.; Zhao, Q.; Yu, S.W.; Su, Y.S. A study on traditional teaching method transferring to E-learning under the COVID-19 pandemic: From Chinese students' perspectives. *Front. Psychol.* **2021**, *12*, 632787. [CrossRef]
46. Hong, Y.; Kim, J.-S.; Xiong, L. Media exposure and individuals' emergency preparedness behaviors for coping with natural and human-made disasters. *J. Environ. Psychol.* **2019**, *63*, 82–91. [CrossRef]
47. Yıldırım, M.; Güler, A. Positivity explains how COVID-19 perceived risk increases death distress and reduces happiness. *Pers. Individ. Differ.* **2021**, *168*, 110347. [CrossRef] [PubMed]
48. Wang, K.; Lin, C.L.; Chen, C.D.; Yang, S.C. The adoption of wikipedia: A community-and information quality-based view. In Proceedings of the PACIS 2008, Suzhou, China, 4–7 July 2008; p. 50.
49. Chen, Y.H.; Keng, C.J. Utilizing the Push-Pull-Mooring-Habit framework to explore users' intention to switch from offline to online real-person English learning platform. *Internet Res.* **2019**, *29*, 167–193. [CrossRef]
50. Gefen, D.; Karahanna, E.; Straub, D.W. Trust and TAM in Online Shopping: An Integrated Model. *MIS Q.* **2003**, *27*, 51–90. [CrossRef]
51. Shiau, W.-L.; Sarstedt, M.; Hair, J.F. Internet research using partial least squares structural equation modeling (PLS-SEM). *Internet Res.* **2019**, *29*, 398–406. [CrossRef]
52. Huang, L.C.; Shiau, W.L. Factors affecting creativity in information system development: Insights from a decomposition and PLS-MGA. *Ind. Manag. Data Syst.* **2017**, *117*, 496–520. [CrossRef]
53. Shiau, W.L.; Luo, M.M. Factors affecting online group buying intention and satisfaction: A social exchange theory perspective. *Comput. Hum. Behav.* **2012**, *28*, 2431–2444. [CrossRef]
54. Hair, J.F.; Black, W.C.; Babin, B.J.; Anderson, R.E.; Tatham, R.L. *Multivariate Data Analysis*, 6th ed.; Pearson Prentice Hall: Hoboken, NJ, USA, 2005.
55. Hair, J.F.; Risher, J.J.; Sarstedt, M.; Ringle, C.M. When to use and how to report the results of PLS-SEM. *Eur. Bus. Rev.* **2019**, *31*, 2–24. [CrossRef]
56. Hair, J.; Hollingsworth, C.L.; Randolph, A.B.; Chong, A.Y.L. An updated and expanded assessment of PLS-SEM in information systems research. *Ind. Manag. Data Syst.* **2017**, *117*, 442–458. [CrossRef]
57. Fornell, C.; Larcker, D.F. Evaluating structural equation models with unobservable variables and measurement error. *J. Mark. Res.* **1981**, *18*, 39–50. [CrossRef]
58. Henseler, J.; Dijkstra, T.K.; Sarstedt, M.; Ringle, C.M.; Diamantopoulos, A.; Straub, D.W.; Ketchen, D.J.; Hair, J.F.; Hult, G.T.M.; Calantone, R.J. Common beliefs and reality about partial least squares: Comments on Rönkkö and Evermann (2013). *Organ. Res. Methods* **2014**, *17*, 182–209. [CrossRef]
59. Henseler, J.; Ringle, C.M.; Sarstedt, M. A new criterion for assessing discriminant validity in variance-based structural equation modeling. *J. Acad. Mark. Sci.* **2015**, *43*, 115–135. [CrossRef]