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An Empirical Study on the Reciprocity and Acceptance of Contact-tracing Apps

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Abstract: The "Health Code," a contact-tracing application deployed in China, was instrumental in managing the COVID-19 outbreak. Its success hinged on mutual acceptance and data sharing among users: individuals contributed and accessed personal information to assess and mitigate viral exposure risks. This study integrates the Technology Acceptance Model (TAM) and Social Exchange Theory to explore the psychological drivers of public endorsement of the "Health Code." We administered a survey to 3000 Chinese internet users to validate a moderated mediation model. The findings reveal that reciprocal behavior indirectly shapes attitudes toward the "Health Code" through the perceived risk and utility. However, the perception of COVID-19 risk partially attenuates this effect. The endorsement of the "Health Code" emerges from a symbiotic process, underpinned by a system of reciprocal data exchange. Findings confer theoretical and practical implications on propagating public health technologies, highlighting the motivating potential of reciprocal appeals and data transparency, while adapting strategies to evolving pandemic threats. Limitations concerning sample representativeness and model generalizability are discussed alongside prospective avenues exploring changing attitudes and automated tracing protocols.

Keywords: contact-tracing apps; COVID-19; public health crisis; reciprocity; technology acceptance

1 INTRODUCTION

When Ming, a university student from Peking University, was about to enter a shopping mall, he was stopped by a security guard who requested that he scan the "Health Code" before proceeding. Simultaneously, several others at the entrance were also engaged with the "Health Code" trying to gain access. Despite complaints about slow internet speeds, there was a general sense of acceptance among them. Ming reflected on the evolution of the "Health Code": Initially, its adoption was driven by mandatory measures, but it soon became a staple in the daily life of Chinese citizens. Ming personally recognized its inconvenience, but also acknowledged its importance in safeguarding health by tracking the proximity of potentially infected individuals during the pandemic. He noted that its effectiveness hinges on widespread compliance, suggesting that a sense of reciprocal responsibility is necessary for its success. The "Health Code" mentioned in the narrative is a Chinese iteration of contact-tracing apps designed to help control the spread of coronavirus disease (COVID-19). It functions primarily by gathering personal data to identify individuals who may have been in proximity to an infected person, thereby tracking infection chains [2, 3]. Utilizing QR codes and big data, the "Health Code" evaluates an individual's risk of contagion based on factors like physical health, travel history, and connections with possible carriers [4], in addition to vaccination status and nucleic acid test results. Users are assigned a color-coded status reflecting their risk level and mobility permissions, a requirement for accessing public spaces in China [5]. Each province implements its own version of the "Health Code" (e.g., Beijing's "Health Kit," Shanghai QR Code, Guangdong Health Code), varying in name and interface but maintaining technological uniformity and similar usage patterns for national consistency. These "Health Codes" are government-managed and typically integrated into popular commercial platforms such as WeChat and Alipay. By December 2020, approximately 900 million people in China had registered for a "Health Code" [6], exceeding the active user rate threshold (i.e., 60%) necessary for the app to effectively contribute valuable insights, aiding the government in virus containment efforts [7].

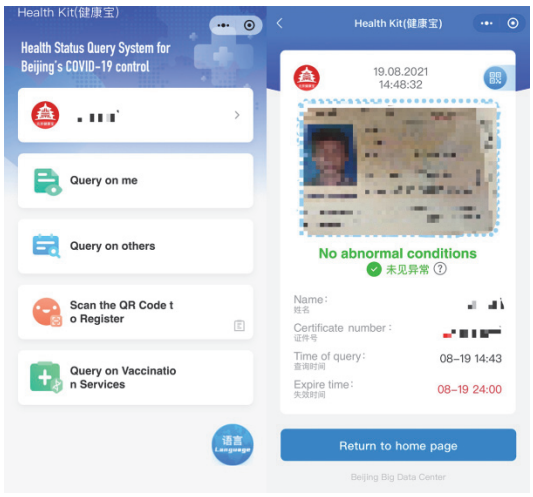

Figure 1 The initial interface and the interface displayed after scanning the QR code of the "Health Kit" deployed in Beijing

The success of contact-tracing apps relies heavily on public acceptance [8]. While past research has explored various factors influencing the acceptance of these apps in different social scenarios [8-13], there remains a gap in understanding specific technological and contextual features of these apps as they are applied to current public health crises, as pointed out in recommendations for future directions in technology acceptance research [14]. Contact-tracing apps fundamentally operate on the principle of data sharing, which involves managing the visibility and accessibility of personal information. From the lens of social exchange theory, personal data is viewed as an object of social exchange. People engage in a "benefit-risk" evaluation, tending to share data and accept contact-tracing apps when they perceive the public health benefits to outweigh their personal privacy and security concerns [15]. However, the benefits and risks in this context are not solely derived from individuals exposing their data. Instead, they stem from the involvement of others: by sharing personal data, data owners allow others to be informed of their whereabouts and health status. Simultaneously, the perceived risks are fueled by concerns

over data breaches or misuse by others. Similarly, the data owners' self-interests depend on others sharing their tracks and facing similar risks. This reciprocal dynamic forms the basis of the research questions posed in the current study:
RQ1: How does reciprocity influence the acceptance of contact-tracing apps, and in what ways does it manifest during this process?
RQ2: What role does the context of a crisis situation play in shaping this reciprocal dynamic in the acceptance of contact-tracing apps?

