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Factors Determining Public Attitudes Towards Digital Contact Tracing Technologies in Taiwan

Chin-Huai Shih*, Yun-Chien Wu**, Helen K. Liu***, Shun-Wen Wu****

Abstract

Due to the popularization of mobile communication devices, the Internet of Things, and big data analysis techniques, digital contact tracing technologies (DCTs) have become novel tools for governments worldwide to curb the spread of COVID-19. However, concerns about the privacy, technical stability, and accessibility of these technologies have not been studied thoroughly. This paper examines factors related to the public's acceptance of the government's use of four different DCTs: geofencing, big data analysis, short message real-name registration, and the Taiwan Social Distancing App. The analysis of online questionnaires (N=450) with ordinary least squares and logistic regression shows

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* Chin-Huai Shih, Former Research Associate, Department of Political Science, National Taiwan University; M.A., Graduate Institute of Public Affairs, National Taiwan University.

** Yun-Chien Wu, Former Research Assistant, Graduate Institute of Public Affairs, National Taiwan University; M.A., Graduate Institute of Public Affairs, National Taiwan University.

*** Helen K. Liu, Professor, Department of Political Science & Graduate Institute of Public Affairs, National Taiwan University.

**** Shun-Wen Wu, Assistant Professor, Department of Political Science & Graduate Institute of Public Affairs, National Taiwan University, email: shunwu@ntu.edu.tw

that perceived usefulness, privacy concern, trust, pro-social, and compliance are significantly associated with general DCT acceptance. However, when the DCT categories are further divided, only perceived usefulness and political trust can consistently predict positive attitudes. In particular, accepting voluntary DCTs (short message real-name registration and the Taiwan Social Distancing App) has stronger associations with political trust, while the pro-social inclination is only associated with coercive DCTs (geofencing and big data analysis). The primary contribution of this study lies in examining a comprehensive set of factors proposed by previous literature and comparing factors affecting the acceptance of various DCT policies. This study also endorses the simultaneous deployment of multiple DCTs to bolster policy compliance.

Keywords: COVID-19, digital contact tracing (DCT), public attitude, perceived usefulness, political trust

I. Introduction

Contact tracing is used to identify, assess, and manage individuals who may be in close contact with an infected person (WHO, 2020a). This approach has effectively reduced infection transmission in the past, such as severe acute respiratory syndrome (SARS) and the Ebola virus (Kleinman & Merkel, 2020; Williams et al., 2020). Due to the prevalence of digital infrastructure and mobile devices in recent years, during the 2020 COVID-19 epidemic, digital contact tracing (DCT) has substantially augmented governments' contact tracing capacity by lowering the intensive need for the workforce to collect and analyze personal contact data as done in the past (Ferretti et al., 2020; WHO, 2020b).

Recognizing the advancement of DCT, governments worldwide deployed various DCT policies during COVID-19 outbreaks. For example, Taiwan used GPS, base station signals, and surveillance monitoring to manage infected patients directly through mobile phone locations. Others, such as Israel (Winer, 2020), South Korea (Dudden & Marks, 2020), Hong Kong (Hui, 2020), and the Chinese government introduced a "health codes system" in 2020 to help the government monitor and trace the transmission of COVID-19 (Mozur et al., 2020).

Despite clear advantages over traditional contact tracing, persistent citizen concerns regarding DCTs, such as privacy, technical stability, and accessibility, have not been

studied thoroughly (WHO, 2020b; Klar & Lanzerath, 2020). These concerns hinder the full adoption of voluntary measures, increase resistance to more coercive ones, and ultimately undermine the effectiveness of DCT policies (Cencetti et al., 2021). The significance of these issues is underscored by the substantial cost of maintaining DCT systems. For instance, the National Communications Commission allocated over NT$ 200 million for dedicated epidemic control cellphones, mobile phone positioning for quarantine, and sending epidemic control messages (Executive Yuan, 2021). Understanding the factors influencing DCT acceptance is essential for accurately assessing the cost-effectiveness of DCT deployment and justifying budget use.

Building on existing studies, we investigate factors determining public attitudes toward four DCTs adopted in Taiwan. As Taiwan adopted various types of digital contact tracing technologies with varying policy instruments concurrently, we then could examine the variance of the public's DCT acceptance patterns along with the coercive – voluntary spectrum (Bali et al., 2021; Carley & Miller, 2012). An online survey (N=450) was conducted through Web Survey NTU (National Taiwan University, 2022) with a nationally representative sample pool of more than 20,000 participants. Through ordinary least squares (OLS) and logistic regression models, factors such as perceived usefulness, privacy concern, technology fear, trust, and pro-social affect the public's perception of the government's use of DCTs are thoroughly examined while controlling for individual characteristics.

Although many previous efforts have been devoted to deriving factors associated with citizens' acceptance of DCT from various disciplines, we have identified two specific gaps in the DCT literature. The first is the need for a comprehensive examination of factors proposed by the previous literature and their associated interaction on DCT acceptance; the second is to differentiate the effects of the specific factors on different types of DCT designs, given that multiple DCTs are often applied simultaneously. Therefore, this study aims to answer the following research questions:

1. What are the factors associated with the acceptance of DCTs in Taiwan?
2. Does the extent to which these factors covary with acceptance vary across different types of DCTs? What are the possible explanations?

II. Factors Affecting DCT Attitudes

To identify the essential factors associated with the perceived acceptance of DCTs,

we conducted a thorough search through the Web of Science Database on July 9th, 2021 with combinations of keywords between “contact-tracing” or “health surveillance” and “COVID-19”, “technology”, “policy”, “acceptance”, or “public attitude” to build our analytical framework. Based on their relatedness to digital contact tracing for epidemic control, 112 studies were selected after reading through the titles and abstracts, with 51 remaining after reading their content. 32 of them are devoted to the empirical testing of factors affecting DCT attitudes while the others are conceptual or practical discussions on the acceptance of DCT.

Eventually, our review summarized six potential factors that affect DCT attitudes from the reviewed studies, based on three criteria: (1) The factors included in this study should be discussed in those studies that examine factors in different countries, indicating their potential as a universal factor or concern. (2) The conceptual overlaps of the factors should be minimized by combining similar concepts or constructs. (3) The factors can be applied to the four DCT policies (discussed in the next section) implemented in Taiwan. Also, discussions were held within our research team to minimize subjectiveness when deriving the six factors. Studies related to these factors are further incorporated to form the hypotheses below.

A. Perceived Usefulness

The public’s acceptance of DCT depends in large part on its effectiveness. Perceived usefulness has been extensively examined in previous technology adoption research and has proved to foster data governance intention among Taiwanese bureaucrats (Li et al., 2023). Research by Velicia-Martin et al. (2021) shows that the willingness to use a contact tracing app depends on its effectiveness. Redmiles (2020) pointed out that accuracy can affect users’ acceptance of providing information and installing the app. That is, when the app provides users with wrong information, the public may doubt the app’s validity, which in turn affects download intentions. Utz et al. (2021) conducted a cross-country empirical study in Germany, the United States, and China, finding that technical glitches negatively impacted user acceptance. In addition, another UK study found that expectations of low coverage of contact tracing apps can influence attitudes toward the app (Williams et al., 2021).

