Since January 2020 Elsevier has created a COVID-19 resource centre with free information in English and Mandarin on the novel coronavirus COVID-19. The COVID-19 resource centre is hosted on Elsevier Connect, the company's public news and information website.

Elsevier hereby grants permission to make all its COVID-19-related research that is available on the COVID-19 resource centre - including this research content - immediately available in PubMed Central and other publicly funded repositories, such as the WHO COVID database with rights for unrestricted research re-use and analyses in any form or by any means with acknowledgement of the original source. These permissions are granted for free by Elsevier for as long as the COVID-19 resource centre remains active.
The imprinting effect of SARS experience on the fear of COVID-19: The role of AI and big data

Haitang Yao, Wei Liu, Chia-Huei Wu, Yu-Hsi Yuan

ARTICLE INFO

Keywords:
COVID-19  
SARS  
Imprinting theory  
Public health  
Artificial intelligence  
Big data

ABSTRACT

The worldwide outbreak of the COVID-19 has significantly increased the fear of individuals, which brings severe psychosocial stress and adverse psychological consequences, and become a serious public health problem. Based on the imprinting theory, this study investigates whether childhood experiences of SARS have an imprinting effect that significantly influences the fear of COVID-19. Furthermore, we propose that this effect is contingent on the applications of AI and big data. We test our framework with a sample of 1871 questionnaires that covered students in universities across all provincial regions in China, and the results suggest that the imprinting of SARS increases the individuals’ fear of COVID-19, and this effect is reduced with the applications of AI and big data. Overall, this study provides a novel insight of the fear caused by the childhood experience of the similar health crisis and the unique role of AI and big data applications into fighting against COVID-19.

1. Introduction

Since the first known outbreak of the Corona Virus Disease 2019 (COVID-19) in China in December 2019, it has become an unprecedented global public health crisis. Up to December 29, 2020, there were already 80,155,187 confirmed cases of COVID-19 worldwide, resulting in a total of 1,771,128 deaths. Most scholars have linked and compared this outbreak with the Severe Acute Respiratory Syndrome (SARS) in 2003, finding that the virus spreads much more easily in the community than SARS due to the longer incubation period of COVID-19 before the onset of clinical symptoms. Although the number of SARS deaths is relatively small compared to other infectious diseases, SARS has had a powerful negative psychological impact on populations in many countries. A higher COVID-19 infection rate means millions of people may be coping with isolated lives and anxiety spikes, causing a significant impact on mental health at the individual level. Evidence suggests that a variety of psychiatric comorbidities emerged in the aftermath of the SARS epidemic, with common problems including fear of infectious disease, anxiety, depression and uncertainty. This fear of infection may be based in part on their experience from previous infectious disease outbreaks (e.g. SARS, MERS, Ebola), which is referred to as imprinting, the process by which a focal entity develops characteristics that reflect the salient features of the environment during a brief period of susceptibility. These characteristics have persisted despite significant changes in the environment in subsequent periods.

Since its introduction in biology, imprinting theory has effectively explained the influence of the environmental characteristics of organizations on strategic choices, organizational behavior, and operational practices after their establishment. The application of imprinting theory at the individual level has also received increasing attention from scholars. The theory suggests that an individual’s early experience can shape his or her values and influence the behavioral decisions through imprinting effects. Considering that the imprinting effect of childhood have a lasting effect on individuals despite subsequent changes in the environment, especially those individuals whose traumatic experiences occur in distant childhood, the probability of Post-traumatic Stress Disorder (PTSD) is three times higher than in other periods. Therefore, applying imprinting theory to the individual level, it can be expected that individuals’ memories of childhood will...
have a lasting effect on their perception of COVID-19 [10]. Even though 17 years have passed since the SARS outbreak, those who experienced SARS during childhood, we argue, alter their perception of the current outbreak. The purpose of this study is to investigate whether childhood experiences of SARS have an imprinting effect that significantly influences the fear of COVID-19.