2 LITERATURE REVIEW, HYPOTHESIS DEVELOPMENT AND RESEARCH MODEL

To support our study, we have conducted a comprehensive review exploring the topics including reciprocity, TAM based studies, 'benefit-risk' calculus and knowledge about public health crisis. Based on the findings of the literature, we proposed the hypotheses of our study.

2.1 Reciprocity

The significance of Social Exchange Theory [16] in predicting the use of collective technologies is well-recognized [17]. From this theoretical standpoint, reciprocity is viewed as an external benefit that motivates social exchanges based on relationships [18]. This is rooted in the tendency of individuals to seek maximization of benefits while minimizing risks and costs in any exchange [19]. In this context, when people assist others, they often do so with the expectation of future rewards and reduced risks. In the scope of this study, reciprocity is defined as a collective rationality that encompasses both a concern for the health of others and a positive expectation of receiving help in return, particularly in the context of deciding whether to accept contact-tracing apps. Reciprocity is often invoked to elucidate knowledge-sharing behaviors in virtual communities, where the sharing of knowledge by members is a critical source of collective value [20, 21]. In such environments, the willingness to share knowledge is propelled by the anticipation of future assistance from others [22]. Additionally, participants in online communities who engage in knowledge sharing often operate under the principle of reciprocity [23], finding that they tend to receive help more swiftly when they request it [24]. In the context of contact-tracing app acceptance, individuals who believe in the reciprocal health benefits are more inclined to perceive the usefulness of the "Health Code". When the "Health Code" is broadly accepted for its role in controlling COVID-19, it fosters a sense of communal support and kindness. This perception can lead to a reduced perception of risks associated with the use of the "Health Code". Consequently, Hypotheses 1 and 2 have been formulated as follows:
Hypothesis 1: Reciprocity has a negative effect on perceived risk associated with contact-tracing apps.
Hypothesis 2: Reciprocity positively influences the perceived usefulness of contact-tracing apps.

2.2 Technology Acceptance Theories

The Technology Acceptance Model (TAM), introduced by Davis [25], has been established as a robust and effective framework for examining the factors influencing an individual's adoption of new technology [26]. It postulates that a user's intention to use a technology is influenced by its perceived usefulness and ease of use. Perceived usefulness is defined as the degree to which a person believes that using the technology will improve their job performance. Perceived ease of use, on the other hand, relates to how effortless the user expects the technology to be [25]. However, their impacts vary; meta-analyses suggest a stronger influence of perceived usefulness on behavioral intention, while the impact of perceived ease of use is more contentious [26, 27]. In this study, we adapt the TAM as a foundational framework in a simplified form [28], focusing primarily on the "perceived usefulness → intention to use" pathway, while controlling for other factors. In the Technology Acceptance Model (TAM), perceived usefulness is a central factor theorized to mediate the impact of external beliefs on the acceptance of technology [25]. As research in technology acceptance has expanded into more complex arenas, such as consumer behavior, the concept of perceived risk has been integrated into the model. Previous empirical studies have established a negative correlation between perceived risk and both perceived usefulness and attitudes towards usage (or behavioral intention) in various contexts, including e-service [28], e-government [29], and online applications [30]. During the COVID-19 pandemic, the acceptance of contact-tracing apps has been shown to be positively influenced by perceived usefulness [31] or performance expectancy [9]. Conversely, privacy concerns or discomfort [12], as well as privacy and security issues [32], have been identified as obstacles to the adoption of these apps. Based on these insights, Hypotheses 3-5 have been developed as follows:
Hypothesis 3: Perceived risk negatively influences perceived usefulness of the "Health Code".
Hypothesis 4: Perceived risk negatively affects the acceptance attitude towards the "Health Code. "
Hypothesis 5: Perceived usefulness positively affects the acceptance attitude towards the "Health Code. "

2.3 A "Benefit-Risk" Calculus

Tracking prompts consideration of the balance between the desire to preserve physical health and safety and the fundamental rights to dignity and privacy [33]. Individuals are inclined to share personal information when the perceived advantages, such as public health benefits, outweigh the potential negative impacts, like the encroachment of surveillance [34]. For managing COVID-19, digital applications have demonstrated effectiveness, yet they also pose challenges in terms of privacy and usability [2]. The trade-off between privacy and efficacy is crucial in the adoption of COVID-19 contact-tracing apps [35]. In Spain, evidence suggests that when faced with the dilemma of health versus privacy, the majority opted for health [13]. Contrastingly, in German-speaking regions, the adoption of contact-tracing apps has been hindered by privacy concerns, which outweighed perceived benefits [36]. In China, the "Health Code" was perceived as a potential risk to data security, highlighting a growing tension between public values and individual privacy [4]. Thus, the acceptance of contact-

tracing apps can be viewed as a process of weighing the benefits and risks associated with personal data. Hypothesis 6: Reciprocity indirectly influences the acceptance attitude towards the "Health Code" with this effect being mediated by both perceived risk and perceived usefulness.

