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Impact of digital device utilization on public health surveillance to enhance city resilience during the public health emergency response: A case study of SARS-CoV-2 response in Thailand (2020–2023)

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Abstract

Objective: This study aims to examine the impact of digital devices on public health surveillance, the impact of public health surveillance on resilient cities, and the impact of digital devices on resilient cities.

Methods: Questionnaires were issued to residents of Thailand during the severe acute respiratory syndrome coronavirus 2 response (2020–2023). In total, 1025 valid responses were recorded from Thai nationals and expatriates. Exploratory factor analysis, confirmatory factor analysis, and structural equation modeling were used to assess the model through IBM SPSS 23 and AMOS 23.

Results: Digital devices have a strong positive direct effect on public health surveillance ($\beta = 0.73$, $p \leq .001$), public health surveillance has a strong positive direct effect on resilient cities ($\beta = 0.79$, $p \leq .001$), and digital devices have a low positive direct and a moderate indirect effect on resilient cities ($\beta = 0.13$, $p \leq .001$, and $\beta = 0.58$, $p \leq .001$, respectively). The use of digital devices in data collection, analysis, and dissemination, positively impacted public health surveillance, considering five dimensions: medical and vaccine, individual, health care, epidemiological, and disease. Meanwhile, using digital devices in public health surveillance positively impacted the resilience of cities, considering three dimensions: socioeconomic, institutional, and living. The causal relationship model of the digital device utilization on public health surveillance enhancing the resilience of the cities met all the necessary criteria: $X^2/df = 2.802$, comparative fit index = 0.953, goodness of fit index = 0.901, normed fit index = 0.935, Tucker–Lewis index = 0.935, root mean square of approximation = 0.048, and root of mean square residual = 0.043. This indicates the model fits the empirical data.

Conclusion: Digital devices are vital tools in collecting, analyzing, and disseminating public health surveillance-related data during the public health emergency. This, in turn, can improve medical and vaccine, individual, health care, epidemiological, and disease surveillance, and also enhance cities' socioeconomic, institutional, and living resilience.

Keywords

Digital device, public health surveillance, city resilience, public health emergency, infectious disease control, Thailand

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Introduction

Public health emergencies (PHEs) that occur by emerging infectious diseases (EIDs) arise unexpectedly and tend to spread far and wide at a rapid rate causing an epidemic.[1] The resulting epidemics caused by EIDs not only have serious negative public health consequences, but also a detrimental knock-on effect on economic activities, social participation, organizational functional operation, and mobility capacity.[2] The latest PHE was the transmission of the severe acute respiratory syndrome coronavirus-2 (SARS-CoV-2) virus that caused coronavirus disease 2019.[3] The World Health Organization (WHO) formally heightened the status of this disease as a public health emergency of international concern (PHEIC) with an official announcement in early 2020 and then characterized it as a full pandemic not long after in the same year.[4] The PHE announcement by the WHO indicated the high risks and potential dangers of the disease and advised of the need for robust public health surveillance to manage the crisis.[5]

Public health surveillance can simply be defined as the timely and ongoing gathering, organization, analysis, interpretation, and distribution of health-related data. This procedure is necessary to plan and design disease prevention and control strategies as well as evaluate the efficacy of these actions.[6] It entails keeping an eye on people's actions, behaviors, and personal or environmental data.[7] Previous studies have shown that public health surveillance is a key reaction to detecting occurrences of infectious diseases, and an effective response to the further spread of the disease, thus allowing better control of epidemics, and in turn a more rapid and ameliorated return to normalcy.[8–10] Many types of public health surveillance can be used to combat PHEs.[4] First, disease surveillance, such as the collection of data about the disease and the number of infected patients.[7,11,12] Second, medical surveillance consists of collecting and analyzing health history information from a targeted population systematically and continuously.[7,13,14] Third, epidemiological surveillance is the monitoring of people, places, times, and various elements related to the occurrence of the disease.[15–17] Fourth, individual surveillance monitors people at the individual level who may have been or were exposed to the disease and advises them on how to behave in the public sphere without impeding on activities or residences.[16,18,19] The fifth type that can be used to combat PHEs is vaccine surveillance, which monitors the effectiveness, side effects, types, production source, and production date of vaccines; and also measures the level of immunity in the community.[20–22] Lastly, there is health care surveillance, which monitors and notifies the health care system's capacity, providing information on the availability, or lack thereof, of essential resources such as patient beds, medical equipment, medical supplies, and health care personnel, thus giving a better picture of how infected patients can be responded to.[4]

The goal of both public health surveillance and resilient cities during PHEs is to restore the situation to business-as-usual normalcy. A resilient city refers to a city that has the potential to absorb, adjust, and recover when faced with emergencies; and the ability to maintain its functions, such as infrastructure, institution, economy, and society, to be able to continue its work effectively even under the emergencies.[23–25] To enhance the city's resilience during PHEs, digital technologies (digital technology refers to technologies that use two states of binary digits—0 and 1—to create, store, and manipulate data) such as digital devices (digital devices are tools or gadgets that make use of digital technology) serve as means for sending and receiving information between the government and the population, promoting connection and communication, and serving as tools to access or do activities.[26–28] It benefits the public by encouraging awareness of the danger of the disease, allowing them to learn and acknowledge the general information about the disease, and how to follow and conform to the protection and control measures.[29] Digital devices are the tools that assist the government in collecting, analyzing, and monitoring the population's health data and information regarding disease transmission, to reduce rates of infection, and limit the further spread of the disease.[30]

Kichloo et al. supported that digital devices including smartphones, desktop computers, laptops, and modern smart televisions (TVs), have been the devices that have played the role of telemedicine for decades.[26] Similarly, Ohannessian et al. mentioned that telemedicine, particularly video consultations through smartphones, has been promoted and scaled up to reduce the risk of transmission, especially in the UK and the USA.[31] Digital devices are the tools used to share information about health-related events directly between physicians and health care bodies, their patients, or the populace such as news of outbreaks or epidemics, and details on how those at risk should respond.[30] Digital devices can be used in this way to carry out contact tracing, issuing quarantine orders, dynamic symptom monitoring and review, and general data collection and analysis that public health monitors can use to build a greater picture of the current situation and future predictions of how an epidemic will develop, prompting interjection of further policies to negate wider transmission.[15] Overall, using digital devices for data collection, analysis, and dissemination on public health surveillance allows for improvements in the design and implementation of public health surveillance policies.[32]

In reaction to SARS-CoV-2, the Thai government implemented both strict and easing control measures. Strict control measures include curfews, lockdowns, and the restriction of locations and borders. The areas under surveillance were separated into five zones during the easing control measures, denoting the five degrees of severity of the situation. Every day, the areas were evaluated and categorized. In high-danger zones, tight surveillance was implemented, while limits in other places were loosened. Under the public health surveillance measure, people were free to go about their daily lives, including going to work. Thailand attempted to prevent and control the disease while also promoting economic recovery by easing control measures. The details of disease prevention and control measures implemented in Thailand during the SARS-CoV-2 response can be found in regulations No. 1 to No. 47 issued under section 9 of the Emergency Decree on Public Administration in Emergency Situation B.E. 2548 (2005).[33] Interestingly, government initiatives such as vaccination mandates, mandatory vaccination status required for work or school attendance, etc., social distancing initiatives, contact tracing and isolation activities/rules, and city-wide lockdowns may have affected community movement and interaction.

During the PHE, the Thai government used digital devices such as smartphones, desktop computers, laptops, and modern smart TVs to continuously disseminate real-time updates of information on the PHE and appropriate public health surveillance measures, while the public accessed such information through the same digital devices. This raises the public's awareness about the disease or infection, ultimately enhancing improved self-care and protection. However, there were certain limitations associated with how digital devices were used for public health surveillance during the SARS-CoV-2 response. Specifically, it is noted that the public received public health surveillance information insufficiently, and some of the information did not reach all population groups it was intended for and should have reached.[34] Therefore, the comparatively small participation rate in surveillance activities serves to reduce the effectiveness of public health surveillance. Additionally, one serious challenge against speedy recovery from the PHE in Thailand was the dissemination of fake news on social media.[35] There was a constant circulation of fake news concerning a virus variant and areas at risk of infection during that period. It was a gross act of misinformation, and as a result, the public became confused and panicked. This in turn negatively impacted their mental health.[36] Consequently, it became imperative for the government to take action to promote the dissemination of accurate and official information from trustworthy sources (governmental and non-governmental). Moreover, to ensure data and information are disseminated to all groups, including vulnerable populations who may lack access to digital devices or possess limited literacy skills, the data or information dissemination should also be made accessible on many non-digital devices.

It must be noted here that there are practical problems to be addressed here regarding the effectiveness of using digital devices for public health surveillance. Using the case of this study as an example, the role of digital devices for public health surveillance in Thailand is still rare, and so the full effects of a nationwide rollout with all citizens of the country connected to at least one form of the media using any of the devices is unknown.[37,38] The use of digital devices for public health surveillance in Thailand is still in an exploratory phase, thus making it a compelling topic for research and inquiry. Furthermore, there are theoretical problems with the use of digital devices for combatting PHEs. Primarily, studies on the utilization of digital devices in public health surveillance during PHEs are still rare, and therefore it is currently inconclusive as to whether digital devices can support surveillance during PHEs in the way they are intended.[23,39] On this basis, it is also difficult to know which types of digital communication methods and public health surveillance ought to be promoted to control PHEs most effectively.[40] In addition, some studies have simultaneously mentioned the three aspects: digital device, public health surveillance, and resilient city, but have made only a minor mention of the role of public health surveillance in particular.[23,41,42]

It is imperative to assess the resilience of the city regarding PHEs, taking into account the functions of digital devices and public health surveillance. The use of digital devices in public health surveillance has been documented in earlier research.[15,38,43] It remained unclear, nevertheless, what kind of digital devices are needed to be utilized and how exactly they ought to be used for public health surveillance. In addition, there is a paucity of data regarding the contributions of digital devices and public health surveillance to the restoration of regular city operations.[42] Furthermore, there is insufficient data in the prior literature to draw conclusions about the relationships that exist between digital devices and public health surveillance, digital devices and resilient cities, public health surveillance and resilient cities, and the relationships that exist between digital devices, public health surveillance, and resilient cities.[10,42,44] Therefore, it is the gaps that are necessary to investigate and clarify these relationships.