Although COVID-19 has many similarities to SARS, the external context in which COVID-19 occurred at the time of its onset has been very different. Nowadays, the emergence and mature application of information technologies such as artificial intelligence (AI), big data, cloud computing and high-speed broadband network, have played a great role in the prevention and control of the current epidemic. It has been argued that AI and big data is necessary pandemic control, using thermal imaging to scan public spaces for potentially infected people and implement social isolation and lockdown measures. For example, through the Health Code in China, a kind of capturing individual location and health data, government departments at all levels are able to grasp the travel path of all citizens, familiarize themselves with the latest epidemic map, issue early warning signals to the public, improve the efficiency of government management. It has no doubt that the use of AI and big data not only enables health care policymakers to prepare for disease outbreak, make well-informed decisions, and improve the efficiency of government management, but also provides more information about the outbreak. It also reduces the fear of an outbreak among individuals compared to the use of traditional methods during SARS.

This study seeks to investigate whether the imprinting effect derived from the SARS experience is an important determinant of the fear of COVID-19, and how the application of AI and big data has impact on the imprinting effect. Drawing on imprinting theory [6], we argue that imprinting from the SARS experience significantly exacerbates the fear of COVID-19, and this effect is negatively moderated by the application of AI and big data. To empirically investigate these questions, we conducted an analysis on a sample of 1873 questionnaires covered students in universities across all provincial regions in China, to capture their experience of SARS and the fear of COVID-19. We also selected the Health Code as the measure of AI and big data application. Our results conclusively supported our hypotheses.

Our studies contribute to the literature in three ways. First, our study enriches the use and understanding of the imprinting theory in different contexts. Past studies on imprinting theory at the individual level has focused on the impact of imprinting on their careers [e.g. 11], entrepreneurs’ decision making and their choices of current and future opportunities [e.g. 12]. We extend it to examine individual responses to public crisis events. We particularly demonstrate that the sensitive period of imprinting occurs at the “key developmental stages” [11], especially with respect to this novel and universally dominant fear. Second, our study determines the new boundary condition of the imprinting theory, which highlights the unique role of the application of AI and big data in easing the fear of COVID-19 derived from the SARS experience. Third, our findings provide empirical evidence for policy makers to actively respond to the COVID-19 outbreak by developing the application of AI and big data.

2. Literature review and hypotheses

2.1. The fear of COVID-19

A rapid increase in the number of individuals infected with the COVID-19 virus worldwide has increased public concern and fear in many countries [12]. For instance, in a survey of 44,000 participants conducted in Belgium in early April 2020, the number of people reporting anxiety (20%) or depressive disorder (16%) increased substantially compared to a similar survey conducted in 2018 (i.e., 11% and 10% prevalence, respectively).

Fear is directly associated with its transmission rate and medium (rapid and invisible) as well as its morbidity and mortality. As fear increases, individuals may face severe psychosocial stress, and findings have suggested that the fear of COVID-19 predicts depression, anxiety, and stress. Fear may also result in the negative impact on personal health [13], and further lead to other psychosocial challenges including stigmatization, discrimination, and loss [14]. In addition, various psychological, sociological, and genetic factors have been associated with the fear of COVID-19 [15]. For example, Satici, Saricali [16] found that the fear of COVID-19 was positively associated with the intolerance of uncertainty, but negatively associated with mental health. Mertens, Gerritsen [17] also reported that intolerance of uncertainty, health anxiety, risk to loved ones, and consulting additional sources of information (e.g., conventional media, social media, and professional media) were associated with fear of COVID-19. Lin, Broström [18] stated that the fear of COVID-19 is associated with insomnia. That is, when an individual worries and fears COVID-19, his or her brain is stimulated and excited [19]. Asmundson and Taylor [20] noted that excessive fear can negatively affect well-being, generating phobias or symptoms of social anxiety.

However, current treatment on COVID-19 worldwide has mainly focused on infection control, effective vaccine, and treatment cure rates [21,22]. Psychosocial aspect has yet to be thoroughly considered. In order to reduce the fear of COVID-19 and control its adverse psychological consequences, several investigations were conducted, including access to fear scales [21,23], exploring the causes of fear and influencing effects [24]. Ahorsu, Lin [21] developed and validated a scale to assess the fear of COVID-19 (FCV–19S), which helps scholars to assess the level of fear in the population during the COVID-19 pandemic [25]. Similar tests have been conducted in various contexts, such as the USA [26], Italy [27], Japan [28], New Zealand [23]. Taylor, Landry [15] developed the COVID Stress Scales (CSS) and identified five factors of stress and anxiety symptoms associated with the coronavirus in two large samples from Canada and the United States. These assessments of the fear of COVID-19 help support public policies and programs to address the psychological and public health problems caused by the pandemic of COVID-19.