Hypothesis 1: Individuals who felt that DCTs are useful in epidemic prevention were more likely to report a higher acceptance of DCTs.

B. Privacy Concerns

The dilemma of privacy and public health has long been a topic of constant discussion with respect to contact tracing. Privacy concerns are among the most important considerations for adopting contact tracing apps. People fear the government's capacity to make unwarranted use of their personal information after the epidemic (Altmann et al., 2020; Williams et al., 2021). Altmann et al. (2020) found that concerns about online security and privacy and a lack of trust in the government's data utilization were the main barriers to adopting contact tracing apps. Zhang et al. (2020) found that the American people's willingness to download contact tracing apps depended in part on the privacy protection features of the apps. Park et al. (2021) found that Koreans are more willing to accept contact tracing apps than publicized footprints because the latter are more likely to infringe on individual privacy. However, privacy risks ultimately are acceptable because applications effectively achieve public good (Li et al., 2021). Culture also has a role to play in the public's perception of privacy concerns. Although Asian countries generally accept contact tracing apps more readily than European and American countries (Altmann et al., 2020; Utz et al., 2021), the issue of privacy remains important as the privacy concerns of citizens might hinder the adoption of national card services (Chi, 2000).

Hypothesis 2: Individuals who reported a higher privacy concern were less likely to report a higher acceptance of DCTs.

C. Technology Fear

Technology Fear refers to the irrational fear or anxiety caused by the side effects of modern technology, including the fear of the potential impact of technological development on society or the environment and the fear of using advanced technology or equipment (Osiceanu, 2015; Khasawneh, 2018). Troisi et al. (2022) believe technology anxiety was essential to behavioral intentions in COVID-19. Anxiety can ultimately lead to the rejection of technology and even induce technophobia, which makes individuals feel more anxious about ICT and produces a lasting negative emotional response. Nimrod (2018) shows that this phenomenon is especially prominent among seniors and thus poses more risks to their well-being. Khasawneh (2018) developed a technophobia scale that measures Technology Fear more broadly without being confined to computer phobia.

Hypothesis 3: Individuals who strongly feared new technologies were less likely to report a higher acceptance of DCTs.

D. Trust

Political support enhances people's willingness to abide by the law (Marien & Hooghe, 2011; Bargain & Aminjonov, 2020; Zetterholm et al., 2021), making acceptance of the government's administrative measures easier. In the Taiwanese context, political trust is an important factor in shaping citizens' willingness to adopt e-government initiatives (Lee, 2011, 2019).

Devine et al. (2021) linked public trust in government with COVID-19 epidemic prevention outcomes, showing that public trust was associated with compliance with government public health policies in the early stages of the COVID-19 pandemic. Regarding empirical research, Gesser-Edelsburg et al. (2020) showed that trust in the public health system significantly impacts the public's willingness to comply with health guidance measures. Using data on global COVID-19 attitudes and beliefs of 108,918 respondents in 178 countries, Gozgor (2021) found that older and healthier people trust their government more, while more educated people have less trust. Furthermore, the Covid-19 crisis is said to have had a "Rally around the flag" effect that increased support for political leaders (Schraff, 2021; Fancourt et al., 2020), but this effect tended to wear off quickly (Gozgor, 2021).

However, few studies also found that citizens' acceptance of public health measures had nothing to do with trust in the government. Yuen et al. (2021) and Hartley & Jarvis (2020) found that although the pro-democracy protest movement in Hong Kong since 2019 has led to a low level of trust in the government, it has also enhanced civil society's experience of collective mobilization. As such, it strengthened civil society regarding self-mobilization, leading to the voluntary adoption of epidemic prevention measures in the communities before the government's order to do so.

Hypothesis 4: Individuals who trusted their current government officials were more likely to report a higher acceptance of DCTs.

E. Pro-social

A sense of collective social responsibility can also influence willingness to use DCT apps. Studies have found that altruism is one of the critical reasons people support contact tracing apps. Trang et al. (2020) pointed out that an app's social benefits and social norm goals lead to higher acceptance than the user's interests. Megnin-Viggars et al. (2020) show that a person's motivation to use contact tracing apps is strongly influenced by a sense of

social responsibility, which overshadows other concerns about the app. A nationwide survey experiment in the United States found that the benefits of contact tracing apps (protecting themselves and slowing the spread of the virus) are more significant than the indirect impact of privacy concerns (Li et al., 2021). Williams et al. (2021) showed that social pressure and civic responsibility increase their motivation to use contact tracing apps because their potential public health benefits outweigh privacy concerns.

Hypothesis 5: Individuals with a higher pro-social spirit were more likely to report a higher acceptance of DCTs.

F. Compliance in a democratic society

The various public health coercive measures adopted by governments in response to the threat of COVID-19 inevitably limited individual rights and determined to what extent the government could restrict civil rights (Kavanagh & Singh, 2020). Studies suggest a positive relationship with compliance to governmental measures because the flow of information is transparent, and people have the civil liberties and political rights to influence and even change policies (Greer et al., 2020; Gozgor, 2021). However, Schmelz (2021) pointed out that adopting coercive measures in a democracy may crowd out citizens' support for and compliance with COVID-19 epidemic prevention policies. Greitens (2020) argued that in consolidated democracies, their historical experience with dictatorships has raised awareness of the costs of surveillance. Thus, they redesigned the related measures to make them compatible with democracies, which yielded an effective response and protected democratic values.

Hypothesis 6: Individuals with higher compliance toward the government were more likely to report a higher acceptance of DCTs.

III. DCTs in Taiwan

As our study focuses on citizens' acceptance of DCT policies, four DCTs that were closer to their everyday experiences during the pandemic are the focus of this study. Their design and usage are introduced and summarized in Table 1.

Table 1

Digital Contact Tracing Technologies Used in Taiwan

Name	Function	Coercive vs. Voluntary (Dudás & Szánt, 2021; Guan et al., 2021)
Geofencing (GF)	Isolate confirmed cases and ensure compliance with quarantine regulations	Most Coercive
Big data analysis (BDA)	Use a variety of personal data to reconstruct personal footprints and monitor the spread of the epidemic	Coercive
1922 Short Message Service System (SMS)	Sending an SMS to provide personal information when entering buildings with a QR code to assist the case investigation	Voluntary
Taiwan social distancing app (TSDA)	Let users know they have been in contact with a confirmed case through Blue Tooth.	Most Voluntary

Source: The table is compiled by this study, with references from Lee (2020), Chen et al. (2020), Ministry of Health and Welfare (2020a, 2020b, 2020c, 2021a, 2021b, 2021c, 2022), g0v (2021), Huang (2022), Dudás & Szánt (2021), and Guan et al. (2021).