To address the above-recognized practical and theoretical problems, this study aims to examine the above gaps by investigating how digital devices play a role in public health surveillance, and how these affect resilient cities. The significance of digital devices in public health surveillance to enhance city resilience encompassing data collection, analysis, and dissemination will be investigated. This study investigates four categories of digital devices: smartphones, desktop computers, laptops, and modern smart TVs (in Thailand, the TV signal has transitioned from analog to digital, enabling access to TV channels in all regions where the signal is available) because these four types of digital devices have become integral to our daily lives, most of the individuals possess these user-friendly devices, and again, a few studies supported the use of these digital devices in telemedicine.[31,44] The three primary latent variables (digital device, public health surveillance, and resilient city) will be examined to discover the relationship and their influence in the context of PHE

Table 1. Factors of each latent variable.

Items	Indicators	Reference
DD1	Smartphone[31]	Ohannessian et al., 2020
DD2	Desktop computer[44]	Bryndin, 2020
DD3	Laptop[40]	Ali and Khan, 2023
DD4	Modern smart television[83]	Nagata et al. 2022
PHSL1	Daily number of cases (confirmed cases, recovered cases, and death cases)[11]	Morgan et al., 2021
PHSL2	Virus variants such as S, Alpha, Delta, and Omicron[11]	Morgan et al., 2021
PHSL3	Symptoms of each virus variant infection[11]	Morgan et al., 2021
PHSL4	Characteristics/spreading rate of each virus variant[11]	Morgan et al., 2021
PHSL5	Risk and safe areas[12]	Hohl et al., 2020
PHSL6	Your general and health information[13]	Trout, 2011
PHSL7	Your infection test results[13]	Trout, 2011
PHSL8	Vaccination history/vaccine passport[13]	
	(recording the name of vaccines that vaccinated and the number of doses)	Trout, 2011
PHSL9	Assessment of current symptoms such as cough, sore throat, etc.[13]	Trout, 2011
PHSL10	Mental health assessment such as anxiety, stress, etc.[13]	Trout, 2011
PHSL11	Check-in/check-out facilities during services[15]	He et al., 2020
PHSL12	Overcrowding info about the intended place to visit[15]	He et al., 2020
PHSL13	Tracking info of infected individuals at the place where visited[15]	He et al., 2020
PHSL14	Notification via SMS or phone call about the presence of infected individual(s) at the place where visited[15]	He et al., 2020
PHSL15	Available to assess whether stores or places you visited follow the prevention and control measures or not[17]	Sirilak, 2020
PHSL16	Recommendation for mask wearing[18]	Finger et al., 2021
PHSL17	Recommendation for distancing at 1–2 m[18]	Finger et al., 2021
PHSL18	Recommendation for frequent hand washing[18]	Finger et al., 2021
PHSL19	Recommendation for regular cleanliness[18]	Finger et al., 2021
PHSL20	Recommendation for overcrowding avoidance[18]	Finger et al., 2021
PHSL21	Type of vaccine[20]	Sahni et al., 2023

(continued)

Table 1. Continued.

Items	Indicators	Reference
PHSL22	Dates of vaccination[22]	Zell et al., 2000
PHSL23	Vaccination reaction (normal/side effect)[20]	Sahni et al., 2023
PHSL24	Vaccine production source[84]	ShamaeiZadeh et al., 2024
PHSL25	Immunization level in the community/the report of the national updates on vaccinated population figures[22]	Zell et al., 2000
PHSL26	The availability or lack of patient beds[4]	Ibrahim, 2020
PHSL27	The availability or lack of medical equipment[4]	Ibrahim, 2020
PHSL28	The availability or lack of medical personnel[4]	Ibrahim, 2020
PHSL29	The availability or lack of vaccines[4]	Ibrahim, 2020
PHSL30	The availability or lack of medicine[4]	Ibrahim, 2020
RC1	Online work or study[23]	Qiu et al., 2022
RC2	Public transportation usage[23]	Qiu et al., 2022
RC3	Internet accessing[85]	Shi et al., 2023
RC4	Access to water, electricity, gas, and fuel[86]	Liu and Song 2020
RC5	The work of organizations (organizations physical delivery of service)[23]	Qiu et al., 2022
RC6	The coordination between organizations[23]	Qiu et al., 2022
RC7	Continuous government's response to emergencies[87]	Di Gregorio et al., 2022
RC8	The coordination of the central government and other government agencies in response to the emergency[87]	Di Gregorio et al., 2022
RC9	Buy/sell products or services online[23]	Qiu et al., 2022
RC10	Do financial transaction online[23]	Qiu et al., 2022
RC11	Normal wage/salary/income (financial status)[23]	Qiu et al., 2022
RC12	Basic amenities: food, drinking water, clothing, medicine, and housing[23]	Qiu et al., 2022
RC13	Follow to preventive measures recommended by the government[88]	Suleimany et al., 2022
RC14	Communicate and do social activities through online (seminars, meetings, and other activities)[88]	Suleimany et al., 2022
RC15	Share knowledge or information about self-protection to others[23]	Qiu et al., 2022
RC16	Access learning resources online[23]	Qiu et al., 2022

Note. DD, digital device; RC, resilient city; PHSL, public health surveillance.

response in Thailand. Concisely, the main purposes of the study are:

1. To examine the impact of digital devices on public health surveillance;
2. To examine the impact of public health surveillance on resilient cities; and
3. To examine the impact of digital devices on resilient cities.

Methods

Instrument

The instrument is a questionnaire of self-report response, which aims to collect information on the impact of digital device utilization on public health surveillance to enhance city resilience during the PHE response in Thailand (2020–2023). The questionnaire is divided into four parts: part 1: basic information; part 2: digital device; part 3: public health surveillance; and part 4: resilient city. The government's announcement of lowering control measures (not strict control measures) is the exclusive subject of part 4 of this study.

Different questions/statements were prepared to address each of the areas. The measuring instrument from part 2 to part 4 consists of 50 questions aimed to evaluate the level of agreement of respondents on three areas, being hence distributed as follows: digital device: 4; public health surveillance 30; and resilient city: 16. Throughout parts 2–4, respondents were asked to indicate their level of agreement with each given statement by using a 5-point ordinal Likert scale,[45] where each value had the following meaning: strongly disagree is represented by 1; disagree is represented by 2; neutral represented by 3; agree is represented by 4; and strongly agree is represented by 5.[45,46] The higher the score, the higher the level of agreement.

Questionnaire validity and reliability tests

A survey of the literature was used to create the study's questionnaire. Other references or sources' queries were added into the questions (Table 1). The content validity assessment was conducted using the index of item-objective congruence (IOC). A team made up of three specialists from different fields conducted this evaluation: one was from the field of public health, one from engineering, and one from political science.[47,48] Each specialist assessed the relevance of each question using an ordinal scale of +1, 0, or −1, where +1 indicates that a question is appropriate, 0 signifies uncertainty regarding a question's appropriateness, and −1 denotes that a question is inappropriate.[47,49] A satisfactory IOC is considered to be 0.5 or higher.[50] In this study, the content validity of the screening tool for all questions achieved an IOC of 1.00 exceeding 0.5, thereby confirming their content validity.

The questionnaires were distributed to a tryout sample through online after the content validity evaluation. According to Saha and Kumari and Connelly, a pilot test's sample size should be between 5 and 10% of the study's expected overall sample size.[51,52] For a pilot study whose goal is a preliminary survey, Johanson and Brooks recommended that a minimum of 30 representative participants from the population of interest be included.[53] In a similar vein, Bujang et al. noted that assessing the reliability of the questionnaire usually requires a minimum sample size of at least 30 respondents.[54] Because of this, the study is regarded as having a pilot test consisting of 105 samples, or 10.24% of all replies (which ranges from 5 to 10% of the overall sample size), with the reliability assessed by the Cronbach's α coefficient. Three primary latent variables including digital device (DD), public health surveillance (PHSL), and resilient city (RC), had Cronbach's α values of 0.760, 0.957, and 0.950, respectively, all above 0.7, indicating reliability.[55]

The findings of the validity and reliability evaluations showed that, prior to being used in the process of gathering data, the questionnaires used in this study were both valid and reliable.

Study participants and sampling

The questionnaire was created and gathered through Google Forms between December 2023 and February 2024. The questionnaire was prepared in Thai and then translated into English. Therefore, two versions of the questionnaire were provided: the Thai language version and the English language version. Data were obtained through an online questionnaire survey of responses from both Thais and expatriates (non-Thai nationalities include visitors, foreigners, and immigrants who are permanent employees) who were living in Thailand from 3 January 2020 (the date Thailand started on case detection) through 5 May 2023 (the last day that the WHO announced the end of PHEIC).[56,57] Being resident in Thailand between these two dates for at least 6 months for the entire period was an essential criterion for respondents. The questionnaire was only administered to participants who agreed on a voluntary basis (following an informed consent procedure). A respondent can only fill out the questionnaire one time (one person, one response). This study did not offer any remuneration or reward for respondents.

