



Developing a Minimum Dataset for a Mobile-based Contact Tracing System for the COVID-19 Pandemic

Mostafa Shanbehzadeh ¹ and Hadi Kazemi-Arpanahi ^{2,3,*}

¹Department of Health Information Technology, School of Paramedical, Ilam University of Medical Sciences, Ilam, Iran

²Student Research Committee, Abadan University of Medical Sciences, Abadan, Iran

³Department of Health Information Technology, Abadan University of Medical Sciences, Abadan, Iran

*Corresponding author: Department of Health Information Technology, Abadan University of Medical Sciences, Abadan, Iran. Email: h.kazemi@abadanums.ac.ir

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Abstract

Context: Contact tracing is a cornerstone community-based measure for augmenting public health response preparedness to epidemic diseases such as the current coronavirus disease 2019 (COVID-19). However, there is no an agreed data collection tool for the unified reporting of COVID-19 contact tracing efforts at the national level.

Objectives: The purpose of this research was to determine the COVID-19 Contact Tracing Minimal Dataset (COV-CT-MDS) as a prerequisite to develop a mobile-based contact tracing system for the COVID-19 outbreak.

Methods: This study was carried out in 2020 by a combination of literature review coupled with a two-round Delphi survey. First, the probable data elements were identified using an extensive literature review in scientific databases, including PubMed, Scopus, ProQuest, Science Direct, and Web of Science (WOS). Then, the core data elements were validated using a two-round Delphi survey.

Results: Out of 388 articles, 24 were eligible to be included in the study. By the full-text study of the included articles and after the Delphi survey, the designed COV-CT-MDS was categorized into two clinical and administrative data sections, nine data classes, and 81 data fields.

Conclusions: COV-CT-MDS is an efficient and valid tool that could provide a basis for collecting comprehensive and standardized data on COVID-19 contact tracing. It could also provide scientific teamwork for health care authorities, which may lead to the enhanced quality of documentation, research, and surveillance outcomes.

Keywords: Contact Tracing, COVID-19, Coronavirus Mobile Application, Data Collection, Pandemic

1. Context

Contact tracing is a principal public health practice for containing further propagation of the virus through limiting contacts between infected cases and persons adjacent to them (eg, family members, health care providers, healthcare personnel, etc.) (1-3). Contact tracing is principally significant for the COVID-19 outbreak, where a large number of carriers are silent, pre-symptomatic, or may present only mild symptoms and are thus usually not tested, despite having the potential to promulgate the disease (4). In the context of COVID-19, contact tracing is a public health response to detect and inform those individuals who may have been in close contact with an infected person every day for two weeks (5, 6). Accordingly, if an individual is confirmed positive for COVID-19, every other individual who had possibly been in close contact is tracked and recommended to go into protective self-quarantine

for cutting off the transmission chain of the disease in the community (7).

To overcome the limitations of traditional contact tracing, digital-based contact tracing has been adopted (8). One promising type of digital contact tracing is the implementation of mobile-based contact tracing applications (apps). Such apps use mobile devices to promptly detect and alert users who may be in close contact with a confirmed-COVID-19 case (9). Due to the wide accessibility and affordability of mobile devices, employing mobile-based contact tracing apps can lead to making the public health process of contact tracing more efficient on a massive scale (10).

Mobile-based contact tracing systems offer a practical solution to controlling the spread of COVID-19; however, standardized data collection as one of the designing specification criteria to achieve a uniform and mass tracing app

acceptance is a great challenge (11, 12). Moreover, from a data management perspective, the novelty of COVID-19 has created major gaps in data harmonization, integration, and unified reporting of disease as a basis for investigating many unfamiliar clinical aspects and outcomes of the disease, characterizing the public health threat, and supporting health authorities' decisions (13).

The human-to-human spread of COVID-19 requires active case identification, that is, early confinement, timely testing, and treatment, besides detection and future tracking of persons who may be in close contact with infected cases (14). Meanwhile, a large number of reports inflowing the health care systems from varied networks and formats need to be validated. Current surveillance systems are generally not constructed to meet such data requirements. Moreover, vagueness and postponement of surveillance data due to isolated and heterogeneous health information systems are a barrier to data exchange among these systems, which have led to limited consistency of epidemiologic studies (15).

To our knowledge, no comprehensive data collection template currently exists that has been designed to capture high-quality, consistent, and standardized data regarding COVID-19 contact tracing.

