Understanding the adoption of the mask-supply information platforms during the COVID-19

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Abstract
Since late 2019, coronavirus disease 2019 (COVID-19) has led to a significant increase in the demand for medical resources. To publish data on face mask supplies, the Taiwanese government collaborated with program developers to construct a mask-supply information transitional platform (MITP). To comprehend the adoption of MITP, the study proposes a research model that integrates the health behavior model (HBM) and IS/IT continuance model for examining the factors affecting intention to use an MITP. Survey data collected from 524 respondents indicated that (1) intention to use an MITP is directly influenced by perceived threat of COVID-19 and beliefs toward using the MITP; (2) cues to action directly influence the perceived threat of COVID-19; and (3) perceived ease of use of MITP is a significant determinant of perceived usefulness of MITP. These results provide practical guidelines for health authorities and government to develop health information systems and strategies to control pandemics.

Keywords Usage intention · Health behavior model · IS/IT continuance model · Mask-supply information platform · COVID-19

JEL Classification M15

Introduction
Since late 2019, coronavirus disease 2019 (COVID-19) has been causing considerable problems worldwide. This newly discovered coronavirus disease is highly infectious, and its symptoms include fever, dry cough, aches and pains, diarrhea, loss of smell, and shortness of breath (WHO, 2021a). By the end of 2021, more than 320 million cases of and more than 5.5 million deaths from COVID-19 have been confirmed in 213 countries, with numbers still increasing (WHO, 2021b).

Taiwan, near China (where the COVID-19 pandemic first appeared), was originally predicted to have the second-highest number of COVID-19 cases in the world (PBS, 2020); however, the number of confirmed COVID-19 cases in Taiwan at the end of 2021 is approximately 17,000. A key factor in helping Taiwan to fight COVID-19 before a vaccine being available is the belief of Taiwanese people that wearing face masks can prevent infection; this belief is partly the result of Taiwan’s experience with an outbreak of severe acute respiratory syndrome (SARS). During the COVID-19 pandemic in 2020, the Taiwanese government made it mandatory to wear face masks when using public transportation. Moreover, to prevent people from panic-buying face masks and thus causing the price of face masks to skyrocket, the Taiwanese government introduced a name-based rationing system for the purchase of face masks (Taiwan Centers for Disease Control [CDC], 2020).

According to the name-based rationing system, people are allowed to buy five face masks per national health insurance card every 7 days. Because a limited quota of face masks is available in pharmacies each day, people swarmed pharmacies to buy face masks in the early days of the COVID-19 pandemic. However, the public had limited or no information regarding the daily face mask inventory of pharmacies. Consequently, people spent considerable time queuing...
up but were still unable to purchase face masks. Thus, to address this problem in the name-based mask rationing system, the Taiwanese health authority collaborated with voluntary program developers to develop a mask-supply information transitional platform (MITP) for releasing open data regarding the face mask inventories of all pharmacies in Taiwan.

An MITP provides information about the inventories and locations of all pharmacies in Taiwan or the nearest pharmacies according to users’ location (through the global positioning system). Users can locate the nearest pharmacy stocked with face masks, reducing the search costs involved in purchasing face masks. In the first half of 2020, more than 130 MITPs were available in Taiwan. Some of them use web maps, and others use mobile applications or chat-bots as media (National Health Insurance Administration, 2020). Since the beginning of the COVID-19 pandemic, numerous epidemic prevention–related information systems have become available and been broadly used in Taiwan. However, this rapid and heavy use of IT/IS (Information Technology/Information System) has been rare in the past, and few studies have explored this IS/IT usage phenomenon. Therefore, this study aimed to identify the determinants of MITP usage intention to provide practical implications for the future development of such health information systems.

To investigate the factors that influence individual intention to use health-related systems (HRS) (e.g. health apps, health application, e-health, and health record system), past studies have used several research frameworks and perspectives, such as Technology Acceptance Model (TAM) (Bhattacherjee & Hegner, 2018; Cho, 2016; Huang & Ren, 2020), Elaboration Likelihood Model (ELM) (Chen et al., 2018; Zhang et al., 2018), information disclosure (Huang et al., 2019), value co-creation (Windasari et al., 2021), and service quality (Kim et al., 2019). While past research has provided rich explanations for people’s intentions to adopt HRS, there are two gaps in these studies, requiring further thought. First, past research has not considered people’s intentions to adopt HRS from the health and medical field. It is evident that most studies analyze HRS from the IS/IT domain. Second, past studies have investigated the use of HRS in states of non-urgent need. Therefore, these studies were less able to observe HRS use behavior under threat of disease.

In order to fill the above research gaps, this study is based on the Health Belief Model (HBM), a research model in the public health field (Champion & Skinner, 2008; Huang et al., 2016), but also incorporates variables (perceived usefulness and perceived ease of use) commonly used in the IS/IT field for analyzing the intention of adopting health-related systems (Bhattacherjee, 2001; Bhattacherjee & Premkumar, 2004; Gefen & Straub, 2000; Venkatesh et al., 2011; Yan et al., 2021a). HBM is often used to study people’s disease-related cognition and behavior—that is, the relationship between beliefs and taking health/medical behaviors. The two variables, perceived usefulness and perceived ease of use, are factors that can highly explain the intention of using information systems in the IS/IT field (Gefen & Straub, 2000; Yan et al., 2021a, 2021b). Especially for information systems that are not functionally complex, the explanatory power of these two variables is critical (Bhattacherjee, 2001; Bhattacherjee & Premkumar, 2004). Therefore, this study combined these two variables with HBM to investigate the factors that influence individual intention to use an MITP during the COVID-19 pandemic in Taiwan. We believe that the results of this study can extend the current literature on the explanation and prediction of health-related behaviors, especially in the IT/IS domain during the COVID-19 pandemic.

The remainder of this paper is organized as follows. “Literature review” provides a review of the related literature. “Research model and hypotheses” presents the research model and hypotheses. “Research methodology” describes the research methodology used to identify the factors influencing usage intention of an MITP. “Data analysis and results” presents the findings obtained after analyzing the empirical data. “Results” presents the findings, theoretical and practical implications, and limitations of this study, and also provides recommendations for future research.

**Literature review**

**IS/IT continuance model in the context of health care**

Current research primarily explains the determinants of the continued adoption of health-related systems, while research using HBM to think about the user’s behavior of health-related systems is rare. Table 1 summarizes the recent literature on IS/IT continuance model in the context of health-related systems. Many scholars use TAM or TAM-related constructs to predict continuance intention. For instance, Cho (2016) combined the post-acceptance model and TAM and found that satisfaction, perceived usefulness, perceived ease of use, and confirmation of expectations are significantly associated with continuance intention for mobile health apps. Beldad and Hegner (2018) expanded TAM to include social influences and trust, and found that perceived usefulness, perceived ease of use, and injunctive social norms have a significant influence on users’ continuance intention for health apps. More recently, Huang and Ren (2020), based on TAM, also pointed out that the effect of perceived usefulness on continuance intention is moderated by exercise self-efficacy.

In addition to the above research, some scholars use new models to predict the user’s continuous intention of HRS.
Table 1  Summary of previous IS/IT research in the context of health care