The questionnaire was distributed online through social media platforms (Line and Facebook). The questionnaire was administered utilizing both convenience sampling and snowball sampling as the predominant methods for establishing sampling. Respondents were recruited via social media platforms (which included both current personal and group contacts and allowed them to invite others in their network to also complete; as well as being open to the general public—anyone who had the link to the questionnaire was welcome to complete it, so long as they met the criteria). Five or ten times per estimated parameter are considered for the sample size of this study.[58,59] Consequently, this study processed data from 1025 valid responses and was thus adequate enough to represent the Thai population (>400).[60] The Cronbach's α values of three primary latent variables of DD, PHSL, and RC are 0.848, 0.958, and 0.952, respectively, which were more than 0.70, indicating reliability.[55]

Statistical analysis

To evaluate the model, this study used exploratory factor analysis (EFA), confirmatory factor analysis (CFA), and structural equation modeling (SEM), which employed a statistical tool of IBM SPSS 23 and AMOS 23.

EFA is used to collect factors with similar meanings within the same group to find the underlying correlations between observable variables.[61] In this study, EFA is also used to explore the new dimensions. EFA consists of four steps: (1) factor extraction, (2) factor rotation, (3) factor scoring, and (4) name creation.[62] Linear combinations were created using principal component analysis (PCA).[63] The varimax rotation approach is an orthogonal rotation technique that can be used to simplify factors.[62]

The factor loading was then utilized to confirm the CFA methodology, with indicated values larger than 0.5.[64] CFA was employed to confirm the structures of three primary latent variables. The reliability was assessed using Cronbach's α values larger than 0.7 and the composite reliability (CR) values greater than 0.6.[55,64] The convergent validity was confirmed by an average variance extracted (AVE) of equal to or more than 0.5.[64] Discriminant validity was established when the measurement model contains no redundant items and is distinctly separate from other constructs.[65,66]

Finally, SEM is a multivariate technique for assessing causal relationships that includes regression and factor analysis to evaluate both observable and unobserved variables.[67] To assess whether the developed model fits the empirical data, the suggested thresholds were used to estimate the developed model: the relative chi-squared index (CMIN/DF or $\chi^2/df < 3.00$),[68] comparative fit index (CFI > 0.90),[69] goodness of fit index (GFI > 0.90),[70] normed fit index (NFI $\geq$ 0.90),[65] Tucker–Lewis index (TLI > 0.90),[69] root mean square of approximation (RMSEA < 0.08),[71] and root of mean square residual (RMR < 0.05).[70] Discussion of these indices can be found in Hair et al.[72]

Hypotheses development

A review of the literature was used to determine the conceptual model that was utilized for this study. The conclusions reached are depicted in Figure 1. Four hypotheses make up this investigation: hypotheses 1 (H1), 2 (H2), 3 (H3), and 4 (H4). The following diagram's categories are explained in the sections below:

H1: Digital devices have a positive effect on resilient cities.

The government relies on digital devices to effectively communicate and disseminate information related to public health surveillance to the public. This, in turn, improves city resilience. As a result, the public becomes more aware of diseases and infections, how to prevent, and how to control them. In the end, this strengthens the public's ability to withstand the worst effects of the PHE, such as lockdown, economic collapse, social disintegration, and institutional failure.[73–75] This hypothesis can be represented as H1+.

H2: Digital devices have a positive effect on public health surveillance.

When it comes to data collection, analysis, and dissemination, digital devices are of a huge help to public health surveillance. This helps to improve strategic planning and decision-making throughout the PHE, which in turn improves public health surveillance performance. By using digital devices for public health surveillance, the public and the government may keep an eye on people's health, spot illness trends and outbreaks, and provide information for relevant public health policies and actions.[26,76,77] This hypothesis can be represented as H2+.

H3: Public health surveillance has a positive effect on resilient cities.

The effectiveness of the government's public health surveillance program is directly correlated with the cities' ability to withstand the negative impacts of the pandemic. For the restoration of normalcy during the PHE, the government's initiatives in public health surveillance—which include disease monitoring, personal health information collection, epidemiological assessment, personal protective measures, vaccine distribution, and health care readiness assessment—are essential. Damages from the PHE include social distancing, company closures, limitations on day-to-day activities, and economic downturns. The rate at which compromised city services recover is positively correlated with the effectiveness of public health surveillance.[10,78] This hypothesis can be represented as H3+.

H4: Digital devices have a positive indirect effect on resilient cities through public health surveillance.

Fighting the negative consequences of the PHE, which is a result of efficient public health surveillance, requires responsible digital device use. The more successfully a city monitors its public health, the more resilient it is and

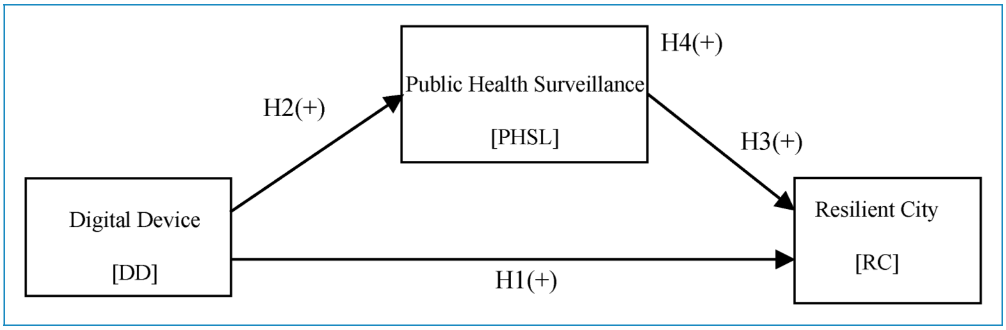

Figure 1. Proposed conceptual model for this study.

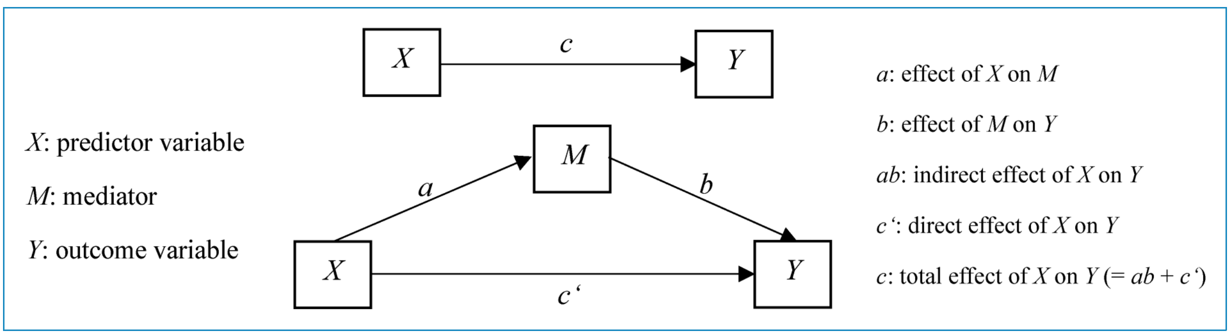

Figure 2. Simple mediation model (based on Demming et al.[81]).

the faster it returns to normal during a pandemic. The government employs digital devices as essential tools for data collection, analysis, and dissemination connected to public health monitoring. This helps with the development and execution of suitable policy and strategy plans that counteract the negative impacts of potential PHE in the future. In the meantime, the public can use these same digital devices to access crucial data connected to public health surveillance and become informed about the current state of affairs during the PHE. Therefore, for a city to be resilient during and resume normalcy after, citizen participation as well as government action are essential. Furthermore, the more effective the government's public health surveillance program is, the faster the rate of recovery of degraded city operations. This program includes disease monitoring, personal health information gathering, epidemiological assessment, personal protective measures, vaccination distribution, and health care readiness assessment.[42,79,80] This hypothesis can be represented as H4+.

To measure H4, the PHSL is the mediator between DD and RC or not, this question is addressed by estimating the indirect effect through the mediator M, following the simple mediation model shown in Figure 2.[81] If the indirect effect ab is statistically significant, some form of mediation occurs.[82] According to Zhao et al., the mediation is divided into full mediation or partial mediation: (1) if the direct effect is not significant is full mediation and (2) if the direct effect is significant is partial mediation (if indirect effect and direct effect have opposing sings, it is competitive partial mediation, but if it is not opposing signs, it is complementary partial mediation).

Results

General characteristics of subjects

Table 2 shows the demographic characteristics of the respondents. A total of 1025 valid respondents were reported. The majority are Thais 98.54%, with most from central Thailand 23.90%. The respondents were 50.24% female and 49.76% male. Most age were 43–58 years old with 43.41%, and married 62.73%. The majority held a bachelor's degree (42.73%). The most occupations are company employees at 32.59%, followed by civil servants at 25.95%. The majority of income is 15,001–30,000 baht with 36.68%. In total, 46.93% of the respondents had been infected at least one time, 31.51% two times, 13.17% never infected, 5.95% three times, and 2.44% more than three times.

Characteristic of study variables

Exploratory factor analysis. EFA was employed to group similar variables and assign appropriate names to the newly formed groups for representation. The Kaiser–

Table 2. Sociodemographic characteristics of the respondents in Thailand ($n = 1025$).

Characteristics	Category	*n*	%
Nationality	Thais	1010	98.54
	Foreigners	15	1.46
Gender	Male	510	49.76
	Female	515	50.24
Age	14–22	130	12.68
	23–42	349	34.05
	43–58	445	43.41
	59–77	101	9.85
Marital Status	Single	363	35.41
	Married	643	62.73
	Divorced	19	1.85
Education	Primary School	1	0.10
	Junior High School	9	0.88
	High School	88	8.59
	Diploma	96	9.37
	Bachelor's Degree	438	42.73
	Master's Degree	301	29.37
	Doctor Degree	92	8.98
Occupation	Student	158	15.42
	Self-owned business/ freelance	253	24.68
	Company employee	334	32.59
	Civil servant	266	25.95
	Housewife/housemen	10	0.98
	Other	4	0.39
Monthly income (baht)	Less than 5000	112	10.93
	5000–15,000	137	13.37
	15,001–30,000	376	36.68
	30,001–50,000	240	23.42
	50,001– 85,000	114	11.12
	More than 85,001	46	4.49
Region	North	182	17.76
	Central	245	23.90
	Northeastern	164	16.00
	East	150	14.63
	West	124	12.10
	South	160	15.61
Infected	More than 3 times	25	2.44
	3 times	61	5.95
	2 times	323	31.51
	1 time	481	46.93
	Never	135	13.17

Meyer–Olkin (KMO) measure of sampling adequacy was employed to assess the suitability of the data for factor analysis. Bartlett's test of sphericity was used to clarify correlation adequacy between the items. According to Table 3, the results of KMO of DD, PHSL, and RC are 0.806, 0.954, and 0.940, respectively, calculated based on the correlation between the variables with values closer to 1 suggesting the variables are correlated. The data are satisfactory for factor analysis, significant at 81, 95, and 94% of the data gathered.[89] Bartlett's test of sphericity of DD, PHSL, and RC is highly significant by the *p*-value of 0.000 (p-value <0.05), degree of freedom (*df*) of 6, 435, and 120, respectively, and χ^2 of 1756.651, 23,693.175, and 13,898.734, respectively, which is suggested that the matrixes are correlation, not identity matrixes.[90] Therefore, EFA is appropriate.

