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The Coronavirus Disease 2019 (COVID-19) pandemic has reshaped human behaviors and switched communication systems from face-to-face to digital communication technologies. This study aimed to examine how digital transformation practices affect human behavioral change digitally, and how perceived COVID-19 severity affects digital transformation practices and behavioral decisions. We use the traditional theory of planned behavior (TPB) to determine new behavioral roles in the digital era, namely digitally planned and transformed behavior. The quantitative survey method was designed to collect cross-sectional data from 550 Thai citizens to provide the conceptual evidence of key proximal measures of digital attitude, digital social norms, digital behavioral control perception, and the digital behavioral decision to predict digitally planned and transformed behavior. The results show that people are more likely to digitalize than before, which predicts the decision to behave digitally at 93.9% of the variability, more than 75% of the predictive power of the total variance suggested by Hair, Ringle, and Sarstedt [1]. However, the higher the COVID-19 severity, the more likely digital transformation is impactful ($\beta = 0.481$). This study provides interesting evidence that people struggle to transform their digital behavior during the pandemic. We demonstrate that digital transformation can offer the desired consequences by cultivating digital attitudes, promoting digital social norms, increasing digital behavioral control perception, and enhancing digital behavioral decisions.

1. Introduction

The pandemic has disrupted the economies and changed communication systems to digital systems [2]. As human behaviors have moved through the COVID-19 pandemic, they need to reconsider their activities to confirm the new normal of digitalization. This means that digital transformation must emphasize the digital transformation of people, processes, and technologies. Human behaviors must embrace a much-accelerated transition to digital channel adoption. The effect of the new COVID-19 pandemic has speeded up and changed human intention to adopt digital technologies by several years [3]. The term “digital transformation” has become so ubiquitous that it is descending into the face-to-face territory. A COVID-19 disruption stimulates the move of human behaviors to digitalization, which its disruptive nature is regarded in an imperceptible light of a great opportunistic creation of innovation and transformation [4]. Despite early forecasts that the coronavirus would have a greater impact on the global economy than Severe Acute Respiratory Syndrome (SARS), the digital economy is revealing no signs of slowdown [5]. Humans recognize the importance of digital technology as a critical component of all the physical activities, digitalization in health remains in focus. In addition, digitalization allows people to keep social and physical distancing. This research undertakes an evaluation of planned behaviors’ digital transformation to create a new concept, namely Digitally Planned and Transformed Behavior (DPTB). In turn, it investigates the theoretical concept’s effect on human behavior and addresses the resulting implications for a digitally planned and transformed behavior framework. In this context, research questions are formulated:

(1) How do digital transformation practices affect behavioral change digitally?
(2) How do COVID-19 influence digital transformation practices and behavioral decisions digitally?

There exists a considerable body of literature on the applicability of TPB to figure out how the vaccine can help people avoid getting the virus.
[6], find a safe place [7], hoard during the pandemic (Long and Khoi 2020), and minimize the cost of the COVID-19 pandemic to the environment [8]. However, these studies have not taken digital transformation into account. Although the recent study by Barrutia and Echebarria [9] finds that the pandemic results in a more favorable attitude of public managers towards information communication technology, Barrutia and Echebarria [9] focus on the attitude change generated by the pandemic rather than the prediction of digital behavior.

The current research sheds light on the digital transformation of planned behaviors. The importance of digital transformation and new normal practices’ role stems from the outbreak of the virus. The theory of planned behavior (TPB) plays an important role in delivering insight of this phenomenon. The TPB model is based on the premise that people make decisions to engage in specific behaviors by linking ‘attitude towards digital behavior’, ‘social norms’, and ‘perceived behavioral control’ to behavioral intention in the digital. In other words, these three considerations guide any action of a person [10,11]. Such roles of digital transformation and new normal practices emphasizes the importance of individual behavior in the study of DPTB. Many studies have focused on efforts to identify the COVID-19 effects and human behavioral decision to follow a particular behavior. Lucarelli, Mazzoli and Severini [8] find that there are relationships between the human behavioral beliefs and responses, climate change, and COVID-19. Han et al. [7] find that a positive significance of human behaviors and perceived knowledge of COVID-19. That is the COVID-19 knowledge can be the vital driver of social norms and attitudes to generate an approachable decision. Thus, it is assumed that there exists human behavioral decision’s importance and the COVID-19 disruption. As a result of social pressure, digital-transformed activities and good hygiene practices are required. How strong an attempt the people make to engage in the digital behavior and how much control that they have over the behavior (behavioral control) are dominant in whether they engage in the behavior or not [12]. The gap exists because the relationship between human behavior, digital transformation, and COVID-19 has not yet been clarified, so it’s not obvious which one is dominant in decisions and behavior. However, both effects transform human behavioral responses to digitalization. There is a propensity for people to transform and change behaviors they consider, causing them to behave in a digital way.

The current research is motivated by the change in digital use and the current state of COVID. The proportion of internet users increased from 2% (between 2019 and 2020) to 7.4% (between 2020 and 2021) [13,14]. As the pandemic continues, Thailand’s digital penetration stands at 69.5% [14]. The current COVID-19 situation accelerates digital transformation across Thailand, and all sectors are disrupted, making them transform their activities digitally. Examples of digital transformed behavioral change include internet usage, e-payment, remote working and online learning and innovative collaboration tools [15]. At the beginning of the crisis, the focus was on business continuity. However, the issue is shifting towards innovation, in which firms are focusing on digital transformation to outperform other firms. As the COVID-19 outbreak is based on the viral infection [16], the people health risk is frightening and uncontrollable, causing an epidemic of terror. The unfiltered and unbalanced information affects health decisions [17]. Although the digitally planned and transformed behavior is not yet evident in the Thailand Government’s Action Plans for Digital Transformation, the government has introduced the Thailand 4.0 economic model, which emphasizes digital improvements of citizen wellbeing. Under the 12th national economic and social development plan, the Thai government also promotes the digital economy through the technology-and-accessibility improvement [18]. It, therefore, comes to the right time for the transformation of digital-planned behaviors.

