

COVID-19 smart surveillance: Examination of Knowledge of Apps and mobile thermometer detectors (MTDs) in a high-risk society

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Abstract

Background: Technological innovations gained momentum and supported COVID-19 intelligence surveillance among high-risk populations globally. We examined technology surveillance using mobile thermometer detectors (MTDs), knowledge of App, and self-efficacy as a means of sensing body temperature as a measure of COVID-19 risk mitigation. In a cross-sectional survey, we explored COVID-19 risk mitigation, mobile temperature detectable by network syndromic surveillance mobility, detachable from clinicians, and laboratory diagnoses to elucidate the magnitude of community monitoring.

Materials and Methods: In a cross-sectional survey, we create in-depth comprehension of risk mitigation, mobile temperature Thermometer detector, and other variables for surveillance and monitoring among 850 university students and health-care workers. An applied structural equation model was adopted for analysis with Amos v.24. We established that mobile usability knowledge of APP could effectively aid in COVID-19 intelligence risk mitigation. Moreover, both self-efficacy and mobile temperature positively strengthened data visualization for public health decision-making.

Results: The algorithms utilize a validated point-of-center test to ascertain the HealthCode scanning system for a positive or negative COVID-19 notification. The MTD is an alternative personal self-testing procedure used to verify temperature rates based on previous SARS-CoV-2 and future mobility digital health. Personal self-care of MTD mobility and knowledge of mHealth apps can specifically manage COVID-19 mitigation in high or low terrestrial areas. We found mobile usability, mobile self-efficacy, and app knowledge were statistically significant to COVID-19 mitigation. Additionally, interaction strengthened the positive relationship between self-efficacy and COVID-19. Data aggregation is entrusted with government database agencies, using natural language processing and machine learning mechanisms to validate and analyze.

Conclusion: The study shows that temperature thermometer detectors, mobile usability, and knowledge of App enhanced COVID-19 risk mitigation in a high or low-risk environment. The standardizing dataset is necessary to ensure privacy and security preservation of data ethics.

Keywords

COVID-19 surveillance, knowledge of app, mobile thermometer detectors (MTD), mobile intelligence, risk mitigation

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Introduction

Thermometer Apps and its knowledge availability is trending as a convenient method of surveillance to detect symptoms of infections to avoid the spread of COVID-19 viruses. Nano-biotechnologies have expressed expertise that, to manage continues and post-COVID-19 infections, a key step is frequent self-testing for tracking, persuasion, and sensitization of the pandemic.¹ Despite the benefits, nucleic acid-based diagnostics are complex, time-consuming, and impractical. We rely too much on tests that take a long time to administer, causing patients to obtain their test findings late. It necessitates sophisticated laboratories and competent people, which limits COVID-19 diagnostic noncompliance. This technology application in smart-mobile intelligence surveillance has become a key step to tracking or self-check the virus, especially towards SARS-COV-2. There is a global concern about managing the spread of COVID-19 pandemic. Many health experts recommended self-care and innovative alternatives to a person's CoV-2 self-testing. Several means of self-testing but not limited to (i) easy to access self-testing thermometer; (ii) a centralized hub to monitor day-to-day temperature mobility of citizens; (iii) personal protective equipment connected to digital health for quantitative detection mechanism; and (iv) in the appropriation of recognizing human body temperature for selective sensing of COVID-19. In this way, transmission has been suppressed, human exposure has been reduced, and community technological actions have been empowered using portable hand devices. Expanding community-based surveillance requires technology to foster two-way communication, developing sensitive and mobile thermometer detectors (MTDs) for public health emergency measures in societies.

The current research is a selective COVID-19 for rapid health surveillance is necessary for rapid case identification with smart technology applications in improving access to bridge inequality technology infrastructure² self-testing is recommended as the best alternative to managing the pandemic. This study provides key insights into mitigation controlling strategic COVID-19, social support improving efficiency, and window closing people's attitudes, perceptions, and behaviors towards technology assisted artificial intelligence-supported the International Health Regulation³ and WHO's calls for surveillance in society. MTD apps surveillance to mitigate COVID-19 has been understudied among industries and scholars. Personalized prevention and treatment can also be achieved by combining artificial intelligence-supported graphene with current MTD approaches, contributing to the population's real-time mobility.¹ The ongoing social scientific efforts toward technology-assisted MTD COVID-19 mitigation apps, as in Figure 1, shows multiple smart-technologies in digital health. Even fully vaccinated persons, still requires continuous self-daily-check, hence, MTD developing strategies for COVID-19 testing at any setting with wireless network. Figure 1 indicated epidemiological mobile surveillance, computer sensors, and AI trackers.

Technologies related to mobile self-efficiency has enabled disease management in health systemic prevention and control transmission in a broader perspective, of which COVID-19 infection is not an exception. The emergence of the COVID-19 public health crisis pushed up the digital revolution in channeling these technologies to smartphones with 75% global subscriptions.⁴ Smart-thermometer apps in health systems in society have been a part of WHO's real-time surveillance of influenza outbreaks among digital health technologies.⁵ This innovativeness follows the trajectory of the emerging 204 billion apps downloaded in 2019,⁶ and as of January 2020, 3.8 billion were internet-based active users. As such, digital technologies were enlisted as a form of COVID-19 infection surveillance among high-risk populations. Although researchers have predicted the potency of smart thermometers to predict and avert epidemics,⁷ the validation and long-term detection are yet to gain prominence in post-COVID-19 public health prevention. With the emerging MTD, self-testing is a critical supervened across individuals' age, education, and geographical settings, and with knowledge of the app, accessibility, and aggregated data, among the global concerns.^{7,8}

Mobile usability literature has raised concerns about the characteristics of mobile user perception and the effective use of smart thermometers in digital health.⁹ This evidence suggests potential mobile self-efficacy can enhance usability to influence smart thermometers designed and projected for COVID-19 contactless detection in support of clinical laboratory diagnoses.¹⁰ Similarly, personal knowledge of the app follows a simple mobile usability process to alert individuals about COVID-19 status.¹¹ The adequacy and capacity to use mobile technology and the knowledge of app become crucial for adopting smart-thermometers (MTD). Indicators like self-efficacy in technology adoption have been vital for learning (Yang, 2020) and support positive health outcomes in care settings.¹² This current study projects that smart-thermometer detector (MTD), self-efficacy, knowledge of app, and mobile usability are vital domains to explore in mitigating COVID-19 infections among high-risk populations and in a complex society.