The factor grouping is based on varimax rotation, each variable weighs heavily on only one of the factors, and the factor loading on each factor exceeds 0.5, those with a value of less than 0.50 were removed to enhance the model fit.[30,91] The remaining items were retained from EFA results (factor loading >0.5). The items were gathered into new groups and renamed, some remained in the previous group. First, the result of PCA of DD was shown of one component with eigenvalues exceeding 1, as 69.092% of

Table 3. KMO and Bartlett's test result.

Digital device (DD)		
Kaiser-Meyer-Olkin measure of sampling adequacy		0.806
Bartlett's test sphericity	Approx. χ^2	1756.651
	df	6
	Sig.	0.000
Public health surveillance (PHSL)		
Kaiser-Meyer-Olkin measure of sampling adequacy		0.954
Bartlett's test sphericity	Approx. χ^2	23,693.175
	df	435
	Sig.	0.000
Resilient city (RC)		
Kaiser-Meyer-Olkin measure of sampling adequacy		0.940
Bartlett's test sphericity	Approx. χ^2	13,898.734
	df	120
	Sig.	0.000

KMO, Kaiser-Meyer-Olkin.

variance which can explain the data 69.092% as shown in Table 4, consistent with the scree plot that shows the eigenvalue of the component (Figure 3). The scree plot's inspection shows that this analysis can extract one component (Table A in the Appendix). The questions have a factor loading greater than 0.5 (factor loading >0.5), which indicates that these four variables (DD1, DD2, DD3, and DD4) can clearly explain the factor of DD. Second, the result of PCA of PHSL was shown of five components with eigenvalues exceeding 1, as 15.859, 14.526, 14.416, 13.686, and 10.657% of the variance, respectively, which can explain the data (69.145%). The scree plot's inspection shows that this analysis can extract five components (Table B in the Appendix). The five components are named: (1) medical and vaccine surveillance (MVS); (2) health care surveillance (HS); (3) individual surveillance (IS); (4) epidemiological surveillance (ES); and (5) disease surveillance (DS). A question was removed as the factor loading is less than 0.5 (Table C in the Appendix). The remaining questions have a factor loading greater than 0.5 (factor loading >0.5), which indicates that the indicators can explain the factor of PHSL. Third, the PCA of RC was shown of three components with eigenvalues exceeding 1, as 27.984, 23.777, and 21.838% of the variance, respectively, which can explain the data (73.599%). The scree plot's inspection shows that this analysis can extract three components. The three components named: (1) institutional resilience (IR); (2) socioeconomic resilience (SR); and (3) living resilience (LR), as shown in Table D of the Appendix. All question has a factor loading greater than 0.5 (factor loading >0.5) which means the indicators can explain the factors of RC.

Confirmatory factor analysis. Table 5 displays reliability measurements. The Cronbach's α and CR values of all latent variables are from 0.824 to 0.940, and from 0.841 to 0.924, respectively, which are more than 0.7 and 0.6, respectively, indicating satisfactory reliability.[64] The AVE indicates that all latent variables are from 0.500 to 0.707, which met the required value of AVE $\geq$ 0.50, indicating acceptable convergent validity.[67] In addition, discriminant validity is established when the measurement model contains no redundant items and is distinctly separate from other constructs (Figures 4–6).[65,66]

The CFA method was used to determine how the items considered in four indicators consigned to DD, how the items considered in five dimensions consigned to PHSL as a multidimensional variable, and how the items considered in three dimensions consigned to RC as a multidimensional variable. Figures 4–6 illustrate the result obtained including the modification indices proposed by AMOS 23. According to the trajectories of the items with the corresponding factors, it is determined that all items have factor weights greater than 0.50. First, DD, the suggested thresholds for the overall adjustment indicates adequate indices, which met all the necessary criteria: the X^2/df = 2.772, CFI = 0.999, GFI = 0.999, NFI = 0.998, TLI = 0.994, RMSEA = 0.042, and RMR = 0.004. The latent variable DD included four observed variables which can be the indicators of DD: smartphones (DD1), desktop computers (DD2), laptops (DD3), and modern smart TVs (DD4). The Cronbach's α and CR values are 0.848, and 0.846, respectively. The AVE value is 0.582. The factor loading of the observed variables range between 0.689 and 0.896. R^2 are from 0.475 to 0.802. Thus, it is appropriate for SEM. Second, PHSL, the suggested thresholds for the overall adjustment indicates adequate indices, which met all the necessary criteria: the X^2/df = 2.138, CFI = 0.988, GFI = 0.967, NFI = 0.978, TLI = 0.980, RMSEA = 0.033, and RMR = 0.024. The latent variable PHSL included 29 observed variables divided into five dimensions: (1) MVS; (2) HS; (3) IS; (4) ES; and (5) DS. Dimension MSV contains 10 items or indicators: PHSL6, PHSL7, PHSL8, PHSL9, PHSL10, PHSL21, PHSL22,

Table 4. Total variance explained of the factors of DD, PHSL, and RC.

		Initial eigenvalues			Extraction sums of squared loadings			Rotation sums of squared loading		
Variables	Component	Total	% of variance	Cumulative %	Total	% of variance	Cumulative %	Total	% of variance	Cumulative %
DD	1	2.764	69.092	69.092	2.764	69.092	69.092	2.764	69.092	69.092
PHSL	1	13.842	46.140	46.140	13.842	46.140	46.140	4.758	15.859	15.859
	2	2.254	7.514	53.654	2.254	7.514	53.654	4.358	14.526	30.385
	3	1.737	5.790	59.444	1.737	5.790	59.444	4.325	14.416	44.802
	4	1.595	5.316	64.760	1.595	5.316	64.760	4.106	13.686	58.488
	5	1.316	4.385	69.145	1.316	4.385	69.145	3.197	10.657	69.145
RC	1	9.335	58.343	58.343	9.335	58.343	58.343	4.477	27.984	27.984
	2	1.433	8.959	67.303	1.433	8.959	67.303	3.804	23.777	51.761
	3	1.007	6.296	73.599	1.007	6.296	73.599	3.494	21.838	73.599

Note. DD, digital device; RC, resilient city; PHSL, public health surveillance.

PHSL23, PHSL24, and PHSL25. Dimension HS contains five items or indicators: PHSL26, PHSL27, PHSL28, PHSL29, and PHSL30. Dimension IS contains five items or indicators: PHSL16, PHSL17, PHSL18, PHSL19, and PHSL20. Dimension ES contains five items or indicators: PHSL11, PHSL12, PHSL13, PHSL14, and PHSL15. Dimension DS contains four items or indicators: PHAL2, PHSL3, PHSL4, and PHSL5. The Cronbach's α and CR values are from 0.824 to 0.940, and from 0.891 to 0.924, respectively. The AVE values are from 0.500 to 0.707. The factor loading of the observed variables ranged between 0.608 and 0.972. R^2 are from 0.370 to 0.945. Thus, it is appropriate for SEM. Third, RC, the suggested thresholds for the overall adjustment indicates adequate indices, which met all the necessary criteria: the $X^2/df = 2.205$, CFI = 0.992, GFI = 0.977, NFI = 0.985, TLI = 0.986, RMSEA = 0.038, and RMR = 0.016. The latent variable RC included 16 observed variables divided into three dimensions: (1) IR; (2) SR; and (3) LR. Dimension IR contains six items or indicators: RC1, RC2, RC5, RC6, RC7, and RC8. Dimension SR contains five items or indicators: RC11, RC13, RC14, RC15, and RC16. Dimension LR contains five items or indicators: RC3, RC4, RC9, RC10, and RC12. The Cronbach's α and CR values are from 0.906 to 0.917, and from 0.841 to 0.907, respectively. The AVE values are from 0.516 to 0.620. The factor loading of observed variables ranges between 0.636 and 0.867. R^2 is from 0.405 to 0.752. Thus, it is appropriate for SEM (Table 5).