The fear comes not only from physical and mental issues, but also from the unknown and inaction [29]. As the pandemic spread, many countries adopted restrictive lockdowns to avoid infection by the virus. Changes in the environment and the unknown of future developments can also fuel the fear of COVID-19, which is consistent with the past situation of SARS pandemic, have undoubtedly led to concerns about COVID-19 infection and its associated consequences [25].

2.2. Imprinting effect to the fear of COVID-19

Imprinting theory was first introduced by Stinchcombe [30] into organization science from biological foundations. Some studies have proposed an “imprinting effect” or “imprinting mechanism”, in which individuals develop “traits” that are adapted to specific environments. These traits are thought to persist even if the environment changes radically [6,31]. Thus, “imprinting” is a phenomenon that arises from an individual’s external environment, institutional environment, identity cognition, experiences and early-life experiences.

To date, scholars have shown that imprinting is critical to organizations, including influencing outcomes such as venture growth potential [32], turnover rates [33], and organizational ecology [34]. Although organizations have been the dominant level of analysis in much of the literature based on Stinchcombe’s insights, recent years have also seen the emergence of imprinting research at the individual level. This stream of literature focuses on entrepreneurs in organizations, including formal positions [35], bureaucratization [36], careers [37], and entrepreneurs’ intentions and decision [38]. For instance, Mathias, Williams [39] indicated how certain formative experiences acquired during sensitive periods (i.e., sources of imprinting) had a long-term impact on
entrepreneurial decision-making and how different sources of imprinting significantly influenced the opportunities that entrepreneurs chose. Azoulay, Liu [40] illustrated how early career mentors and peers influenced subsequent work choices.

However, not every period in the past has a lasting impact on the individuals. Marquis and Tilsik [6] advanced a three-part definition of imprinting, emphasizing that: (1) the “sensitive period” is understood as a “transition period” rather than simply an “early period” in which focal entity exhibits high susceptibility to external influences; (2) imprinting is a “process” in which elements of its environment are “stamped” on the focal entity during the sensitive period; and (3) imprinting has a persistent effect despite subsequent environmental changes. According to this definition, scholars in previous literature have confirmed Great Depression experience [41], marital experience [42], educational experience [38], early career, significant economic change [6], and the Great Chinese Famine [10] as sensitive periods.

Individuals are more vulnerable to their environment during sensitive periods compared to normal periods. Imprinting theory emphasizes not only that an individual’s previous experience is a process by which the individual interacts with the environment, but also that the individual’s previous experience must occur during the sensitive period. Childhood is the critical period for individuals to understand the world and to maintain permanent memories and personality. Considering that despite subsequent changes in the environments, the imprinting effect of childhood has a lasting effect on individuals, especially those whose traumatic experiences occurred in distant childhood, and a probability that the incidence of PTSD is three times higher than in other periods [9]. Similarly, applying imprinting theory to the individual level, it can be expected that individuals’ memories of childhood will have a lasting effect on their perception of COVID-19 [10]. Although 17 years have passed since the SARS outbreak, those who experienced SARS during childhood, we argue, alter their perception of the current outbreak. Hence, we propose the following hypothesis:

**Hypothesis 1.** the imprinting of SARS increases the individuals’ fear of COVID-19.

### 2.3. The applications of AI and big data

To control the spread of COVID-19, contact tracing is an important public health tool for breaking the chain of virus transmission. There is a general call from scientists and the medical community worldwide to fight against the pandemic, find alternative methods to the rapid screening and prediction process, predict and develop more accurate and reliable vaccines or drugs [43].