2.4 Context of Public Health Crisis

From an instrumental rationality perspective, contact-tracing apps are utilized as a "tool" for containing the COVID-19 virus, essentially aiding in problem-solving. When the severity of the problem escalates, individuals may forego personal benefits in recognition of the urgent need to employ this technology. Previous studies have shown that government surveillance is deemed acceptable when deemed "necessary" [37]. In the context of a public health crisis, the perceived threat of COVID-19 has been identified as a predictor for the acceptance of COVID-19 tracking technology in various countries [8, 10, 11, 13]. This suggests that the greater the perceived risk from COVID-19, the more individuals are inclined to depend on contact-tracing apps. This reliance, in turn, reinforces their belief in reciprocity and consequently reduces their perceived risk, as hypothesized. Based on this understanding, Hypothesis 7 was proposed as follows:

Hypothesis 7: The perception of risk associated with COVID-19 negatively moderates the inverse relationship between reciprocity and perceived risk, subsequently reinforcing the indirect impact of reciprocity on the acceptance attitude towards the "Health Code".

2.5 Research Model

This study aimed to explore the psychological underpinnings of public acceptance of contact-tracing apps during a public health crisis, particularly from a perspective of reciprocity. By integrating the Technology Acceptance Model (TAM) with social exchange theory, reciprocity was introduced as a key precursor within the TAM framework, specifically influencing the "perceived risk → perceived usefulness → intention to use" pathway, while controlling for other potential factors. Additionally, this research examined the moderating effect of COVID-19 risk perception to understand the contextual influence of the crisis situation. From a theoretical standpoint, this research enhances the TAM by integrating a novel exogenous mechanism rooted in reciprocity. Within this framework, data sharing is conceptualized as a fundamental aspect of contact-tracing technology acceptance, adding contextual depth to the theoretical model. On the practical side, this study offers valuable insights for the effective promotion of track tracing technologies, particularly in the context of COVID-19 containment, thereby providing significant managerial implications.

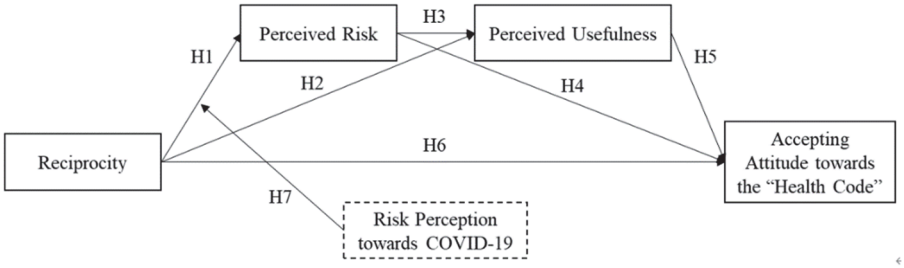

Figure 2 The research model

3 RESEARCH METHODOLOGY

3.1 Data Collection

Data for this study was gathered from 3000 Chinese internet users in March 2021, with the sampling closely aligned with the demographic distribution of Chinese netizens as detailed in the 47-th China Statistical Report on Internet Development [6]. The sample quota was adjusted to account for underrepresentation of individuals under 16 years of age and those from rural areas. The participant group consisted of 51.0% males and 49.0% females, with an average age of 32.5 years (*SD* = 11.45). The age distribution included 15.0% aged between 16 - 19 years, 28.0% between 20 - 29 years, 27.0% between 30 - 39 years, 20.0% between 40 - 49 years, and 10.0% over 50 years. Regarding geographic distribution, 10.0% resided in first-tier cities, 20.0% in new-first-tier cities, 20.0% in second-tier cities, and 50.0% in third-tier cities or below. The urban-rural split was 90.0% urban and 10.0% rural residents. The data collection was conducted by Ipsos (China), a reputable market research firm [38]. Participants from their interviewee-panel completed the questionnaires online. Participation was voluntary, with assurances of anonymity and privacy, and participants were compensated for their involvement.