| Study                        | Factors                                                                 | Theory/Model                      | Results                                                                                                                                 |
|------------------------------|-------------------------------------------------------------------------|-----------------------------------|----------------------------------------------------------------------------------------------------------------------------------------|
| Cho (2016)                   | Effort expectancy, social influence, facilitating conditions,           | TAM + Post-acceptance model       | The study results indicated that perceived usefulness, perceived ease of use, confirmation, and satisfaction are significantly associated with the continuance intention to use health apps. |
|                              | perceived usefulness, perceived ease of use, confirmation, and         |                                   |                                                                                                                                       |
|                              | satisfaction                                                            |                                   |                                                                                                                                       |
| Beldad and Hegner (2018)     | Injunctive social norm, descriptive social norm, trust, health         | TAM                               | The study results indicated that respondents’ intention to continue using a health application is predicated by perceived ease of use, perceived usefulness, and injunctive social norm. |
|                              | valuation, perceived usefulness, and perceived ease of use             |                                   |                                                                                                                                       |
| Huang and Ren (2020)         | Technological function (instruction provision, self-monitoring,        | TAM + Exercise self-efficacy      | The study results indicated that instruction provision, self-monitoring, self-regulation, and goal attainment have an indirect effect on continuance intention through perceived usefulness, and the indirect effect is moderated by exercise self-efficacy. |
|                              | self-regulation, and goal attainment), perceived                      |                                   |                                                                                                                                       |
|                              | usefulness, perceived ease of use, exercise self-efficacy, and         |                                   |                                                                                                                                       |
|                              | perceived enjoyment                                                     |                                   |                                                                                                                                       |
| Huang et al. (2019)          | Information sensitivity, perceived privacy risk, importance of         | The perspective of information     | The study results indicated that perceived privacy risk and satisfaction have a significant influence on discontinuance use intention for health apps, and the constructs of perceived informativeness and information sensitivity have an indirect influence on discontinuance use intention for health apps. |
|                              | information transparency, regulatory protection, confirmation,         | disclosure                        |                                                                                                                                       |
|                              | satisfaction, perceived informativeness, and apps system reliability   |                                   |                                                                                                                                       |
| Chen et al. (2018)           | Perceived usefulness, trust, service quality, information               | Elaboration likelihood model       | The study results indicated that factors of central route and peripheral route positively influence perceived usefulness and users’ trust in using health apps. Perceived usefulness and trust are significantly associated with continuance intention of using health apps. |
|                              | quality, app’s reputation, app’s institution assurance, and privacy   |                                   |                                                                                                                                       |
|                              | concern                                                                 |                                   |                                                                                                                                       |
| Zhang et al. (2018)          | Central behavior, trust, peripheral cues, perceived e-health literacy, | Elaboration likelihood model       | The study results indicated that satisfaction and trust affect continuance intention of using health apps. Trust mediates the relationship between satisfaction and continuance intention. Perceived e-health literacy affects satisfaction. |
|                              | and satisfaction                                                        |                                   |                                                                                                                                       |
| Windasari et al. (2021)      | Choice, the involvement of healthcare professionals, self-efficacy,    | The perspective of the value co-creation | The study results emphasize the significant positive effect of expert involvement on users’ intention to continue using a healthcare system. Expert involvement not only improves continued use intention, but also realizes the effect of choice. |
|                              | and satisfaction with healthcare system                                 |                                   |                                                                                                                                       |
| Kim et al. (2019)            | Content quality, engagement, privacy, reliability, usability, and      | Five dimensions of service quality | The study results indicated that content quality, reliability, engagement and satisfaction have a significant influence on continuance intention for mHealth services. |
|                              | satisfaction                                                            |                                   |                                                                                                                                       |
For instance, by applying the perspective of information disclosure, Huang et al. (2019) found that perceived privacy risk, satisfaction, information sensitivity, confirmation, and perceived informativeness are significant predictors of discontinuance intention. This indicates that not only individual attitudes, beliefs, and behavioral factors, but also information disclosure factors may predict continuance intention. Recent work also reports that in addition to the effect of perceived usefulness and satisfaction on continuance intention, trust is also a significant factor in the context of health apps (Chen et al., 2018; Zhang et al., 2018). From another standpoint, based on the value co-creation perspective, Windsarsi et al. (2021) found that there is an interaction effect between choice and the involvement of healthcare professionals in shaping continued use intention. Meanwhile, the impact of the involvement of healthcare professionals on continued use intention is moderated by self-efficacy. Moreover, by deriving five major quality dimensions of mHealth services from existing studies (content quality, engagement, reliability, usability, and privacy), Kim et al. (2019) found that only satisfaction and engagement have a positive direct influence on continuance intention for mHealth services, while content quality and reliability have an indirect effect on continuance intention.

From the literature in Table 1, we know that past studies utilized different theories and variables to understand the use intention/behavior of health-related systems. Some studies, such as TAM and TAM-related studies, are based on human cognition, satisfaction, and confirmation to analyze the intention to use a health-related system (Beldad & Hegen, 2018; Cho, 2016; Huang & Ren, 2020). Another group of studies looks at the process factors, influencing intention to use health-related systems from a deliberative perspective (Chen et al., 2018; Zhang et al., 2018). In addition, there are studies to provide new explanations for the intention to use health-related systems in terms of system quality (Kim et al., 2019), information disclosure (Huang et al., 2019), and value co-creation by actors (Windsarsi et al., 2021). While studies from different perspectives have provided interesting findings to help us understand the adoption behavior of health-related systems, two flaws also emerge from these studies. First, these studies of health-related systems are actually not health or medical enough, because they do not employ related concepts in the medical/health field. Most of the research adopts theories and variables from the IS/IT field. Therefore, these studies are likely to ignore some important motivational or belief factors that influence people’s health/medical behavior (or use of health-related systems). Second, these studies do not have the opportunity to observe health-system use behaviors under threat of disease. Most of the health-related systems observing in research are mobile apps or health record systems, of which the main purpose is to improve people’s health conditions. Therefore, what they have observed so far may provide only a limited understanding of the use behavior of health-related systems. Especially for the health system usage behavior caused by the COVID-19 outbreak in recent years, past research obviously may not provide enough findings as a reference.

Even with the above two gaps in past studies, these studies still show some insights into our understanding of health system usage behavior under general needs. Next, we will illustrate the theoretical basis used in this study and explain how we incorporated important variables used in past studies into our research model.

**Health Belief Model**

The Health Belief Model (HBM), which was first developed in the 1950s, is used to explain and predict health-related behaviors. Champion and Skinner (2008) demonstrated that individuals may take action to reduce their risks of developing a disease or condition if they believe that they are likely to develop the disease or condition, that the disease or condition may cause serious consequences, that the action that they would take would lower their susceptibility to and severity of the condition or disease, and that the expected benefits of taking action are greater than the barriers to action. According to the HBM, people’s decisions to participate in preventing, examining, or controlling illness conditions are influenced by six variables. These variables are defined as follows (Champion & Skinner, 2008; Huang et al., 2016):

1. Perceived susceptibility: beliefs about the likelihood of developing a certain disease or condition.
2. Perceived severity: feelings about the seriousness of developing a disease or of not being treated for a disease, including the assessments of both clinical and social consequences.
3. Perceived benefits: the potential benefits of taking actions to reduce the disease threat.
4. Perceived barriers: the potential negative aspects of a particular health action.
5. Cues to action: stimuli that trigger actions and can be bodily or environmental events.
6. Self-efficacy: individuals’ belief in their ability to execute health-related behaviors successfully.

The HBM has been applied to a range of health behaviors, such as preventive behaviors, sick role/adherence behaviors, and clinical behaviors, to study preventive behaviors for the human immunodeficiency virus, breast self-examination, diabetic regimens, and weight change in obese children (Bradley et al., 1987; Champion, 1984; Herold, 1983; Huang et al., 2016; Kirscht et al., 1978). Because the HBM has been applied in numerous areas, various modified forms of the
HBM exist in the literature. We adopted the HBM revised by Champion and Skinner (2008), which is illustrated in Fig. 1. The HBM indicates that health beliefs include susceptibility, severity (susceptibility and severity can be combined as threat), benefits, barriers, and self-efficacy; that individual health beliefs may be affected by demographics (i.e., modifying factors); and that individual health beliefs and cues to action lead to health-related behaviors.

The HBM is a widely used framework in health behavior research. The purpose of this study was to identify the factors that influence individual intention to use an MITP during the COVID-19 pandemic. To increase the applicability of the HBM to the IT/IS domain, we replaced two constructs of the HBM, namely perceived benefits and self-efficacy, with perceived usefulness and perceived ease of use from IS/IT continuance model in our research. These constructs were replaced because the definitions of perceived benefits and self-efficacy are similar to the definitions of perceived usefulness and perceived ease of use from IS/IT continuance model in health apps (Huang & Ren, 2020; Jeyaraj, 2021; Yandasari et al., 2021; Yan et al., 2021a, b). Therefore, we also incorporate the constructs of IS/IT continuance model into our research model.

Behavioral intention

The theory of reasoned action (TRA), which was proposed by Ajzen and Fishbein (1977), is the first to suggest that individuals’ behaviors can be affected by their behavioral intentions. The TRA also suggested that behavioral intention comprises attitudes, which refer to an individual’s positive or negative feeling about a certain behavior, and subjective norms, which refer to the belief that one should comply with the expectations of significant others. According to the TRA, behavioral intention is a critical construct that predicts actual behavior. Subsequently, Folkes (1988) stated that behavioral intention is the action tendency to act in a certain manner. In this study, according to the suggestion above, we defined behavioral intention as the behavioral tendency of using an MITP to prevent COVID-19.

The purpose of this study is to predict individuals’ usage behavior toward an MITP for preventing the spread of COVID-19 according to their behavioral intention. Research on aspects, such as health examination behaviors, Internet-based health applications, web-based EMRs, health E-services, and health apps (Beldad & Hegner, 2018; Chen et al., 2018; Cho, 2016; Huang et al., 2019; Jeyaraj, 2021; Yandasari et al., 2021; Yan et al., 2021a, b; Zhang et al., 2018), has confirmed that behavioral intention or individual behavior can be directly or indirectly influenced by constructs of the IS/IT continuance model (Yan et al., 2021a). Therefore, we used behavioral intention as the outcome variable to explain individuals’ intention of using an MITP according to their health perceptions and beliefs toward using an MITP.

Mask-supply information transitional platform

According to Ainsbury et al. (2000), an information platform collects data automatically, analyzes data, and provides a method for organizing information, thereby helping users to obtain insights for decision-making. Information platforms also provide a stable foundation for the development of various products and services within the platform framework (Choi et al., 2019). Studies indicate that information platforms enable the formation of two-sided or multisided markets that facilitate exchange (Sun et al., 2015). An advantage of an information platform is that it can reduce transaction costs for users on different sides of the market (ITIF, 2018). The primary function of information platforms is to
aggregate suppliers’ product information, which enables platforms to deliver personalized services to consumers and thus assist consumers in their product search and selection according to the product availability and the geographical region of the supplier (Najmul Islam et al., 2020). Information platforms also enhance the visibility of suppliers to potential consumers.