This research aims to extend the traditional measure of planned behavior by developing the concept of DPTB. The study establishes the traditional planned behavior measure through the disruptive change of the digital shift. The research proceeds to evaluate the positive impact of digital transformation following COVID-19 disruption on human planned behavioral responses. This empirical research develops the theoretical impacts and offers insights from the data collected between August and November 2020. Our key research contributions specify the perceived COVID-19 severity to account for digital transformation and behavioral considerations in the context of developing countries such as Thailand. We show that when digital transformation practices result from the COVID-19 pandemic increase, their digitally-transformational decisions may not be strengthened at the peak effect. Our study identifies that digital transformation resulting from the COVID-19 pandemic can be mitigated by cultivating digital attitudes, promoting digital social norms until they implement digital culture, and improving and increasing digital perceived behavioral control.

The remainder of this paper is outlined as follows: Section 2 discusses the theory supporting the analysis of digitally planned and transformed behavior; Section 3 addresses the research model and variables; Section 4 discusses data characteristics; Section 5 analyzes empirical results; Section 6 discusses research findings and implications; and finally, Section 7 summarize the overall arguments.

2. Theory and hypotheses

The theoretical framework is developed from the concepts of digital transformation of the theory of planned behavior, measuring the digital behavioral decision, addressing a virus disruption and perceiving COVID-19 severity.

2.1. Digitally planned and transformed behavior

The new digital innovations and technologies create new experiences by providing innovative connectivity and mobility that surpass that of the traditional dominant behavioral design [19,20]. Matt et al. [21] define digital transformation as a continuous complex system, which companies undertake to shape operations and transform businesses. Hess et al. [22] define the concept as the transformations that change a firm’s entire business model by producing automation or transforming organizational architecture or new products. However, these studies fail to clarify the items to transform and the digital technology to be adopted. According to Saarikko et al. [23]; digital transformation is the socio-cultural course of action that make firms and people adopt new forms of skillsets relevant to the digital landscape. However, this definition fails to address the application of new digital technologies. Digital technology and its holistic effect cannot be transformed and journeyed alone. It requires the interaction of humans’ behavioral design on technological innovation, social life and digital literacy. As digital transformation and human behavior is correlated, redefining the concept of digital transformation is crucial to be relevant to human behavior change. This current research redefines the digital transformation as the transformation process by which people leverage new emerging technologies to create new experiences, models and systems, switching from analog to digital behavior, improving activities and processes by leveraging digital technologies (e.g., social media, cloud, application, etc.).

Ajzen [10] first coined the concept of TPB as an extension of the theory of reasoned action (TRA) [24,25]. Many studies have applied the TPB to predict various categories of behaviors, such as health behavior (see), legislator voting behavior (see Ref. [26], pro-environmental behavior (see Ref. [27], consumer and team member behaviors (e.g., green-buying behavior, [28]; brand loyalty behavior, [29]; and team member’s change-supportive behavior [30], employee turnover behavior [31] and communication behavior (see Ref. [32]). However, it is crucial to address digital transformed behavior, revealing how digital transformation changes human behavior. According to the TPB, it was hypothesized that if people had time to plan their behavior, it is possible to predict their behaviors [33,34]. What is ‘planned’ behavior? Examples of planned behaviors are visiting a website, playing a game,
watching a movie, eating out, reading a book, sunbathing, shopping online, and so on. Since vast majority of our planned behavior is voluntary, the intention remains the strongest overall predictor [35]. The side effect of COVID-19 on human behavioral change is involuntary response to the digitalization as it accelerates digital behavior.

The proximal determinants of human behavior consist of attitudes, subjective norms and perceived behavioral control [10,12,24]. Ajzen [10] define the term attitude as the degree to which a person has a favorable or unfavorable evaluation or appraisal of the behavior in question. The attitude toward a behavior is the individual beliefs about positive and negative behavior [36]. Thus, this paper redefines the term digital attitude as the individual perception towards either digital or physical behaviors. Individuals transform their behavior digitally when they have a positive attitude [6] to adopt protective technologies in response to the threat of illness [37]. A person who has a favorable attitude toward a digital-transformed or digital-transforming action will be more likely to engage in that behavior. According to Yeo, Goh, and Rezaei [38]; attitude consistency plays a positive role in changing behavior (i.e., the behavior that a person does online). However, it is believed that there is something more nuanced about digital transformation that is sometimes missed. The change in mindset, attitudes, and even organizational culture are all necessary components of the transformation [9]. Attitude is a potent predictor of behavioral decisions [39]. Hence, we hypothesized that (see Fig. 1):

**H1.** Digital attitude has a direct effect on human’s behavioral decisions to transform digitally.

The term subjective norm is a social pressure to comply with people’s behavioral views, primarily expressed by observing others’ behaviors [10]. However, individuals’ normative beliefs and the rewards can powerfully persuade people to perform the behavior. Those individuals may be family members, parents, spouses, experts and so on [6,40]. Armitage and Conner [41] mentioned that the subjective norms construct is a weak indicator of behavioral intention in that an individual’s behaviors may depend on social influences, social support and personal choices. Behavioral economics explains that herding behavior and social influence encourage people to decide and increase their engagement [42]. Social or public attention plays a critical role in determining the behaviors that have collective implications [43], such as the intention to introduce online and offline systems [44]. Physical distancing or social distancing is acknowledged digitally, in which social connection occurs when people are physically apart [45]. We coin the new term, digital social norm, which is standards and practices based on public shared values and rewards about how people should act, either physically or digitally on specific circumstances. Social norms are usually utilized as a guideline for acceptable behavior, not as a source of social pressure [46]. Peer and public opinion influence individual decisions to engage in digital use [47]. Digital social norms are what motivate other people to use digital technologies to change their business models and social interactions [48,49]. A digital social norm-based intervention strategy is personalized normative feedback, which corrects people’s inaccurate normative estimates by giving them personalized feedback that compares their own behavior, their own estimates of what other people do, and what other people actually do [50]. Digital social norms can also be used in marketing campaigns that entail publicly emphasizing the actual norms for behavior, which can influence views and promote digital behavior on a larger scale [51]. The construct of digital social norms is one of the behavioral predictors of digital-transformed or transforming decisions. Accordingly, the following hypothesis was developed (see Fig. 1):

**H2.** Digital social norms have a direct impact on human’s behavioral decisions, which are transformed digitally.

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**Fig. 1.** Research and theoretical framework.
Perceived behavioral control (PBC) is the behavioral outcome that people cannot control. Self-efficacy is a key antecedent of information technology behavior [52] that positively influence people to perform a task [53]. Self-efficacy and controllability are the same notions of perceived behavioral control [54]. Thus, perceived behavioral control reflects accessibility to the resources (e.g., time or money) and opportunities [55] to perform a digital-transformed behavior. Thus, we use the term digital perceived behavioral control that refers to (1) how individuals perceive their confidence in using digital technology (i.e., digital self-efficacy) and (2) how they control the use of digital technology based on available resources and experience (i.e., digital controllability). This construct has been very important in explaining how people act, even if they do not say they are digitally transformed out loud. It is based on a specific situation and is not the same as the locus of control, which is a general sense of how much control they think they have [54].