Recent studies have shown that AI and big data are promising technologies adoption by various healthcare providers as they offer better scalability, faster processing power, and even better reliability than humans for specific healthcare tasks [44]. Healthcare industries and clinicians worldwide employed various AI technologies to address the challenges during the outbreak [45]. The application of AI used in the Covid-19 pandemic includes medical imaging to support COVID-19 diagnosis, suggesting new compounds that may hold promise for drug development, tracking patients on the trail of infected individuals. For instance, Bullock, Luccioni [45] conducted an extensive review of the rapidly emerging literature and identified specific applications of AI and big data at three different scales: the molecular scale, including drug discovery-related research; the clinical scale, including individual patient diagnosis and treatment; and the societal scale, including epidemiological and infodemic research. Jiang, Coffee [46] proposed an AI that can predict with 80% accuracy which individuals infected with COVID-19 may develop acute respiratory distress syndrome (ARDS).

There is no doubt that the applications of AI and big data not only enable health care policymakers to prepare for the current COVID-19 epidemic, make well-informed decisions, and improve the efficiency of government management, but also provide more information about the outbreak, which improves individuals’ understanding and confidence of the COVID-19. These applications can also change individuals’ experience and imprinting about the applications of traditional methods during the SARS epidemic, and further reduce the fear of COVID-19. Thus, we hypothesize:

**Hypothesis 2.** the application of AI and big data negatively moderates the positive relationship between the imprinting of SARS and individuals’ fear of COVID-19.

### 3. Methodology

#### 3.1. Sample and data collection

We employed a cross-sectional survey to test our hypotheses. Respondents included about 2000 general undergraduate students in universities across all provincial regions in China. The education system in China has a clear reference range for the age of students entering each stage of schooling [47], hence all of the respondents were between the ages of 19 and 23, with an average age of 20.59. In this survey, the age at which they experienced the 2003 SARS pandemic was 2–6 years old, which is an appropriate setting to capture the SARS imprinting in their childhood [48]. During the survey period, students still need to be isolated at home due to the COVID-19 outbreak and were not allowed to return to school, thus we developed the electronic questionnaire and posted online to collect data. In order to avoid common method variance, we conducted the surveys at two separate times [49]. Finally, we received a total of 1871 valid questionnaires for further analysis.

We also collected data from other sources to complement the survey data. Regional COVID-19 pandemic data were collected from the website of the National Health Commission of the People’s Republic of China.2 Regional public healthcare data and economic development data were sourced from the 2019 China Health Statistical Yearbook and the 2019 China City Statistical Yearbook separately. We also manually collected the pandemic lockdown restrictions and pandemic-related policies that released by the local governments from official pandemic prevention service platforms3 [50].

#### 3.2. Measures

**Dependent variable.** Following the FCV-19S scale that measure an individual’s fear level of COVID-19 [21], Fear of COVID-19, the dependent variable in this study, was assessed by the item “I am very afraid of COVID-19”. The item is endorsed on a 5-item Likert scale and students rated ranging from 1 (strongly disagree) to 5 (strongly agree). Higher score indicates greater levels of the fear of COVID-19.

**Independent variables.** We followed Wang, Du [51] and used the experience in the childhood to measure SARS imprinting. We used a 5-item Likert scale to assess the levels of imprinting by the item “I have deep impression on SARS pandemic that took place in 2003” and the scale ranged from 1 (strongly disagree) to 5 (strongly agree). Higher score indicates deeper imprinting of the SARS.

Considering that the technology of AI and big data such as the Health Code has been applied to general population in China [52], we can directly observe the respondents’ attitude of using such application. **AI and big data application** were also measured by a 5-item Likert scale asking respondents that “Do you agree that AI and big data technology can help with pandemic mitigation and public health prevention”. The scale ranged from 1 (strongly disagree) to 5 (strongly agree).

**Control variables.** We included several individual characteristics from the survey to control for potential interference. Gender was measured as the binary indicator, coded as 1 if the respondent is male.