Information platforms are server implementations that can be divided into four parts, namely those involved in (1) data retrieval; (2) data classification and storage; (3) information browsing, query, analysis, and report creation; and (4) desktop integration (Ainsbury et al., 2000). The concept of information platforms has been applied in various contexts, such as online health knowledge sharing, industrial symbiosis networks, electronic marketplaces, the sharing economy, and the global labor market (Fraccascia & Yazan, 2018; ITIF, 2018; Standing et al., 2010; Zhang et al., 2020).

MITP is an information platform established by Taiwan to solve the demand for masks during the COVID-19 epidemic. Later, based on the knowledge of this platform, it was also extended to inquire about the distribution of vaccines. MITP was originally an official version, as well as many versions later developed by private information companies. As mentioned in the introduction, there were once more than 130 platforms with similar functions in Taiwan. However, because the functions are too similar, many versions appear and disappear at once. The following figures list some of the most commonly used versions. Figures 2 and 3 are examples of the tablet version, while Figs. 4 and 5 are examples of the mobile app version. As can be seen from the four examples, the main function of MITPs is to provide instant and correct information on face mask resources. Users can specify an area and then search for nearby face mask resources. After the system searches (about five seconds), it will display the number of face masks in stock (some are distinguished by color, with green for sufficient quantities; yellow for tight quantities; and red for insufficient stocks) at the pharmacies around users, allowing them to buy them.

In addition, MITPs have the function of grabbing the number of face masks. As shown in Fig. 4, when a user finishes searching, he/she will see the number of face masks. The number displayed by MITPs is calculated by the government backend system based on parameters, such as the population, the number of regional housing, the number of pharmacies, and so on. Although an MITP does not have the function of calculating the number of face masks, it must determine when to update the information on the number of face masks.

From the user interface, the system functions of MITP are simpler and easier to use than the large-scale information systems. Even though an MITP needs to connect to the government’s database system to obtain relevant data, users do not need to worry about the complicated database processing behind it. Accordingly, based on the system characteristics described above for MITP, we are going to deduce the research hypotheses.

**Research model and hypotheses**

To understand individuals’ intention to use an MITP for preventing the spread of COVID-19, we developed a research model based on the HBM combined with the constructs from IS/IT continuance model. According to the above literature review, we propose that an individual’s intention to adopt an MITP is affected by the perceived threat of COVID-19, belief toward using the MITP (i.e., perceived barriers, perceived usefulness, and perceived ease of use), and cues to

![Fig. 2 Example 1 of MITP](image)
obtain face masks (e.g., news campaigns, coughing symptoms, and recommendations from the government or family members). In addition, we posit that the perceived threat of COVID-19 (i.e., belief about the likelihood and seriousness of being infected with COVID-19) is influenced by cues to action (i.e., cues to obtain face masks).

The research model is displayed in Fig. 6. The hypotheses of the research model are described in the following sections.

**Relationships among perceived usefulness, perceived ease of use, and intention to use an MITP**

Behavioral intention refers to the behavioral tendency of the actor before the action (Folkes, 1988). Existing research believes that the behavioral intention is affected by the user’s beliefs and attitudes (Bhattacherjee & Premkumar, 2004; Venkatesh et al., 2011). For example, the TAM and TAM-related research indicates that behavioral intention can be affected by perceived usefulness and perceived ease of use (Bhattacherjee, 2001; Davis, 1989; Gefen & Straub, 2000; Venkatesh et al., 2003). Additionally, in recent IS/IT continuance research, many scholars also use behavior intention as a variable to predict usage behavior (Beldad & Hegner, 2018; Huang & Ren, 2020; Huang et al., 2019), and believe that belief is a core variable that drives users to use IT/IS. Since the composition of beliefs is complex, in order to highlight the user’s cognition of IS/IT usage, ease of use and usefulness are two variables commonly used by researchers as the composition of beliefs (Bhattacherjee & Premkumar, 2004; Venkatesh et al., 2011). For example, in the Venkatesh et al. (2011)’s study, they pointed out that the user’s belief in the use of technology (e-government systems) is composed of five factors, namely perceived usefulness (PU), effort expectancy (EE), social influence (SI), facilitating conditions (FC), and trust. In the Yan et al. (2021a)’s study, they summarized a series of studies related to the continuous use of IT/IS, and pointed out that usefulness and ease of use are the two variables most used to predict usage intention. Yan et al. (2021a) also pointed out that usefulness and ease of use belong to the user’s belief in technology. Furthermore, according to the systematic characteristics of MITP we mentioned earlier, the interface and functionality of most MITPs are relatively simple and much easier than the large-scale information systems. Therefore, combining the findings of past studies and the systematic characteristics of MITP, we consider “usefulness” and “ease of use” as the two basic beliefs variables for predicting usage intention of MITP. The research hypotheses are as follows:

**H1:** Perceived usefulness of an MITP positively influences intention to use the MITP.

**H2:** Perceived ease of use of an MITP positively influences intention to use the MITP.

Additionally, past research (including TAM, extended TAM, and IS/IT continuance models) has pointed to a high correlation between perceived ease of use (PEU) and perceived usefulness (PU). For example, in the model of Davis (1989), PU is defined as the subjective probability that a prospective user’s usage of a specific application system will increase his/her job performance within an organisational context (Davis 1989), while PEU refers to the degree to which the prospective user expects the
system to be free of effort (Davis 1989). Numerous studies have shown that if a system is perceived as easier to use, it is considered more useful and nicer (Bhattacherjee, 2001; Venkatesh, 2000; Venkatesh et al., 2003, 2011; Yan et al., 2021a). Previous studies have also revealed that PEU has a significant effect on PU toward adoption of a specified IS/IT (Bhattacherjee, 2001; Venkatesh, 2000; Venkatesh et al., 2003, 2011; Yan et al., 2021a). For an MITP, because it is an information platform for epidemic prevention, the premise of most developers designing the system is to confirm that it is easy to use. Therefore, we believe that PEU may also affect PU during the use of an MITP; therefore, this study proposes the following hypothesis:

**H3:** Perceived ease of use of an MITP positively influences perceived usefulness of the MITP.

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**Relationship between perceived barriers of an MITP and intention to use the MITP**

According to the HBM, perceived barriers are associated with individual behaviors and may stop individuals from taking actions (Champion & Skinner, 2008). Huang et al. (2016) indicated that the difficulty (e.g., embarrassment, pain, and fear) and time cost of undergoing health examination reduce individuals' intention to perform self-examination. A study on usage behaviors toward salt-restriction spoons indicated that people are less likely to use such spoons in the prevention of hypertension if they believe that using these spoons may lead to a change in the taste they are accustomed to and perceive this change as a barrier (Chen...
Understanding the adoption of the mask-supply information platforms during the COVID-19 pandemic

et al., 2013). Furthermore, a study that predicted treatment intention among premenopausal women with hypoactive sexual desire disorder (HSDD) indicated that women with fewer treatment barriers (e.g., embarrassment about discussing desire problems with a physician and partner disagreement) are more willing to be treated (Chou & Shih, 2018). Accordingly, perceptual barriers are also a kind of belief, and when perceived barriers increase, behavioral intention decreases. Consequently, similar to past research, we posit that a higher number of barriers to the use of an MITP reduces the likelihood of people using the MITP. Thus, the following hypothesis is proposed:

**H4:** Perceived barriers of an MITP negatively influence intention to use the MITP.

**Relationships among perceived threat of COVID-19, intention to use an MITP, and cues to action**

The HBM suggests that if individuals perceive a disease or health condition as a threat, they are likely to engage in health-related behaviors (Orji et al., 2012). Becker and Maiman (1975) suggested that perceived threat is the combination of perceived susceptibility and perceived severity. A study on health examination behavioral intention reported that individuals’ beliefs concerning the likelihood of becoming ill directly influence their intention to perform self-examination (Huang et al., 2016). A study on treatment intention among premenopausal women with HSDD revealed that women with a greater awareness of the seriousness of mental health injury caused by HSDD are more likely to accept treatments (Chou & Shih, 2018). Moreover, a study that predicted iron-fortified soy sauce consumption intention determined that if consumers’ perceived susceptibility and perceived severity of iron deficiency anemia increase, their intention to buy iron-fortified soy sauce also increases (Sun et al., 2006). In conclusion, perceived threat, consisting of perceived susceptibility and perceived severity, is associated with behavioral intention. Under the COVID-19 epidemic, because of uncertain changes in the epidemic, people may also perceive the threat from COVID-19 and consider to take actions to protect themselves from infection. Therefore, we believe that individuals are likely to use an MITP when they perceive COVID-19 as a threat. The following hypothesis is proposed:

**H5:** Perceived threat of COVID-19 positively influences intention to use an MITP.

In HBM, past research has shown that cues to action influence people’s intentions to take medical behaviors. For example, Hochbaum (1958) argued that the readiness to take action (i.e., perceived susceptibility and perceived benefits) can be reinforced by cues, such as illness symptoms and media publicity, which then prompt actions. According to Stretcher and Rosenstock (1997), cues to action affect perceived threat, which in turn affects behavioral intention. For instance, a study on usage behaviors toward salt-restriction...
spoons suggested that cues to action influence people’s cognition toward hypertension (i.e., perceived susceptibility and perceived severity) (Chen et al., 2013). Furthermore, a study on older adults’ food-handling behaviors confirmed that cues to action concerning safe food handling are positively related to perceived threat of foodborne illness (Hanson & Benedict, 2002). Therefore, according to past research, we can comprehend that “cues to action” refer to various information channels related to medical behavior. Take a particular disease as an example, awareness of that particular disease may increase when people receive action cues from multiple sources. Meanwhile, people may also feel more uneasy about the disease and want to take precautions because they are exposed to more suggestive messages. In the context of using MITPs, clues to action, such as news campaigns, coughing Kock symptoms, and advice from governments and friends about the use of face masks to prevent COVID-19, also come from far and wide. These various sources of cues may increase an individual’s perceived threat to COVID-19 and cause people to act preventively when they feel threatened by contagion. Thus, the following hypothesis is proposed:

**H6:** Cues to action positively influence perceived threat of COVID-19.

**Relationship between cues to action and intention to use an MITP**

The HBM indicates that cues to action, which are stimuli that trigger actions, are related to individual behaviors. A study on health examination behavioral intention reported that cues to action regarding self-examination, such as doctor recommendations, media campaigns, and personal experience with illness, considerably influence individuals’ intention to undergo health examination (Huang et al., 2016). Chou and Shih (2018) revealed that premenopausal women are more likely to receive HSDD treatment when they acquire support from a partner or family members, are exposed to television or Internet promotion, or receive telephone reminders from a hospital. Nowrouzi-Kia and McGeer (2014) indicated that external cues, such as encouragement from family members, professional colleagues, and employers, are significantly related to influenza vaccination among trainee physicians (Chen et al., 2013; Hanson & Benedict, 2002; Nowrouzi-Kia & McGeer, 2014), have indicated that gender, age, education level, and area of residence may affect health-related behaviors. Therefore, we incorporated the aforementioned parameters as control variables in the research model.

**Control variables**

 Scholars have suggested that demographic factors, such as socioeconomic status, education level, sex, and age, are associated with health-related behaviors (Champion & Skinner, 2008; Conner & Norman, 2005). Furthermore, several studies on health-related behaviors, including usage behaviors toward salt-restriction spoons, older adults’ food-handling behaviors, and influenza vaccination among trainee physicians (Chen et al., 2013; Hanson & Benedict, 2002; Nowrouzi-Kia & McGeer, 2014), have indicated that gender, age, education level, and area of residence may affect health-related behaviors. Therefore, we incorporated the aforementioned parameters as control variables in the research model.

**Research methodology**

**Questionnaire development**

A questionnaire comprising four sections was designed to test the research model. The first section of the questionnaire elaborates the purpose of this study. The second section introduces MITPs and provides some examples of MITPs. In the third section, a 7-point Likert scale is used to score each item for every construct. The fourth section inquires about respondents’ basic information, face mask usage habits, and perspectives on the COVID-19 pandemic. The questionnaire is presented in Appendix 1.

**Item development**

To ensure the validity of our survey content, the survey items for each construct were developed by rewording scales from related studies to fit the research context. Perceived threat was defined as an individual’s belief about the likelihood and seriousness of being infected with COVID-19. Because perceived threat can be regarded as the combination of perceived susceptibility and perceived severity (Becker & Maiman, 1975), we used the items provided by McClanahan et al. (2007) for perceived susceptibility and perceived severity to measure perceived threat. Perceived barriers and intention to use an MITP were defined as potential negative aspects and behavioral tendency, respectively, of using an MITP to prevent the spread of COVID-19 in Taiwan. The items used for measuring these parameters were modified
versions of the corresponding items proposed by McClenahan et al. (2007). In addition, cues to action were defined as bodily events or environment events that trigger individuals’ action to obtain face masks. These cues were also measured using the relevant items of McClenahan et al. (2007). As per the study of Davis (1989), Huang and Ren (2020), and Yan et al. (2021a), perceived usefulness and perceived ease of use were defined as an individual’s belief regarding whether the use of an MITP would reduce the search cost of purchasing face masks and belief regarding the ease of use of the MITP, respectively. Each item was measured on a 7-point Likert scale ranging from 1 for “strongly disagree” to 7 for “strongly agree.” All the survey items were suggested and reviewed by two researchers.

Basic information

To determine the respondents’ background, motivations of using MITPs, and perceptions of COVID-19, the fourth section of the adopted questionnaire collects basic information regarding the respondents, including their sex, age, education level, occupation, area of residence, and income; face mask usage habits, including the number of face masks used per week, average time spent wearing face masks each day, average time spent purchasing face masks, and type of face masks used; and average time spent on receiving information about COVID-19 each day and perceptions of the COVID-19 pandemic. Some of these characteristics were treated as control variables in this study.

Study design and procedure

Because this study was conducted in Taiwan, we translated the original questionnaire from English to Chinese so that the respondents could clearly understand the meaning of each item. In addition, we used an online survey for data collection because it allows for an unlimited number of respondents, overcomes geographical restrictions, and has a low cost and response time (Denscombe, 2006). The data were collected from March 3 to 31, 2020. We posted the online questionnaire on social media, such as Facebook and bulletin board systems, to reach a large population. Moreover, we provided incentives to attract more respondents and increase the completion rate. For example, after the data collection was completed, we randomly sampled 20 qualified respondents and offered them gift cards.

Data analysis and results

We used structural equation modeling (SEM) to validate the research model and proposed hypotheses. SEM is a statistical method that involves factor analysis and path analysis. It has been applied in various fields, such as psychology, business administration, and health care. We employed partial least square (PLS) to analyze the survey data. According to Marcoulides (1998), an appropriate sample for PLS should be more than 10 times larger than the number of endogenous constructs. Because the research model of this study contains seven endogenous constructs (including constructs and control variables), the current sample size of 524 met the requirements of PLS. In addition, according to the discussion about the issue of sample size from Hair et al. (2019), the inverse square root method and the gamma-exponential method are the new approaches to be suggested for minimum sample size calculations (Kock & Hadaya, 2018). Therefore, we employed the two methods to estimate sample size and reported in Table 2. The results show that our sample size of 524 is far over the requirements of the two methods. Finally, we used SmartPLS 3.3.0 for conducting PLS analysis. Data analysis was performed using the two-step approach of Anderson and Gerbing (1988). First, the measurement model was examined to assess the validity and reliability of the scales. Second, the structural model was examined to assess the strength of the path relationships among the constructs. This two-step approach is described in detail in a later section.

Table 2 Minimum sample size calculations with the inverse square root method and the gamma-exponential method

| Path    | Path coefficient | Sample size estimation by Inverse square root method | Sample size estimation by Gamma-exponential method |
|---------|------------------|------------------------------------------------------|---------------------------------------------------|
| PUM-IUM | 0.325            | 59                                                   | 45                                                |
| PEUM-IUM| 0.244            | 104                                                  | 91                                                |
| PEUM-PUM| 0.680            | 14                                                   | 11                                                |
| PBM-IUM | -0.128           | 378                                                  | 364                                               |
| PST-IUM | 0.218            | 131                                                  | 117                                               |
| CA-PST  | 0.531            | 22                                                   | 11                                                |
| CA-IUM  | 0.023            | 59                                                   | 45                                                |

Significance level = 0.05; Power level = 0.8
Table 3 presents the detailed information of the 524 respondents. In all, 44.7% of the respondents were men, and 55.3% of the respondents were women. The 20–29 years age group accounted for the largest proportion of respondents (46.6%). In addition, those with a bachelor’s degree accounted for the largest proportion of the respondents (60.1%), followed by those with a master’s degree or above (34.4%). With regard to occupation, most of the respondents were students (34%), followed by those working in the service industry (16.8%) and IT industry (7.6%). Most of the respondents resided in northern Taiwan (46.7%), followed by southern Taiwan (31.3%); central Taiwan (34.8%); eastern Taiwan (1%); and Kinmen, Penghu, or Matsu (0.2%). Moreover, most of the respondents earned NT$25,000–50,000 per month (41%), followed by those who earned less than NT$25,000 per month (39.5%).

Most of the respondents (64.1%) used 2–4 face masks every week possibly because of the restriction of the name-based rationing system. With regard to the daily mask usage, most of the respondents wore face masks for 4–6 h every day (29.8%), followed by those who wore face masks for 1–3 h (28.8%) and 7–9 h (21.6%). Furthermore, most of the respondents only waited less than 1 min in queues when purchasing face masks (23.5%), followed by those who waited for 11–20 min (22.5%) and 1–10 min (19.7%). Surgical masks were the most commonly used mask type.

Most of the respondents (36.6%) spent 20–40 min receiving information on COVID-19, followed by those who received information for less than 20 min (32.6%) and 41–60 min (21.4%). More than half of the respondents (51.5%) believed that the COVID-19 pandemic would slow down in 4–6 months. With regard to respondent perceptions of the COVID-19 pandemic, most respondents believed that insufficient knowledge was available regarding viruses and felt nervous, disturbed, and anxious when facing the COVID-19 pandemic. We inferred that the respondents’ perspectives on COVID-19 might be associated with the length of time that they received information about COVID-19.