In combating the COVID-19 outbreak and mitigating the rate of infections, intelligence surveillance and technology assisting people were consequential to achieving global positive health outcomes. The study analyzed MTD-assisted COVID-19 wireless integrated technology, managed collaboratively by health professionals to collect real-time health data based on self-testing. Conceivably, MTD in mHealth apps can real samples collect health records to justify any changes of health concerning control COVID-19 strategic mitigation and claimed projected validation of clinical use along self-tested diagnoses. Improving public health intervention is inured to public attitudes toward technology-driven enforcement for government and future decision-making. The main

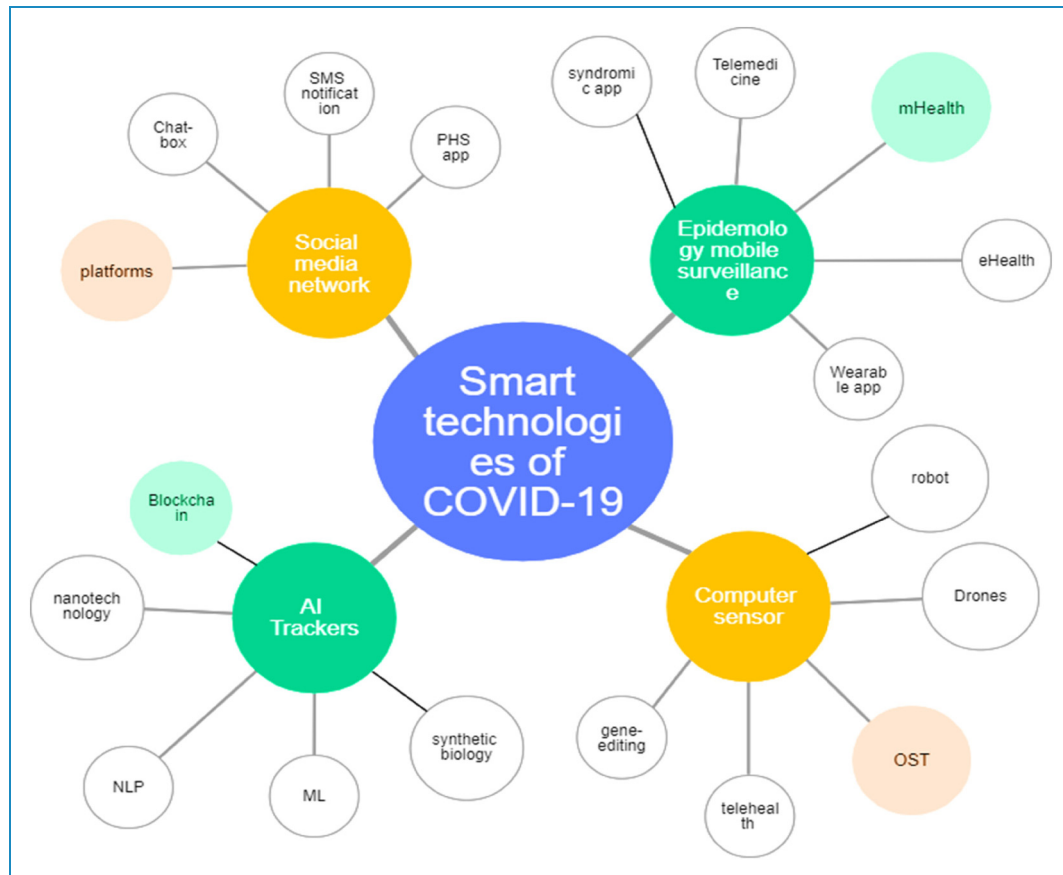


Figure 1. Represents some identified smart technologies classified in this study.

research objective is to extend evidence on how mobile usability enhanced scientific systemic surveillance through smart-thermometer self-check as SARS-Cov-2 pandemic risk mitigation.

Smart thermometer COVID-19 case notification

COVID-19 signs and symptoms notifications, as shown in Figure 2 procedures, is traditionally known as a QR health code system. It is an approach adopted for all public places, including smart cities, especially in communities and institutions. The smart-technology linked people's previous health records to present surveillance of any suspicious signs of fever anomalies. Data aggregated is neither noisy nor public; results of pop-up notifications are kept confidential, and private and laboratory diagnoses authenticate decisions. MTD proposed technology follows COVID-19 scale up by professional health experts to elucidate clinical and laboratory diagnoses under any body symptoms of feverish temperature anomalies, as in Figure 2. Also, an established health system can computerized health scanning of symptomatic short-term and long-term to prevent widespread mass testing of population. The information-sharing support will argue health policymaking through mobile-health digital technology.¹³

Few studies have explored the role of societal actions in improving public health and strategic multiple social requirements. The WHO categorization in Table 1 shows that the community transmission (CT) categorization is divided into four levels, from low incidence (CT1) to very high incidence (CT4).² Using the barometer and altimeter apps, people can self-test and report body temperature and point-of-care-testing (POCT) using smart thermometer experiences with built-in sensors and GPS for monitoring and tracking. COVID-19 adjusting the test procedures with smart technologies, such as smart thermometers, wearable sensors, smartphones, and web servers, to determine low CT1-CT4 is reasoning with technicalities. Therefore, real-time mobile data can involve regulations from the government to the telecoms. Mobile devices' collaborative and interactive capabilities are transforming public health and social measures (PHSM) into a mobile digital culture (MDC) (wireless tracking of SARS-COV-2). The COVID-19 risk mitigation setup is continuously monitored, tracked, and remote-checked (Figure 2) as predictability of mitigation. This variability nexus was examined to consolidate evidence on mobile usability linked with mHealth apps necessitated by conditions under the umbrella of "mobile temperature detector (MTD)" (Figure 3).