A. Geofencing

One of the first DCTs to be adopted during the pandemic in Taiwan was geofencing (GF) (Ministry of Health and Welfare, 2020a, 2020b, 2020c). It utilized GPS data from cell phones to monitor the locations of individuals required to be quarantined. If the person under quarantine left the quarantine address or turned off their phone, the system would send a text message alert to the police and local officials. The latter would send a team of officers to check on the person. Those who were confirmed having left their residence without a reason would be issued a heavy fine up to NT$ 1,000,000 by the officers (Lee, 2020).

B. Big Data Analysis

Another DCT measure frequently used at the onset of the pandemic was big data analysis (BDA). A typical case was the Diamond Princess Cruise incident investigation in

February 2020, which verged on being a criminal investigation (Chen et al., 2020). The officials gleaned sensitive personal information, such as GPS, credit card records, monitors, and mobile phone locations, to construct the travel footprints of the confirmed cases. The "Cell Broadcasting Information System" sent text messages to warn the public to pay attention to their health condition if they had overlapped footprints with the confirmed cases (Ministry of Health and Welfare, 2021b). In May 2021, the Central Government authorized local governments to publish the footprints of confirmed cases and launched active case investigations to identify individuals with higher risks of infection (Ministry of Health and Welfare, 2021a).

C. 1922 Short Message Service System

Given the severe community outbreak in May 2021, the Central Epidemic Command Center (CECC) launched the "1922 Short Message Service System" (SMS) to improve the efficiency of case investigation and reduce human contact with papers and pens while making real-name registration before entering any public space. The system requested store owners and site managers to apply for a QR code, which was to be posted at every entrance of a public space. After scanning the QR code, those entering the site would send the location code via text message to the 1992 particular line of the CDC to complete the registration for free (g0V, 2021). The CDC was able to quickly identify and track those who had overlapped footprints with the confirmed through time stamps and the location code of the SMS. Although the CDC constantly exhorted citizens to use this system, only restaurants failing to implement this policy would be fined, not citizens (Ministry of Health and Welfare, 2021c).

D. Taiwan Social Distancing App

Based on the application programming interface (API) provided by Google and Apple, the Executive Yuan and Taiwan AI Labs jointly launched the Taiwan Social Distancing App on March 12, 2021, which used Bluetooth connection on cell phones to log the time a user made contact with infected individuals. The app served to protect users' privacy in several ways, including not requiring personal information, generating a random ID every 14 days, and deleting the ID afterwards (Ministry of Health and Welfare, 2022). In response to the subsequent infection peak, health officials abolished the SMS on April 27, 2022, and the BDA on April 25, 2022, to save epidemic-prevention resources which were put into exhaustive case investigations while promoting and encouraging people to download the

TSDA as a complementary voluntary measure (Huang, 2022).

E. DCT Policy Instruments: Coercive－Voluntary Tradeoff

The four types of DCTs were combined to control the virus's spread and maintain social normality during the course of the pandemic. The fact that more than one type of DCT was deployed underlies the theoretical concerns in viewing DCT as a single concept. Except for the abovementioned technical differences, the DCT measures implemented can be categorized as different policy instruments.

To systematically capture how the differences in policy instrument choice elicit a range of citizens' policy acceptance, we adopted the "coercive–voluntary" spectrum in policy process literature (Bali et al., 2021; Carley & Miller, 2012) as a guide for the four DCTs' typological similarity. The spectrum highlights the tradeoff in determining the stringency, or leniency, of a policy design for reaching a given goal. For instance, a policy aimed at reducing industrial greenhouse gas emissions can involve options like imposing hefty fines on excessive emitters (more coercive), creating economic incentives through emission trading, promoting industry self-regulation, or non-compulsory norms and persuasion (more voluntary). Shifting from coercive to voluntary policies results in varying short-term effectiveness, enforcement costs, political feasibility, and long-term compliance (Carley & Miller, 2012; Fu et al., 2020; Guan et al., 2021), which constantly sparks debates in regulatory policy design (Lai et al., 2018).

During the COVID-19 pandemic, the tradeoff became salient in formulating disease control policies (Bali et al., 2021; Fu et al., 2020). Several public administration and policy scholars have tapped into how the hard and soft policies determine the acceptance of epidemic prevention measures in varying conditions. Experimental evidence demonstrates that Americans are more supportive of coercive policies than soft nudges regarding life-and-death public health issues (Treger, 2021). A similar comparison in Hungary shows that direct experience with COVID-19 reduced support for strict public health regulations but not for softer measures (Dudás & Szántó, 2021). Moreover, the effectiveness of soft COVID-19 prevention policies in gaining public acceptance hinged on their ability to foster a consensus of public values among citizens and policymakers, especially when nudges were employed as complementary measures (Guan et al., 2021).

Although these studies provide *prima facie* support that the coercive－voluntary distinctions of DCT policies could affect citizens' acceptance, their exact type and magnitude remain unclear. The four studied DCTs offer an opportunity for us to explore

and compare how positions on the coercive – voluntary spectrum shape acceptance patterns, addressing our second research question. Specifically, GF and BDA are closer to the coercive side because the government unilaterally initiates both without the consent or cooperation of citizens. GF imposes an even more substantial limitation on personal freedom by confining a person's freedom of movement by the threat of daunting penalties. In contrast, SMS and TSDA rely heavily on citizens' spontaneous cooperative behaviors. SMS is slightly less voluntary than TSDA because it imposes regulations on business owners. Table 1 summarizes the relative ranking of the four DCTs along the spectrum.

IV. Research and Method

A. Data collection

This study was conducted as a questionnaire survey after the informed consent of the subjects and after being adequately anonymized. The survey was administered by Web Survey NTU[1] from May 17, 2022 (Tuesday) to May 23, 2022 (Monday). The platform randomly drew 3,000 samples from the verified list of about 20,000 representative members aged 20 and above and sent unique questionnaire codes to those selected. Those who completed the survey were given an NT$ 50 gift certificates. Due to the schedule of this study, the questionnaire was closed after 450 respondents were received. The limitations of this design will be discussed in the last part of this study.

The concerns of "common method bias" in our data collected from a single questionnaire are minor. Firstly, standard method bias is typically more prominent in non-cognitive or behavioral questions (Favero & Bullock, 2014, pp. 296-289). In our study, most questions focus on measuring cognition or perception, so we only needed to ensure they would accurately reflect the subjects' perceptions. Accordingly, we considered intra-individual response variability (IRV), which assesses response consistency through the individual response standard deviation (Dunn et al., 2018). Highly consistent answers often indicate insufficient effort (Hong et al., 2020). Analyzing IRV across 33 Likert scale questions, we identified six subjects with an IRV of 0, signifying uniform responses from

[1] The composition of the members was strictly monitored by the platform to maintain authenticity and representativeness of the Taiwan population. For more information on the methodologies utilized by NTU Web Survey to recruit and manage its members to ensure membership authenticity and survey quality, please view https://ntuwebsurvey.org/post/7.

start to finish. Excluding these anomalies, the remaining 444 valid samples showed no unusually low IRV. Harman's single-factor test also revealed that the first factor accounted for 42.3% of the variance for all five-point questions, which is below the widely accepted 50% threshold (Hu & Bentler, 1999).