Structural equation modeling. All structural models were evaluated with the mathematical sign positive (+) or negative (−). Path coefficients are used to observe the relationship between latent variables (DD is an exogenous variable that is not influenced by other variables in the model, and PHSL and RC are endogenous variables that are caused by other variables in the model) to examine the hypotheses.[92] The *p*-values indicated that all path coefficients were significant (Tables 6–8). The results confirmed all hypotheses (H1, H2, H3, and H4). Path coefficients below 0.30 are considered low, between 0.3 and 0.6 are moderate, and more than 0.60 are considered strong.[93] DD had a low positive effect on RC with a significant path coefficient of 0.13 (confirmed H1), and had a strong positive effect on PHSL with a significant path coefficient of 0.73 (confirmed H2). PHSL had a strong positive effect on RC with a significant path coefficient of 0.79 (confirmed H3). DD had a moderate positive indirect effect (positive impact) on RC through PHSL with a significant path coefficient of 0.582 (confirmed H4). The model for testing the impact of digital device utilization on public health surveillance to enhance city resilience during the

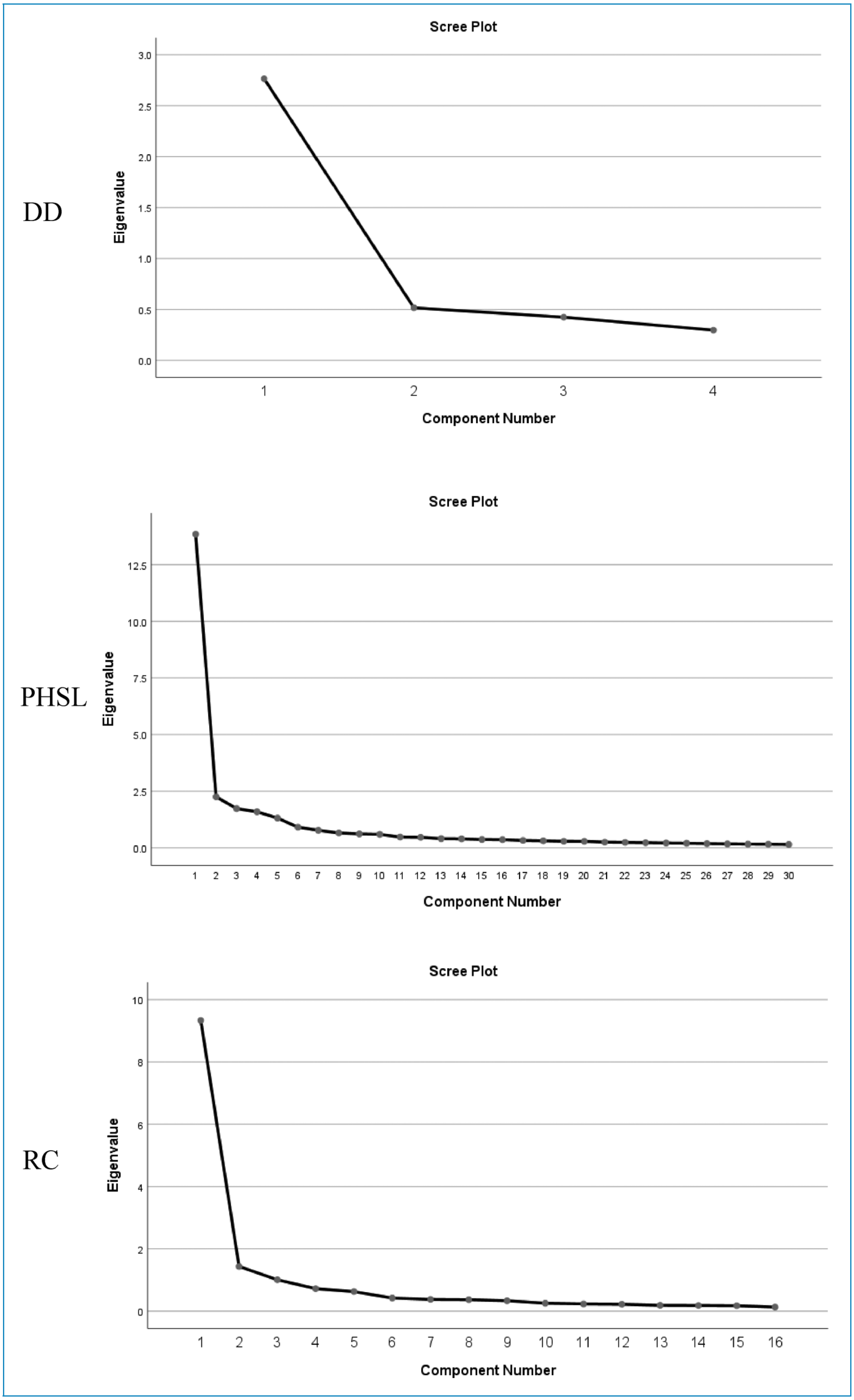

Figure 3. Scree plot of loading of the factors of digital device (DD), public health surveillance (PHSL), and resilient city (RC).

Table 5. Measurement reliabilities.

Variables	AVE	CR	Cronbach's α	Factor loading				
				Coefficient	SE	*t*	Standard coefficient	R^2
DD1	0.582	0.846	0.848	0.887	0.041	21.393	0.740	0.548
DD2				0.930	0.047	19.953	0.689	0.475
DD3				1.214	0.052	23.249	0.896	0.802
DD4				1.000	–	–	0.710	0.505
CMIN/*df* = 2.772, CFI = 0.999, GFI = 0.999, NFI = 0.998, TLI = 0.994, RMSEA = 0.042, RMR = 0.004								
PHSL6	0.500	0.891	0.907	0.961	0.038	25.281	0.718	0.516
PHSL7				0.870	0.039	22.275	0.659	0.435
PHSL8				0.827	0.033	24.705	0.671	0.450
PHSL9				0.861	0.043	20.223	0.608	0.370
PHSL10				0.861	0.041	21.180	0.616	0.380
PHSL21				0.705	0.025	27.677	0.625	0.390
PHSL22				0.700	0.056	19.940	0.664	0.441
PHSL23				0.900	0.061	19.198	0.715	0.511
PHSL24				1.000	0.060	18.252	0.719	0.517
PHSL25				0.900	–	–	0.707	0.500
PHSL16	0.693	0.918	0.928	0.813	0.023	35.358	0.856	0.733
PHSL17				0.762	0.024	31.194	0.783	0.614
PHSL18				0.677	0.024	27.721	0.714	0.510
PHSL19				1.000	–	–	0.931	0.866
PHSL20				0.858	0.023	37.138	0.863	0.744
PHSL26	0.643	0.899	0.940	1.130	0.038	29.999	0.960	0.921
PHSL27				0.997	0.027	37.237	0.869	0.754
PHSL28				1.048	0.026	40.921	0.921	0.848
PHSL29				1.000	–	–	0.865	0.748
PHSL30				0.987	0.022	44.218	0.849	0.721
PHSL11	0.707	0.924	0.915	0.780	0.030	26.303	0.827	0.684

(continued)

Table 5. Continued.

				Factor loading				
Variables	AVE	CR	Cronbach's α	Coefficient	SE	t	Standard coefficient	R^2
PHSL12				0.911	0.030	29.942	0.868	0.753
PHSL13				0.874	0.029	30.633	0.850	0.722
PHSL14				1.000	–	–	0.834	0.696
PHSL15				0.875	0.030	29.093	0.825	0.680
PHSL2	0.691	0.899	0.824	0.805	0.049	16.339	0.790	0.624
PHSL3				0.784	0.047	16.844	0.801	0.641
PHSL4				0.731	0.044	16.605	0.745	0.555
PHSL5				1.000	–	–	0.972	0.945
CMIN/df = 2.138, CFI = 0.988, GFI = 0.967, NFI = 0.978, TLI = 0.980, RMSEA = 0.033, RMR = 0.024								
RC1	0.620	0.907	0.917	1.000	–	–	0.688	0.473
RC2				1.161	0.082	14.213	0.730	0.533
RC5				1.454	0.097	15.037	0.867	0.752
RC6				1.501	0.100	14.957	0.818	0.670
RC7				1.512	0.105	14.459	0.822	0.676
RC8				1.400	0.099	14.207	0.787	0.619
RC11	0.562	0.864	0.907	1.000	–	–	0.636	0.405
RC13				1.428	0.076	18.802	0.814	0.663
RC14				1.463	0.077	19.106	0.725	0.526
RC15				1.192	0.069	17.245	0.728	0.529
RC16				1.443	0.075	19.310	0.829	0.688
RC3	0.516	0.841	0.906	1.000	–	–	0.677	0.458
RC4				0.982	0.040	24.484	0.668	0.447
RC9				1.370	0.079	17.351	0.769	0.591
RC10				1.354	0.076	17.703	0.795	0.632
RC12				1.396	0.079	17.681	0.672	0.452
CMIN/df = 2.205, CFI = 0.992, GFI = 0.977, NFI = 0.985, TLI = 0.986, RMSEA = 0.038, RMR = 0.016								

Note. DD, digital device; RC, resilient city; PHSL, public health surveillance, AVE, average variance extracted; CR, composite reliability; SE, standard error; CMIN, the ratio of the minimum discrepancy; df, degree of freedom; CFI, comparative fit index; GFI, goodness of fit index; NFI, normed fit index; TLI, Tucker–Lewis index; RMSEA, root mean square of approximation; RMR, root of mean square residual.

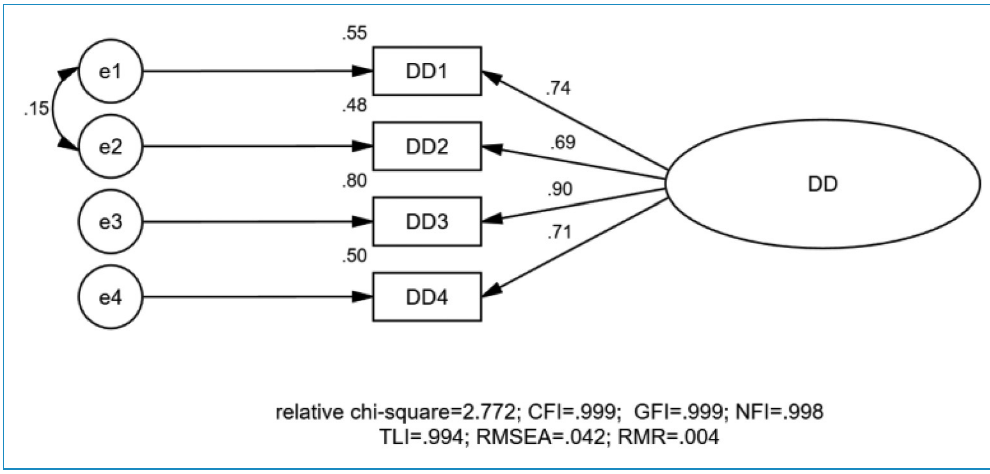

Figure 4. CFA of digital device (DD) factors after model modification.