Hence, this study justifies using behavioral change theory developed human transformation technology is effective in supporting people. Majority of human behavior is socially influenced [60], it shows that the from the theory of planned behavior. Since this theory assumes that the influences individuals attitudes, beliefs, emotions and behaviors, organizational strategies and social issues must be the human side of behavioral decision. To this end, we predict a rise in identifying areas where technology is underutilized to enhance change. Thus, we develop the following hypothesis (see Fig. 1):

H3. Digital perceived behavioral control has a direct effect on human’s behavioral decisions to transform digitally.

Our research focus on human behavior is on customer, employee and business behaviors. Connected with the digital transformation phenomena, it is important to identify human characteristics likely to influence human abilities to perform digital tasks (e.g. self-efficacy and attitudes), their interests (e.g. motivation), and their relations and differences (e.g. social behavior) [57]. Talents, habits, personalities, organizational strategies and social issues must be the human side of digital transformation [58]. In return, human transformation is to identify areas where technology is underutilized to enhance change adoption. To this end, we predict a rise in digital planned and transformed behavior. By considering how technological design and development influences individuals’ attitudes, beliefs, emotions and behaviors, human transformation technology is effective in supporting people [59]. Hence, this study justifies using behavioral change theory developed from the theory of planned behavior. Since this theory assumes that the majority of human behavior is socially influenced [60], it shows that the essence of human aspects (i.e., cognitive and affective factors) play a crucial role in digitizing human activities. Moreover, behavioral control belief plays an important role in self-efficacy for learning. TPB is an important theoretical development to test new hypotheses, address digital behavioral circumstances and change people’s behavior. Accordingly, we develop the following hypotheses (see Fig. 1):

H4. Digital transformation has a direct impact on digital attitudes.

H5. Digital transformation has a direct impact on digital social norms.

H6. Digital transformation has a direct impact on perceived behavioral control.

2.2. Measuring digital behavioral decision

All goal-directed behavior is assumed when people intend to carry out a given task [61,62]. With the same technology, humans’ past experiences determined their decision-making [63] regarding the use of new digital technologies. A behavioral intention reflects an individual’s motivation to engage in action [64]. The terms intention and decision are interchangeably used in this research. Existing studies measured the dimensions of intention through repeating patterns, recommendations and positive mentions [65]. Some studies identified behavioral intention in terms of period/point [66]. However, this study adds experience-based decisions because peoples are more likely to have more favorable attitudes towards digital (future) performance if they can learn new technologies. Thus, we define the concept of “digital behavioral decision” as how people evaluate either physically or digitally the form of behavior they adopt. It is the motivational factors that play a prior-conscious-decision role in a certain behavior that is the stronger the behavioral decision to perform the behavior, the more likely the digitally transformed or transforming behavior will be performed. This behavioral decision is based on their experience. Hence, this decision supports the theory of planned behavior in understanding and predicting digital behavior. Chinnas, Myers, and Hess [67] showed that the public digital strategy is important for the transformation of organizational, citizen and community. The digital technology service providers must incorporate digital and human aspects [68]. In addition, people explore the digital transformation through positive public perception to formulate and implement a digital transformational effort. Thus, we develop the following hypothesis (see Fig. 1):

H7. Digital transformation practices have a direct impact on digital behavioral decisions.

2.3. A virus disruption: perceived COVID-19 severity

COVID-19 is a complex category of viruses that cause mild to severe respiratory infections in humans and animals [69,70]. The pandemic is the worst-case as the viruses spread beyond a country’s boundaries. A closer look shows the re-emergence of the global pandemic every decade. The chronology of epidemics and pandemics was evident with Acute Respiratory Syndrome (SARS) occurred in 2003, Influenza A H1N5 (bird flu) in 2007, H1N1 (swine flu) in 2009, Middle East Respiratory Syndrome in 2012 and Ebola Virus Disease (EVD) in 2014 [71]. Towards the end of 2019, a novel coronavirus designated as COVID-19, subsequently named SARS-CoV-2, emerged in Wuhan City of China and caused a global pandemic [72]. The recent literature (see Ref. [73] shows that the severity of COVID-19 has been found in a couple of the emerging variant waves of concern, such as Alpha, Beta, Delta, Gamma, and Omicron. Other evolved characteristics include Deltacon and Plurona [74]. The new variant waves are a reminder that this pandemic is far from over in 2022.

However, prevention has been adopted to limit its spread as no effective cure for COVID-19 [75]. At the community level, people are advised to respect social distancing and follow hygiene measures (i.e., wearing masks and washing hands properly) to prevent disease transmission. The infected individuals are isolated in a separate room [76]. To respect social distancing norms, people pursue digitalization more acutely than ever, embracing digital activities and interaction (such as remote work and online learning) and modifying everyday behaviors to match a new reality. The digital economy leads to an unprecedented convergence of people [77]. Technology innovation has transformed different spheres digitally such as education, medical healthcare facilities, semiconductors, manufacturing, computers, automobiles and telecommunication [78]. During risk situations and crises, Hong and Kim [79] used empirical evidence that showed that digital technology is used to carry out tasks such as content-oriented crisis communication, organizational response and the organization’s official statements.

Cepal [80] argued that quarantine and social isolation associated with the COVID-19 paralyzed the national economy. Jain et al. [81] quantified its impact with confirmed death cases. Irigoyen-Camacho
measure the perceived severity of COVID-19 to the likelihood, magnitude and significance of negative outcomes. Some studies showed the negative effect of severity on behaviors and decision makings (see Refs. [79,83,84]). Thus, higher levels of perceived COVID-19 severity led to low levels of behavioral change. This current research incorporates the individual’s risk status as an essential condition for transforming behaviors digitally. Existing studies have applied planned behavior theory to understand the effect of COVID-19 on behavioral change (see Refs. [6-8]). However, they focused on different behavioral results (especially health and tourism behaviors) during the pandemic. Accordingly, the severity of COVID-19 is the prime determinant of digitally transformed behavior, the subjective norms of society and behavioral control (self-efficacy). As COVID-19 continues to disrupt human activities, the status quo has been shaken up like never before, and human interaction is followed by social distancing measures [42]. Quick-thinking humans have been quick to adopt digital strategies to ensure behavioral continuity, whether online or off. Perceived COVID-19 severity is linked to a new normal of practice where digital has become central to every interaction [85]. When its severity increases, people are more likely to use digital technology, thereby intending to change their behavior online. Perceived COVID-19 severity as an accelerator is, therefore, another force to predict digital transformation and fast-moving human behavioral change. The hypotheses are therefore formulated that (see Fig. 1):

H8. The perceived severity of COVID-19 is more likely to influence digital transformation practices.