2. Objectives

To address this priority, the current study aims to determine a minimum dataset (MDS) as an essential measure before the design and implementation of a digital contact tracing system. Accordingly, we sought to develop a COVID-19 Contact Tracing Minimal Dataset (COV-CT-MDS) based on mobile devices due to their ability to appropriately document contact tracing data during COVID-19.

3. Methods

This was a cross-sectional study conducted in 2020 following a combination of literature review and a broad discussion with a multidisciplinary team of involved health-care experts, as follows.

3.1. Literature Review

3.1.1. Search Strategy

A systematic review was undertaken to extract the primary data elements to include in COV-CT-MDS. This systematic review was reported according to the recommendations of the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) statement (16). PubMed,

Scopus, Web of Science (WOS), Science Direct, and ProQuest databases were reviewed between 1 January 2020 and 20 December 2020 to determine the required data elements, features, and attributes for designing a mobile-based COV-CT-MDS. The following search terms were used (designed using English MeSH keywords) to maximize the output from literature findings: [COVID-19 OR Novel coronavirus OR SARS-CoV-2 OR n-CoV2] AND [Mobile phone OR Smartphone OR Cell phone OR Mobile Apps OR Mobile health] AND [Contact tracing OR Contact tracking].

3.1.2. Study Selection

Two independent researchers (M: SH and H: K-A) reviewed the titles and abstracts of the articles extracted from the initial search, and then full-text articles were obtained for detailed evaluation. Finally, we read the full text of articles and recognized potentially eligible studies to be included in the systematic review.

The following criteria were considered as the inclusion criteria:

- (1) Type of a study: Original or review research papers were selected, and newspapers, reports, editorial, letters, posters, and conference papers were not examined.
- (2) Date of publication: Papers published between 1 January 2020 to 20 December 2020
- (3) Language: English language
- (4) Text availability: Full-text papers with the keywords in the title or abstracts
- (5) Content analysis: At least two of the following reporting parameters: (1) basic/general, (2) clinical, (3) para-clinical, (4) geo-locational, and (5) contact/exposure data classes.

Finally, the probable data elements to be included in the COV-CT-MDS were recorded in a checklist with two administrative and clinical sections.

3.1.3. Data Extraction

For each eligible research, the following information was extracted based on a designed data extraction form, which included the first author, country, year of publication, study design, and reporting data classes in the two non-clinical and clinical data categories. The results were organized under the following categories: (1) data categories, (2) data classes, (3) data fields, and (4) data features and attributes.

3.2. Delphi Technique

3.2.1. Questionnaire Design

After conducting the necessary literature review and receiving expert advice, we developed a questionnaire. We invited 20 experts, including five infectious diseases specialists, five virologists, five health information management (HIM), and five clinical epidemiologists, in a two-round Delphi survey. The questionnaire included the following parts: (1) demographical data, (2) clinical finding, (3) geolocation location, (4) relocation data, and (5) contact/exposure data.

3.2.2. Data Analysis

The experts participating in the study were asked to score the tabulated data elements in terms of their importance using a five-point Likert scale (ranging from 1: “very slightly important” to 5: “highly important”). Data fields with less than 50% agreement were excluded in the first round, while those with greater than 75% agreement were included in the primary round. Those with 50% to 75% agreement were surveyed in the second round, and if there was 75% consensus over a subject, it was regarded as a final data field.

4. Results

4.1. Characteristics of Included Studies

A total of 388 articles were retrieved from the literature search. After the removal of duplicate articles and those not meeting the inclusion criteria, 24 articles that satisfied all the inclusion criteria were included in the analysis. [Figure 1](#) summarizes the selection process (PRISMA chart).

4.2. Identifying the Proposed Data Field

The proposed data fields after the literature review were divided into administrative and clinical data sections, nine data classes, and 198 data fields ([Table 1](#)).

Several data fields were excluded after the second round of Delphi. Thus, of the 198 proposed data fields, 117 fields were excluded from the study, and 81 data fields were finalized ([Table 2](#)).

The final reporting template is composed of two data sections, nine data classes, and 81 data fields. [Table 3](#) lists the data sections, classes, fields, their formats and values, and corresponding reference SNOMED-CT codes.

5. Discussion

Contact tracing is known as a crucial surveillance measure in avoiding the spread of epidemic diseases such as the current COVID-19. During this epidemic, contact tracing data should be integrated across healthcare data collection systems at the national level ([34](#)). However, data are gathered from stand-alone recording and reporting systems largely manually generated via the contact tracing process. Data collection is a crucial strategic preparation measure for governments and health officials battling the COVID-19 epidemic ([36](#)).