3.2 Measurements

Our research model incorporated eight multi-item constructs, with five serving as primary constructs and three as covariates. The main constructs were reciprocity, perceived risk, perceived usefulness, risk perception towards COVID-19, and accepting attitude towards the "Health Code". The covariates included perceived ease of use (or effort expectancy), social influence, and facilitating conditions. Additionally, demographic factors such as gender, age, education level, and Internet experience were controlled [39, 40]. The measurement instruments were adapted from existing literature and tailored to fit the context of the "Health Code" in China. The construct of reciprocity was modified from [17], shifting the context from knowledge to data sharing. Perceived risk was based

on adaptations from [29] and [41]. Perceived usefulness and ease of use were derived from Davis [25], while social influence, facilitating conditions, and attitudes towards the "Health Code" followed the adaptations from [39]. Notably, we replaced 'intention to use' or 'behavioral intention' with 'accepting attitude towards the "Health Code"' to account for the influence of administrative enforcement in China, which could skew genuine acceptance of the technology. Risk perception towards COVID-19 was adapted from [42]. Each construct was measured on a 7-point Likert scale, ranging from 1 (strongly disagree) to 7 (strongly agree). The reliability of all measures was high (Cronbach's $\alpha > .80$) in this study (refer to Tab. 1), and detailed items are listed in Multimedia Appendix A. Regarding measurement specifics, education was categorized from 1 (primary school or below) to 6 (master's degree or above), with a mean of 3.49 ($SD = 0.97$). Internet experience was gauged by the number of years using the Internet, with an average of 12.37 years ($SD = 5.54$).

3.3 Data Analysis Approach

Initially, descriptive statistics and a correlation matrix were computed. Following this, the PROCESS macro by Hayes [1] was employed to test and validate the proposed model. Specifically, Model 6 from PROCESS was used to assess the mediation effects of perceived risk and perceived usefulness, while Model 83 was applied to examine the moderating influence of COVID-19 risk perception. Additionally, to evaluate the significance of indirect effects, the bootstrapping method outlined by [43] was utilized. This approach is recognized for its reliability in generating bias-corrected bootstrap confidence intervals. The significance of the effects is inferred when these confidence intervals do not include zero. For this study, 95% bias-corrected confidence intervals were generated using 5,000 resamples of the data, providing a robust examination of the indirect effects in the research model.

4 RESULTS

4.1 Descriptive Statistics and Correlations.

Tab. 1 presents the descriptive statistics for all variables and their zero-order correlations. Notably, reciprocity ($Mean = 5.85$, $SD = 1.08$), perceived usefulness ($Mean = 5.76$, $SD = 1.07$), and accepting attitude towards the "Health Code" ($Mean = 5.75$, $SD = 1.11$) scored relatively high. In contrast, perceived risk ($Mean = 3.80$, $SD = 1.70$) and risk perception towards COVID-19 ($Mean = 3.64$, $SD = 1.44$) were relatively low.

Key correlations observed were as follows:

Reciprocity was negatively correlated with perceived risk ($r = –0.187$, $P < 0.01$), but positively associated with perceived usefulness ($r = 0.711$, $P < 0.01$) and accepting attitude towards the "Health Code" ($r = 0.833$, $P < 0.01$). Perceived risk had negative correlations with both perceived usefulness ($r = –0.162$, $P < 0.01$) and accepting attitude towards the "Health Code" ($r = –0.200$, $P < 0.01$). Perceived usefulness was positively linked to accepting attitude towards the "Health Code" ($r = 0.715$, $P < 0.01$). Interestingly, risk perception towards COVID-19 was negatively related to reciprocity ($r = –0.133$, $P < 0.01$) and perceived usefulness ($r = –0.072$, $P < 0.01$), but it had a positive correlation with perceived risk ($r = 0.557$, $P < 0.01$). These correlations suggest intricate relationships between the various constructs in the study, particularly highlighting the roles of reciprocity and perceived risk in shaping attitudes towards the "Health Code".

4.2 Test of the Mediation Effect

Tab. 2 presents the results supporting Hypotheses 1 - 5. The findings indicate a negative relationship between reciprocity and perceived risk ($B = –0.3238$, $SE = 0.0495$, $P < 0.001$, Model 1), and a positive relationship between reciprocity and perceived usefulness ($B = 0.1909$, $SE = 0.0185$, $P < 0.001$, Model 2), thus confirming Hypotheses 1 and 2. Additionally, perceived risk was found to negatively affect perceived usefulness ($B = –0.0213$, $SE = 0.0068$, $P = 0.0016$, Model 2) and the accepting attitude towards the "Health Code" ($B = –0.0378$, $SE = 0.0055$, $P < 0.001$, Model 3), supporting Hypotheses 3 and 4. Perceived usefulness showed a positive link to accepting attitude towards the "Health Code" ($B = 0.0754$, $SE = 0.0149$, $P < 0.001$, Model 3), validating Hypothesis 5. Tab. 3 reveals the indirect effect of reciprocity on the acceptance of the "Health Code" ($B = 0.0005$, $SE = 0.0002$, 95% $CI = [0.0002, 0.0011]$), mediated by perceived risk and perceived usefulness, supporting Hypothesis 6. Additionally, the separate indirect effects of reciprocity on acceptance through perceived risk ($B = 0.0122$, $SE = 0.0025$, 95% $CI = [0.0078, 0.0175]$) and perceived usefulness ($B = 0.0144$, $SE = 0.0048$, 95% $CI = [0.0060, 0.0246]$) were also found to be significant. These results underscore the complex interplay between reciprocity, perceived risk, and perceived usefulness in shaping attitudes towards the "Health Code".