H9. The perceived severity of COVID-19 is more likely to influence humans’ attitudes towards behaving and transforming digitally.

H10. The perceived severity of COVID-19 is more likely to influence humans’ subjective social norms.

H11. The perceived severity of COVID-19 is more likely to influence humans’ behavioral control perception.

H12. The perceived severity of COVID-19 is more likely to influence digital behavioral decisions.

3. Model and variables

The methodology is in two phases. The first phase expresses the features of the digital behavioral decisions based on the digital transformation and disruption that affect behaviors in Thailand. This phase describes measuring instruments and a list of variables. Fig. 1 illustrates how the perceived severity of COVID-19 affects the digital transformation and human behavioral change, which depend on our empirical findings. Table 1 shows the key definitions of the constructs employed in this study.

The hypotheses are tested in the second phase using a structural equation function of digital behavioral decision, a latent variable approach to behavioral intention/decision tested in the existing literature (see Refs. [6,8,86]). To evaluate the twelve hypotheses, the digital behavioral decision function takes the following form:

$$
\eta_{DBD} = \beta_1 \eta_{DA} + \beta_2 \eta_{SN} + \beta_3 \eta_{TB} + \eta_1 \eta_{COVID} + \zeta_i
$$

where $\eta_{DBD}$ is the latent variable ($\eta$) is measured by a set of digital behavioral decision designs (i.e., how people transform or change their behavior in response to the digitalization); the digital behavioral decision function is estimated based on planning/consideration (DBD$_1$), individual experience (DBD$_2$) and future likelihood (DBD$_3$). Two item scales (DBD$_1$ and DBD$_3$) were adapted and modified from existing literature by Ajzen [12]; Chirico et al. [86] and Prasetyo et al. [6]. However, one item scale (DBD$_2$) was developed by Hertwig [87] and Wendel [88].

Individuals’ attitudes, $\eta_{DA}$, are a latent vector of the affective domain. For example, an individual who has positive attitudes towards digital transformation (i.e., using digital tools to integrate and transform faster) can positively influence their behaviors and those around them. The measurement parameters of digital attitude are designed to capture good feelings about digital technology (DA$_1$), individual’s positive mindset on digitalization (DA$_2$) and likeness of being online (DA$_3$). These parameters were taken from previous studies by Ajzen [10]; Chirico et al. [86]; Han et al. [7] and the TPB pattern of question settings.

Digital social norm, $\eta_{SN}$, is the social pressures and expectations that are put on people to engage or not to engage in digital behavior. These three items related to three dimensions of the digital social norm are accepted by the majority on a global scale, namely, staying at home and working from home (DSN$_1$), hybrid working environment whether online or offline (DSN$_2$), and the online protocols from the community, government, firm, school, or others (DSN$_3$). These measurement items were developed and modified based on the research by Bavel et al. [45] and Prasetyo et al. [6].

Estimating an individual’s ability to perform a digital behavior is important in predicting a digital behavioral decision, denoted as $\eta_{DBD}$.

---

**Table 1**

| Constructs | Definitions | References |
|------------|-------------|------------|
| Digital attitude | Individual beliefs, knowledge, mindsets, and prejudices towards either digital or physical behaviors. | This study used the definitions of Ajzen [10]; Hollett et al. [36]; and Saarikko et al. [23] as a basis to develop the term ‘digital attitude’. |
| Digital social norm | Standards and practices based on public shared values and rewards about how people should act, either physically or digitally on specific circumstances. | This study termed and developed ‘digital social norm’ based on the definitions by Ajzen [10]; Lee and Tsai [65]; Prasetyo et al. [6]; and Saarikko et al. [23]. |
| Digital perceived behavioral control | It is how individuals perceive their confidence in using digital technology (i.e., digital self-efficacy) and how they control the use of digital technology based on available resources and experience (i.e., digital controllability). | This study coined the term “digital perceived behavioral control,” adopted from Ajzen [54]; Zolait [56]; and Saarikko et al. [23]. |
| Digital behavioral decision | It is how people evaluate either physically or digitally the form of behavior they adopt. It is the motivational factors that play a priori-conscious-decision role in a certain behavior that is the stronger the behavioral decision to perform the behavior, the more likely the digitally transformed or transforming behavior will be performed. | The term ‘digital behavioral decision’ was developed depending on the definitions by Ajzen [10]; and Saarikko et al. [23] with few modifications to suit the current study. |
| Digital transformation practices | The transformation process by which people leverage new emerging technologies to create new experiences, models and systems, switching from analog to digital behavior, improving activities and processes by leveraging digital technologies (e.g., social media, cloud, application, etc.). To scope down digital transformation practices, this study developed this term from Matt et al. [21]; Hess et al. [22]; and Saarikko et al. [21]. |
| Perceived COVID-19 severity | The likelihood, magnitude, and significance of negative consequences associated with COVID-19. | The term ‘perceived COVID-19 severity’ was relied upon by Inigoyn-Camacho et al. [82]. |
The integration of digital technology into all areas of human life is crucial to aggregating modern tools, solving human problems and satisfying human needs. We adapted a three-item scale from studies by Ajzen [54]; Lucarelli et al. [8]; and Prasetyo et al. [6] to assess indicators satisfying human needs. We adapted a three-item scale from studies by crucial to aggregating modern tools, solving human problems and

Here, the current research analyses digital transformation in-depth and estimates a set of digital transformation concepts for IT citizens embarking on digital journeys and decision-making processes during the COVID-19 pandemic, denoted as \( \eta_2 \). We developed and modified five items from research by Kaewsang [15]; Law et al. [89]; and Mergel, Edelmann, and Haug [90] to assess the use of digital technologies and tools (\( DT_1 \)), coordination, communication, and collaboration in digital platforms and channels (\( DT_2 \)), electronic payment and transactions (\( DT_3 \)), evaluation of data, information, and digital content (\( DT_4 \)), and digitally visual and interactive activities (\( DT_5 \)).