The CoV-CT-MDS is a promising tool to meet some of the data necessary for epidemiology contact tracing leading to a validated template for the documentation of active case finding for public health practice and research purposes. Determining a core data set or MDS from a scientific perspective and according to the actual demands of users is the most central prerequisite for the design and development of any information system or app in the healthcare industry ([38](#)). It can be advantageous for designers and vendors of health information systems to simplify and accelerate the development of such systems and reduce the possibility of their failure ([39](#)). From this point of view, in this study, the CoV-CT-MDS can be used as a basis for the effective collection and management of data related to COVID-19 contact tracing using related information systems or apps.

In the initial months of the pandemic, contact tracing measures were recorded through manual data collection tools (eg, in Excel sheets, spreadsheet), which was a time-intensive, resource-demanding, and error-prone process ([18](#), [40](#)). Additionally, the conventional approaches did not always offer inclusive data about the number of investigated contacts, the nature of the relationship between cases and contacts, the number of contacts, who in turn, become cases, and the first and last days of follow-up surveillance ([21](#), [41](#)). To cope with these issues, it is essential to develop a contact tracing system that enables standardized data recording and accelerates the surveillance of contacts and outbreak paths ([31](#), [42](#)). This system allows intervallic analyses for the creation of standard reports and offers detailed epidemiological analysis for the identification of high-risk exposures and targeting of contact tracing efforts ([21](#), [41](#), [43](#)).

Implementing an active and responsive contact tracing strategy would be a valuable containing measure for avoiding the transmission of COVID-19. In this context,