PHE response: a case study of SARS-CoV-2 response in Thailand (2020–2023) passed all the required tests: $X^2/df = 2.802$, $CFI = 0.953$, $GFI = 0.901$, $NFI = 0.935$, $TLI = 0.935$, $RMSEA = 0.048$, and $RMR = 0.043$. Thus, the modification model is considered acceptable and overwhelmingly fits the empirical data.

Discussion

This study evaluated a conceptual model of the impact of digital device utilization on public health surveillance to enhance city resilience during the PHE response: a case study of SARS-CoV-2 response in Thailand (2020–2023) by using EFA, CFA, and SEM. The data were collected from both Thai and non-Thai participants. The number of non-Thai participants is lower than that of the Thai participants. The hypothesis analysis showed that all four hypotheses were confirmed. During the PHE (SARS-CoV-2 response) in Thailand, the Thai government placed strict control measures in crisis events and placed easing control measures in other events. This study focused on and analyzed the data for the period the government used the easing control measure. To deal with the PHE that may arise in the future, the government can verify the role of digital devices in public health surveillance to bring the situation and the functions of the cities back to normal.

Analyzing the components that impact the digital device. The results from the EFA method showed four components influencing the performance of digital devices (69.092% of total variance), which contain four items or indicators: smartphones, desktop computers, laptops, and modern smart TVs. It indicates that the use of digital devices can be measured from these four items or indicators. The data showed that these four types of digital devices play a positive role in influencing resilient cities in disseminating data or information on public health surveillance and influencing public health surveillance in collecting, analyzing, and disseminating data or information on public health surveillance.

Analyzing the dimensions that impact the public health surveillance. The results from the EFA method showed five dimensions influencing the performance of public health surveillance. The first dimension is MVS (15.859% of total variance), which contains 10 items or indicators: general information and health information, infection test results, vaccination history/vaccine passport (recording the name of vaccines that vaccinated and the number of doses), assessment of current symptoms, mental health assessment, vaccine type information, dates of vaccination, vaccine reaction (normal/side effects), vaccine production source, and immunization level in the community/the report of national updates on vaccinated population figures.[13,20,22,84] It indicates that MVS can be measured from these 10 items or indicators. The data showed that personal, health, and vaccination information needs to be collected. Also, the assessment of physical symptoms or mental health is required periodically. The second dimension is HS (14.526% of total variance) and contains five items or indicators: reporting the availability or lack of patient beds, medical equipment, medical personnel, vaccines, and medicine.[4] It showed that HS can be measured from these five items or indicators. The data or information about the availability or lack of these items is important for the health care system. If the data show there is a shortage of some items, it is beneficial to find or prepare enough and in time. The third dimension is IS (14.416% of total variance), which comprises five items or indicators: wearing a mask, 1–2 m distancing, hand washing, regular cleaning areas, and avoiding crowded areas.[18] It indicates that IS can be measured from these five items or indicators. These five personal protection measures are the measures that need the cooperation from individual level to reduce the spread of illnesses. The public is required to adjust their behavior

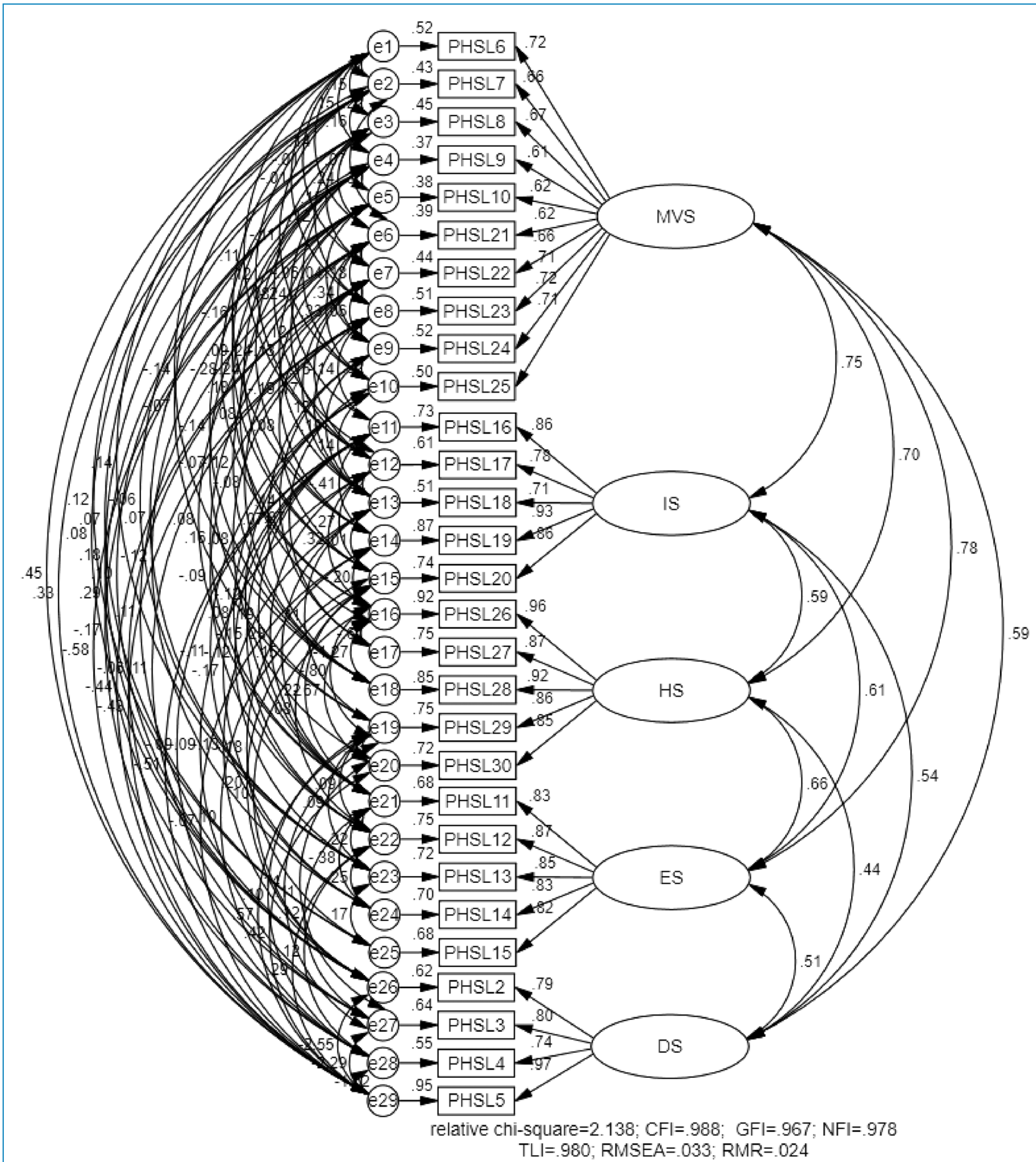

Figure 5. CFA of public health surveillance (PHSL) factors after model modification.

to avoid the infection. The fourth dimension is ES (13.686% of total variance), which contains five items or indicators: check-in and check-out facilities during services, overcrowding info about the intended place to visit, tracking info of infected individuals at the place where visited, notification via SMS or phone call about the presence of infected individual(s) at the place where visited, and available to assess whether stores or places where visited follow the prevention and control measures or not.[15,17] This showed that ES can be measured from these five items or indicators. Digital devices help to find new cases, and the cause of outbreaks, track people, show the density of people in the store or any place, check-in and check-out, contact people, and do a questionnaire to assess whether a place is following the measures. The data or information about public health surveillance that the public and the government share or exchange through digital devices promote disease prevention and control.

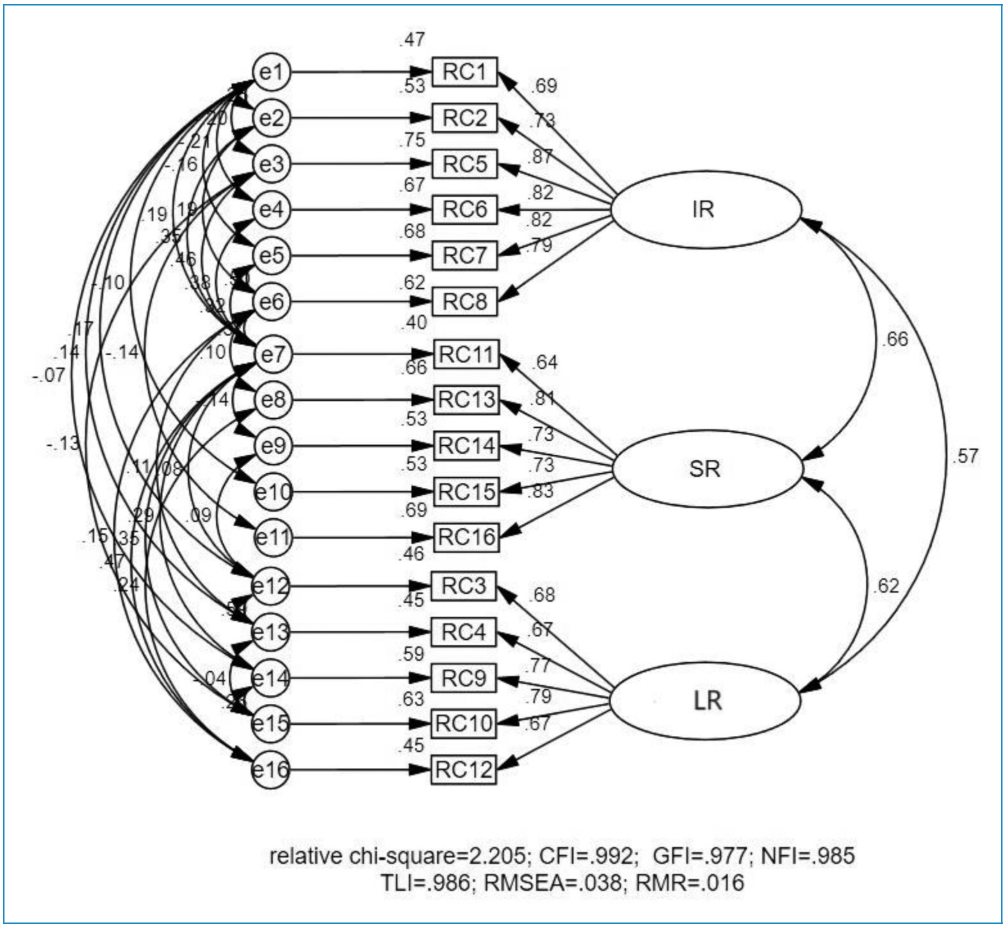

Figure 6. CFA of resilient city (RC) factors after model modification.