The effect of COVID-19 denoted as \( COVID \) is estimated as the magnitude of its severity, based on research by Han et al. [7]; Lucarelli et al. [8]; and Prasetyo et al. [6]. A detailed list of questions for all variables is in Appendix.

This study follows an epistemological positivist methodology. We believe that COVID-19 severity and digital transformation practices constitute knowledge of digitally transformed and planned behavior. This epistemological positivist assumes that acceptable, valid, and legitimate knowledge is constituted by some things. This study aims to investigate if there was digitally planned and transformed human behavior during the pandemic. As positivism relies on experience as a valid source of knowledge; the human experience is a valid source of knowledge that can help us achieve our goal. That is, people experience the pandemic and it forces them to digitalize their activities. When digitally planned and transformed behavior can be thought of as a variation in the actions of individuals or in the relationships that exist between individuals, the epistemological positivist methodology was appropriately justified. To explain this digitally planned and transformed behavior phenomenon, causality must be demonstrated.

A structural equation modelling (SEM) regarding the probability of linking the latent-based constructs is conducted. SEM is suitable for this analysis because (1) it tests a theoretical model of digital behavioral decision from empirical data, and (2) observes variables as ordinal Likert scales of the agreement. This research collects primary data to address the research problem.

4. Data and sample

Data were distributed to sample Thai citizens through the electronic survey to prevent the spread of COVID-19 and respect social distancing. Quick Response code and Google form were used to distribute data. This survey distribution is an example of digital transformation practices, carried out from August to November 2020.

The whole population (N) of interest of Thai citizens was approximately 69,625,582 [91], which determines the sample size of a given survey. The sample size for SEM was recommended. According to Krejcie and Morgan [92]; a formula to determine the sample size for a finite population (\( N = 69,625,582 \)) was around 385 when considering confidence level of 95%, the margin of error of 5% and population proportion of 50% (i.e., the worst-case percentage). This formula leads to the sampling size ranging from 25 to 65 years with 59.82% identified as female. The net of personal monthly income was between 15,000 and 30,000 THB (see Table 2).

5. Empirical results

This study performed various tests to check data validity, data reliability and model fit. Table 3 reported the results. To determine the reliability and validity of the model measurement, IBM SPSS AMOS 26 was used to conduct SEM [98].

5.1. Step 1: confirmatory factor analysis (CFA)

CFA is the first step to determine the factor structure of our dataset and measurement models [99]. We aimed to estimate the convergent validity and reliability, discriminant validity, multicollinearity and goodness of model fit.

First, all standardized factor loadings exceeded the required threshold of 0.6 as recommended by Anderson and Gerbing [100]. As for the construct reliability, the figures for composite reliability (CR) and Cronbach’s alpha (\( \alpha \)) were above 0.7, indicating that multiple indicators met internal consistency for each construct [96]. The average variance extracted was higher than the acceptable level of 0.5 [101], supporting convergent validity. Theoretically, this evidence showed that different indicators belonged to each construct.

Second, common method bias (CMB) revealed that the study employed one self-report survey of the data on all the variables of interest. The variation in response is produced by the instrument rather than by the respondents’ natural predispositions, which the instrument aims to expose [102]. In other words, the variances create a response

Table 2
Sample characteristics.

| Demographic Category | Total | Percentage (%) |
|----------------------|-------|----------------|
| Gender               |       |                |
| Male                 | 221   | 40.18          |
| Female               | 329   | 59.82          |
| Age                  |       |                |
| 25–35                | 166   | 28.91          |
| 36–45                | 189   | 31.27          |
| 46–55                | 159   | 26.80          |
| 56–65                | 36    | 6.02           |
| Occupation           |       |                |
| Government officer   | 134   | 22.37          |
| Officer              | 177   | 29.51          |
| Freelancer           | 128   | 21.51          |
| Entrepreneur         | 92    | 15.73          |
| Others (serv, student)| 19   | 3.23           |
| Income/month         |       |                |
| 5000–14,999          | 106   | 17.93          |
| 15,000–29,999        | 212   | 35.85          |
| 30,000–44,999        | 172   | 29.17          |
| More than 45,000     | 60    | 9.91           |
| Region               |       |                |
| North                | 33    | 5.55           |
| North-eastern        | 150   | 25.00          |
| Central              | 180   | 30.00          |
| South                | 78    | 12.88          |
| West                 | 73    | 12.32          |
| Eastern              | 32    | 5.38           |
bias that either inflate or deflate estimates [103]. Harman’s single-factor analysis is inappropriate for measuring common bias because the latent factor is more sophisticated and obsolete. Thus, we introduce a common latent factor (CLF) to evaluate the standardized regression weights of all bias that either inflate or deflate estimates [103]. Harman’s single-factor analysis is inappropriate for measuring common bias because the latent factor is more sophisticated and obsolete. Thus, we introduce a common latent factor (CLF) to evaluate the standardized regression weights of all observed variables using the CFA and a common latent factor. However, only one variable (i.e., COVID-19 severity) was excluded in the analysis since it was not a latent variable. Using composite items that represent five latent constructs, this paper tested a five-construct measurement model. The differences in absolute value between standardized regression weights without CFL and with CFL (suggested less than 0.20).

Table 3
Construct reliability and validity.

| Constructs | Indicators | λ  | AVE | CR  | Cronbach | VIF | λ_{CLF} | Δ    |
|-----------|------------|----|-----|-----|----------|-----|---------|------|
| ATT       | AT1        | 0.779 |     |     |           |     | 2.545   | 0.731 | [0.048]|
|           | AT2        | 0.716 |     |     |           |     | 2.053   | 0.744 | [0.028]|
|           | AT3        | 0.774 | 0.573 | 0.801 | 0.798    |     | 2.5     | 0.71  | [0.064]|
| SN        | SN3        | 0.738 |     |     |           |     | 2.193   | 0.695 | [0.043]|
|           | SN2        | 0.741 |     |     |           |     | 2.217   | 0.719 | [0.022]|
|           | SN1        | 0.671 | 0.5147 | 0.76 | 0.792    |     | 1.818   | 0.669 | [0.002]|
| PBV       | PBV1       | 0.76  |     |     |           |     | 2.37    | 0.757 | [0.003]|
|           | PBV2       | 0.749 |     |     |           |     | 2.283   | 0.755 | [0.006]|
|           | PBV3       | 0.771 | 0.578 | 0.804 | 0.803    |     | 2.463   | 0.677 | [0.094]|
| DT        | DT3        | 0.794 |     |     |           |     | 2.703   | 0.68   | [0.114]|
|           | DT2        | 0.859 |     |     |           |     | 2.817   | 0.753 | [0.106]|
|           | DT1        | 0.803 |     |     |           |     | 2.817   | 0.699 | [0.104]|
|           | DT4        | 0.821 |     |     |           |     | 3.067   | 0.67  | [0.151]|
|           | DT5        | 0.747 | 0.649 | 0.902 | 0.902    |     | 2.262   | 0.67  | [0.077]|
| DBD       | DBD3       | 0.805 |     |     |           |     | 2.841   | 0.662 | [0.143]|
|           | DBD4       | 0.814 |     |     |           |     | 2.967   | 0.669 | [0.145]|
|           | DBD5       | 0.849 | 0.677 | 0.863 | 0.862    |     | 3.584   | 0.666 | [0.183]|