---

2 See: [http://www.nhc.gov.cn/xcs/yqtb/list_1370.html](http://www.nhc.gov.cn/xcs/yqtb/list_1370.html)
3 See: [http://gjzwfw.www.gov.cn/col/col633/index.html](http://gjzwfw.www.gov.cn/col/col633/index.html)
and 0 female. Age was measured as the year since the respondent was born. Family income was measured as an ordinal variable, coded as 1 for less than 60 thousand RMB, 2 for 60–80 thousand RMB, 3 for 80–100 thousand RMB, 4 for 100–120 thousand RMB and 5 for more than 120 thousand RMB of the total annual income of family members. Confidence was measured as a 5-item Likert scale to assess the confidence level in return to normal economic and social conditions, ranging from 1 (strongly disagree) to 5 (strongly agree).

We also controlled for several regional pandemic and economic factors that might affect the estimations. Pandemic severity was measured as the number of local confirmed cases scaled by the local population at the city level. Medical resource was measured as the number of hospital beds per 10,000 people at the city level. Economic development was measured as the natural logarithm value of the amount of gross domestic product per capita at the city level. Unemployment was measured as the unemployment rate at the city level. Lockdown was measured as a binary indicator, coded as 1 if the lockdown policy was introduced by the city governments and 0 otherwise. Crisis policy was measured as the number of policies related to social restriction, social security and economic support issued by the provincial governments since the pandemic began [50]. Finally, we included Regional dummy to control for the unobserved heterogeneities at the provincial level.

### 3.3. Estimation methods

As our dependent variable in this study is an ordinal variable, the ordinary least squares regression model will not yield consistent parameter estimates. Accordingly, we used an ordered regression model to test our hypotheses [53]. In addition, considering there are many similarities between COVID-19 pandemic and SARS pandemic in 2003, a concern may raise that the experience of the current pandemic might provoke the experience of SARS from the memory in their childhood, which could cause reverse causality, a serious endogeneity issue. Therefore, we included the instrumental variable in the estimations to control for such potential risks. We used the Fear of SARS, measured as a 5-item Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree) to assess the fear level of SARS, as the instrumental variable. It is highly associated with the individual’s experience of SARS, but is relatively exogenous to, or only loosely related to the fear of COVID-19. We then performed a Durbin-Wu-Hausman endogeneity test using the Fear of SARS as an instrumental variable [54]. The result of the test ($\chi^2 = 367.06, p = 0.000$) rejects the null hypothesis of no endogeneity, thus confirming the endogeneity of SARS imprinting. In addition, we also conducted a Two-stage Least Squares (2SLS) approach to estimate our sample, aiming to check the robustness of our instrumental variable and estimation results.

### 4. Results

#### 4.1. Descriptive statistics and correlations

Table 1 presents the descriptive statistics and correlations among the variables used in this study. The average values of Fear of COVID-19 is 3.26 (SD = 0.88), SARS imprinting is 2.33 (SD = 1.16), AI and big data application is 4.01 (SD = 0.92). Except for Medical resource and Economic development (0.59), the correlations among other explanatory variables are smaller than 0.5. We calculated the variance inflation factor (VIF) and found the maximum value is 1.89, with the mean value of 1.23, which are far below the general cutoff point of 10 [55]. Thus, multicollinearity is not a major issue in this study.

#### 4.2. Tests for hypotheses

Table 2 reports the first-stage and second-stage results estimated by the ordered regression model and the 2SLS model. In each model of the first stage, the coefficients of the instrumental variable, Fear of SARS, is significant ($p < 0.001$), suggesting the instrumental variable is not under-identified. Hypothesis 1 predicts a positive relationship between the imprinting of SARS and the fear of COVID-19. In Model 2, the coefficient of the variable SARS imprinting is positive and significant at the 0.1% level ($\beta = 1.539, p < 0.001$), which strongly supports Hypothesis 1.

Hypothesis 2 predicts that AI and big data application negatively moderates the positive relationship between SARS imprinting and fear of COVID-19. As shown in Model 4, the coefficient of the interaction term SARS imprinting $\times$ AI and big data application is negative and significant at the 0.1% level ($\beta = -7.766, p < 0.001$), indicating that the positive effect of SARS imprinting on the fear of COVID-19 is weakened for the application of AI and big data. Thus, Hypothesis 2 receives support.