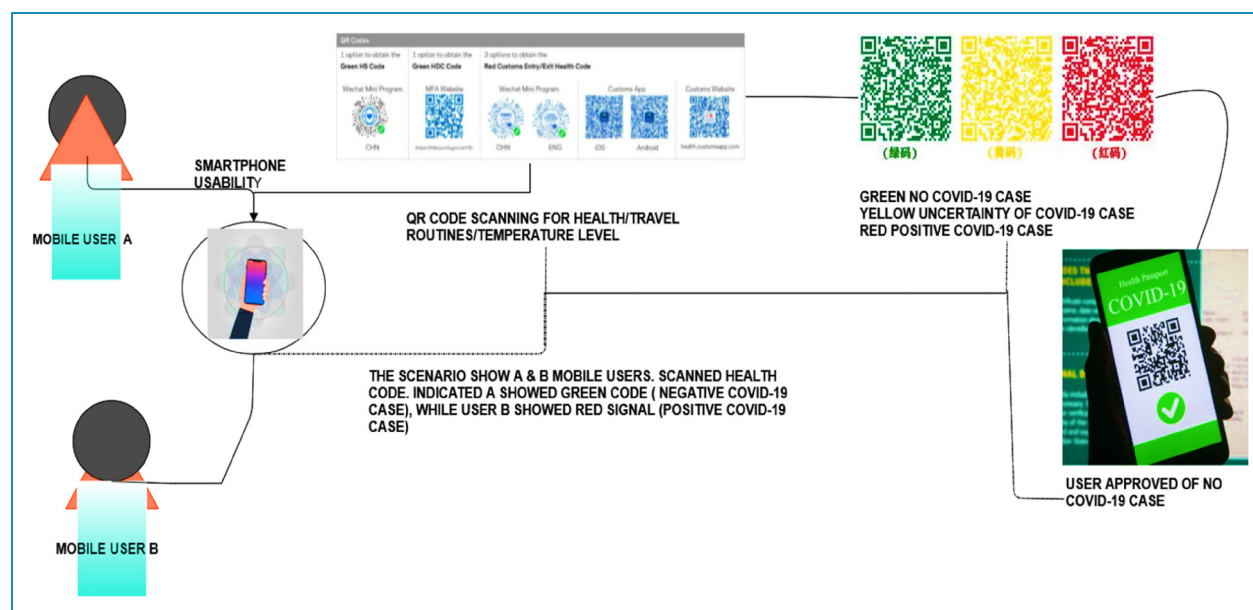


Figure 2. Smart thermometer scanning QR health code system. Pope up notification signals Red, Yellow, or Green to determine individual COVID-19 status.

Table 1. Descriptions of the categories of surveillance classification by WHO.

Categories names	Communities/areas with:
Community transmission level 1 (CT1)	<i>Low incidence</i> of locally acquired, widely dispersed cases detected in the past 14 days, with many of the cases not linked to specific clusters; transmission may be focused in certain population sub-groups which support a Low risk of infection for the general population.
Community transmission level 2 (CT2)	Moderate incidence of locally acquired, widely dispersed cases detected in the past 14 days; transmission less focused in certain population subgroups. Moderate risk of infection for the general population.
Community transmission level 3 (CT3)	High incidence of locally acquired, widely dispersed cases in the past 14 days; transmission widespread and not focused in population sub-groups. High risk of infection for the general population.
Community transmission level 4 (CT4)	Very high incidence of locally acquired, widely dispersed cases in the past 14 days. Very high risk of infection for the general population.

Note circumstances where Covid-19 surveillance is not robust, a lack of identified cases should not be interpreted as an absence of transmission.

Methods and measurements

The study adopted a cross-sectional survey and generated an online survey link shared to collect data.¹⁴ Quantitative method and data analysis powered this study to understand mobile intelligence on risk mitigation,¹⁵ MTDs, and other variables for surveillance of low and high areas of the virus (see Table 2 of constructs). The online participants consented while being ethically assured of their anonymity and confidentiality of the data provided. Using a pilot test, three health, behavior, and technology experts evaluated all of the instruments and measurements via a Tencent meeting before completing

the resulting online survey. This study included 50 experts from five universities who revised the instruments based on their experience and expertise. Participants learned how to use mHealth apps towards COVID-19 taming technical required mitigation. Between March and July 2021, a workshop on the benefits of smart technology in managing COVID-19 was systematized. It was done in five sessions, twice for students, once for health professionals, and twice for employees, all using snowball sampling techniques. Tencent meeting attendees were given the created link to answer questionnaires after a briefing and consent agreement. Students (327 and 381), healthcare professionals (207), and employees were all sampled (119

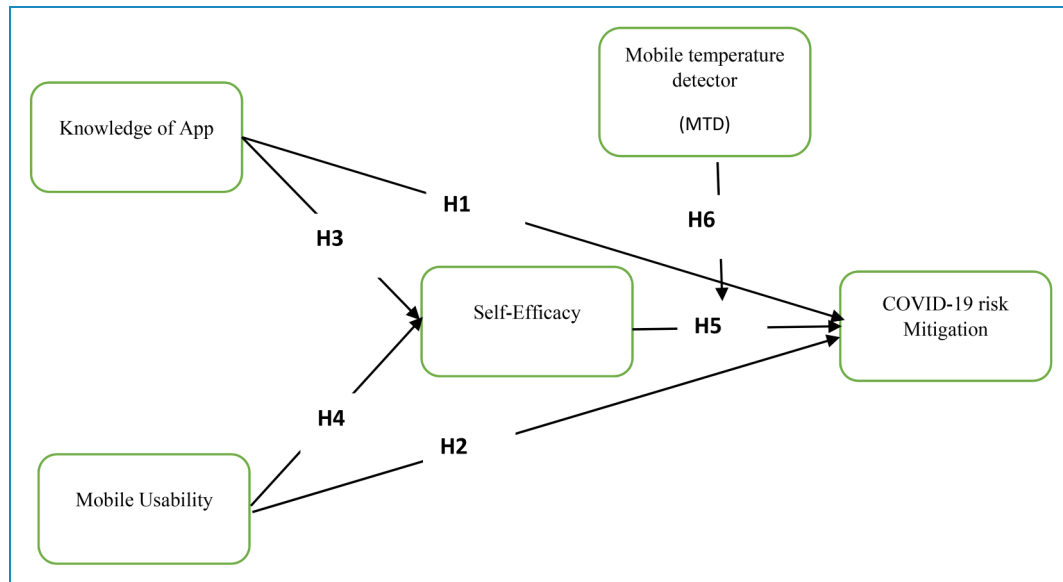


Figure 3. Conceptual model of hypotheses development.

Table 2. Definitions and hypotheses development.

Constructs explained	Expounded constructs	Sources/ Authors
Knowledge of APP	Application technologies are available to support patients, doctors, pharmacists, and evolving “end-to-end” encrypted personal data.	Refs. 16–18
Mobile usability	The degree to which mobile technology enables easy and quick access to health information via smartphone visualization.	Refs. 17, 19–21
Self-efficacy	The belief in the capacity to perform daily activities with smartphone technology.	Refs. 22,23
Mobile temperature detector (MTD)	Technology infuses sensor with smartphone to test body temperature through machine learning.	Refs. 24–26
COVID-19 risk mitigation	Manage disease preparedness response actions with smart digital technology health aggregation and analysis that support community, organization, and government policies.	Refs. 27–29
Hypotheses development		
H1	Knowledge of the App is positively associated with COVID-19 risk mitigation, ensuring balance and harmony within communities.	
H2	Mobile usability has positive effects on COVID-19 risk mitigation for appropriate surveillance.	
H3	Knowledge of the App is positively associated with self-efficacy in strengthening surveillance systems.	
H4	It is beneficial for self-efficacy to strengthen surveillance testing capacity when mobile usability is high.	
H5	Self-efficacy has positive effects on COVID-19 risk mitigation.	
H6	The MTD system has moderate self-efficacy for implementing immediate reporting of COVID-19 temperature tests in the university community.	