Note.

- λ_{CLF} = the standardized regression weights (SRW) of a CFA model with the CLF.
- Δ = the differences in absolute value between standardized regression weights without CFL and with CFL (suggested less than 0.20).

The path coefficients were diagnosed to test the hypotheses. The direct effects of proximal determinants of the intended behavior on the digital behavioral decisions were investigated (H1–H3). The significant results (see the proposed model appraisal in Table 5) showed that digital attitude had a positive effect on digital behavioral decisions (β = 0.448, t = 5.235, p < 0.001), supporting H1. Both digital social norms (β = 0.82, t = 5.1, p < 0.001) and digital behavioral control perception (β = 0.24, t = 3.609, p < 0.001) showed a positive effect on the digital behavioral decision, confirming H2–H3 respectively.

H4–H7 show the effects of digital transformation practices on digital planned behavior. Digital transformation practices had a positive effect on digital attitude (β = 0.73, t = 14.143, p < 0.001), digital social norms (β = 0.799, t = 13.511, p < 0.001) and digital behavioral control perception (β = 0.697, t = 13.025, p < 0.001) at a significant level of 0.1%. In contrast, digital transformation practices had a negative direct relationship with the digital behavioral decision (β = −0.349, t = −2.522, p < 0.05), thereby supporting these hypotheses at a significant level of 5%.

Another set of hypotheses showed the effects of COVID-19 severity on digital transformation practices and digital planned behavior (H8–H12). The findings (Table 2) confirmed that the severity of COVID-19 had a positive impact on digital transformation practices (γ = 0.481, t = 11.151, p < 0.001), digital attitude (γ = 0.208, t = 5.372, p < 0.001), digital social norms (γ = 0.154, t = 3.754, p < 0.001) and digital behavioral control perception (γ = 0.187, t = 4.499, p < 0.001). However, the finding contrasted with the digital behavioral decision—a negative behavior—at the 0.1% significance level (γ = −0.177, t = −4.026, p < 0.001).

6. Discussion

This study tested a model to investigate how COVID-19 severity influences the digital transformation of planned behavior via mediating digital transformation practices. We conceptualize and test the effects of digital transformation of the theory of planned behavior on digitally planned and transformed behaviors. We evaluated three proximal antecedents of digitally planned and transformed behavior on each dimension, bringing new insights into the dimensionality of digital transformation linked to human behavioral change. Our model predicts that 93.9% of the variation in the digital behavioral decision is explained by digital attitude, digital social norm, digital behavioral control perception, digital transformation practices and COVID-19...
severity. This R-squared value of latent variables is a pretty good explanation for why people make different digital decisions because it was more than the 75% of variance as recommended by Hair, Ringle, and Sarstedt [1]. However, other variables explained the remainder not included in the model. Compared with the traditional model of planned behavior, our model explains approximately 25–50% of the variance for intentions or decisions [10,46]. In line with previous research, our study reveals that individuals’ perception of COVID-19 influences their behaviors [7,8] and the level of physical behavioral transformation [108]. Our results demonstrate that the COVID-19 severity has significant positive impacts on digital transformation practices, but diminishes the extent of digital behavioral decisions. Thus, digital transformation practices significantly impact digital attitude, digital social norms and digital behavioral control perception, which reduces digital behavioral decisions.

These results are contrary to our expectation that as COVID-19 is more severe, people are more likely to digitalize their behaviors. Thus, digital-based activities are more sophisticated than physical-based since the humans’ status quo bias might lead to staying with the current provider to achieve physical interaction [42]. The preventive measures of COVID-19 also urge individuals to participate in hygiene habits and digital technology [109]. Our results suggest that it is critical to consider

Fig. 2. Structural model testing.

### Table 4

| Heterotrait-Monotrait Ratio of Correlations (HTMT) | IT | NN | PC | SN |
|--------------------------------------------------|----|----|----|----|
| NN                                               | 0.854 | -   | -   | -   |
| PC                                               | 0.761 | 0.781 | -   | -   |
| SN                                               | 0.865 | 0.828 | 0.670 | -   |
| AT                                               | 0.829 | 0.821 | 0.672 | 0.705 |
the digital decision-making journey and the human side of digital transformation [58].

The strong evidence in support of H1 suggests that an attitude towards digital-transformed and -transforming behavior is a determinant of digital behavioral decisions. Our findings reveal that, during the pandemic, Thai citizens tend to feel okay about digital technology while 63.7% of the variability is explained by the response data. It appears that those people tend to have an individual’s positive mindset on digitalization (explained by 49.2% of variance) and to have a strong preference for being online (with a moderate explanation of variance at 59.4%). We could see that these manifested activities were able to well explain the latent activities of digital attitude. Thus, predicting how people will act is a big part of how they feel [39]. Based on the positive significant link between digital transformation and the shape of digital attitude in the Thailand setting, H4 is likely to conclude that digital transformation practices positively affect the mindset, preference, and feelings of people. When people notice that digital transformation matters, there might be an increase in their attitude towards digital-transformed and -transforming behavior at 73%. H9 indicates that the direct effect of perceived COVID-19 severity is assumed to be a cause of digital attitude. The finding of H9 is consistent with Barrutia and Echebarria [9]; which recognized that, during COVID-19, the general public has become more positive about information communication technology as a whole.