Table 6. Path's coefficient and their significance.

Hypotheses	Paths	Standard path coefficient	*p*-value	Status
H1(+)	DD → RC	0.131	***	Confirmed
H2(+)	DD → PHSL	0.734	***	Confirmed
H3(+)	PHSL → RC	0.793	***	Confirmed

Note. DD, digital device; PHSL, public health surveillance; RC, resilient city.
***$p < 0.001$.

The fifth dimension is DS (10.657% total variance), which holds four items or indicators: virus variants, symptoms of each virus variant infection, characteristics/spreading rate of each virus variant infection, and risk and safe areas.[11,12,83] It showed that DS can be measured from these four items or indicators. The generation of information about the disease including virus variants, symptoms of each virus variant, characteristics/spreading rate of each virus variant, and risk and safe areas are the information to let the public understand the level of danger, know the basic information, which they can avoid the danger of the infection.

Analyzing the dimensions that impact resilient cities. The results from the EFA method show three dimensions that are influencing city resilience. The first dimension is 'IR' (27.984% of the total variance). This dimension looks at a total of six items or indicators: the capability to work or study online; the availability of public transport; the ability of the organization to function normally; the organization's coordinating ability; the government's ability to continuously respond to an emergency; and the government agency's coordination toward responding to an emergency. IR can be measured using these six items or indicators. By looking at IR we can assess how organizations can keep working, even when faced with issues of emergencies.[87,94] The second dimension to be examined is SR (23.777% of total variance). This dimension looks at five items or indicators: cooperation in following prevention and control measures; the capability to communicate and participate in social activities through online (seminars,

Table 7. Results of the causal influence of the structural equation modeling.

Dependent variables	R^2	Influence	Independent variables: DD	PHSL
PHSL	0.507	Direct effect	0.734***	–
		Indirect effect	–	–
		Total effect	0.734***	–
RC	0.793	Direct effect	0.131***	0.793***
		Indirect effect	0.582***	–
		Total effect	0.713***	0.793***

Note. DD, digital device; PHSL, public health surveillance; RC, resilient city. The sign – means there is no parameter of the hypotheses.
***$p < 0.001$.

Table 8. Result of mediating variable measurement.

Model	Standard coefficient
Direct effect	
DD → RC (c)	0.713***
Indirect effect with a mediator	
DD → PHSL (a)	0.734***
PHSL → RC (b)	0.793***
DD → RC (c′)	0.131***
Indirect effect (a × b)	0.582***

Note. DD, digital device; PHSL, public health surveillance; RC, resilient city.
***$p < 0.001$.

meetings, and other activities); self-protection information sharing; the capability to access learning resources online; and the capability to keep the financial status. This dimension showed that people can do social and economic activities during an emergency.[95,96] The third dimension is 'LR' (21.838% of total variance). It comprises five items or indicators: the capability to access internet services; the capability to supply water, electricity, gas, and fuel; the capability to buy or sell products or services online; the capability to conduct normal financial transactions; and the capability to access basic needs: food, drinking water, clothing, medicine, and housing. This dimension showcases that people can perform their daily activities even while facing difficult events.[97–99]

With the structural model, the regression path estimate was established based on the correlation coefficients among DD, PHSL, and RC. Objective 1 to examine the impact of digital devices on public health surveillance is answered by the result of H2. Objective 2 to examine the impact of public health surveillance on resilient cities is answered by the result of H3. Objective 3 to examine the impact of digital devices on resilient cities is answered by the result of H1 and H4. First, it must be noted that DD has a strong positive direct effect on PHSL, with a significant path coefficient of 0.73 ($\beta = 0.73$, $p < 0.001$), thus confirming H2. Kichloo et al., Yabe et al., and Haldane et al. discovered that digital devices are useful tools for data collection, analysis, and dissemination in public health surveillance. This improves decision-making and strategic planning.[26,76,77] The results of these studies are in line with this finding. The findings of this research demonstrate how digital devices support public health surveillance by facilitating the collection, analysis, and dissemination of data on population health, disease trends, and outbreaks during the PHE. Such data like this can then be used for strategic planning, policy development, and effective decision-making during subsequent pandemics. People can use their digital devices to get data or information on public health surveillance, which increases public participation in these activities as well as government participation. The efficiency of PHE response is greatly enhanced by the joint efforts of the public and government in public health surveillance. The data or information that influence public health surveillance performance cover five dimensions. These are inclusive of MVS (0.94), followed by IS (0.81), HS (0.76), ES (0.73), and DS (0.71), respectively (Table 9). The public can access the data or information, and the activities related to public health surveillance through digital devices including laptops, smartphones, desktop computers, and modern smart TVs. Second, PHSL has a strong positive direct effect on RC, as indicated by a significant path coefficient of 0.79 ($\beta = 0.79$, $p < 0.001$), thus confirming H3. Consistent with the conclusions of Stoto et al. and Capolongo et al., public health surveillance plays a crucial role in assessing response capacity in the event of a PHE and positively influences the restoration of normalcy during PHEs.[10,78] The findings of this research demonstrate a direct correlation between the ability of communities to tolerate the negative consequences of the pandemic and the success of public health surveillance programs implemented by the government. The restoration of normalcy depends on government efforts in public health surveillance, which include disease monitoring, gathering personal health information, epidemiological analysis, putting personal protective measures into place, distributing vaccines, and evaluating

Table 9. Validity measurement and factor loading of latent variables.

Latent variables	Observed variables	Coefficient	SE	t	Standard coefficient	R^2
DD	DD1	1.000	–	–	0.760***	0.578
	DD2	1.085	0.046	23.775	0.729***	0.531
	DD3	1.291	0.046	28.005	0.861***	0.742
	DD4	1.112	0.048	23.079	0.706***	0.498
PHSL	MVS	1.117	0.047	1.117	0.936***	0.877
	IS	0.807	0.038	0.807	0.813***	0.662
	HS	1.299	0.061	1.299	0.757***	0.573
	ES	1.132	0.060	18.946	0.727***	0.529
	DS	1.000	–	–	0.714***	0.510
RC	IR	1.000	–	–	0.874***	0.763
	SR	0.882	0.034	25.596	0.891***	0.794
	LR	0.895	0.036	24.927	0.870***	0.756

Note. CMIN/df = 2.802, CFI = 0.953, GFI = 0.901, NFI = 0.935, TLI = 0.935, RMSEA = 0.048, RMR = 0.043.
***p < 0.001.

health care readiness.[10] The effectiveness of a city's public health surveillance system is strongly correlated with its ability to withstand the negative effects of pandemics, including heightened social separation, business closures, living restrictions, and economic downturns. Cities can recover from disruptions to their fundamental activities and continue to exist more quickly when public health surveillance is conducted with more efficiency.[10,78] Third, DD has a low positive direct effect on RC, with a path coefficient of 0.13 ($\beta = 0.13$, $p < 0.001$), confirming H1. This finding is consistent with the findings of Kaufmann et al., Wang et al., and Liu et al., who mentioned that digital devices are beneficial for information dissemination and communication, ultimately effectively enhancing city resilience.[73–75] The study's outcome demonstrates that digital devices are beneficial for the government in terms of public health surveillance-related information and data dissemination. Subsequently, the general public has access to these data and information via smartphones, laptops, desktop computers, and modern smart TVs. The public benefits greatly from having access to such information and data since it ensures that the public is aware of the type of sickness or infection, how to prevent it, and how to control it. Consequently, this strengthens the city's ability to withstand the worst consequences of PHE, including lockdowns, recessions, societal collapse, and institutional shortcomings.[23,73] In this study, the usage of digital devices for communication and data sharing related to public health surveillance to improve city resilience during pandemic outbreaks is positively correlated with low rates of return to normalcy. It is imperative to acknowledge that the management of potential PHEs is also contingent upon the government's implementation of efficient public health surveillance and the active involvement of the public in these endeavors.[100] Fourth, DD has a moderate positive indirect effect on RC through PHSL ($\beta = 0.58$, $p < 0.001$), as PHSL serves as a complementary partial mediator between DD and RC, thus confirming H4. To improve city resilience during the PHE, government agencies might use digital devices for a variety of public health surveillance tasks, including data collection, processing, and distribution.[42,79,80] This is consistent with the findings of Aina et al., Sharifi, and Siders and Gerber-Chavez. The study's findings demonstrate that using digital devices to improve public health surveillance can also improve communities' ability to withstand pandemics. To manage the negative consequences of the PHE and get back to a pre-emergency state, effective public health surveillance is essential. The public has access to these data or information through digital devices, which the government uses for data collection, analysis, and dissemination related to public health surveillance. This helps the government develop and carry out appropriate