4.3 Test of the Moderated Mediation

Tab. 4 presents the results related to Hypothesis 7, indicating that the interaction between reciprocity and risk perception towards COVID-19 positively predicted perceived risk ($B = 0.0425$, $SE = 0.0189$, $P = 0.0245$, Model 1 of Tab. 4). This partially supports Hypothesis 7. Further analysis involved plotting simple slopes to examine the relationship between reciprocity and perceived risk at varying levels of COVID-19 risk perception.

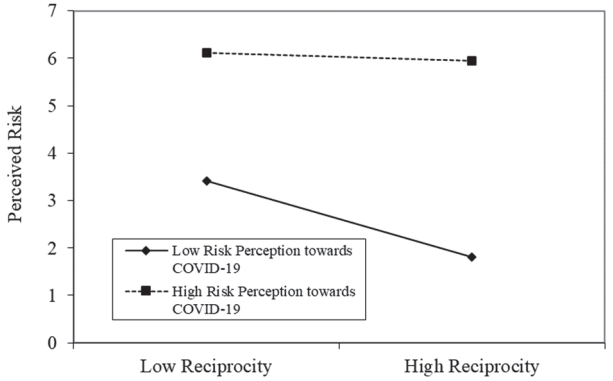

Figure 3 Interaction effect of reciprocity and risk perception towards COVID-19 on perceived risk

As illustrated in Fig. 2, the negative relationship between reciprocity and perceived risk was weaker when participants' perception of COVID-19 risk was high (*B* for high COVID-19 risk perception = –0.0877, *SE* = 0.0521, *t* = –1.6815, *P* = 0.09). Conversely, this negative relationship was stronger when the COVID-19 risk perception was low (*B* for low COVID-19 risk perception = –0.2104, *SE* = 0.0483, *t* = –4.3592, *P* < 0.001). This finding contrasts with the anticipated direction of the moderating effect proposed in Hypothesis 7, suggesting a more nuanced interaction between reciprocity and risk perception in shaping attitudes towards perceived risk.

Table 1 Descriptive statistics, alpha coefficients, and correlations

	Mean	SD	1	2	3	4	5	6	7	8	9	10	11	12
1. Gender	-	-	-											
2. Age	32.50	11.45	0.031	-										
3. Internet experience	12.37	5.54	0.004	0.294[a]	-									
4. Education	3.49	0.97	–0.061[a]	–0.285[a]	0.096[a]	-								
5. Perceived ease of use	5.76	1.04	–0.032	–0.133[a]	0.014	0.218[a]	(0.873)[c]							
6. Social influence	5.61	1.11	–0.036[b]	–0.036[b]	0.022	0.147[a]	0.668[a]	(0.846)[c]						
7. Facilitating conditions	5.67	1.10	–0.057[a]	–0.061[a]	0.027	0.171[a]	0.693[a]	0.789[a]	(0.844)[c]					
8. Reciprocity	5.85	1.08	–0.071[a]	–0.123[a]	0.018	0.205[a]	0.708[a]	0.742[a]	0.775[a]	(0.878)[c]				
9. Perceived risk	3.80	1.70	0.032	0.149[a]	–0.018	–0.137[a]	–0.142[a]	–0.100[a]	–0.124[a]	–0.187[a]	(0.952)[c]			
10. Perceived usefulness	5.76	1.07	–0.010	–0.101[a]	0.015	0.182[a]	0.780[a]	0.680[a]	0.683[a]	0.711[a]	–0.162[a]	(0.881)[c]		
11. Risk perception towards COVID-19	3.64	1.44	0.044[b]	0.145[a]	–0.074[a]	–0.239[a]	-0.077[a]	–0.004	–0.038[b]	–0.113[a]	0.557[a]	–0.072[a]	(0.839)[c]	
12. Accepting attitude towards the "Health Code"	5.75	1.11	–0.047[b]	–0.094[a]	0.009	0.176[a]	0.711[a]	0.780[a]	0.829[a]	0.833[a]	–0.200[a]	0.715[a]	–0.071[a]	(0.882)[c]

[a] $P < 0.01$, [b] $P < 0.05$, [c] Internal reliabilities (alpha coefficients) for the constructs.

Table 2 Testing the mediation effect of perceived risk and perceived usefulness on accepting attitude towards the "Health Code"