This study provided strong evidence to support H2, implying that digital social norms are a proximal factor of digital behavioral decision-making, with a standardized effect of 82%. Our findings show that the customary codes of digital-transformed and -transforming behavior in a group are likely to impact in social context decisions, which could be explained by 78.1% of the total variance of digital social norms. We further found that Thai citizens tend to follow general social norms during the COVID-19 pandemic. They still require a hybrid working environment (predictive power explained at 56.7% of variability), rather than a purely online environment. Most of them stay at home and work from home (predictive power explained at 46.5% of variability). They also keep up with the online protocols announced by the community, government, firm, school, or others (predictive power explained at 56.7% of variability). Regarding H5, it is found there is a positive link between digital transformation practices and digital social norms. We believe that the digital transformation movement has begun to exert pressure in the social context. Meanwhile, the effect of H10, which tested the effect of perceived COVID-19 severity on digital social norms, confirms that people have been paying attention to the digital world. That is to say, sample citizens, match their digital strategy around them. A similar pattern of results was obtained in the study of Hudek et al. [110] that found people tend to transform themselves digitally (i.e., from traditional to virtual job/career) as a result of a material or social support if digital technology infrastructure is well established or set up. In the end, COVID-19 has played a big part in both the results of the digital transformation and in the future of what generations’ digital social norms will look like after a new normal is set in place.

Concerning H3, the relationship between digital perceived behavioral control and digital behavioral decisions shows that most citizens with digital self-efficacy, digital technology resources required, and digital knowledge and skills have the relatively high intentional performance to change their behavior. Simultaneously, it is found that those people believe that they can control their digital behavioral decisions despite remote work or study. It appears that 58.5% of its total variance can be explained by the fact that they tend to be confident in their individual perceptions of digital literacy self-efficacy, 54.4% found that they tend to have sufficient resources for digital technology, and 60.8% found that they tend to have knowledge and skills in digital competence. The findings are directly in line with previous findings by Zolait [56] that found technological facilitating conditions, resource-related facilitating conditions, and self-efficacy are essential for great predictors of digital behavioral decisions. What is different from our finding is that Zolait [56] suggests that the availability of government support would help to facilitate individuals’ intention to use information technology. Looking at the impact of digital transformation generated by the COVID-19 pandemic, H6 reveals that 64.3% of the variance explains that people tend to perceive the ease of doing all online activities. This is further confirmed by H11 that the perceived COVID-19 severity affects their perception of digital behavioral control. No matter how easy or difficult it is to digitalize all activities as possible, it implies that the pandemic forces people to believe that they could perform online in order to save lives.

Looking at the effect of perceived COVID-19 severity on digital transformation practices, there is a great deal more going on. Our findings show that our assumptions yielded contradictory results. H7
shows that people tend to be less interested in digitally transformed or transforming behavior. This could lead us to conclude that they still persist with a variety of digital activities. It means that people still require social and physical interaction. However, without a choice, they must digitally transform their behavior anyway. H12 also shows that digital transformation practices generated by the COVID-19 pandemic are likely to shift their behaviors more rapidly than they could accept their behavioral decision to digitalize. That’s why both H7 and H12 have a negative effect on how people decide digitally. However, it is true that the more people perceive the severity of COVID-19, the more digital technologies and tools, 69.7% found that they tend to coordinate, communicate, and collaborate through digital platforms and channels, 61% found that they prefer electronic payment and transactions, 65.2% found that they care for the evaluation of data, information, and digital content; and 53.8% found that they have a propensity for digitally visual and interactive activities during the pandemic. This is confirmed by H8 that the COVID-19 pandemic caused significant changes in an increase in digital transformation practices by 48.1%.

To sum up, our discussions confirm that COVID-19 might change how people think about digital transformation and make it more meaningful.

6.1. Theoretical implications

From the theoretical perspective, this study re-specifies the traditional theory of planned behavior to elaborate on a new context of digital transformation. There are three key theoretical implications of our findings.

First, our research differed from prior studies (e.g. Refs. [7,8,86,111, 112]), because we leveraged the deductive approach to build new concepts and identify the boundary of the traditional theory to fit the new context of digital transformation of planned behavior—digitally planned and transformed behaviors. Our findings provide the following insights into scenarios:

- When people perceive the severity of COVID-19, they tend to feel good about digitalizing their activities, and they further decide to transform their behaviors digitally.
- When people perceive the severity of COVID-19, they tend to digitalize their activities according to most influencers around them, and they further decide to transform their behaviors digitally.
- If people perceive the severity of COVID-19, they tend to digitalize their activities when they believe that they can control the difficulty of digital technology, and they further decide to transform their behaviors digitally.
- Although the perceived COVID-19 severity significantly increases the tendency of digital transformation, digital transformation practices generated by the pandemic tend to diminish human decisions to go digital.
- Perceived COVID-19 severity reduces individuals’ decisions no matter how they transform digitally or not.

Second, our findings identified one of the essential research gaps, which takes both COVID-19 and digital transformation into account and demonstrated how COVID-19 influences digital transformation practices and behavioral decisions digitally. We could see that digital transformation practices as a result of the effect of perceived COVID-19 severity provided significant evidence of an inverse relationship with human behavioral decisions during the pandemic. In Thailand, the digital perceived behavioral control role is more dominant. Again, theoretically, the digital context might explain why attitude and mindset could be dominant [9], as Thais perceive that doing online activities may be an additional cost that they need to bear with and implement in the process of digital transformation. That could be the reason why our findings indicate an inverse relationship with digital behavioral decisions. Our findings provide the inverse insight that COVID-19 forces them to change their behaviors regardless of how poorly planned their decisions are.

Third, this study extended the applicability of theory of planned behavior (TPB) in a way that the key constructs were theoretically conceptualized and developed to meet a more comprehensive description in the digital edge. This study proposes that digital behavioral decisions are one of the key constructs for understanding and predicting digitally planned and transformed behaviors. Measuring digital behavioral decisions is an ongoing challenge. Still, the affective domains influence human learning and behavior [113]. Hence, either past or present experience-based decisions affect behavior [87]. Experience plays an important role in digital transformation and interactive behavioral change [88]. Regardless of how awesome digital technology is now, if people have already been taught that it’s not effective to go digital, they will find it difficult to overcome. Or, if they have previously tried to succeed at their behavior using digital technology and have not seen any progress, they’re less likely to try again. Our study recommends that the scale be developed regarding experience-based decision making.