B. Variables Measurement

Our survey questions were drawn from a broad range of literature to capture the concepts of the studied variables in alignment with previous studies. The wording was revised to fit Taiwan's context based on the pioneering local survey from the Election Study Center Association of NCCU (2021). The survey question sources can be found in Appendix 2. As a result, exploratory factor analysis (EFA) was performed to test the validity of each construct measured by our adapted questions. Stata 16 was employed for all the data analysis provided below.

(A) Dependent variable: Acceptance of DCT

In the questionnaire, we measured both subjects' "support" and "acceptance" toward different types of DCTs separately with the five-point Likert scale, corresponding to "strongly disagree" (scored as 1), "disagree," "neutral," "agree," and "strongly agree" (scored as 5). In all, eight questions for the four DCTs were composed.

EFA shows that the first factor with the highest explained variance in the EFA already accounted for more than 88.3% of the total variation of the eight indicators. The factor loadings all fell within the range of 0.683 and 0.808. Only one factor had an eigenvalue exceeding the threshold of one, meaning that one latent variable can sufficiently explain the eight indicators. Also, Cronbach's α of *General Acceptance of DCTs* was as high as 0.91 (see Table 2). Therefore, this result yields a solid basis for considering these questions as indicators of subjects' general acceptance of the government's use of DCTs in epidemic prevention. The first factor in the EFA was then extracted as our first dependent variable. OLS was performed as indicated below to test our hypothesis as the variable turned semi-continuous after dimension reduction.

Table 2

Factor Analysis of Multiple-item Variables

Concept	Question number	Factor Loading	Cronbach's alpha
General Acceptance of DCTs	CT1	0.683	0.913
	CT2	0.752	
	CT3	0.741	
	CT4	0.766	
	CT5	0.805	
	CT6	0.794	
	CT7	0.750	
	CT8	0.806	
Perceived Usefulness	PU1	0.684	0.829
	PU2	0.674	
	PU3	0.765	
	PU4	0.635	
Privacy Concern	PV1	0.802	0.860
	PV2	0.766	
	PV5	0.717	
Technology Fear	TF2	0.746	0.878
	TF3	0.892	
	TF4	0.812	
Trust	PT1	0.921	0.937
	PT2	0.917	
	PT3	0.819	
Pro-social	S1	0.612	0.717
	S2	0.609	
	S3	0.665	
Risk Perception	RP2	0.745	0.797
	RP3	0.755	

Source: This study.

Except for the general acceptance, we further focused on the subjects' acceptance of each type of DCT. The scores they got from their acceptance and support for four DCTs were converted into four binary variables by mean. If the mean scores of the two questions were greater than or equal to 4 (agree or strongly agree), the variable was coded as accepted (1), otherwise not accepted (0). The proportions of accepted and unaccepted responses in the four DCTs were reasonably even. Logistic regression was performed to see how the independent variables covariated distinctively to these four dependent variables. A seemingly unrelated estimation was used to compare whether the coefficients of each pair of models were significantly different from the others.

(B) Independent variables

Based on the previous empirical studies, we selected the six factors possibly related to the *General Acceptance of DCTs* by the five-point Likert scale items, as in measuring our dependent variables: *Perceived Usefulness*, *Privacy Concern*, *Technology Fear*, *Trust*, *Pro-social*, and *Compliance*. In addition, people's willingness to comply with public health actions was said to relate to their risk perception and direct experience of COVID-19 (Dryhurst et al., 2020), so we included COVID-19 risk perception, COVID-19 experiences and fear of being quarantined as controls, together with demographic information such as gender, age, monthly income, education level, and living in the northern regions where the outbreaks occurred (Keelung, New Taipei, Taipei, Taoyuan, Hsinchu, Miaoli). [2]

EFA was performed on all of the items including *Perceived Usefulnes*s, *Privacy Concern*, *Technology Fear*, *Trust*, *Pro-Social*, and *Risk Perception* constructs to establish the measurement validity and reliability of the latent variables measured by more than a single item. The preliminary result with varimax rotation is presented in Appendix 1. Only those with an eigenvalue higher than one are shown, while factor loadings lower than 0.6 have been blanked. Six latent constructs almost precisely correspond to the questions measuring them, indicating that the scale used in this paper has a solid degree of construct and discriminant validity. Items with a factor loading less than 0.6 in their corresponding factors (PV3, PV4, RP1, RP4, and RP5) and a cross-loading larger than 0.6 (TF1) were removed. The same EFA method was repeated after deletion, and the results remained similar. The cumulative explained variance of the six factors is 63%, exceeding the general acceptable threshold of 60% (Hinkin, 1998). Table 2 summarizes the factor loadings of the remaining items from each construct and the statistics of their internal consistency reliability (Cronbach's alpha, which falls in the range of 0.72 to 0.93.) Hence, we extracted the factor scores of the first six factors from it for subsequent analysis.

The VIFs of the six main explanatory factors range from 1.05 to 3.14, significantly lower than the strict threshold of 3.3 (Kock, 2015). Therefore, collinearity was not an issue. The descriptive statistics of the leading research and control variables are presented in Table 3. Composite variables were all standardized to increase their comparability in the following analysis.

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[2] Since there are few item nonresponses in the subjects' subjective judgment of the importance of complying with epidemic prevention measures (C1), COVID-19 experience, and demographic information, we performed mean and mode (for categorical or ordinal variables, respectively) imputation to keep those subjects from falling out in the subsequent analyses. The number of imputations in each variable is at most six, which is minor compared to a 444 sample size.

Table 3

Descriptive Statistics for each Variable (N = 444)

Variable Name	Mean / Percentage	SD
Dependent Variables (Acceptance)		
General Acceptance of DCTs	0.00	0.966
GF	0.50	
BDA	0.55	
SMS	0.59	
TSDA	0.52	
Independent Variables		
Perceived Usefulness	0.00	0.881
Privacy Concern	0.00	0.888
Technology Fear	0.00	0.925
Trust	0.00	0.957
Pro-social	0.00	0.800
Compliance	4.39	0.785
Control Variables		
Gender (male=1)	0.52	
Risk perception	0.00	0.831
Covid-19 Experience		
Performed Rapid Test	0.43	
Had Family Members or Friends Tested Positive	0.43	
Fear of being Quarantined	0.35	
Age		
20-29 years old	0.20	
30-39 years old	0.27	
40-49 years old	0.22	
50-59 years old	0.19	
over 60 years old	0.12	
Income		
Below 29,999 NT	0.24	
30,000-49,999 NT	0.41	
50,000-99,999 NT	0.31	
Above 100,000 NT	0.05	
Education		
Below High School	0.16	
College	0.62	
Graduate School	0.21	
Northern Region	0.54	

Note. For binary variables, only their percentages in the 444 samples are presented in the table.
Source: This study.