Predictors	Model 1 (Perceived risk)				Model 2 (Perceived usefulness)				Model 3 (Accepting attitude towards the "Health Code")			
	B	*SE*	*t*	*P*	*B*	*SE*	*t*	*P*	*B*	*SE*	*t*	*P*
Gender	0.0424	0.0605	0.70	0.48	0.0647	0.0224	2.89[b]	0.004	0.0154	0.0182	0.84	0.40
Age	0.0176	0.0029	5.97[a]	< 0.001	0.0003	0.0011	0.23	0.81	0.0000	0.0009	–0.05	0.96
Internet experience	–0.0137	0.0058	–2.36[c]	0.018	–0.0004	0.0022	–0.18	0.86	–0.0024	0.0017	–1.37	0.17
Education	–0.1125	0.0336	–3.35[a]	< 0.001	–0.0008	0.0124	–0.06	0.95	–0.0116	0.0101	–1.15	0.25
Perceived ease of use	–0.0389	0.0444	–0.88	0.38	0.5033	0.0164	30.62[a]	< 0.001	0.0633	0.0153	4.14[a]	< 0.001
Social influence	0.1074	0.0477	2.25[c]	0.024	0.1423	0.0177	8.05[a]	< 0.001	0.1647	0.0145	11.35[a]	< 0.001
Facilitating conditions	0.0268	0.0515	0.52	0.60	0.0744	0.0191	3.90[a]	< 0.001	0.3333	0.0155	21.45[a]	< 0.001
Reciprocity	–0.3238	0.0495	–6.54[a]	< 0.001	0.1909	0.0185	10.34[a]	< 0.001	0.3617	0.0153	23.70[a]	< 0.001
Perceived risk					–0.0213	0.0068	–3.15[b]	0.0016	–0.0378	0.0055	–6.85[a]	< 0.001
Perceived usefulness									0.0754	0.0149	5.07[a]	< 0.001
R^2	0.0605				0.6757				0.8003			
F	24.09[a]			< 0.001	692.25[a]			< 0.001	1198.14[a]			< 0.001

[a] $P < 0.001$, [b] $P < 0.01$, [c] $P < 0.05$.

Table 3 Indirect effects of reciprocity on accepting attitude towards the "Health Code" through the mediators

Indirect Paths	*B*	*SE*	95% Bootstrap *CI*[a]	
			Lower limit	Upper limit
Reciprocity → Perceived risk → Accepting attitude towards the "Health Code"	0.0122	0.0025	0.0078	0.0175
Reciprocity → Perceived usefulness → Accepting attitude towards the "Health Code"	0.0144	0.0048	0.0060	0.0246
Reciprocity → Perceived risk → Perceived usefulness →Accepting attitude towards the "Health Code"	0.0005	0.0002	0.0002	0.0011

[a] *CI* = confidence interval. *CI* is based on the bootstrapping of 5000 samples.

Table 4 Testing the moderated mediation effect of risk perception towards COVID-19 on accepting attitude towards the "Health Code"

Predictors	Model 1 (Perceived risk)				Model 2 (Perceived usefulness)				Model 3 (Accepting attitude towards the "Health Code")			
	B	*SE*	*t*	*P*	*B*	*SE*	*t*	*P*	*B*	*SE*	*t*	*P*
Gender	–0.0016	0.0511	–0.03	0.97	0.0647	0.0224	2.86[b]	0.004	0.0154	0.0182	0.84	0.40
Age	0.0098	0.0025	3.93[a]	< 0.001	0.0003	0.0011	0.23	0.81	0.0000	0.0009	–0.05	0.96
Internet experience	0.0008	0.0049	0.17	0.87	–0.0004	0.0022	–0.18	0.86	–0.0024	0.0017	–1.37	0.17
Education	0.0628	0.0288	2.18[c]	0.03	–0.0008	0.0124	–0.06	0.95	–0.0116	0.0101	–1.15	0.25
Perceived ease of use	–0.0209	0.0375	–0.56	0.58	0.5033	0.0164	30.62[a]	< 0.001	0.0633	0.0153	4.14[a]	< 0.001
Social influence	–0.0110	0.0404	–0.27	0.79	0.1423	0.0177	8.05[a]	< 0.001	0.1647	0.0145	11.35[a]	< 0.001
Facilitating conditions	–0.0103	0.0436	–0.24	0.81	0.0744	0.0191	3.90[a]	< 0.001	0.3333	0.0155	21.45[a]	< 0.001
Reciprocity	–0.3038	0.0776	–3.92[a]	< 0.001	0.1909	0.0185	10.34[a]	< 0.001	0.3617	0.0153	23.70[a]	< 0.001
Risk perception towards COVID-19	0.3889	0.1133	3.43[a]	< 0.001								
Reciprocity x Risk perception towards COVID-19	0.0425	0.0189	2.25[c]	0.0245								
Perceived risk					–0.0213	0.0068	–3.15[b]	0.0016	–0.0378	0.0055	–6.85[a]	< 0.001
Perceived usefulness									0.0754	0.0149	5.07[a]	< 0.001
R^2	.3317				0.6757				0.8003			
F	148.36[a]			< 0.001	692.25[a]			< 0.001	1198.14[a]			< 0.001

[a] $P < .001$. [b] $P < .01$. [c] $P < .05$.

Table 5 Index of moderated mediation of reciprocity's conditional indirect effects on accepting attitude towards the "Health Code" through the mediators

Indirect Paths	Index	SE	95% Bootstrap CI[a]	
			Lower limit	Upper limit
Reciprocity → Perceived risk → Accepting attitude towards the "Health Code"	–0.0016	0.0008	–0.0033	–0.0001
Reciprocity → Perceived risk → Perceived usefulness →Accepting attitude towards the "Health Code"	–0.0001	0.0000	–0.0002	0.0000

[a] *CI* = confidence interval. *CI* is based on the bootstrapping of 5000 samples.