Examination of the structural model

After examining the measurement model, we used PLS to test the structural model by calculating the path coefficient (β) and R² value. The value of β, which is between 0 and 1, indicates the level of influence that one construct has on another. The value of R² indicates the percentage of variance in the outcome variable that is explained by the predictor variable. By adopting SmartPLS 3.3.0, we ran the PLS algorithm to obtain the path coefficients and R² values. The bootstrapping algorithm was then employed to determine the statistical significance (p value) of the paths. According to the suggestion of Hair et al. (2014), the number of bootstrap samples should be larger than that of qualified samples; therefore, we set the number of bootstrap samples as 5000 to achieve a stable result. To evaluate the quality of the structural model, we also checked the standardized root mean square residual (SRMR) of the structural model in order to evaluate the potential model misspecification issue. We find that the SRMR of our structural model is 0.072, which does not exceed the recommended cutoff value of 0.08. The value of normed-fit index (NFI) is 0.885, which is slightly smaller than the recommended square root of a construct’s AVE should be larger than the correlation coefficients between this construct and any other constructs (Table 5). Second, we also adopted the guideline suggested by Henseler et al. (2015), using HTMT indicators to evaluate differential validity (Table 6). If the value of HTMT is less than 0.9, this represents that there is a discriminant validity between the two reaction constructs (Henseler et al., 2015). By these two methods, all constructs met the aforementioned guideline. Thus, all the constructs in this study had satisfactory discriminant validity.

Examination of the measurement model

We used SmartPLS 3.3.0 for the operations of “PLS Algorithm”, and the resulting "outer loading" reports generated from the results of the operations are used to determine the strength of the relationship between individual item variable and its common construct by the absolute value of these factor loading, and then delete the item variables with lower absolute factor loadings. Therefore, the results of the subsequent reliability and validity analysis can reach an acceptable range. Subsequently, we employed PLS to test the reliability and validity of the measurement model. Composite reliability (CR), average variance extracted (AVE), and Cronbach’s α are commonly recommended reliability indicators in PLS. According to Hair et al. (1998), a CR higher than 0.7, an AVE of at least 0.5, and a Cronbach’s α value higher than 0.7 indicate construct reliability. The data in Table 4 indicate that the constructs used in this study satisfied the reliability criteria.

To assess the discriminant validity, first, we adopted the guideline suggested by Fornell and Larcker (1981) that the square root of a construct’s AVE should be larger than the correlation coefficients between this construct and any other constructs (Table 5). Second, we also adopted the guideline suggested by Henseler et al. (2015), using HTMT indicators to evaluate differential validity (Table 6). If the value of HTMT is less than 0.9, this represents that there is a discriminant validity between the two reaction constructs (Henseler et al., 2015). By these two methods, all constructs met the aforementioned guideline. Thus, all the constructs in this study had satisfactory discriminant validity.
Table 3  Sample characteristics

| Item                          | N  | %    |
|-------------------------------|----|------|
| Gender                        |    |      |
| Male                          | 234| 44.7 |
| Female                        | 290| 55.3 |
| Age                           |    |      |
| Less than 20 years old        | 41 | 7.8  |
| 20–29 years old               | 244| 46.6 |
| 30–39 years old               | 123| 23.5 |
| 40–49 years old               | 80 | 15.3 |
| 50–59 years old               | 24 | 4.6  |
| 60–69 years old               | 12 | 2.3  |
| Over than 70 years old        | 0  | 0    |
| Education level               |    |      |
| Primary School                | 0  | 0    |
| Junior High School            | 14 | 2.7  |
| Senior High School            | 15 | 2.9  |
| College/University            | 315| 60.1 |
| Above Master                  | 180| 34.4 |
| Occupation                    |    |      |
| Student                       | 178| 34   |
| Information Communication     | 35 | 6.7  |
| Finance/Insurance             | 23 | 4.4  |
| Information Technology        | 40 | 7.6  |
| Teaching                      | 21 | 4    |
| Civil Servants                | 30 | 5.7  |
| Medical Staff/Pharmacist      | 10 | 1.9  |
| Manufacturing                 | 39 | 7.4  |
| Service Industry              | 88 | 16.8 |
| NGO                           | 8  | 1.5  |
| Retired                       | 13 | 2.5  |
| Other                         | 39 | 7.4  |
| Residential area              |    |      |
| North                         | 224| 42.7 |
| Middle                        | 130| 24.8 |
| South                         | 164| 31.3 |
| East                          | 5  | 1    |
| Kinmen, Penghu, or Matsu      | 1  | 0.2  |
| Income per month              |    |      |
| Less than NTD 25,000          | 207| 39.5 |
| NTD 25,000–50,000             | 215| 41   |
| NTD 50,001–75,000             | 68 | 13   |
| NTD 75,001–100,000            | 21 | 4    |
| More than NTD 100,000         | 13 | 2.5  |
| How many face masks do you use every week? | | |
| Only 1 mask                   | 69 | 13.2 |
| 2–4 masks                     | 336| 64.1 |
| 5–7 masks                     | 92 | 17.6 |
| 8–10 masks                    | 15 | 2.9  |
| 11–13 masks                   | 7  | 1.3  |
| 14–16 masks                   | 2  | 0.4  |
| More 16 masks                 | 3  | 0.6  |
Table 3 (continued)

| Item                                                                 | N   | %   |
|----------------------------------------------------------------------|-----|-----|
| How many hours do you wear your face mask every day?                 |     |     |
| Less than 1 h                                                        | 54  | 10.3|
| 1–3 h                                                                | 151 | 28.8|
| 4–6 h                                                                | 156 | 29.8|
| 7–9 h                                                                | 113 | 21.6|
| 10–13 h                                                              | 38  | 7.3 |
| 14–16 h                                                              | 10  | 1.9 |
| 17–20 h                                                              | 2   | 0.4 |
| More than 20 h                                                       | 0   | 0   |
| How long do you line up to get your face masks?                      |     |     |
| Less than 1 min                                                      | 123 | 23.5|
| 1–10 min                                                             | 103 | 19.7|
| 11–20 min                                                            | 118 | 22.5|
| 21–30 min                                                            | 72  | 13.7|
| 31–40 min                                                            | 52  | 9.9 |
| 41–50 min                                                            | 23  | 4.4 |
| 51–60 min                                                            | 7   | 1.3 |
| More than 1 h                                                        | 26  | 5   |
| How many minutes do you receive every day about the COVID-19 information (from Newspapers, TV, Internet, social media, friends, or family)? |     |     |
| Less than 20 min                                                     | 171 | 32.6|
| 20–40 min                                                            | 192 | 36.6|
| 41–60 min                                                            | 112 | 21.4|
| More than 60 min                                                     | 49  | 9.4 |
| How many months do you think that the COVID-19 epidemic will slow down? |     |     |
| Less than 1 month                                                    | 5   | 1   |
| 1–3 months                                                           | 142 | 27.1|
| 4–6 months                                                           | 270 | 51.5|
| 7–9 months                                                           | 54  | 10.3|
| 10–12 months                                                         | 26  | 5   |
| More than 1 year                                                     | 27  | 5.2 |
| How many months do you expect that the COVID-19 vaccine might be under clinical trial? (any country not only Taiwan) |     |     |
| Less than 1 month                                                    | 42  | 8   |
| 1–3 months                                                           | 158 | 30.2|
| 4–6 months                                                           | 119 | 22.7|
| 7–9 months                                                           | 60  | 11.5|
| 10–12 months                                                         | 29  | 5.5 |
| More than 1 year                                                     | 116 | 22.1|
| What is your operating system for your mobile device?                |     |     |
| iPhone OS                                                             | 232 | 44.3|
| Android                                                               | 286 | 54.6|
| Windows Mobile                                                       | 3   | 0.6 |
| Symbian                                                              | 2   | 0.4 |
| Other                                                                | 1   | 0.2 |
| How many Apps are there on your mobile device?                       |     |     |
| 1–10 App(s)                                                          | 64  | 12.2|
| 11–20 Apps                                                           | 166 | 31.7|
| 21–30 Apps                                                           | 153 | 29.2|
| 31 or more Apps                                                      | 141 | 26.9|
approximately 44% of the variance in intention to use an MITP. However, cues to action ($\beta = 0.005$, $p > 0.05$) had no significant influence on intention to use an MITP. Therefore, H1, H2, H4, and H5 are supported, whereas H7 is not supported.

Perceived ease of use of an MITP ($\beta = 0.680$, $p < 0.001$) had a significant influence on perceived usefulness of the MITP and explained 46% of the variance in this parameter; thus, H3 is supported. Furthermore, cues to action ($\beta = 0.531$, $p < 0.001$) significantly affected perceived threat of COVID-19, and explained 28% of the variance in perceived threat of COVID-19; therefore, H6 is supported.

In addition, the individual effect sizes for the exogenous variables (using $f^2$) were reported in Table 7 (Cohen, 1992). Cohen’s effect size values of 0.02, 0.15, and 0.35 suggest small, medium, and large effects.

Finally, the control variables of this study did not have a significant influence on intention to use an MITP. The analysis results are presented in Appendix 2. In summary, the results supported six of the seven proposed hypotheses.

### Results

We developed a research model that integrates the HBM and IS/IT continuance model to investigate the factors that influence individual intention to use an MITP during the COVID-19 pandemic in Taiwan. The HBM provides an understanding of health-related behavior intention, and the adopted constructs of the IS/IT continuance model are fundamental determinants of individual belief and intention to use an IT or IS (Davis, 1989; Huang & Ren, 2020; Yan et al., 2021a). Therefore, we adopted these two models to determine individuals’ health IT usage intention comprehensively.