In addition, the results estimated by the 2SLS model were reported in Models 5–8, and the coefficients on the variables SARS imprinting ($\beta = 1.071, p < 0.001$) and its interaction term SARS imprinting $\times$ AI and big data application ($\beta = -6.254, p < 0.05$) are consistent with the results estimated by the ordered regression model in Models 1–4. The instrumental variable also passed the under-identification test ($p < 0.001$), and weak identification test ($F$ statistic = 214.717, larger than the 10% maximal IV size 16.38), confirming its relevance and strength as a valid instrumental variable [56].

#### 4.3. Robustness check

We first conducted the alternative measure on key variables to test the robustness of our estimated results. As the measure on the variable AI and big data application was conducted based on a general attitude of using such application, we also looked into a way to capture a more

| Variables | Mean | S.D. | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) |
|-----------|------|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|
| Fear of COVID-19 | 3.26 | 0.88 | 1 | | | | | | | | | | | |
| SARS imprinting | 2.33 | 1.16 | 0.14 | 1 | | | | | | | | | | |
| AI and big data application | 4.01 | 0.92 | 0.07 | 0.02 | 1 | | | | | | | | | | |
| Gender | 0.32 | 0.46 | -0.07 | 0.13 | -0.01 | 1 | | | | | | | | | |
| Age | 20.58 | 1.35 | 0.12 | 0.20 | -0.04 | 0.07 | 1 | | | | | | | | |
| Family income | 2.54 | 1.53 | 0.03 | -0.01 | 0.01 | -0.02 | 0.10 | 1 | | | | | | | |
| Confidence | 4.35 | 0.80 | -0.05 | -0.05 | 0.26 | -0.04 | -0.11 | -0.07 | 1 | | | | | | |
| Pandemic severity | 0.45 | 4.13 | 0.01 | 0.01 | -0.00 | 0.01 | 0.00 | -0.00 | -0.03 | 1 | | | | | |
| Medical resource | 59.76 | 20.91 | -0.02 | 0.02 | -0.00 | 0.02 | -0.02 | 0.10 | -0.05 | 0.12 | 1 | | | | |
| Economic development | 11.22 | 0.49 | 0.02 | 0.01 | -0.00 | 0.03 | 0.07 | 0.22 | -0.04 | 0.10 | 0.59 | 1 | | | |
| Unemployment | 4.53 | 2.33 | -0.04 | 0.01 | 0.04 | -0.02 | -0.07 | -0.14 | 0.02 | -0.03 | -0.18 | -0.41 | 1 | | |
| Lockdown | 0.65 | 0.48 | -0.02 | -0.01 | 0.00 | 0.03 | 0.05 | 0.11 | -0.08 | 0.06 | 0.42 | 0.39 | -0.20 | 1 |
| Crisis policy | 73.14 | 25.54 | -0.03 | -0.06 | -0.04 | 0.06 | 0.10 | -0.02 | 0.07 | 0.02 | 0.17 | -0.29 | 0.19 | | |

Note: N = 1871; Correlations $| r | \geq 0.05$ are significant at $p \leq 0.05$. 

---

H. Yao et al. Socio-Economic Planning Sciences 80 (2022) 101086
direct attitude of AI and big data application on COVID-19 pandemic. Thus, we considered an alternative measure on AI and big data application, which was measured as a 5-item Likert scale to assess the improvement of AI and big data application on the fear of COVID-19, ranging from 1 (strongly disagree) to 5 (strongly agree). The robust results reported in Table 4 suggested that the coefficients on the variables consistent with the main results, confirming the robustness of our estimations.

In addition, considering that the transmission of SARS in 2003 was concentrated in two regions, Beijing City and Guangdong Province, accounting for 84.07% of all confirmed cases in China, the respondents’ SARS imprinting may have been heterogeneous across regions. Thus, we re-regressed the models using the sample selected from Beijing City and Guangdong Province and checked whether our findings are robust. The results reported in Table 4 suggested that the coefficients on the variables SARS imprinting ($\beta = 1.557, p < 0.001$) and its interaction term SARS imprinting $\times$ AI and big data application ($\beta = -8.231, p < 0.001$) are significant, which are consistent with the main results reported in Table 2. These suggest that our estimated results are robust.