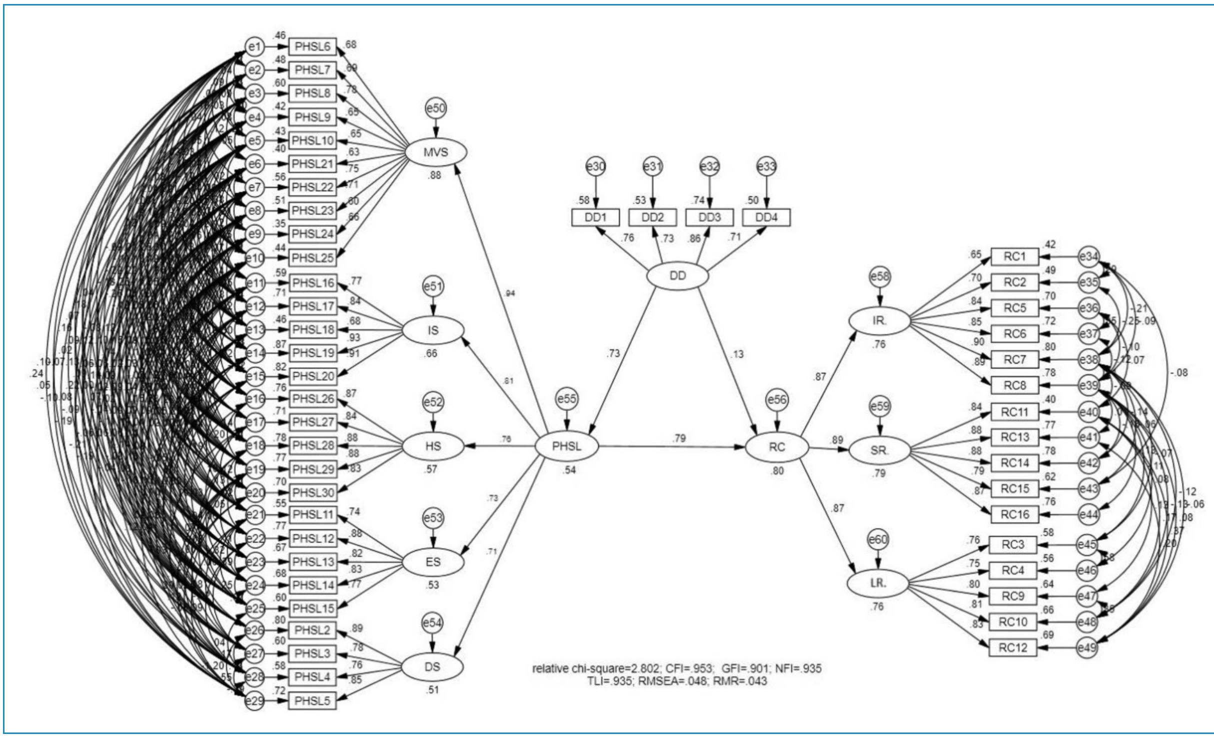

Figure 7. Graphics results of the final structural model.

policies and strategic plans for future PHEs. It is important to acknowledge that public participation greatly improved the government's ability to conduct effective public health surveillance, which means that government-run public health surveillance and proactive community engagement programs are essential for managing PHEs.[42,75]

The modification model used the following testing tools to test the overall model's fitness. The χ^2/df value is 2.082 met the recommended value of <3.0.[68] CFI was 0.953 which is within the recommended threshold of >0.9.[69] The GFI value is 0.901 which is within the acceptable threshold of >0.9.[70] NFI was 0.935 which is within the recommended value of ≥0.9.[65] TLI value is 0.935 which is within the recommended threshold of >0.9.[69] RMSEA value is 0.048 which meets the recommended value of <0.08.[71] Last, the RMR value is 0.043 which met the recommended value of <0.05.[70] Thus, the result of the modification model is considered acceptable and overwhelmingly fits the empirical data (Figure 7).

Conclusion

The model of the impact of digital device utilization on public health surveillance to enhance city resilience during the PHE response: a case study of the SARS-CoV-2 response in Thailand (2020–2023) demonstrates how digital device usage improves city resilience through four hypotheses. In total, 1025 legitimate questionnaire responses from Thai citizens and expatriates (those of non-Thai nationality) who were living in Thailand at the time of the SARS-CoV-2 response were gathered, and data were analyzed using SPSS 23 and AMOS 23. The findings of this study indicate that the five dimensions that comprise the PHSL factors are MVS (10 indicators); IS (five indicators); HS (five indicators); ES (five indicators); and DS (four indicators). Three dimensions make up the RC factors: SR (five indicators), IR (six indicators), and LR (five indicators). The four components of the DD factors are smartphones, desktop computers, laptops, and modern smart TVs. All four hypotheses are confirmed. The structural model's conclusion demonstrates the causal relationship between three primary latent variables. It was verified that the use of digital devices improves public health surveillance in data collection, analysis, and dissemination, which improves city resilience. Because digital device use improves public health surveillance, it also increases city resilience.

In response to the PHE (SARS-CoV-2 response), Thailand emphasized and implemented MVS and IS, followed by HS, ES, and DS, respectively, during the implementation of easing control measures (relaxation periods of the control measures). The public and government exchanged data and information regarding public health surveillance using digital devices including laptops, smartphones, desktop computers, and modern smart TVs, respectively, thus enhancing the performance of the diversely implemented surveillance. The ability of the people to participate in government-recommended or mandated public health surveillance initiatives and to obtain data or information about these initiatives was beneficial, most importantly in the return of normalcy to the well-being of the public. Even in the face of emergencies, institutional collapses, socioeconomic downturns, etc., the city maintained its resilience, and its operations persisted including socioeconomic, institutions, and living dimensions, respectively, until normalcy was completely restored.

This study's contribution is the methodology it offers for assessing the variables that affect public health surveillance and a city's ability to withstand PHEs. This paper theoretically clarifies how the government might use public health surveillance to return an unstable populace during a PHE to normalcy. Translated, public health policymakers can use the 29 elements of public health surveillance as a guide to break the impasse and improve the effectiveness of public health surveillance. In the end, they can use digital devices for data collection, analysis, and dissemination of study findings connected to public health. Guidelines to improve municipal functions during a PHE can also be based on the 16 city resilience characteristics.

Strengths

The statewide survey on the use of digital devices in public health surveillance during the SARS-CoV-2 response (2020–2023), which aims to promote city resilience in Thailand during the pandemic, is this study's strongest point. This study explained how the Thai government used digital devices—laptops, smartphones, desktop computers, and modern smart TVs—to collect, analyze, and disseminate data related to public health surveillance during the SARS-CoV-2 response (2020–2023). This improved public health surveillance—five different dimensions—including medical and vaccine; individual; health care; epidemiological; and disease surveillance. It also improved cities' socioeconomic, institutional, and living resilience.

Limitations and future research

This study has some limitations. First, the data from only 15 non-Thai participants were recorded. Second, the questionnaire was distributed by non-probability sampling (convenience sampling). It can collect data conveniently, relatively faster, and cost less. However, there is another unit of the population that has no chance of being sampled. Thus, the responses received and analyzed may be less diverse in opinions. Third, there was no differentiation made between data or information gathered from citizens in urban and rural areas for public health surveillance. Fourth, this study examines the general function of digital devices in public health surveillance through three lenses: data collection, analysis, and dissemination of data or information related to public health. However, it does not specify the precise function of each of these functions in public health surveillance. Certain digital gadgets are limited to sharing public health-related data or information; they cannot gather and analyze it, and vice versa. Fifth, this study's collected basic information such as age, region, and digital media information was only intended to be used for sociodemographic characterization, which did not use them as the independent or control variables. The results of this study could be impacted by the size of the sample and/or the inclination to utilize digital media, which depends on variables like age, location (rural or urban), etc. Sixth, there are vulnerable groups of people who might not have access to digital devices or who might not be literate enough to use one, which means that they might not be able to access data or information shared by digital devices, as well as, they cannot do or access the questionnaire of this study.

Future studies can examine PHE response in Thailand and other regions or nations from a variety of angles, including disease prevention and control measures and policies, comparisons of vaccines and virus variants, perceptions of health information in rural and urban areas, the role of village health volunteers during the PHE, the role of data management in improving PHE response, and the use of cutting-edge technologies like big data, cloud computing, artificial intelligence, and so forth. Furthermore, it is possible to investigate additional public health monitoring facets, including event-based and active surveillance.[4] In addition, there are numerous additional dimensions and indicators of a resilient city that can be developed and included in further studies.

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Appendix

Table A. Rotated factor matrix of the factors in digital device.

Item	Factor loading
DD1	.834
DD2	.811
DD3	.883
DD4	.794

Note. DD, digital device.

Table B. Rotated factor matrix of the factors in public health surveillance.

	Factor loading				
Item	1	2	3	4	5
PHSL2					.776
PHSL3					.816
PHSL4					.780
PHSL5					.719
PHSL6	.716				
PHSL7	.740				
PHSL8	.729				
PHSL9	.832				
PHSL10	.740				
PHSL11				.718	
PHSL12				.737	
PHSL13				.786	
PHSL14				.723	
PHSL15				.774	
PHSL16			.796		
PHSL17			.801		
PHSL18			.768		
PHSL19			.735		
PHSL20			.789		
PHSL21	.760				
PHSL22	.713				
PHSL23	.771				
PHSL24	.701				
PHSL25	.783				
PHSL26		.707			
PHSL27		.817			
PHSL28		.823			
PHSL29		.810			
PHSL30		.833			

Note. PHSL, public health surveillance.

Table C. Results of cutting the question of public health surveillance.

	Factor Loading				
Item	1	2	3	4	5
PHSL1	.408	.063	.282	.172	.443

Note. PHSL, public health surveillance.

Table D. Rotated factor matrix of the factors in resilient city.

	Factor loading		
Item	1	2	3
RC1	.630		
RC2	.705		
RC3			.816
RC4			.820
RC5	.809		
RC6	.797		
RC7	.804		
RC8	.806		
RC9			.714
RC10			.729
RC11		.521	
RC12			.570
RC13		.773	
RC14		.752	
RC15		.775	
RC16		.790	

Note. RC, resilient city.