and 316). Snowballing strategies explain non-probability techniques that target samples difficult to find in various COVID-19 intelligence, surveillance, management, and digital health applications. At the end of the procedure, 1350 people had signed up, accounting for 67% of the population. The study setting is in the Anhui province, with an estimated population of 7,829,000 inhabitants as of 2020.^{30,31} In terms of technological innovations, the city is a model of civilization.³²

Procedure and measures

Outcome variable: the study adapted a criteria review for the initial impacts of global risk mitigation measures taken during the combatting of the COVID-19 pandemic.³³ These indicators for “COVID-19 Mitigation” were characterized by risk mitigations in the context of disasters (proportionate, adequate, self-containment, global impact) and were modified as self-reported questions.³⁴ Examples: “I feel relief with the degree of technology measures on COVID-19,” “enough efforts rendered on fighting the pandemic,” “I agree to some good policies applied during the pandemic,” “there are available possibilities to contain the virus,” and “the community compliance measures for the pandemic.” With items scored using 5-point Likert scale from strongly disagree¹ to strongly agree⁵ aimed to assess COVID-19 risk mitigation (outcome variable) based on the technology of health apps.

The scales for mobile usability were based on popularity and broad level conceptualization (e.g. behavior, attitude, addiction, and habit) and were presented in the survey. Several participants had previously used health-related APPs related to COVID-19 surveillance in China (e.g. health code and “Wanshintong”). Mobile usability was scaled on MTUAS bases, *Media and Technology Usage and Attitudes Scale* (MTUAS). The overall MTUAS comprises of 66-items that aim to examine³⁵ International Journal of Human-Computer Studies technology and media usage more widely. However, this study used 6-items from a subscale, which focuses on mobile usability (items 11,18,20, 22, and 24), an example of the questions: “I feel the impulse to use smartphones,” “I need to spend any amount of time on a smartphone to achieve satisfaction,” “I tried to spend less time on a smartphone but all in vain,” “my recreational activities are reduced due to smartphone usability,” and “my life would be joyless had not there been smartphone usability.”³⁶ Each item is scored on a 5-point Likert scale from “Never”¹ to “All the time,”⁵ where appropriate measure is taken for mobile usability items.

Hierarchical structures and analytical model for mobile Apps stickiness measuring scale for Knowledge of APPs.³⁷

Based on experts and professionals, developers recommended a hierarchical structure of mobile App stickiness in the following dimension (control, communication, responsiveness, context, mobile self-efficacy, promotion/

advertisement). However, this study uses 6-items out of 18 measures.³⁷ Example of the question “I do easily and smoothly browse the App,” “I do often get feedback from the system,” “Apps designs functional, operational, behavior optimized to a user,” “the information designed is relevant, interesting, and meets the needs and preferences of users,” “I simple operate and understand the system,” and “the audiovisual/content easy to grasp.” Each item is scored on a 5-point Likert scale Strongly disagree¹ to strongly agree.² A higher score is associated with high-level expectancy, and a low score is low expected efficacy.

Mediating variable: Hierarchical structure model of mobile self-efficacy scale.³⁷ The user’s perceived efficacy and behaviors intention to continue using the App if they deemed the process/technology serves as a means of creating satisfaction.²³ Examples of mobile self-efficacy 6-items are: “No strenuous efforts using the app,” “I feel easy operating the apps daily,” “the app information is useful,” “I perceive the app’s content as effective, joyful and fun,” and “I am confident in the ability to apply the technology.” The SMTRPM scale explored personalized, intelligent, graphic, non-invasive, and real-time patient health monitoring.³⁸ The overall architecture is divided into three main levels: (1) the hardware system (sensors, smart nodes, and wireless capability); (2) network structures (ad hoc and Internet modes); and (3) the software system (the nurse server interface, mobile nurse monitor and virtual patient file). The main assessment is generating digital people’s body temperature status. Example of Body Temperature (BT) modified: “... support cutting-edge technology smart self-measure of body temperature,” “temperature behavior remote at a distance of 20 m safer than near,” “automatic BT is time-sensitive,” and “smart BT adjust color indication anomalies from red, blue, green.” Higher scores correspond to higher BT and user applications indicative of status.

Data analysis

For analysis, demographic indicators such as gender, age, education, and mobile user experience were considered in Table 3 for descriptions. The study used the Structural Equation Model of Amos (ver.24) to analyze predictors’ interrelationships and predict variables.³⁹ We first explored factor analysis to decide on the multiple-factor solution. Again, the exploratory factor analysis (EFA), Bartlett test sphericity, was explored for significant correlation, and aligned items were measured for onward analysis in EFA. The CFA estimated the minimum sample accepted (Max R(H)), maximum shared variance (MSV), average variance extract (AVE), and composite reliability (CR) are shown in Table 4.⁴⁰ Amos Plug-in³⁹ was used to assess the reliability and validity of the items evaluated (see Table 4). Finally, all index based on the sum score was statistically determined and reported in this study for technology-based assistance during and after the sampled population. Significantly, the

Table 3. Demographics/correlations of the study.

Descriptive statistics/correlation						
	Frequency	%	Valid %	Standard deviation	Mean	
Age	18–25 years	351	42.2	42.2	0.661	1.67
	25–35years	422	50.7	50.7		
	35–45years	44	5.3	5.3		
	45–55years	15	1.8	1.8		
Gender	Male	630	75.7	75.7	0.429	1.24
	Female	202	24.3	24.3		
Education	High school	12	1.4	1.4	0.897	4.02
	College	29	3.5	3.5		
	Bachelor	167	20.1	20.1		
	Post-graduate	346	41.6	41.6		
	PhD	278	33.4	33.4		
Mobile use experience	< 2 years	22	2.6	2.6	0.996	3.65
	3–5 years	76	9.1	9.1		
	6–9 years	250	30.0	30.0		
	10–15 years	309	37.1	37.1		
	> 15 years	175	21.0	21.0		
Constructs	Age	Gender	Education	Mobile Exp.	SUS	MTUAS
Age	1	–0.194**	0.145**	0.219**	0.039	–0.017
					0.002	0.032
					–0.046	0.065

(continued)

Table 3. Continued.