The study further examined the conditional indirect effects of reciprocity on the acceptance attitude towards the "Health Code" mediated by perceived risk and perceived usefulness. Of all the indirect pathways evaluated, only the pathway "reciprocity → perceived risk → accepting attitude towards the 'Health Code'" was found to be significant (as detailed in Tab. 5). The analysis showed that for participants with a high level of COVID-19 risk perception, the indirect effect of reciprocity on acceptance of the "Health Code" was weaker ($B = 0.0033$, $SE = 0.0021$, 95% CI = [–0.0008, 0.0077]) compared to those with a lower risk perception level ($B = 0.0079$, $SE = 0.0024$, 95% CI = [0.0036, 0.0129]). The moderated mediation index was reported as follows: Index = –0.0016, SE = 0.0008, 95% CI = [–0.0034, –0.0001]. This suggests that when reciprocity interacted with COVID-19 risk perception, its indirect effect on acceptance of the "Health Code" mediated by perceived risk was diminished. While this finding aligns partially with Hypothesis 7, it also indicates an opposite direction of effect, highlighting a more complex relationship between reciprocity, risk perception, and technology acceptance.

5 DISCUSSION

This research enriches our understanding of the psychological dynamics behind the acceptance of the "Health Code" in China during the COVID-19 pandemic, particularly from a reciprocal standpoint. To unravel how reciprocity influences the acceptance of the "Health Code" our revised research model incorporated reciprocity into the core framework of the Technology Acceptance Model (TAM). The findings from the moderated mediation analysis revealed that reciprocity is inversely related to perceived risk while positively influencing perceived usefulness. Additionally, the study confirmed the "perceived risk → perceived usefulness → intention to use" pathway, further elucidating that reciprocity's impact on acceptance attitude towards the "Health Code" is mediated by both perceived risk and perceived usefulness. However, this indirect effect is partially moderated by the risk perception towards COVID-19. This study thus contributes both theoretical insights and practical implications, as discussed below.

Theoretical Implications

This study advances the field of contact-tracing app acceptance by focusing on the underlying logic of data sharing. Given that the effectiveness of such apps relies on network effects, especially in crisis situations, incorporating concepts like reciprocity as an antecedent and COVID-19 risk perception as a moderator into the Technology Acceptance Model (TAM) provides deeper insights into the public acceptance of the "Health Code" in China. This approach adds a novel exogenous mechanism to TAM, contextualized within the specific scenario of a public health crisis. Key insights from this study include: Data as a Core Analytical Unit: Personal data is central to understanding public acceptance of contact-tracing apps. The shift in perception of data from a private to a public good reflects its evolving role in social exchanges. People increasingly recognize personal data's social exchange value, weighing benefits and risks in their acceptance decisions. This shift underlines the need to view data as an exchange object, foundational to assessing the usefulness and risks associated with contact-tracing technologies. Reciprocity in Psychological Mechanisms: The study highlights reciprocity as a crucial psychological factor in public acceptance of technologies geared towards public health crises. Empirical results suggest that reciprocity can be effectively integrated into TAM as a predictive factor for app acceptance. This aligns with the idea that data sharing is a reciprocal action, with reciprocity shaping the boundaries and rules around privacy. In a pandemic context, this reciprocity encourages collective participation, balancing the benefits of a digital prevention network against the risks of data disclosure. Variability of Reciprocity's Effect: The study found that the influence of reciprocity on technology acceptance varies with the severity of the public health crisis. Contrary to expectations, the negative relationship between reciprocity and perceived risk weakens as COVID-19 risk perception increases. In more threatening pandemic conditions, self-preservation instincts might override collective rationality, diminishing the effectiveness of reciprocity. This indicates a complex interplay between altruism and egoism in the face of crisis, impacting the perceived exchange value of data and the effectiveness of reciprocity in technology acceptance. Overall, this study provides valuable theoretical and practical implications for understanding and enhancing the public acceptance of contact-tracing apps, particularly in the unique context of a public health crisis.

Practical Implications

The role of contact-tracing apps as a key technological tool in managing the COVID-19 pandemic has become critically important, especially given the need for widespread public acceptance during such a severe public health crisis. In China, the extensive use of the "Health Code" has been instrumental in effectively controlling the spread of COVID-19 through the creation of a digital prevention network. However, in other countries, the acceptance of similar contact-tracing technologies remains relatively limited [48]. This discrepancy underscores the importance of understanding and enhancing public acceptance of these apps for the broader scope of global public health. The insights provided by the current study offer valuable guidance for strategies aimed at increasing the adoption and effective use of contact-tracing apps worldwide. Firstly, fostering a sense of reciprocity and collective rationality among the public is crucial. This can