V. Findings

Table 4 presents three OLS regression models with *Acceptance of DCT* being the dependent variable. Model I is a baseline model that only contains control variables. The overall explanatory power of Model I is low. Its adjusted R^2 shows that the control variable only explains 1% of the total variation of the dependent variable, and the F-test is not significant. Namely, the subjects' attitudes toward those DCTs are unrelated to their demographic and objective variables. This result justifies our attempt to examine the role of subjective and perceptional factors.

Table 4

General Acceptance of Digital Contact Tracing Technologies

	Model I		**Model II**	
	B	s.e.	β	s.e.
Main Variables				
Perceived Usefulness			0.673***	(0.028)
Privacy Concern			-0.184***	(0.032)
Technology Fear			0.05	(0.031)
Trust			0.226***	(0.029)
Pro-social			0.081***	(0.027)
Compliance			0.163***	(0.036)
Control Variables				
Risk Perception	0.075	(0.056)	0.038	(0.027)
Covid-19 Experience				
Performed Rapid Test	0.002	(0.107)	0.044	(0.065)
Had Family Members or Friends Tested Positive	0.094	(0.102)	0.05	(0.058)
Fear of being quarantined	0.061	(0.102)	-0.13**	(0.064)
Gender (male=1)	-0.105	(0.095)	-0.116**	(0.056)
Age (base: 20-29 years old)				
30-39 years old	0.327**	(0.149)	0.022	(0.084)
40-49 years old	0.293*	(0.156)	0.058	(0.095)
50-59 years old	0.110	(0.170)	0.102	(0.094)
Over 60 years old	0.246	(0.192)	0.047	(0.109)

Table 4 (continued)

	Model I		Model II	
	B	s.e.	β	s.e.
Income (base: Below 29,999 NT)				
30,000-49,999 NT	-0.084	(0.119)	-0.009	(0.077)
50,000-99,999 NT	-0.321**	(0.144)	-0.104	(0.083)
Above 100,000 NT	-0.346	(0.285)	-0.167	(0.145)
Education (base: Below High School)				
College	-0.148	(0.149)	0.027	(0.078)
Graduate School	-0.001	(0.187)	0.092	(0.110)
Northern Region	0.092	(0.103)	0.064	(0.061)
Intercept	-0.019	(0.197)	-0.009	(0.117)
R-squared	0.048		0.695	
Adjusted R-squared	0.010		0.679	
F test	$p = 0.162$		$p < 0.001$	

Note. *** p<0.01, ** p<0.05, * p<0.1; the standard deviation in the table is the robust standard deviation.

Source: This study.

Model II contains both the control and the main explanatory variables. *Perceived Usefulness* is the one with the most prominent effect among the variables in the model. Its one standard score increases significantly uplifted the subjects' general acceptance of DCTs by 0.673 standard scores. *Privacy Concern* is the only variable significantly decreasing the subjects' general acceptance of DCTs. Trust in government officials has a relatively larger effect so that one standard store increase leads to a 0.226 increase in the acceptance of DTCs. *Technology Fear* is inconsistent with our theoretical expectations. In general, the explanatory power of Model II is excellent. The adjusted R^2 implies that the above variables explained nearly 70% of the dependent variable's variation. As for control variables, women had a significantly more positive attitude toward DCTs in epidemic prevention than men; subjects who expressed concern about being quarantined were more resistant to the use of DCTs.

Table 5 presents the response to whether subjects accepted a certain DCT from among the four logistic regression models. The Pseudo R^2 statistics of the four models are higher than 0.2, implying an excellent explanatory power to citizens' DCT acceptance (McFadden,

Table 5

Logistic Regression Models for each of the DCTs

	GF		BDA		SMS		TSDA	
	B	s.e.	β	s.e.	β	s.e.	β	s.e.
Main Variables								
Perceived Usefulness	1.447***	(0.177)	1.577***	(0.186)	1.944***	(0.209)	1.900***	(0.218)
Privacy Concern	-0.382***	(0.136)	-0.554***	(0.140)	-0.451***	(0.153)	-0.136	(0.142)
Technology Fear	-0.172	(0.128)	0.119	(0.131)	0.0900	(0.152)	-0.163	(0.150)
Trust	0.325**	(0.139)	0.377***	(0.141)	0.710***	(0.147)	0.936***	(0.152)
Pro-social	0.229*	(0.121)	0.576***	(0.139)	0.0256	(0.158)	0.195	(0.138)
Compliance	0.339**	(0.147)	0.226	(0.144)	0.518***	(0.152)	0.205	(0.148)
Control Variables								
Risk Perception	0.374***	(0.128)	0.316**	(0.140)	0.0539	(0.150)	0.0465	(0.141)
Covid-19 Experience								
Performed Rapid Test	-0.207	(0.271)	0.174	(0.272)	0.289	(0.290)	0.150	(0.278)
Had Family Members or Friends Tested Positive	0.188	(0.262)	0.518**	(0.264)	0.349	(0.289)	-0.0321	(0.255)
Fear of Being Quarantined	-0.107	(0.261)	-0.0746	(0.273)	-0.152	(0.285)	-1.090***	(0.294)
Gender (male=1)	-0.179	(0.247)	0.366	(0.265)	-0.644**	(0.281)	-0.0358	(0.269)
Age (base: 20-29 years old)								
30-39 years old	-0.242	(0.364)	-0.0996	(0.385)	0.640	(0.415)	0.247	(0.405)
40-49 years old	-0.0250	(0.394)	-0.0966	(0.398)	0.538	(0.425)	0.209	(0.429)
50-59 years old	0.227	(0.425)	-0.400	(0.422)	0.916**	(0.456)	-0.155	(0.447)
Over 60 years old	0.408	(0.528)	0.544	(0.613)	0.117	(0.652)	-0.141	(0.565)
Income (base: below 29,999 NT)								
30,000-49,999 NT	0.378	(0.332)	0.304	(0.341)	-0.00518	(0.365)	-0.104	(0.334)
50,000-99,999 NT	0.210	(0.381)	-0.0639	(0.373)	-0.411	(0.411)	-0.367	(0.404)
Above 100,000 NT	0.951	(0.585)	-0.0826	(0.563)	-0.183	(0.654)	-0.436	(0.608)
Education (base: Below High School)								
College	-0.0696	(0.369)	0.119	(0.422)	0.297	(0.475)	-0.0743	(0.407)
Graduate School	0.333	(0.447)	0.474	(0.517)	0.619	(0.558)	-0.113	(0.525)
Northern Region	0.182	(0.253)	0.256	(0.262)	-0.363	(0.284)	0.0349	(0.269)
Intercept	-0.333	(0.513)	-0.541	(0.576)	0.241	(0.614)	0.638	(0.538)
Pseudo R-squared	0.287		0.330		0.388		0.359	
ROC-AUC	0.843		0.858		0.884		0.874	

Note. ***p<0.01, **p<0.05, *p<0.1; the standard errors in the parentheses are the robust standard deviation. ROC-AUC is the abbreviation for the area under the receptive operating characteristic curve. It is meant to indicate how well our models classify respondents who accept the DCT or not.

Source: This study.