Descriptive statistics/correlation					
	Frequency	%	Valid %	Standard deviation	Mean
Gender	1	0.000	−0.067	−0.141**	−0.036
Education		1	0.097**	0.012	−0.036
Mobile Exp.		1		0.522**	0.233**
SUS				1	0.506**
MTUAS					1
MTD					1
SE					1
K-App					1
C-19					1

**Correlation is significant at the 0.01 level (2-tailed).
*Correlation is significant at the 0.05 level (2-tailed).

method employed for data analysis, Tencent meeting room allowed interactivity, flexibility, accessibility and convenient of the sample population to expedite action on the data.⁴¹ The method employed was to overcome crowd-gathering of high transmission risk of COVID-19 and to abide by social distancing demands in the lives of social settings.

Result

The results of this study greatly contribute to control variables of age, gender, education, and mobile user experience significantly impacted mobile user subscriptions and wireless connectivity in Table 3, based on individual mobile usability, user experience, and mobile population base. The range of 18–25 years and 25–35 years have been the most experienced users of mobile digital health. About 76% were male, while 24% were female. Most respondents' mobile use experience ranges 6–9 years, 10–15 years, and above 15 years, 30, 37, and 21%, respectively. Also, mobile user experience was correlated with all the constructs in Table 3. The demographics and the main constructs' validity and reliability were examined in Table 4,^{42,43} while Table 3 shows descriptive frequencies, mean, SD, and zero-correlations.

Structural model results analysis

In the model Fit Indexes showed measurements evaluated in Table 6, Hair et al. (2012) recommended multiple measurements and considered cutoff fit models susceptible to measurement quality (Hu and Bentler, 2009; McNeish et al., 2018). Usually, three types of model fit are considered: absolute fit, incremental fit, and parsimonious fit.⁴⁴ Even though literature can vary in cutoff points, this study reported on model fit measures assessed and evaluated CFA.⁴⁵ Table 6 further confirms the CFI > 0.95 and SRMR < 0.08, solidified evidence of RMSEA < 0.06 in the model fit index^{40,44} presented in Table 6. The model

shows satisfactory > 0.06 standardized factor loadings based on the parameter estimates, which is indicative of overall model fit of the study. Again, Table 5 shows HTMT evidence that best-analyzed discriminant validity without any redundancy. The HTMT is significant because the results show below threshold of 0.850 for strict and 0.900 for liberal discriminant validity.⁴⁶

Hypotheses tested results

After the cross-examination of hypotheses, knowledge of the app is positively associated with COVID-19 risk mitigation with ($\beta = .488$, $t = 6.534$, $p < .005$). Similarly, hypothesis two of mobile usability is positively associated with COVID-19 risk mitigation for appropriate surveillance ($\beta = .072$, $t = 2.637$, $p < .008$). The third hypothesis, which examined app knowledge, is positively associated with app usage's mobile self-efficacy to strengthen intelligence surveillance systems ($\beta = .447$, $t = 10.293$, $p < .005$). It was hypothesized that mobile usability positively influenced self-efficacy for strengthened surveillance testing capacity ($\beta = .099$, $t = 4.964$, $p < .005$) is confirmed. Dissimilarity in hypothesis indicated five of self-efficacy

Table 5. HTMT analysis assessment of discriminant validity.

MU	SE	MTD	C19	KAPP
MU				
SE	0.558			
MTD	0.34	0.416		
C-19	0.328	0.35	0.242	
K-APP	0.468	0.607	0.389	0.432

Note: MU = mobile usability, SE = self-efficacy, MTD = mobile temperature detector, C-19 = COVID-19 risk mitigation, KAPP = knowledge of APP.

Table 4. Model reliability and validity measures.

Constructs	CR	AVE	MSV	Max R(H)	1	2	3	4	5	6
MU	0.828	0.828	0.585	0.123	1.007	0.865				
SE	0.854	0.854	0.543	0.346	0.87	0.350***	0.837			
MTD	0.886	0.886	0.61	0.18	0.901	0.185***	0.425***	0.881		
C19	0.871	0.871	0.6	0.078	0.991	0.194***	0.280***	0.121**	0.875	
KAPP	0.832	0.832	0.555	0.346	0.839	0.262	0.588	0.395	0.268	0.845

Note: MU = mobile usability, SE = self-efficacy, MTD = mobile temperature detector, C19 = Covid-19 risk mitigation, KAPP = knowledge of APP, CR = composite reliability, AVE = average variance extract, MSV = maximum shared variance, Max R(H) = minimum sample accepted. Significance = † $p < .100$, * $p < .050$, ** $p < .010$, *** $p < .001$.

showed no association with COVID-19 risk mitigation ($\beta = .052$, $t = .754$, $p < .449$). Finally, hypothesis six stated that MTD technical requirements moderate on self-efficacy to implement digital wireless monitoring of COVID-19 cases in high/low geographical settings ($\beta = -0.183$, $t = -3.454$, $p < .005$) is confirmed (see Table 7 of all the hypotheses).

Table 6. Model fit measures.

Measure	Estimate	Threshold	Interpretation
CMIN	450.261	-	-
DF	100	-	-
CMIN/DF	4.503	Between 1 and 3	Acceptable
CFI	0.97	>0.95	Excellent
SRMR	0.056	<0.08	Excellent
RMSEA	0.065	<0.06	Acceptable
PClose	0	>0.05	Not estimated
Measure	Terrible	Acceptable	Excellent
CMIN/DF	>5	>3	>1
CFI	<0.90	<0.95	>0.95
SRMR	>0.10	>0.08	<0.08
RMSEA	>0.08	>0.06	<0.06
PClose	<0.01	<0.05	>0.05

Discussion

The current study explored technology surveillance of COVID-19 based on smartphone usage against the backdrop of health apps applicable in mitigating SARS-COV-2 infection in mobility. An integrated MTD intelligence plays a key role in mitigating SARS-COV-2 based on symptoms widely accepted form of stalking the coronavirus disease. The study result is consistent with live experience accounts in mobile user adaptability knowledge of App⁴⁷ and useful alternative to laboratory diagnoses. The descriptive demographics of age, gender, and education were the experience of the mobile user population. Statista (2020) reports that 5 billion mobile users worldwide, about two-thirds of the global population, acceptable technology-telemedicine integration during a pandemic. Increasingly, mobile penetration is expected to be 73%, with 63% of smartphone users skyrocketing in Asia and America.

Progressively, the study aims to determine the routine mobile users and knowledge of app-independent inputs moderated by MTDs' self-efficiency to risk mitigation for COVID-19. This work examines the effect of MTD as a technology-assisted intelligence, interoperability surveillance system for government, telecom companies, and individuals with personal health code aggregations. The paper discusses the results of the estimated model of COVID-19 risk mitigation, which focuses on MTD, and self-efficacy, and the overall model fit indicates the strength of correlation of COVID-19 risk mitigation. This work has presented a novel approach in Figure 4, a comprehensive conceptual model fit measure is shown as the coefficient of determination (R^2), or squared multiple correlations. R^2 measures are approximated as the total variation in the effect construct explained by the variation of COVID-19 mitigation. Presently, the scheme demonstrated medium and higher explanatory power relative to MTD. According to Cohen (1992), the large effect of R^2 ranges between 0.30% and

Table 7. Results of the tested hypotheses.