5. Discussion and conclusion

Most articles have investigated the similarities and differences between SARS and COVID-19, but little attention has been paid to how SARS affects COVID-19. Based on imprinting theory, we find that the imprinting derived from SARS increases the individuals’ fear of COVID-19, and the applications of AI and big data negatively moderate the positive relationship between the imprinting of SARS and individuals’ fear of COVID-19. Such results provide fruitful theoretical contributions and practical implications that improve our understanding on the applications of AI and big data and public health issues regarding COVID-19.

Our study not only validates early research findings that imprinting highlights the enduring impact of prior history on organizational outcomes by demonstrating how organizations (or individuals) assume elements of their environment persist beyond the founding phase [56], but also enriches the understanding of the imprinting theory in different contexts. Past studies on imprinting theory at the individual level have focused on the impact of imprinting on their careers [e.g. 11], entrepreneurs’ decision making and their choices about current and future opportunities [e.g. 12]. We extend this to examine individual reactions to public health events, especially the COVID-19. In particular, we demonstrate that the sensitive period of imprinting occurs at the “key developmental stages” [11], particularly for this novel and universally dominant fear. Second, our study identifies a new boundary condition of the imprinting theory, which highlights the unique role of the applications of AI and big data in easing the fear of COVID-19 derived from the SARS experience.

In this study, we find that respondents showed great concern about
the epidemic and all national and local policies in response to the virus. In addition, after the outbreak, the government became more concerned about the impact of COVID-19 pandemic on women, adolescents, university students, and nurses [21,58]. Our findings indicate that the epidemic and all national and local policies in response to the virus.

Some limitations of this study are worth noting. This study was conducted among university students across China mainland. Although the sample size is sufficiently large, the representativeness is not good enough as the population ages between 19 to 23 with a high level of education to obtain information about SARS and COVID-19 both domestically and internationally. In addition, due to the epidemic, our survey was conducted online and we had no control over whether they completed it independently during the process of answering the questions, which might limit the generalizability of our results to a broader population. Future research can investigate and extend our findings to other types of research objects and other contexts beyond China.

**Author contributions**

Haitang Yao performed Investigation, Writing – original draft, Writing – review & editing and Conceptualization. Wei Liu performed Methodology, Writing – original draft, Writing – review & editing, Conceptualization and Supervision. Chia-Huei Wu performed Writing – original draft, Writing – review & editing. Yu-Hsi Yuan performed Writing – review & editing.

**Acknowledgement**

This work was supported by the National Social Science Fund Youth Project of China (Grant No.17CJY0119).

---

**Table 3**

Robustness check: Alternative measure on AI and big data application.

| Variables          | Model 1          | Model 2          | Model 3          | Model 4          |
|--------------------|------------------|------------------|------------------|------------------|
|                    | First stage      | Second stage     | First stage      | Second stage     |
| Fear of SARS       | 0.436***         | −0.169***        | 0.005            | −0.409***        |
|                    | (0.094)          | (0.105)          | (0.195)          | (0.099)          |
| Age                | 0.222***         | −0.231***        | 0.123            | −0.292***        |
|                    | (0.023)          | (0.040)          | (0.069)          | (0.041)          |
| Family income      | −0.026           | 0.092**          | 0.012            | 0.012***         |
|                    | (0.029)          | (0.031)          | (0.061)          | (0.030)          |
| Confidence         | −0.072           | −0.025           | 0.067            | −0.357***        |
|                    | (0.056)          | (0.060)          | (0.110)          | (0.060)          |
| Pandemic severity  | 0.004            | −0.026           | −0.007           | 0.004            |
|                    | (0.015)          | (0.017)          | (0.034)          | (0.017)          |
| Medical resource   | 0.003            | −0.007           | −0.007           | 0.019**          |
|                    | (0.004)          | (0.004)          | (0.009)          | (0.005)          |
| Economic development | −0.036         | 0.162            | 0.333            | −0.993***        |
|                    | (0.165)          | (0.175)          | (0.356)          | (0.184)          |
| Unemployment       | 0.003            | 0.080*           | 0.043            | −0.058           |
|                    | (0.031)          | (0.033)          | (0.063)          | (0.033)          |
| Lockdown           | −0.089           | 0.155            | −0.024           | 0.094            |
|                    | (0.120)          | (0.126)          | (0.254)          | (0.126)          |
| Crisis policy      | −0.020           | 0.067            | 0.150            | −0.458***        |
|                    | (0.049)          | (0.050)          | (0.113)          | (0.053)          |
| AI and big data application | 0.147***        | 0.001            | −5.868***        | 19.583***        |
|                    | (0.044)          | (0.048)          | (0.255)          | (1.038)          |
| Fear of SARS       | 0.670***         | 0.316***         | (0.048)          | (0.099)          |
|                    | (SARS imprinting | 1.557***         | 3.298***         | 0.080)          |
|                    | 2.496***         | −8.321***        | (0.103)          | (0.442)          |
|                    | (AI and big data | 0.007            | 0.12              | 0.82             |
|                    | Regional dummy   | Included          | Included          | Included          |
|                    | Log likelihood   | −2549.62         | −2090.27         | −2090.27         |
|                    | LR               | 366.67***        | 564.39***        | 4501.35***       |