The results confirmed that perceived usefulness of an MITP, perceived ease of use of the MITP, perceived barriers of the MITP, and perceived threat of COVID-19 significantly affected intention to use the MITP. This finding is consistent with those of previous studies. In addition, perceived usefulness of an MITP had the greatest influence on intention to use the MITP, followed by perceived ease of use of the MITP, perceived threat of COVID-19, and perceived barriers of the MITP.

In contrast to the findings of previous studies, cues to action did not have a significant effect on intention to use an MITP (H7) because we only inquired about cues that triggered individuals to obtain face masks. We did not investigate people’s perceived behavioral control for obtaining face masks, which refers to perceptions on the ease or difficulty of obtaining face masks (White et al., 2015). According to the theory of planned behavior, which is a successor of the TRA, perceived behavioral control is influenced by the availability of resources and opportunities as well as the perceived significance of these resources and opportunities for performing behaviors (e.g., pharmacies only have a limited number of face masks in stock each day). Perceived behavioral control is a determinant of behavioral intention (Taherdoost, 2018). Therefore, cues to obtain face masks are not direct determinants of individuals’ intention to use an MITP.
We may still need to investigate individuals’ perceptions of the ease or difficulty of obtaining face masks for achieving a more comprehensive understanding of how the stimuli for obtaining face masks influence intention to use an MITP.

Our results indicated that perceived ease of use of an MITP was a significant predictor of perceived usefulness of the MITP and that cues to action significantly influenced perceived threat of COVID-19. These findings are consistent with those of previous studies. Our results also indicated that cues to action did not have a direct influence on intention to use an MITP; however, cues to action indirectly affected intention to use an MITP through the perceived threat of COVID-19.

**Theoretical implications**

The current results have several theoretical implications. First, one of our findings shows that MITP users are more likely (with high intent) to employ MITP when they feel threatened by COVID-19. Through this case, this finding seems to reveal a new condition for adopting IS/IT. As we know, enterprise information systems and personal applications are the main areas where people use IT/IS on a daily basis (Bhattacherjee & Premkumar, 2004; Venkatesh et al., 2011). Past research has done a lot of in-depth analysis of the adoption of enterprise information systems and personal applications. However, in recent years, due to the outbreak of COVID-19, people’s daily state has changed. Therefore, in the state of the epidemic, what kind of responses do people use to face IS/IT, and under what circumstances may people voluntarily adopt IS/IT to protect themselves?

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### Table 4 The reliability of the measurement model

| Construct | Indicator | Factor Loading | Cronbach’s α | Composite Reliability | AVE |
|-----------|-----------|----------------|--------------|------------------------|-----|
| PST       | PST9      | 0.772          | 0.838        | 0.886                  | 0.608 |
|           | PST10     | 0.777          |              |                        |      |
|           | PST12     | 0.809          |              |                        |      |
|           | PST13     | 0.782          |              |                        |      |
|           | PST15     | 0.757          |              |                        |      |
| PBM       | PBM1      | 0.896          | 0.871        | 0.915                  | 0.734 |
|           | PBM2      | 0.926          |              |                        |      |
|           | PBM3      | 0.932          |              |                        |      |
|           | PBM8      | 0.640          |              |                        |      |
| PUM       | PUM2      | 0.862          | 0.934        | 0.950                  | 0.792 |
|           | PUM4      | 0.896          |              |                        |      |
|           | PUM5      | 0.898          |              |                        |      |
|           | PUM6      | 0.921          |              |                        |      |
|           | PUM7      | 0.872          |              |                        |      |
| CA        | CA1       | 0.624          | 0.763        | 0.848                  | 0.585 |
|           | CA2       | 0.841          |              |                        |      |
|           | CA4       | 0.813          |              |                        |      |
|           | CA5       | 0.763          |              |                        |      |
| PEUM      | PEUM1     | 0.875          | 0.925        | 0.947                  | 0.817 |
|           | PEUM2     | 0.870          |              |                        |      |
|           | PEUM3     | 0.944          |              |                        |      |
|           | PEUM4     | 0.923          |              |                        |      |
| IUM       | IUM1      | 0.896          | 0.946        | 0.961                  | 0.862 |
|           | IUM2      | 0.952          |              |                        |      |
|           | IUM3      | 0.960          |              |                        |      |
|           | IUM4      | 0.904          |              |                        |      |

### Table 5 Discriminant validity suggested by Fornell and Larcker (1981)

| Construct                                      | PST   | PBM   | PUM   | PEUM  | CA    | IUM   |
|------------------------------------------------|-------|-------|-------|-------|-------|-------|
| Perceived Threat of COVID-19 (PST)             | 0.779 |       |       |       |       |       |
| Perceived Barriers of MITP (PBM)               | 0.075 | 0.857 |       |       |       |       |
| Perceived Usefulness of MITP (PUM)             | 0.214 | 0.337 | 0.890 |       |       |       |
| Perceived Ease of Use of MITP (PEUM)           | 0.083 | 0.581 | 0.680 | 0.904 |       |       |
| Cues to Action (CA)                            | 0.531 | 0.10  | 0.387 | 0.291 | 0.765 |       |
| Intention to Use MITP (IUM)                    | 0.282 | 0.371 | 0.587 | 0.564 | 0.323 | 0.928 |

The bold numbers on the table denote the square roots of the AVE.

### Table 6 Discriminant validity suggested by Henseler et al. (2015)

| Construct                                      | CA    | IUM   | PBM   | PEUM  | PST   | PUM   |
|------------------------------------------------|-------|-------|-------|-------|-------|-------|
| Cues to Action (CA)                            |       |       |       |       |       |       |
| Intention to Use MITP (IUM)                    | 0.373 |       |       |       |       |       |
| Perceived Barriers of MITP (PBM)               | 0.183 | 0.405 |       |       |       |       |
| Perceived Ease of Use of MITP (PEUM)           | 0.363 | 0.598 | 0.642 |       |       |       |
| Perceived Threat of COVID-19 (PST)             | 0.644 | 0.316 | 0.104 | 0.093 |       |       |
| Perceived Usefulness of MITP (PUM)             | 0.466 | 0.617 | 0.369 | 0.73  | 0.42  |
Obviously, these issues have not been deeply explored in the past. From the research results, we have preliminarily observed that under the COVID-19 epidemic, in addition to the old factors (perceived ease of use and perceived usefulness), the reason why people are willing to use IS/IT, perceived threat may be an important trigger condition. This is because under the premise that life is priceless, when people are threatened by the epidemic, most people may take immediate steps to protect themselves based on fear of the disease and being dragged down by it. Even though the function of MITPs is simple in Taiwan, it mainly provides information for people to buy face masks. However, based on the anxiety about COVID-19, Taiwanese people have a high willingness to accept assistance from MITPs. Thus, following this finding, we speculate that in addition to the complexity of system function, the main consideration by people is that MITPs can provide information (on where to buy face masks) to reduce threats of COVID-19. The finding shows that perceived threat influences the intention to use MITPs. Compared with the rational cognitive factors on the use of IS/IT proposed by previous studies (Beldad & Hegner, 2018; Bhattachjee & Premkumar, 2004; Cho, 2016; Huang & Ren, 2020; Venkatesh et al., 2011), this study clearly revealed an irrational cognitive factor in the context of the COVID-19. We believe that this finding is an important contribution to understand the use of IS/IT in an urgent needed environment.

Second, this study found that cues to action directly affect perceived threat. Although the H7 of this study is not supported, the cue to action still plays an important role in the research model of this study. As discussed in the literature, clues to action are stimuli that trigger people to take action (Champion & Skinner, 2008; Huang et al., 2016). In the context of COVID-19, it refers to the information people receive about the COVID-19 outbreak, triggering the possibility of action. Our findings show that cues to action influence people’s perceived threats to COVID-19, but not people’s intention to use MITPs. Based on the past research, we can understand that as people receive information about the epidemic from different sources, they interpret the content of the information before making a decision. However, in the case of the COVID-19 outbreak, because most of the information at first stage was confusing, it was disturbing whether the information was true or not. Thus, our findings show that cues to action increase people’s perceived...
threat to COVID-19 (hypothesis 6). But in the meanwhile, hypothesis 7 is not supported by data analysis. This result is different from previous studies and, while surprising, is also reasonable. This is because, in our research model, we hypothesized that cues to action might influence people’s intention to use an MITP. However, the intent of using MITP is not actually a direct preventive action strategy. It belongs to the precursor behavior of people obtaining information about medical resources (i.e., face masks). Past HBM studies have suggested that cues to action have an impact on taking medical-related behaviors, yet have not clearly pointed out that cues to action also influence behaviors in obtaining medical information. Therefore, it is a difference between our study and past studies. That is, conceptually, people’s medical behavior and people’s access to medical information must be carefully distinguished.