1979, p. 306). The area under the receptive operating characteristic curve (ROC-AUC) of the four in Table 5 are all above 0.8 and even approaching 0.9 for SMS and TSDA, which are considered excellent fits (Hosmer & Lemeshow, 2013, p. 177). According to seemingly unrelated estimations that compared the six factors' coefficients across the four models (Appendix 3), except for the GF and BDA pair, all the other pairs of the four models have significantly different coefficients in six major explanatory factors. The difference between SMS and TSDA is only significant on a marginal level. The general pattern shows that the coercive – voluntary spectrum determines the overall similarity of the four models' coefficient estimations.

As shown in Table 5, *Perceived Usefulness* and *Trust* are the most consistent explanatory variables throughout the four models. One standard score increase in *Perceived Usefulness* could increase the log odds of a subject accepting all DCTs by more than 1.45. In the SNS and TSDA models, the effects are as large as 1.94 and 1.90, respectively. One standard score increase in *Trust* increases the log odds of subjects accepting SMS and TSDA by 0.71 and 0.94, respectively. However, the effect sizes shrink to around 0.35 in the GF and BDA models, which is even lower than for such variables as *Privacy Concern* and *Pro-social* in these two models. The seemingly unrelated estimation comparing coefficients of *Trust* in the four models only finds significant coefficient differences when comparing more coercive DCTs (GF, BDA) with more voluntary ones (SMS, TSDA). This implies a strong relationship between citizens' political trust and favorability of voluntary DCT. Overall, only Hypothesis 1 and 4 are fully sustained by the data.

The model of TSDA is the only one in which *Privacy Concern* does not have a significant negative effect. In contrast, one standard score increase in the *Privacy Concern* reduces the log odd of an individual taking a positive attitude towards BDA by 0.55, the highest among the four. Pro-social significantly improves the possibility that a person holds a positive stance on the government's utilization of GF and BDA, the more coercive measures among the four. Subjects with higher *Compliance* are more likely to accept GF and SMS.

The control variables also provided interesting information. Subjects with a higher risk perception of contracting COVID-19 were more inclined to coercive measures, such as GF and BDA. Having relatives or friends diagnosed with COVID-19 increases a subject's log odds of accepting BDA by 0.52 compared to those who did not. Those who conveyed worries about being quarantined had considerably lower log odds of accepting TSDA by 1.09. Finally, the log odds of males showing a positive attitude to SMS is 0.64 lower than that of females. Table 6 summarizes all the hypothesis testing results, and their

corresponding evidence can be found in Figure 1.

Table 6

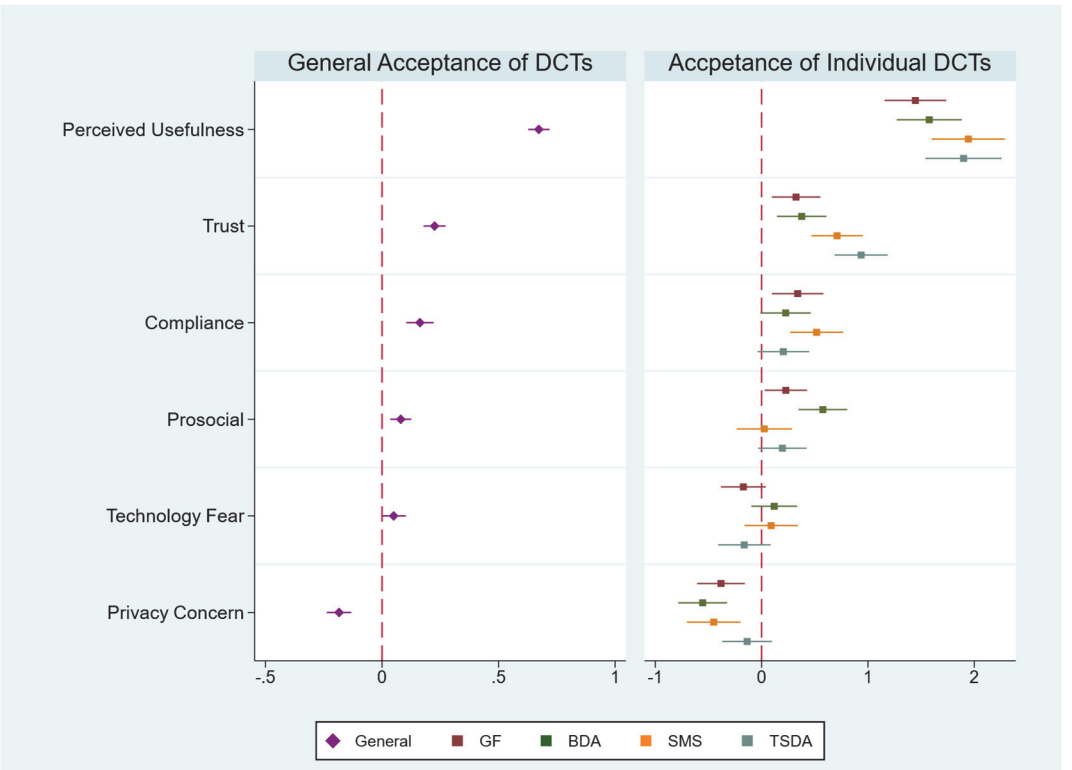
Hypothesis Testing Results

Hypothesis	Evidence	Verdict
Hypothesis 1: Individuals who felt that DCTs are useful in epidemic prevention are more likely to report a higher acceptance of DCTs.	General DCT GF BDA SMS TSDA	Supported
Hypothesis 2: Individuals who reported a higher privacy concern are less likely to report a higher acceptance of DCTs.	General DCT GF BDA SMS	Partly Supported
Hypothesis 3: Individuals who expressed a stronger fear of new technologies are less likely to report a higher acceptance of DCTs.	-	Not Supported
Hypothesis 4: Individuals who had more trust in the reigning government officials are more likely to report a higher acceptance of DCTs.	General DCT GF BDA SMS TSDA	Supported
Hypothesis 5: Individuals who bore a higher pro-social spirit are more likely to report a higher acceptance of DCTs.	General DCT GF BDA	Partly Supported
Hypothesis 6: Individuals who considered following the instructions from the government important are more likely to report a higher acceptance of DCTs.	General DCT GF SMS	Partly Supported

Source: This study.

Figure 1

Coefficients of the Main Explanatory Variables and Their 90% Confidence Intervals.



Source: This study.

VI. Discussion and Conclusions

This study has the following findings, which need further discussion. First, through factor analysis, our study confirms the commonality in accepting four distinctive DCT measures. Five of the factors (*Perceived Usefulnes*s, *Privacy Concern*, *Trust*, *Pro-Social*, and *Compliance*) identified in previous literature relate to citizens' general acceptance of DCTs, and they have explained the vast majority (over 70 percent) of the variance. These results overlap with the major findings on privacy concerns, social norms, and trust in the government from the latest meta-analysis of DCT acceptance done by Kuo (2023). With that in mind, our study validates that these DCT acceptance factors mentioned in the previous literature can be broadly applicable among the Taiwanese samples of this study.