**Table 4**

Robustness check: Sample selected from Beijing and Guangdong province.

| Variables          | Model 1          | Model 2          | Model 3          | Model 4          |
|--------------------|------------------|------------------|------------------|------------------|
|                    | First stage      | Second stage     | First stage      | Second stage     |
| Fear of SARS       | 0.736*           | −3.442***        | −0.235           | −0.464           |
|                    | (0.367)          | (0.721)          | (0.914)          | (0.420)          |
| Age                | 0.485***         | −1.875***        | 0.048            | −0.143           |
|                    | (0.130)          | (0.366)          | (0.350)          | (0.151)          |
| Family income      | −0.110           | 0.555***         | 0.127            | 0.010            |
|                    | (0.108)          | (0.318)          | (0.266)          | (0.127)          |
| Confidence         | −0.019           | 0.014            | 0.312            | −0.407*          |
|                    | (0.179)          | (0.211)          | (0.485)          | (0.225)          |
| Pandemic severity  | −1.099           | 6.096***         | 2.683            | −0.994           |
|                    | (1.928)          | (2.090)          | (5.810)          | (2.087)          |
| Medical resource   | 0.016            | −0.067***        | 0.011            | −0.020           |
|                    | (0.012)          | (0.018)          | (0.040)          | (0.014)          |
| Economic development | 1.336            | −6.233***        | −1.268           | 0.159            |
|                    | (1.492)          | (1.697)          | (4.717)          | (1.540)          |
| Unemployment       | 0.040*           | −0.225           | 0.470            | −0.498*          |
|                    | (0.188)          | (0.208)          | (0.521)          | (0.224)          |
| Lockdown           | −2.697*          | 9.832***         | −0.505           | 0.394            |
|                    | (1.375)          | (2.303)          | (4.452)          | (1.324)          |
| Crisis policy      | 0.015            | −0.055*          | −0.029           | 0.031            |
|                    | (0.020)          | (0.026)          | (0.064)          | (0.022)          |
| AI and big data application | 0.147***        | 0.007            | 0.111            | −6.593***        |
|                    | (0.180)          | (0.204)          | (1.184)          | (1.398)          |
| Fear of SARS       | 0.358*           | 1.190*           | (0.179)          | (0.529)          |
|                    | (SARS imprinting | 3.790***         | 1.131***         | 0.681)          |
|                    | × 2.645***       | −2.948***        | (0.450)          | (0.547)          |
|                    | Al and big data | Included          | Included          | Included          |
|                    | Regional dummy   | Included          | Included          | Included          |
|                    | Log likelihood   | −197.10          | −123.08          | −26.20           |
|                    | LR               | 26.67**          | 51.05***         | 368.46***        |
|                    | Number of        | 0.06             | 0.17             | 0.88             |
|                    | Observations     | 139              | 139              | 139              |

Note: Standard errors are in parentheses. *p < 0.1, **p < 0.05, ***p < 0.01, ****p < 0.001.