Third, we repurpose and extend HBM to use behaviors of health information platforms. Compared with the IS/IT model, HBM is better to explain medical-related behaviors because it originates from the public health field and has been applied to medical behavior issues in many cases (Champion & Skinner, 2008; Huang et al., 2016). These studies indicate that the relationship between the variables in HBM is clear. However, it also limits the application field of HBM. In this study, we extend HBM to the scope of IS/IT, because IS/IT-related models are difficult to explain the phenomenon of using MITPs. However, using the HBM alone, it is also difficult to cover the IT characteristics of MITPs because the original HBM did not have an IS/IT mindset. Therefore, we combined two of the most commonly used constructs (perceived usefulness and perceived ease of use) in the IS/IT model into the original HBM. The results reveal that our proposed model has an explanatory power (R² = 0.44) for the phenomenon of the use of MITPs. This also indicates that under the COVID-19 epidemic, the use of information platforms may take into account the basic characteristics of IS/IT on the one hand. On the other hand, since MITP is established to provide medical resource information in Taiwan, the citizens may use the platform for medical-related reasons. While MITP is a case in Taiwan’s fight against COVID-19, if COVID-19 remains a threat, information platforms with similar purposes may emerge in other countries and regions. Therefore, we believe that our research model and findings provide useful guidance for future theoretical thinking on information systems related to COVID-19.

Practical implications

This study provides several practical implications for health authorities, IT/IS developers, and platform designers. First, according to our research results, we determined people’s intention of using an MITP and the factors affecting the intention. The present findings can be used in medical resource management and decision-making (i.e., for the equitable allocation of epidemic prevention resources) for epidemic prevention. For example, understanding people’s intention to use epidemic prevention-related health IT would enable the Centers for Disease Control (CDC) to design plans for controlling, distributing, or allocating medical resources (e.g., face masks, anti-epidemic drugs, and vaccines for COVID-19). Our research results indicate that people may exhibit a high intention to use an MITP if they feel threatened by COVID-19, increasing their demand for face masks. Awareness of this information may help the CDC allocate medical resources more effectively in advance.

Second, if a government wishes to use a health IT (e.g., a health app or platform) to control the COVID-19 pandemic or prevent future epidemics, it must attempt to increase intention to use epidemic prevention–related health IT. According to our results, perceived usefulness and perceived ease of use positively and directly influence intention to use health IT. Consequently, the designers of health IT must understand what people or users are attempting to achieve when using epidemic prevention–related health IT. Such understanding would enable the designers to modify the functions of health IT so that they are more useful for users. In addition, users are more likely to use epidemic prevention–related health IT if they perceive the existence of fewer barriers when using this IT. Therefore, health authorities, IT/IS developers, and platform designers should collaborate to reduce potential negative aspects of using epidemic prevention–related health IT, such as time-consuming functions, incorrect information, the disclosure of private information, and a complicated user interface.

Third, if a government wishes to use technology to prevent and control epidemics, it must not only consider people’s usage of technology but also their perceptions of epidemics. According to our research results, if people perceive a disease to be major threat, they are more likely to use an epidemic prevention–related health IT. Moreover, perceived threat can be positively affected by cues for preventive health behaviors; thus, cues for performing a certain health behavior to prevent disease infection may increase the public’s awareness regarding their susceptibility to and the severity of the disease. Consequently, health authorities can raise public awareness of how infectious a disease is and how severe the conditions caused by disease symptoms are by employing media campaigns on preventive health behaviors; this approach may increase people’s intention to use epidemic prevention–related health IT.

Limitations and future research

This study has some limitations. First, this study included a cross-sectional survey with a 1-month data collection
Understanding the adoption of the mask-supply information platforms during the COVID-19 period, which is a relatively short period. Future studies can conduct surveys over a longer period to obtain additional insights. Second, we performed an online survey to collect data; thus, the opinions of those who rarely use the Internet might have been neglected. Future research may employ both online and offline data collection to obtain data from different representative populations. Third, this study was conducted among Taiwanese participants. Future studies should examine whether the proposed model can be applied in different countries. Four, since convenience sampling was used in this study, the sample may not be representative of the general population in Taiwan (e.g., a high proportion of the student sample in the study). We suggest that follow-up studies can improve sampling methods. Finally, although the results indicated that cues to action had no significant effect on intention to use MITPs, they showed a direct effect on perceived threat of COVID-19. For electronic platforms, it remains to be clarified how information (possibly true or false) from multiple sources can have an adequate impact on behavior, such as the medical behavior or the commercial behavior. Therefore, future research may refer to the results of this study and consider “cues” as an indirect influencing variable to analyze the contributing causes of behavior.

Conclusion

We developed a research model by integrating the HBM and IS/IT continuance model to investigate the factors affecting behavioral intention to use an MITP to prevent the spread of COVID-19. Our findings indicate that the intention to use an MITP is directly influenced by beliefs toward using the MITP (including perceived usefulness of the MITP, perceived ease of use of the MITP, and perceived barriers of the MITP) and perceived threat of COVID-19. In addition, perceived ease of use is a significant determinant of perceived usefulness, and cues to obtain face masks directly influence the perceived threat of COVID-19. Although this study was restricted to Taiwan, we believe that the research findings regarding epidemic prevention–related health IT can provide valuable suggestions for preventing or controlling epidemics in other countries.

Appendix 1: Questionnaire items

Part I. Questionnaire items

Perceived Threat of COVID-19

PST1. My chances of getting COVID-19 are greater if I do not wear a face mask.

PST2. Although I am healthy, if I don't wear a face mask, I will probably get COVID-19.

PST3. I feel that my chances of getting COVID-19 in the future are high if I do not wear a face mask.

PST4. I most likely will get COVID-19 if I do not wear a face mask.

PST5. I worry a lot about COVID-19 if I do not wear a face mask.

Perceived Severity (Champion & Skinner, 2008; McClenahan et al., 2007)

PST6. The thought of pneumonia scares me.

PST7. When I think about pneumonia, I feel nauseous.

PST8. If I get COVID-19, then my career would be endangered.

PST9. When I think about pneumonia, my heart beats faster.

PST10. Getting COVID-19 would endanger my interpersonal relationship.

PST11. My feelings about myself would change if I get COVID-19.

PST12. My financial security would be endangered if I get COVID-19.

PST13. I am afraid to even think about getting COVID-19.

PST14. If I get COVID-19, my entire life would change.

PST15. If I get COVID-19, I may die.

Cues to Action (Champion & Skinner, 2008; McClenahan et al., 2007)

CA1. Government recommends wearing face masks in crowded places to prevent COVID-19.

CA2. News campaigns (e.g., print media, press, TV, radio, or social media) prompted me to prepare face masks.

CA3. The coughing symptoms prompted me to prepare face masks.

CA4. Past experience with SARS or MERS prompted me to prepare face masks.

CA5. Family members or friends prompted me to prepare face masks.

Perceived Usefulness of MITP (Davis, 1989; Huang & Ren, 2020; Yan et al., 2021a)

PUM1. Using MITP makes me to buy face masks faster.

PUM2. Using MITP makes me to buy face masks easier.

PUM3. Using MITP makes me to know where points of sale for face masks are.

PUM4. Using MITP makes me to know where points of sale for face masks are.

PUM5. Using MITP makes me to collect the face mask information quickly.

PUM6. Using MITP enables me to have more accurate information of face masks.

PUM7. Using MITP enables me to access the newest information about the control of face masks.

PUM8. Using MITP can save my time to line up.
Using MITP can help me to buy face masks for my family or friends.

*Perceived Ease of Use of MITP* (Davis, 1989; Huang & Ren, 2020; Yan et al., 2021a)

PEUM1. Learning to operate MITP is easy for me.
PEUM2. I find it easy to get MITP to do what I want it to do.
PEUM3. It is easy for me to become skillful at using MITP.
PEUM4. I find MITP easy to use.

*Perceived Barriers of MITP* (Champion & Skinner, 2008; McClenahan et al., 2007)

PBM1. Using MITP is difficult for me.
PBM2. Using MITP can be time-consuming.
PBM3. MITP interface may be complex.
PBM4. MITP may provide incorrect information.
PBM5. The information of MITP may not be updated timely.
PBM6. Even if the information is provided by MITP, I do not have time to buy face masks.
PBM7. Even if the information is provided by MITP, I hate to line up for buying face masks.
PBM8. I don’t want to provide my present location with my global positioning system to MITP.

*Intention to Use MITP* (Champion & Skinner, 2008; McClenahan et al., 2007)

IUM1. I will use MITP once a week in the future.
IUM2. I will continue to use MITP in the future.
IUM3. I have decided to use MITP in the future.
IUM4. I will strongly recommend others to use MITP.