6.2. Practical implications

The findings of this study have major practical implications not only for managers but also for all associated stakeholders who need to digitalize their work or student experience in Thailand. The findings of this study have ramifications for managers, investors, and regulators. Based on our empirical evidence, key findings can be divided into the following practical implication scenarios:

- Provide employees, students, and customers with time to understand the online protocol and to volunteer and participate in the hybrid working and studying environment. This suggestion is based on the items DSN1–3.
- Ensure that opportunities and resources (information, money, time, and digital literacy skills) are facilitators to new ways of interacting in the virtual world. This is because those who work from home may not have the best equipment, layout, or boundaries, so ensuring their physical wellbeing is important. This recommendation is derived from items DPBC1–3.
- Ask them about their feelings and feedback, and inspire positive mindsets to improve their understanding of experiences with digital technology. This recommendation is derived from the items DA1–3.
- Developing an enterprise architecture for digital transformation helps operational excellence. Thus, the government, state enterprises, and firms must respond to the business requirements of digital and information technology. Private and public enterprises should invest in the resources to create technical capabilities (e.g., enterprise resource planning) to underpin a business capability that leads to a favorable outcome (e.g., cost reduction, productivity, and financial profit). This recommendation is sourced from items DT1–5.

7. Conclusion

The COVID-19 pandemic offers a too rapid shift to the digital landscape [109]. An extraordinary digital leap takes a collaborative approach (i.e., agile) to business-building to rapidly build and scale innovative new businesses either physically or digitally (McKinsey & Company 2020). Despite decades of research, several researchers have continued to be applied Theory of Planned Behavior (TPB) on human behavior. Most recent studies put TPB to understand the effect of COVID-19 on virus preventive [6], safe destination [7], boarding (Long...
and Khoi 2020), and pro-environmental behaviors [8], but the practical application of digitally planned and transformed behavior is relatively neglected to propose in the literature while such behavior results in organizational survival and transformation. What’s more, measures of decision for digital transformation were less consistent in the literature that did not reflect the dimensionality of digital behavioral decision in term of experience. As a result, our aim was to determine and base Ajzen’s [10] theory of planned behavior to conceptualize a new behavioral insight of digitally planned and transformed behavior required for the digital age. In so doing, we use a dataset of informants in Thailand surveyed in 2020. This yielded a dataset of 550 usable observations. In the case of occupation observed, this required significant adjustments not only from government officers, freelancers, office workers and entrepreneurs, but also from students, service workers and the entire society. Overall, our results provide more empirical evidence about a significant effect of COVID-19 severity on digital transformation and digital planned and transformed manner. This supports the research’s hypotheses that digital transformation practices in the new normal and people’s perceived COVID-19 severity are likely to influence their attitude, social norm, behavioral control perception, and decision to digitalize. However, these also answer the two questions raised by this research namely, (1) how digital transformation practices take effect in behavioral change digitally, and (2) how perceived COVID-19 severity influence digital transformation practices and behavioral decision digitally? Our data also suggest that there may still have a long way to go digital because of struggles between behaving in digital manner—it is evident with H7 that digital transformation practices in the new normal will erode people’s digital behavioral decision. Although people adjust despite low readiness for digital tools, informed individuals are likely to undertake digitally planned and transformed behaviors. Thus, new solutions are needed to develop more enterprise architectures and increase an individual’s readiness by providing digital technology resources. However, our data is cross-sectional because the data was collected since the early spreading of the COVID-19 pandemic in the end of 2021. Given the continuous changes experienced by Thai citizens, a longitudinal data analysis using latent growth modeling would be useful to spot potential differences in the results of a more general scope of digital behavioral decisions. The consideration of a multi-trait sample such as vulnerable groups is meaningful to study. What’s more, our model stops at the insight of a behavioral decision, so the prediction of actual behavior disappears. The scale development of actual digital planned and transformed behavior should be taken into account.

Funding

The Research titled “A COVID-19 disruption: The great acceleration of digitally planned and transformed behaviors in Thailand” by Khon Kaen University, International College has received funding support from National Research Council of Thailand (NRCT).

Institutional review board statement

Not applicable.

Informed consent statement

Not applicable.

Author statement

Naruetheradhol P.: Conceptualization, Methodology, Software, Supervision, Software, Validation and Writing – review & editing. Srisathan W.A.: Data curation, Writing – original draft. Visualization, Investigation

Declaration of competing interest

No conflict of interest existed among the authors.

Acknowledgement

The researchers would like to express their gratitude to International College, Khon Kaen University for its assistance. The researchers would like to express their gratitude to all anonymous respondents who took the time to complete questionnaires and to their colleagues who helped us complete this research successfully.

Appendix

| Construct                                      | Measures                                                                                                                                  | Supporting references |
|------------------------------------------------|------------------------------------------------------------------------------------------------------------------------------------------|-----------------------|
| Digital transformation practices (DT)          | DT1: . . . use digital technologies and tools (e.g., Zoom, OneDrive, Drive, AI, Chatbot, the Internet, Facebook, Line, E-mail etc.) to support social interaction. | A COVID-19 disruption: The great acceleration of digitally planned and transformed behaviors in Thailand [89]. |
| Digital behavioral decision (DBD)              | DBD1: . . . I will consider/plan to go digital during the pandemic. DBD2: . . . I decide to digitalize due to a certain level of my experience. DBD3: . . . I am likely to adapt myself to digitalize all activities as possible in the coming future. | Ajzen [12], Chirico et al. [86], Prasetyo et al. [6]. |
| Digital attitude (DA)                          | DA1: . . . I feel good about using digital technologies during the coronavirus outbreak. DA2: . . . Overall, I have a positive mindset to digitalize during the coronavirus outbreak. DA3: . . . I like using digital technologies to support everyday life. | Ajzen [10], Chirico et al. [86], Han et al. [7]. |
| Digital social norm (DSN)                      | DSN1: . . . Most people I know practice social distancing (i.e., stay at home and work from home). DSN2: . . . Most people I know do hybrid work (either physical or digital). DSN3: . . . Most people I know follow the online protocols given by the government, firm, school, or others. | Lucarelli et al. [8], Prasetyo et al. [6]. |
| Digital behavioral control perception (DBP)     | DBP1: . . . I am more confident to digitalize than ever before the coronavirus outbreak. DBP2: . . . I have more resources (e.g., smart devices, internet connection, software license, computer, laptop etc.) necessary to digitalize than ever before the coronavirus outbreak. | Ajzen [54], Lucarelli et al. [8], Prasetyo et al. [6]. |

(continued on next page)
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