However, upon a closer inspection of the acceptance of individual DCTs, only two

factors maintain a consistent positive association with acceptance: perceived usefulness and political trust. This finding corroborates that a person's acceptance of digital health surveillance measures is more than the perceived usefulness often emphasized in the technology acceptance literature (Velicia-Martin et al., 2021). The highly political nature and publicness of the DCT policies rendered political trust a pivotal role in winning citizens' support (Redmile, 2020; Dudás & Szántó, 2021, p13; Schraff, 2021). Our findings further indicate that political trust is especially important for DCT policies that adopt a more voluntary policy instrument, as do SMS and TSDA in our study. This underscores the need for public managers and policy designers to consider public sentiment toward authorities and actively foster an enabling environment through public value creation when utilizing voluntary DCTs for disease control (Moore, 1995; Guan et al., 2021).

Second, while varying in significance and effect sizes across the DCTs, the other factors offer valuable insights for future DCT design and promotion. Privacy concerns are negatively associated with GF, BDA, and SMS but not TSDA. This distinction could be explained by the trade-off between data-first or privacy-first approaches in DCT designs (Fahey & Hino, 2020). Generally, GF, BDA, and SMS are more of a data-first approach as they collect extensive sensitive data (e.g., locations, transactions, and personal connections), thus infringing on citizens' privacy. By contrast, TSDA focuses more on privacy protection via decentralized data storage and user anonymity to accommodate the needs of those who have higher privacy concerns. This exception suggests that privacy and data security apprehensions can be resolved with specific public health surveillance measures if innovative designs and persuasive policies adequately address these concerns. For instance, app developers should provide clear app descriptions and transparently communicate privacy risks related to data collection, usage, and storage to encourage greater adoption (Li et al., 2021).

Third, Taiwanese with stronger pro-social attributes exhibit higher acceptance of more coercive DCTs, challenging Altmann et al. (2020) and O'Callaghan et al. (2021), who emphasize altruistic motivation driving the adoption of voluntary DCTs. The discrepancy may be due to the collectivist inclination of Taiwanese culture, in contrast to Western individualism (Kuo, 2023; Weiss-Sidi & Riemer, 2023), fostering greater tolerance for coercive policies and a greater willingness to sacrifice personal liberties. The role of culture and ideology in shaping preferences for coercive or voluntary policies has also been discussed by Bali et al. (2021) and Carley and Miller (2012). Hence, moral appeals such as "for the collective good" may primarily enhance compliance when paired with compulsory measures in Taiwan.

Fourth, the finding that females are generally more positive toward DCT policies echoes the literature on public service motivation (PSM) and co-production. Females were found to score higher in compassion and attraction to policy-making (DeHart-Davis et al., 2006), the two PSM dimensions shown to be related to more frequent digital co-production (Neumann & Schott, 2023). Parrado et al. (2013) also found that females are more willing to voluntarily devote their efforts to public affairs, and BDA happens to be the only DCT policy that requires no active effort input from citizens and has a positive coefficient for males in Table 5. Indeed, these findings should be interpreted with caution as the coefficients of gender in GF, BDA, and TSDA are not significant.

Overall, the main contributions of this study lie in three aspects. First, our study is the first one to empirically test all six factors simultaneously, while other studies only proposed and examined one or two factors separately. We used EFA to show that these factors are indeed distinguishable from each other and compared their relative importance through multiple model specifications. Therefore, we have broadened the theory of earlier research., The second contribution is that we considered the specific designs of the different DCT policies and demonstrated how the effects of the factors vary across these four DCTs. We also explained these differences by looking at where each policy falls on the coercive-voluntary policy instruments spectrum, thus contributing to the broad literature on regulatory governance. Lastly, this study complements the earlier survey of *hypothetical* DCT in Taiwan (Garrett et al., 2022) by exploring the variation of factors affecting *real-world* DCT acceptance with Taiwan's experience of epidemic prevention.

VII. Policy Implications and Limitations

Regarding policy implications, our findings endorse the simultaneous deployment of multiple DCTs in public health surveillance as they address distinct individual concerns, align with unique demographic characteristics, and thus complement each other. By strategically combining DCTs and employing persuasive policies that emphasize transparency, evidence of effectiveness, information security, and the pursuit of the greater good, governments can enhance compliance with DCT measures, minimizing the policy cost of epidemic control. This remains crucial even in cases where compliance is regulatory (Guan et al., 2021).

Our findings further provide valuable insights into how to foster positive attitudes towards different DCTs. Most importantly, public administration practitioners should strengthen the citizens' perceived usefulness of DCTs and maintain public trust when using

technologies to assist with public health surveillance, as these two factors show strong and consistent connections with people's support for various DCT policies.

Furthermore, public administration practitioners should implement a transparent data protection framework for each DCT to address associated privacy concerns, which are a major obstacle to acceptance for most DCTs. The case of TSDA, being the only exception that is not associated with privacy concerns, suggests that elements of its design (periodically renewed random ID, stipulated period of data retention, etc.) can nullify the association between individual privacy apprehensions and DCT acceptance, providing a valuable reference for future designs of technology surveillance policies.

It is important to recognize the limitations of this study. There is potential selection bias since our sample, although randomly drawn, consists of the 450 earliest respondents. These proactive individuals may have unique characteristics related to DCT acceptance but were not controlled. Additionally, our sample skews towards the younger residents of northern regions and those with higher educational attainment, likely caused by the online nature of the survey conducted during the COVID-19 outbreak. The sample with these feature tendencies (younger and more highly educated) is just the group of people who are more likely to be active online for using DCTs and aligned with the DCTs focus of this study, though this group of people may not totally represent the whole population in Taiwan. Therefore, the results of this study should be generalized more to the younger and higher-education adults in Taiwan.

Secondly, the six factors derived from our literature review may not utterly rule out the subjectiveness involved in our discretion to extract factors although criteria of including or excluding the factors were made by the research team. Factors that are extracted by other scholars may be somewhat different from the six factors derived in this study as many minor qualitative decisions could be made when interpreting and discussing the collected literature (Linde & Willich, 2003). In addition, our model specification that treats all six factors as exogenous variables could be an oversimplification of a more advanced path model often seen in technology acceptance models, which requires further study for hypothesis testing.

Lastly, our study's cross-sectional design prevents us from establishing causal relationships, as we cannot track how acceptance evolved across the different pandemic phases with the six factors. Lastly, Taiwan's cultural idiosyncrasies may limit our findings' generalizability. We expect future researchers to explore international comparative cases or conduct meta-analyses to offer more definitive conclusions.