Hypotheses			β	SE	t-value	p-value	Inference
SE	<—	MU	0.099	0.02	4.964	***	Accepted
SE	<—	KAPP	0.447	0.043	10.293	***	Accepted
SE	<—	MTD	0.148	0.036	4.052	***	Accepted
C19	<—	SE	0.052	0.069	0.758	0.449	NOT
C19	<—	MU	0.072	0.027	2.637	**	Accepted
C19	<—	KAPP	0.488	0.075	6.534	***	Accepted
C19	<—	MTD	-0.183	0.053	-3.454	***	Accepted

Note: MU = mobile usability, SE = self-efficacy, MTD = mobile temperature detector, C19 = Covid-19 risk mitigation, KAPP = knowledge of app.

or 30%. For this case, the model can explain 0.303% or 30.4% of what drives COVID-19 risk mitigation.

This work has presented a novel way of providing technological MTD explanatory power of 0.534% or 50.3% of the variance, while 0.260% or 26% variance is the mediator construct for self-efficacy. Therefore, it contributes to the model an excellent explanation for both the medium and lower indicator of good support. The relationships between constructs are shown in Figure 4. This explicitly explained MTD moderation, mobile self-efficacy as a health scanning technical procedures in self-testing COVID-19 mitigation.

Data were collected following the Tencent's meeting workshop design approach. Figure 4 shows the overall direct and indirect effect of all conceptual model self-efficacy on knowledge of the App and mobile usability significant. In other words, the regression weight of app knowledge ($\beta = 0.47$) and mobile usability ($\beta = 0.34$) is a statistically satisfactory difference. Additionally, these path coefficient estimates confirmed H3 (App knowledge is positively associated with self-efficacy usage to enhance surveillance systems). The application technologies are a novel dimension for telemedicine, telehealth endorsed by the World Health Organization WHO and Global Observatory for eHealth. This study is consistent with the COVID-19 recommended sensitive smart-sensing platform with multiple approaches.⁴⁸ Many community surveillance for COVID-19 will require novel multiple bio-sensor technologies to strengthen the existing technology systems and the scaling-up of additional surveillance back-up, as needed in telemedicine. H4 (mobile usability positively affects self-efficacy in strengthening surveillance testing capacities) is confirmed in the same study. This reliable methodology of detecting COVID-19 is based on computerized tomography and health scan recommendations.

Also, smart health real-time work environment optimization uses multimodal media and body sensor networks.¹⁷ MTD monitoring reinforces the wireless network POC, making contactless self-testing of body temperature in exploring telemedicine mechanisms. Previous studies evaluate that mobile usability can effectively improve health and increase access health management; this is more connected to knowledge of mHealth apps for telemedicine.^{9,49,50} The long-term management of COVID-19 requires mobility of population, the use of mobile broadband and wireless network can integrate mHealth, as supporting system of knowledge of apps, mobile self-efficacy for COVID-19 mitigation.

Furthermore, in Figure 4, predictors of COVID-19 risk mitigation, the direct effects significantly magnified apps and mobile usability knowledge. Therefore, the regression weight of app knowledge ($\beta = 0.144$) and mobile usability ($\beta = 0.22$) is to elaborate on the alternative of intelligence surveillance. COVID-19 risk mitigation is performed based on mobile accessibility and affordability, and the situational crisis of community risk assessment achieved the support of COVID-19. We emphasize the need to use technology intelligence surveillance to suppress and control new cases and clusters of SARS-CoV-2 to rapidly detect infection in low, medium, high geographical areas (Ujiwara et al. 2020; Wenger, Halperin, and Ziga 2009). According to the study path coefficient, H1 (knowledge of the App is positively associated with COVID-19 risk mitigation) is also confirmed. Mobile Apps are alternative interventions to divert depression, self-guided healthcare, and privacy of communication.^{49,51} Implementing and adapting mHealth apps are likely to augment longer-term epidemiological tendencies, such as incidence and mortality in different age groups, which population groups are at

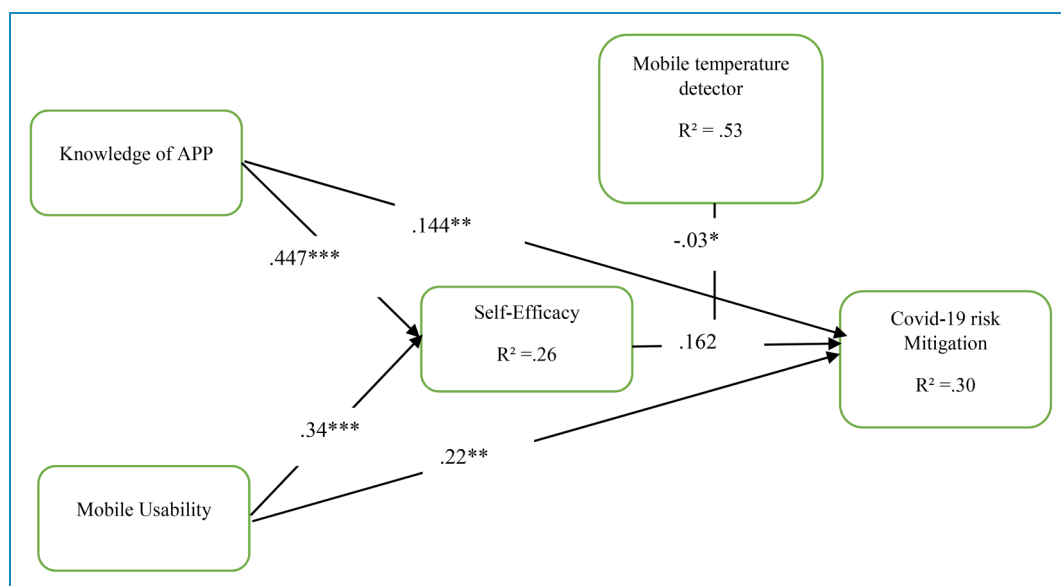


Figure 4. Estimated model results.

higher risk for severe disease and death, and potential epidemiological changes over time. In addition, *H2 (mobile usability has positive effects on COVID-19 risk mitigation for appropriate surveillance)* is confirmed. The study found WHO aims and objectives for national surveillance congruence to enable public health emergencies to reduce/suppress transmission of SARS-CoV-2, thereby bringing down associated morbidity and mortality.^{26,52} These are (Wenger et al.⁵², p. 4): (1) enabling rapid detection, isolation, testing, and management of cases, (2) containment of group/community clusters and outbreaks, especially among vulnerable populations, (3) mobile control measures, while enabling the safe resumption of economic and social activities, and (4) evaluate the impact of the pandemic on health care systems and society. The concepts of civil liberty or public health used for surveillance technologies to tackle the spread of the COVID-19 is tantamount to our concerns.⁵³ Figure 5 presented schematic process of attaining a positive or negative case in closed-settings based on MTD recommendations. The platform is novelty from this study useful for related cases in combination approaches with mobile connected past and present health information tracking process.