**Part II. Basic information**

See Table 3

### Appendix 2: p-Values for control variables

**Table 8** This study divided the respondents into male and female groups and examined whether there were significant differences in the results of the analysis. The results are shown below

| Hypothesis | Path     | p-value new (male vs female) |
|------------|----------|------------------------------|
| H1         | PUM-IUM  | 0.057                        |
| H2         | PEUM-IUM | 0.184                        |
| H3         | PEUM-PUM | 0.241                        |
| H4         | PBM-IUM  | 0.072                        |
| H5         | PST-IUM  | 0.343                        |
| H6         | CA-PST   | 0.869                        |
| H7         | CA-IUM   | 0.140                        |

**Table 9** This study divided the respondents into two groups which are over 30 years old and under 30 years old and examined whether there were significant differences in the results of the analysis. The results are shown below

| Hypothesis | Path     | p-value new (under 30 years old vs over 30 years old) |
|------------|----------|------------------------------------------------------|
| H1         | PUM-IUM  | 0.729                                                |
| H2         | PEUM-IUM | 0.567                                                |
| H3         | PEUM-PUM | 0.770                                                |
| H4         | PBM-IUM  | 0.978                                                |
| H5         | PST-IUM  | 0.977                                                |
| H6         | CA-PST   | 0.851                                                |
| H7         | CA-IUM   | 0.446                                                |

**Table 10** This study divided the respondents into two groups which are below college level and above college level, and examined whether there were significant differences in the results of the analysis. The results are shown below

| Hypothesis | Path     | p-value new (below college level and above college level) |
|------------|----------|----------------------------------------------------------|
| H1         | PUM-IUM  | 0.885                                                   |
| H2         | PEUM-IUM | 0.676                                                   |
| H3         | PEUM-PUM | 0.520                                                   |
| H4         | PBM-IUM  | 0.813                                                   |
| H5         | PST-IUM  | 0.762                                                   |
| H6         | CA-PST   | 0.661                                                   |
| H7         | CA-IUM   | 0.552                                                   |

**Table 11** This study divided the respondents into two groups which are north of central Taiwan and others, and examined whether there were significant differences in the results of the analysis. The results are shown below

| Hypothesis | Path     | p-value new (north of central Taiwan and others) |
|------------|----------|--------------------------------------------------|
| H1         | PUM-IUM  | 0.422                                            |
| H2         | PEUM-IUM | 0.267                                            |
| H3         | PEUM-PUM | 0.229                                            |
| H4         | PBM-IUM  | 0.103                                            |
| H5         | PST-IUM  | 0.777                                            |
| H6         | CA-PST   | 0.246                                            |
| H7         | CA-IUM   | 0.554                                            |

Tables 8, 9, 10 and 11

- Gender.

From the above table, it can be seen that after the MGA analysis, the path of the structural model does not differ due to grouping.
• Age.
  From the above table, it can be seen that after the MGA analysis, the path of the structural model does not differ due to grouping.
• Education.
  From the above table, it can be seen that after the MGA analysis, the path of the structural model does not differ due to grouping.
• Residential Area.
  From the above table, it can be seen that after the MGA analysis, the path of the structural model does not differ due to grouping.

References
Ainsbury, R. D., Al Hussein, H. K., Hinnant, M. C., Lahham, M. M., Ludin, S. L., Putterman, D. S., & Tejada, W. M. (2000). Method and apparatus for performing data collection, interpretation and analysis, in an information platform. Retrieved from https://usptnropcorm/patent/US6078924A. Accessed 2021/8/1.
Ajzen, I., & Fishbein, M. (1977). Attitude-behavior relations: A theoretical analysis and review of empirical research. Psychological Bulletin, 84(5), 888–918. https://doi.org/10.1037/0033-2909.84.5.888
Anderson, J. C., & Gerbing, D. W. (1988). Structural equation modeling in practice: A review and recommended two-step approach. Psychological Bulletin, 103(3), 411.
Becker, M. H., & Maiman, L. A. (1975). Sociobehavioral determinants of compliance with health and medical care recommendations. Medical Care, 13(1), 10–24.
Beldad, A. D., & Hegner, S. M. (2018). Expanding the technology acceptance model with the inclusion of trust, social influence, and health valuation to determine the predictors of German users’ willingness to continue using a fitness app: A structural equation modeling approach. International Journal of Human-Computer Interaction, 34(9), 882–893. https://doi.org/10.1080/10447318.2017.1403220
Bhattacherjee, A. (2001). Understanding information systems continuance: An expectation-confirmation model. MIS Quarterly, 25(3), 351–370. https://doi.org/10.2307/3250921
Bhattacherjee, A., & Premkumar, G. (2004). Understanding changes in belief and attitude toward information technology usage: A theoretical model and longitudinal test. MIS Quarterly, 28(2), 229–254. https://doi.org/10.2307/25148634
Bradley, C., Gamsu, D. S., Moses, J. L., Knight, G., Boulton, A. J. M., Drury, J., & Ward, J. D. (1987). The use of diabetes-specific perceived control and health belief measures to predict treatment choice and efficacy in a feasibility study of continuous subcutaneous insulin infusion pumps. Psychology & Health, 1(2), 133–146. https://doi.org/10.1080/088704468708400320
Champion, V. L. (1984). Instrument development for Health Belief Model constructs. Advances in Nursing Science, 6(3), 73–85. https://doi.org/10.1097/00012272-198404000-00011
Champion, V. L., & Skinner, C. S. (2008). The health belief model. In Health behavior and health education: Theory, research, and practice (4th ed., pp. 45–65). Jossey-Bass.
Chen, J., Liao, Y., Li, Z., Tian, Y., Yang, S., He, C., Tu, D., & Sun, X. (2013). Determinants of salt-restriction–spoon using behavior in China: Application of the Health Belief Model. PLoS ONE, 8(12), e83262. https://doi.org/10.1371/journal.pone.0083262
Chen, Y., Yang, L., Zhang, M., & Yang, J. (2018). Central or peripheral? Cognition elaboration cues’ effect on users’ continuation intention of mobile health applications in the developing markets. International Journal of Medical Informatics, 116, 33–45. https://doi.org/10.1016/j.ijmedinf.2018.04.008
Cho, J. (2016). The impact of post-adoption beliefs on the continued use of health apps. International Journal of Medical Informatics, 87, 75–83. https://doi.org/10.1016/j.ijmedinf.2015.12.016
Choi, G., Nam, C., & Kim, S. (2019). The impacts of technology platform openness on application developers’ intention to continuously use a platform: From an ecosystem perspective. Telecommunications Policy, 43(2), 140–153. https://doi.org/10.1016/j.telpol.2018.04.003
Chou, Y. J., & Shih, C. M. (2018). Using the Health Belief Model to predict those seeking treatment for hypoactive sexual Desire disorder among premenopausal women. Taiwanese Journal of Obstetrics and Gynecology, 57(6), 791–795. https://doi.org/10.1016/j.tjog.2018.10.003
Cohen, J. (1992). A power primer. Psychological Bulletin, 112(1), 155–159. https://doi.org/10.1037/0033-2909.112.1.155
Conner, M., & Norman, P. (2005). Predicting Health Behaviour. McGraw-Hill Education.
Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. MIS Quarterly, 13(3), 319–340. https://doi.org/10.2307/249008
Denscombe, M. (2006). Web-based questionnaires and the mode effect: An evaluation based on completion rates and data contents of near-Identical questionnaires delivered in different modes. Social Science Computer Review, 24(2), 246–254. https://doi.org/10.1080/0894439305284522
Folkes, V. S. (1988). Recent attribution research in consumer behavior: A review and new directions. Journal of Consumer Research, 14(4), 548–565. https://doi.org/10.1086/209135
Fornell, C., & Larcker, D. F. (1981). Evaluating structural equation models with unobservable variables and measurement error. Journal of Marketing Research, 18(1), 39–50. https://doi.org/10.1177/002224378101800104
Fraccascia, L., & Yazan, D. M. (2018). The role of online information-sharing platforms on the performance of industrial symbiosis networks. Resources, Conservation and Recycling, 136, 473–485. https://doi.org/10.1016/j.resconrec.2018.03.009
Gefen, D., & Straub, D. (2000). The relative importance of perceived ease of use in IS adoption: A study of e-commerce adoption. Journal of the Association for Information Systems, 1(8), 1–30. https://aisel.aisnet.org//jais/vol1/iss1/8
Hair, J. F., Black, W. C., Babin, B. J., Anderson, R. E., & Tatham, R. L. (1998). Multivariate data analysis (Vol. 5). Upper Saddle River, NJ: Prentice Hall.
Hair, J. F., Ringle, C. M., & Sarstedt, M. (2014). PLS-SEM: Indeed a silver bullet. Journal of Marketing Theory and Practice, 19(2), 139–152. https://doi.org/10.2753/MTP1069-6679190202
Hair, J. F., Risher, J. J., Sarstedt, M., & Ringle, C. M. (2019). When to use and how to report the results of PLS-SEM. European Business Review, 31(1), 2–24. https://doi.org/10.1108/EBR-11-2018-0203
Hanson, J. A., & Benedict, J. A. (2002). Use of the Health Belief Model to examine older adults’ food-handling behaviors. Journal of Nutrition Education and Behavior, 34, S25–S30. https://doi.org/10.1016/s1499-4046(06)60308-4
Henseler, J., Ringle, C. M., & Sarstedt, M. (2015). A new criterion for assessing discriminant validity in variance-based structural
Understanding the adoption of the mask-supply information platforms during the COVID-19

Yan, M., Filieri, R., Raguseo, E., & Gorton, M. (2021b). Mobile apps for healthy living: Factors influencing continuance intention for health apps. *Technological Forecasting and Social Change, 166*, 120644. https://doi.org/10.1016/j.techfore.2021.120644

Zhang, X., Guo, F., Xu, T., & Li, Y. (2020). What motivates physicians to share free health information on online health platforms? *Information Processing & Management, 57*(2). https://doi.org/10.1016/j.ipm.2019.102166

Zhang, X., Yan, X., Cao, X., Sun, Y., Chen, H., & She, J. (2018). The role of perceived e-health literacy in users’ continuance intention to use mobile healthcare applications: An exploratory empirical study in China. *Information Technology for Development, 24*(2), 198–223. https://doi.org/10.1080/02681102.2017.1283286

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