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Appendix

Appendix 1

Preliminary Exploratory Factor Analysis Results for Main Explanatory Variables

	Trust	Privacy Concern	Technology Fear	Perceived Usefulness	Risk Perception	Pro-social
RP1						
RP2					0.746	
RP3					0.724	
RP4						
RP5						
PU1				0.679		
PU2				0.666		
PU2				0.750		
PU4				0.633		
PV1		0.813				
PV2		0.763				
PV3						
PV4						
PV5		0.742				
TF1		**0.665**				
TF2			0.749			
TF3			0.881			
TF4			0.800			
PT1	0.916					
PT2	0.917					
PT3	0.818					
S1						0.605
S2						0.632
S3						0.656

Note: The values in the cells are factor loadings of each item in the first six factors in the EFA after varimax rotation. Items with a factor loading lower than 0.6 have been blanked. The emboldened loading is the cross-loading higher than 0.6. The corresponding item (TF1) is excluded thereafter.

Appendix 2

Each Research Concept and Its Corresponding Topic

Construct	Item code	Item	Reference	Delete
Acceptance of DCTs	CT1	Do you think the use of "Geofencing" (i.e., a system that locates people through their cell phones to help implement home quarantine measures) to prevent the pandemic is acceptable?	Adapted from Kostka et al. (2020)	
	CT2	Are you willing to scan the QR code of the "1922 SMS System"?		
	CT3	Do you think the use of "big data analysis" (alert messages/CCTV/ footprints of confirmed cases etc.) to prevent the pandemic is acceptable?		
	CT4	Are you willing to download and use "Taiwan Social Distancing"?		
	CT5	Do you support the government's coercive use of "Geofencing" based on the need for epidemic prevention?		
	CT6	Do you support the government forcing people to scan the QR code of the "1922 SMS System" based on the need for epidemic prevention?		
	CT7	Do you support the government using "big data analysis" to disclose the information of confirmed cases?		
	CT8	Do you support the government's launch of "Taiwan Social Distancing"?		
Perceived Usefulness	PU1	Do you think that "geofencing" is an effective way to prevent COVID-19?	Adapted from Walrave et al. (2021); Kostka et al. (2020)	
	PU2	Do you think that the "1922 SMS System" is an effective way to prevent COVID-19?		
	PU3	Do you think big data analysis is an effective way to prevent COVID-19?		
	PU4	Do you think that the "Taiwan Social Distancing" app is an effective way to prevent COVID-19?		
Privacy Concern	PV1	How much do you agree or disagree with the following statement?: I am concerned that public health surveillance tools are collecting too much personal information about me.	Prakash and Das (2022)	
	PV2	How much do you agree or disagree with the following statement?: I am concerned if this app uses my personal information for other purposes without getting my authorization.	Prakash and Das (2022)	
	PV3	How much do you agree or disagree with the following statement?: I believe in the government's ability to manage information security.	Adapted from Election Study Center Association of NCCU (2021)	X

Appendix 2 (continued)

Construct	Item code	Item	Reference	Delete
Privacy Concern	PV4	How much do you agree or disagree with the following statement?: I believe that the government can use people's personal information without their permission in order to prevent the pandemic.	Adapted from Election Study Center Association of NCCU (2021)	X
	PV5	How much do you agree or disagree with the following statement?: I am concerned about my personal information being compromised by the epidemic prevention policy.	Adapted from Prakash and Das (2022)	
Technology Fear	TF1	How much do you agree or disagree with the following statement?: I am fearful that someone is using technology to watch everything that I do.	Khasawneh (2018)	X
	TF2	How much do you agree or disagree with the following statement?: I am terrified that technologies will change the way we live.		
	TF3	How much do you agree or disagree with the following statement?: I am afraid of new technologies because one day they will make us (humans) obsolete.		
	TF4	How much do you agree or disagree with the following statement?: I am fearful that new technologies will someday take over my job.		
Trust	PT1	Do you have confidence in the Central Epidemic Command Center (CECC)?	Adapted from the Election Study Center Association of NCCU (2021)	
	PT2	Do you have confidence in the Tsai administration?		
	PT3	Do you think the current epidemic prevention measures taken by the government are reasonable?		
Pro-social	S1		Adapted from Caprara et al. (2005)	
	S2	How much do you agree or disagree with the following statement?: I feel empathy for those who are in need.		
	S3	How much do you agree or disagree with the following statement?: I help immediately those who are in need.		
Compliance	C1	Do you think it is important to comply with COVID-19 health surveillance measures?	Adopted from Riemer et al. (2020)	
Risk Perception	RP1	How worried are you personally about COVID-19?	Dryhurst et al. (2020)	X
	RP2	How likely do you think it is that you will be directly and personally affected by COVID-19?		
	RP3	How likely do you think it is that your friends and family will be directly affected by COVID-19?		

Appendix 2 (continued)

Construct	Item code	Item	Reference	Delete
Risk Perception	RP4	How much do you agree or disagree with the following statement?: I will probably get sick with COVID-19.		X
	RP5	How much do you agree or disagree with the following statement?: Getting sick with COVID-19 can be serious.		X

Note. Some questions were deleted according to the factor analysis results in Appendix 2.

Appendix 3

Seemingly Unrelated Tests Between Four Models on Six Major Factors

	GF	BDA	SMS
GF			
BDA	9.70		
SMS	10.80*	17.59***	
TSDA	13.32**	18.80***	11.96*

Note. ***p<0.01, **p<0.05, *p<0.1; The values in cells are chi-squared statistics with six degrees of freedom.

Source: This study.

臺灣民眾對數位接觸追蹤技術態度之影響因素

施沁懷、吳芸謙、劉康慧、吳舜文*

《摘要》

鑒於行動通訊裝置、物聯網與大數據分析技術之普及，數位接觸追蹤技術（DCTs）成為在 COVID-19 大流行期間，各國政府用以控制疾病擴散的新興利器，然有關這些技術在隱私、技術穩定性與可近用性等方面的顧慮卻從未止歇。本研究檢視影響公眾對政府使用 DCTs（包含電子圍籬、大數據分析、簡訊實聯制與臺灣社交距離 App）看法之因素。透過最小平方法與邏輯斯回歸分析 450 份網路問卷之結果顯示，認知有效性、隱私考量、政治信任、社會性和法遵性均與 DCT 整體接受度有顯著關聯。惟在細分 DCT 類別後，僅認知有效性和政治信任能穩健地預測公眾正面態度。政治信任與志願性 DCTs（簡訊實聯制、臺灣社交距離）之接受度擁有較強的關聯性；而親社會性僅與強制性 DCTs（電子圍籬、大數據分析）之接受度顯著相關。本文的研究貢獻在於針對過往文獻所提出的因素進行廣泛檢驗，並比較影響多種 DCTs 政策接受度的關鍵因素。本研究結果支持以同時部署多種 DCT 以提升民眾的政策順服度。

[關鍵詞]：新冠肺炎、數位接觸追蹤、民眾接受度、認知有效性、政治信任

* 施沁懷為國立臺灣大學政治學系前計畫研究專員，國立臺灣大學公共事務研究所碩士。
吳芸謙為國立臺灣大學公共事務研究所前研究助理，國立臺灣大學公共事務研究所碩士。
劉康慧為國立臺灣大學政治學系與公共事務研究所教授。
吳舜文為國立臺灣大學政治學系與公共事務研究所助理教授，email: shunwu@ntu.edu.tw