The results of this study will greatly contribute to routine intelligence surveillance for COVID-19 and other infectious diseases. It is crucial to support of body temperature

of COVID-19 mitigation. Using the Figure 5 surveillance system, this study found that a closed setting is highly appropriate for deploying a mobile surveillance system. In this case, the university community and society, in general, is being deployed through intelligence surveillance systems across all sectors with smartphones. They employed mobile usability and mHealth apps for rapid data reporting and visualization, including temperature, tracing, monitoring, and epidemiological analyses within a few seconds. The WHO-recommended surveillance systems across geographical boundaries, especially the vulnerable in a high-risk populated area. The COVID-19 risk mitigation to boost surveillance system detectable with mHealth apps envisages smart-thermometer, and mobile temperature detectors through the mobile self-checks efficacy health care system. Designated as a technology dimension for digital health and a smart thermometer for humanity, POCT is congruent to a self-testing scheme. This study found from the Figure 5 surveillance system that a closed setting is highly appropriate to deploy a mobile technology intelligence system as AI support. Smart-thermometer surveillance contributes a great deal to smart health in society. Ensure daily screening for signs and symptoms of COVID-19 using digital thermometers. The MTD is capable of leading to a positive or negative COVID-19 notification. This is often

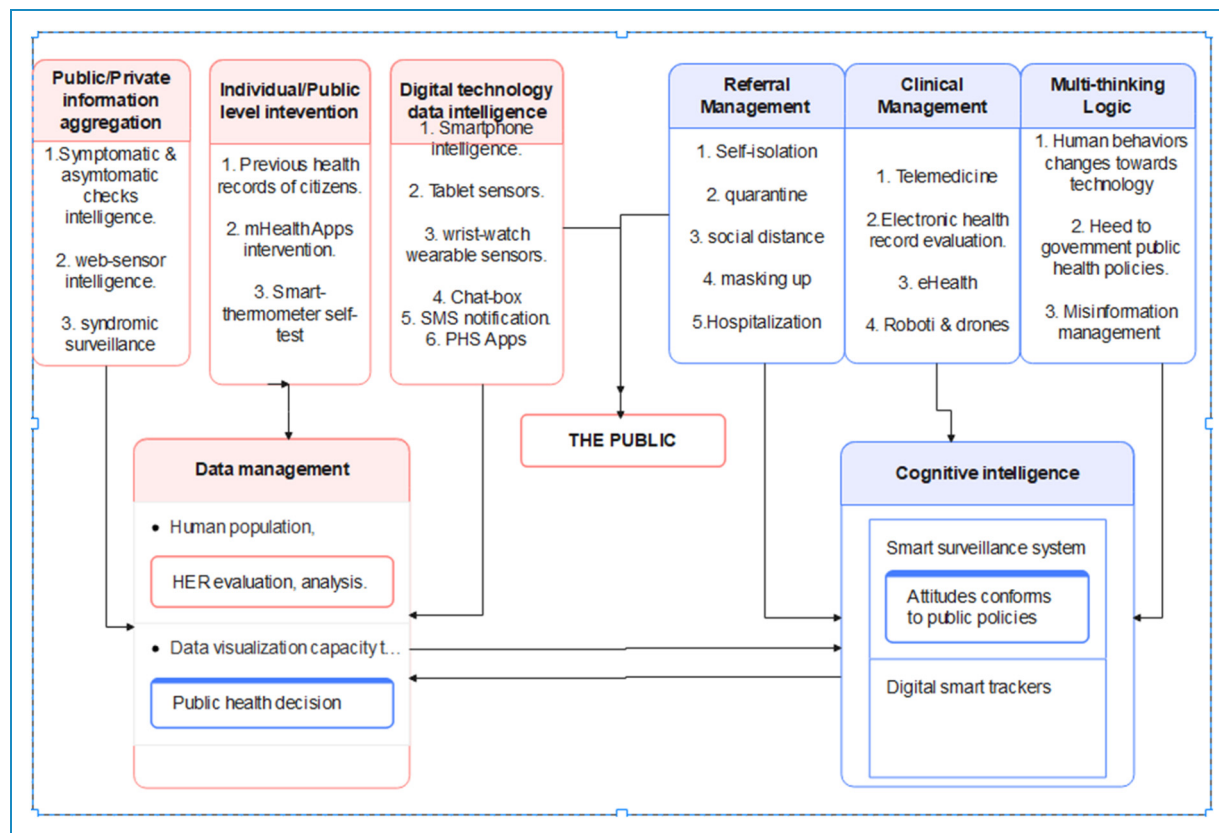


Figure 5. Flow surveillance intelligence integrated public health system for COVID-19 management.

recommended for daily COVID-19 reported mobility of the population.

This study selective MTD self-check (PCT) at home or in a crowd-dense COVID-19 management area, in particular, are suitable for self-testing due to their extremely simple operation and mobility read-out, which is an advantage support thermometer immobility contactless diagnosis or HealthCode scanning. By using this method, the transmission risk of mitigating SARS-CoV-2 can be minimized but limited to COV-2, and not that of COV-3. Especially the unmet study validation and high performance of these technologies, by the development of MTD access to a mobile thermometer, appears to be an advantage in society. *H5 (self-efficacy has positive effects on COVID-19 risk mitigation)* is insignificant. This could be a lack of products manufacturing deficiency related to thermometer checks. To mitigate the risk associated with COVID-19, self-efficacy tendency requires intervention; the lower $R^2 = 30\%$. This evidence resonates with previous findings on self-efficacy, and acceptance of robot usage, and no interaction was found between general self-efficacy and the robot study model.⁵⁴ For instance, the role of self-efficacy that may not have been enhanced in medicine, public health education is an effective intervention for promoting medical students' motivation levels, which has also been developing motivation-related to counseling methods due to insignificance.⁵⁵ Finally, the estimates of *H5 (mobile temperature detector system moderates on self-efficacy to implement immediate reporting COVID-19 tested temperature cases of high/low in the university setting)* are accepted.