be achieved through a combination of ideological and physical strategies. Ideologically, it is important to promote positive social norms and the emotional benefits associated with accepting the app [31]. This involves using various communication channels like mass media, government policies, commercial platforms, and influencers to educate the public about the functionality of contact-tracing apps in controlling COVID-19 and the critical role of their participation. Physically, the implementation of the "Health Code" uses QR code technology based on big data and is strategically placed at key entry points in public spaces. This setup requires individuals to scan the codes and display their health status, reinforcing the visibility and belief in the reciprocal process of community health monitoring. Additionally, integrating the "Health Code" into popular platforms like WeChat and Alipay, which includes features for mutual assistance and checking, empowers grassroots self-governance and embeds the app into the social fabric. Despite some controversy and inconvenience, this approach reflects a collectivist cultural perspective, offering alternative insights into managing public health crises compared to more individualistic approaches typically seen in Western cultures. Secondly, effectively managing the "benefit-risk" balance during the decision-making process for accepting contact-tracing apps is crucial. This involves enhancing the perceived usefulness of these apps while simultaneously reducing perceived risks. To amplify perceived usefulness, it is essential to clearly demonstrate the apps' functionalities to the public. For instance, incorporating dynamic maps within the app to depict the real-time status of the COVID-19 pandemic and containment efforts, along with offering tools for personalized and long-term health tracking [49], can help users recognize the technology's capabilities. Given that robust privacy design is known to positively influence app acceptance [50], ensuring that the perceived usefulness of these apps outweighs their perceived risks is paramount. This can be achieved by implementing stringent data protection measures and communicating them transparently. For example, users should receive a clear and comprehensible statement regarding privacy management practices, including data ownership and control [4], right from the outset. Additionally, providing users with more effective privacy control options, such as the ability to dictate the extent and type of data collected, can significantly enhance trust in data autonomy. The effectiveness of privacy protection can vary depending on the technological form of the app. Apps that use Bluetooth or GPS technology for data collection can pose greater privacy risks due to continuous data tracking [3, 48, 51]. In contrast, QR code-based apps, which are typically used at specific physical locations, offer greater opportunities for privacy protection, as they allow for more controlled data collection in both time and space. Thirdly, promotional strategies for contact-tracing apps must account for the varying levels of the crisis context. As the severity of a crisis escalates, individuals often prioritize self-protection. In such scenarios, as indicated by the partially moderated mediation results, the influence of reciprocity on perceived risk, and consequently on acceptance decisions, may diminish. At this juncture, it becomes crucial to mitigate the negative impact of perceived risk. Focus should therefore shift towards managing the risk component of the "benefit-risk" calculus. This approach involves enhancing the visibility and understanding of the methods employed to reduce risks associated with the use of contact-tracing apps. Practical measures could include regularly releasing detailed reports on data usage, and actively communicating the commitment and capability in terms of data protection. These efforts are essential for building trust and acceptance, especially in times of heightened crisis.

Limitations.

Several limitations in this study have been identified, pointing towards areas for further research. Firstly, our analysis primarily focused on the "perceived usefulness → intention to use" pathway from a simplified version of the Technology Acceptance Model (TAM). To gain a comprehensive understanding of the psychological mechanisms behind the acceptance of track tracing technology, future studies should explore additional factors such as perceived ease of use, social influence, and facilitating conditions for more nuanced practical insights. Secondly, the theoretical relationships explored in this study are context-specific [52]. For instance, research on knowledge sharing indicates that the impact of reciprocity on willingness to share can diminish in the presence of a strong pro-sharing norm [17]. Therefore, future research should consider other contextual factors like culture, social norms, and ideology to deepen the understanding of these dynamics. Thirdly, as we transit into the "Post-Pandemic Era" and COVID-19 containment becomes a routine aspect of life, it raises questions about the continued acceptance of contact-tracing apps. Are people willing to use these apps even as they grow accustomed to the pandemic? The ongoing usage and long-term sustainability of contact-tracing apps are critical areas for future research. This not only has practical implications for sustained pandemic management but also contributes to the broader theoretical discourse on the digital integration into everyday life.

6 CONCLUSION

Contact-tracing apps have demonstrated their effectiveness in COVID-19 containment globally, relying on public acceptance to establish a digital prevention network. This study delved into the psychological underpinnings of contact-tracing app acceptance, adopting a reciprocal perspective that integrates the Technology Acceptance Model (TAM) with social exchange theory. The empirical findings from a survey on the "Health Code" in China indicate that reciprocity indirectly influences attitudes towards the app via the mediating roles of perceived risk and perceived usefulness. Notably, when the perception of COVID-19 risk was heightened, both the link between reciprocity and perceived risk and the mediating effect of perceived risk were diminished. Theoretically, this research enhances TAM by introducing reciprocity as an influential external factor in the evaluation of benefits and risks during the acceptance decision of contact-tracing apps. This influence, however, can be modulated by the severity of the crisis situation. From a promotional perspective, it is crucial to foster a sense of reciprocity

among the public, both through ideological means and visible actions. It is also important to clearly communicate and guarantee the app's usefulness, capabilities, and commitment to social responsibility and security. Moreover, adapting promotional strategies in response to the evolving crisis context and integrating the app into the social fabric are key for effective promotion and acceptance of contact-tracing apps.

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