The path coefficient of self-efficacy ($\beta = .48$), and mobile temperature detector MTD ($\beta = -.03$), the interaction strengthened the positive relationship between self-

efficacy and COVID-19 risk mitigation from Figure 6. This research report is consistent with the pandemic pathways treatment, while surveillance is critical to slow down transmission cases of SARS-CoV-2 infection.²⁶ The present study is expected to contribute smart-thermometer temperature detector suggests boosting nucleic acid and elucidating epidemiological intelligence, antigen-detecting rapid diagnostic tests (Ag-RDTs), and antibody detection (Serology).³⁸ In addition, the surveillance approach concerns government and public health decision-making to help enforce COVID-19 protocols. In this scenario, MTD is meant to establish digital diagnostic systems to supplement long COVID, i.e., already vaccinated or booster SARS-CoV-2 infections, digital health mobility significant risk mitigation. This approach will synchronize HealthCode, to support the National COVID Cohort Collaborative approach to correlate with COVID-19 risk mitigation. For this reason, continuous self-check PCT, mobile contactless were useful components in easy-to-use MTD scalability in real-time. At the same time, consistent with transitioning revolutionary scheming MDC for smart multilevel COVID-19 social network wireless data sensor real-time.³⁸ The technology of smart-thermometer in smart society is a digital health data that identifies an explicit sensing human body temperature as symptoms of COVID-19 output (mobile-crowdsourcing) (Fujiwara et al.⁵⁶, p. 92). Public and private entities can manage daily health scenarios using HealthCode scanning, a neglected approach. Mobile surveillance will connect human past and present health records, any changes in people's daily health representation and visualization scheme. And develop a collaborative network of professional health management, with telecom companies

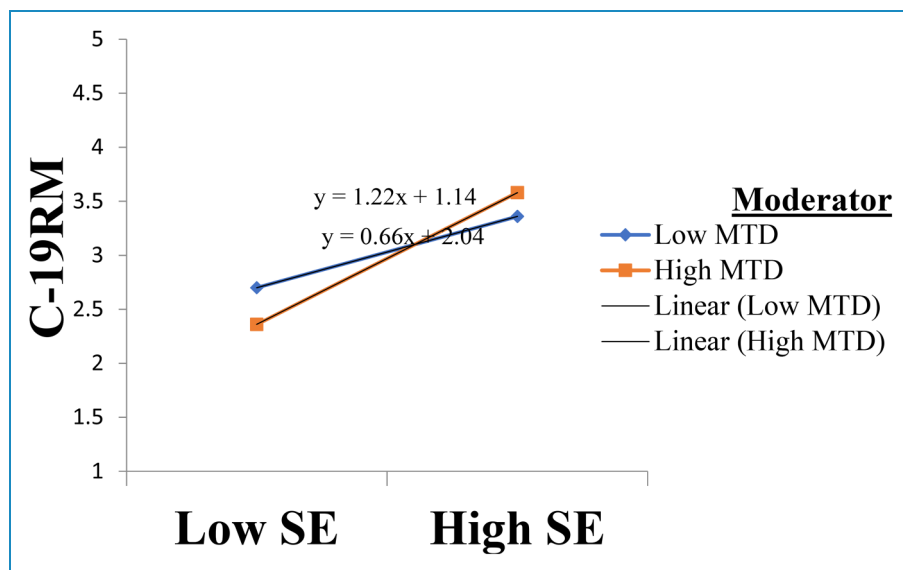


Figure 6. Moderation effects of mobile temperature detector, self-efficacy, and COVID-19 risk mitigation. Note: C-19RM = COVID-19 risk mitigation, SE = self-efficacy, MTD = mobile temperature detector.

managing temperature levels by notifications, such as the Red signal (positive-case/no pass), Yellow signal (travel records in low, medium, and high areas for COVID-19), and Green signal (negative-case/passed). This centralized system intelligence system per public health COVID-19 awareness through population mobility technology assistance models. Significantly, from syndromic intelligence surveillance to public health decision-making intervention, public safety as methods for achieving any closed-settings COVID-19 control is on the horizon.⁵⁷

Conclusion

In summary, observing smart technology systems, social behavior patterns, and smartphone ubiquity in existing public healthcare is critical, especially promoting public awareness in knowledge of apps, smart technology social sciences in self-checks of COVID-19. Among the most verified self-care POCT (SC-POCT) is MTD for COVID-19 scaled up optimized the test differentials from normal flu, and validated as part of adaptability RT-PCT mobile population.⁴⁸ However, COVID-19 signs and symptoms in fever as a primary focus of MTD apps alternative contactless RT-PCT are distinguishable from COVID-3 mitigation. COVID-19 is caused by infection with a coronavirus, while Flu is caused by infection with a flu virus. COVID-19 risk mitigation can attain scalability and connectivity through digital HealthCode evaluation of aggregated data. MTD as a tool to bolster population mobility can be coupled with mHealth intelligence for sustainable digital health from mobile usability and risk reduction self-efficacy.

This study presents empirical evidence on the COVID-19 risk mitigation process with the MTD restraint surveillance system as a feasible crowdsourcing digital health. Technology supports formulating policies and decision-making, critical evidence-based intervention in population mobility. Digital health technology advancement can drive society's interest and attitude towards mobile usability, complemented by continuous contactless self-check efficiency. Temperance enhances overall COVID-19 syndromic intelligence surveillance for convent contactless self-test. Moreover, the study supports wireless network tracking apps and mobility usability in monitoring and mitigating pandemics by balancing normative attitudes toward emerging mHealth technologies. In the study ambiance of mobile usability, we capture mHealth in the public healthcare sector, namely, web-based systemic surveillance for data intelligence, a vital part of the MDC. Scientific knowledge of mHealth and telemedicine domains includes smart technology-driven surveillance and the accomplishment of adoption and MTD depend on mobile usability and self-efficacy, particularly in COVID-19 risk mitigation.

In conclusion, the most standardized format for public health data security, privacy, and ethics is critical to technology-assisted thermometers. The study suggests

that governments and telecommunications companies enter into legal agreements to protect the interoperability of wireless network health data leaks. To enable the government to collaborate with telecommunications companies to ensure transparency and trustworthiness in population mobility data. The results of syndromic surveillance monitoring must be kept private and confidential. COVID-19 monitoring provides valuable rich data made possible by effective and efficient digital technologies. Self-efficacy can be used to strengthen mHealth apps MTDs as part of the mitigation process. Digital smart thermometers are critical in minimizing the pandemic. In terms of big data intelligence in society, public healthcare can reach new heights with an integrated smart thermometer.

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