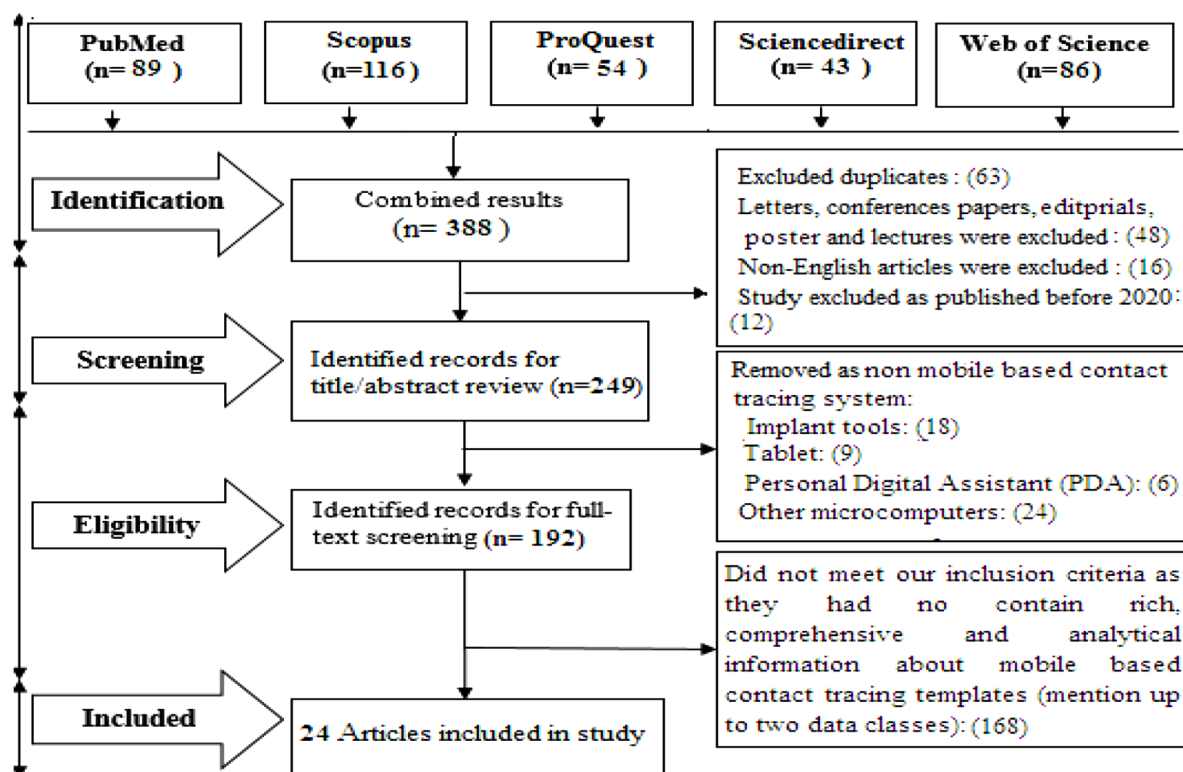


Figure 1. PRISMA chart for the study selection process

mobile technology enabling self-reports and smartphone applications for virtual contact tracing could be used to control disease outbreak and detect as well as quarantine COVID-19 cases and those who may have been exposed to the virus (44). For this purpose, a contact tracing system including timely and accurate data collection process and a unified case reporting template are proposed to guide healthcare authorities for proper interventions (20, 32, 36). There is, therefore, a pressing need for a unified data collection template to swiftly and prospectively collect high-quality data related to recent exposure and mobility patterns of confirmed and suspected individuals (45, 46).

The novelty of COVID-19 with frequent mutations of the virus demands numerous and unknown aspects to be investigated in prospective studies, and thus, studies related to COVID-19 contact tracing are limited at the time of writing this article (December 2020). Hence, the main limitation of this living systematic review is the scarcity of available related resources and lack of data enrichment. Review of only English-language articles is another limitation of the study. However, multiple scientific databases were

broadly reviewed. Future modifications, along with a Delphi survey is recommended to augment the COV-CT-MDS.

5.1. Conclusions

An effective COVID-19 contact tracing system requires reliable and timely information to guide fully informed decisions to contain the further spread of the disease by taking early preventive actions. For developing the COV-CT-MDS, we performed an extensive literature review and expert view to identify the proposed contact tracing data fields and corresponding variables from an evidence-based perspective. The COV-CT-MDS as a unified data collection tool is the first step for developing a mobile-based contact tracing system. This template can provide valuable information for clinicians, health policymakers, and researchers for integrating the COVID-19 contact tracing efforts across Iran's healthcare system. Given the prominence of reliable, accurate, and comprehensive data on COVID-19 surveillance measures, it is suggested that different countries design and implement a comprehensive national MDS for COVID-19 contact tracing.

Table 1. Summary of Characteristics of Included Studies in the Systematic Review

First Author (2020)	Method	Data Classes								
		Administrative				Clinical				
		Basic	Geolocation	Occupational	Relocation	Contact	Exposure	Clinical	Manifestations	Vital Signs
Bassi et al. (17)	Descriptive	*			*			*		
Basu (18)	Case study		*			*				*
Davalbhakta et al. (19)	Review	*		*			*		*	
Ekong et al. (20)	Exploratory review		*		*			*		*
Hassandoust et al. (21)	Developmental	*				*		*		*
Martin et al. (5)	Review	*		*						
Parker et al. (22)	Descriptive		*		*					*
Rahman et al. (23)	Case study	*							*	
Shubina et al. (24)	Retrospective		*			*				
Vuokko et al. (25)	Descriptive		*		*	*				
Prabu et al. (26)	Exploratory review	*		*					*	
Teixeira and Doetsch(27)	Descriptive		*					*		*
Kondylakis et al. (28)	Review	*	*		*				*	
Nakamoto et al. (29)	Developmental	*		*			*			*
Altmann et al. (30)	Retrospective		*			*				
Dar et al. (31)	Developmental	*				*				*
Singh et al. (32)	Review			*					*	
Urbaczewski and Lee(33)	Retrospective	*	*	*			*			
Whaiduzzaman et al. (34)	Developmental	*	*			*		*		*
Bianconi et al. (35)	Descriptive		*	*	*				*	
Grantz et al. (36)	Prospective	*								
Ming et al. (9)	Retrospective	*	*		*	*				*
Wirth et al. (37)	Scoping review			*	*		*			*
Nijsingh et al. (10)	Descriptive	*						*	*	

Table 2. Consensus Thresholds

Decision	Agreement Rate (%)	Frequency
First Round		
Inclusion	< 75	58
Exclusion	> 50	92
Entering in second round	50 - 75	48
Second Round		
Inclusion	< 75	25
Exclusion	> 75	23

Footnotes

Authors' Contribution: Shanbehzadeh: Study concept and design and acquisition of data; Kazemi: Statistical analysis and reporting the results.

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Table 3. Required Data Elements for Contact Tracing

Data Element	Feature Content	Feature Format	SNOMED-CT Category	SNOMED-CT Codes
General Characteristics				
Full name (11-16, 34, 36, 38, 39)		String	Observable entity	371484003
Age (5-9, 12, 14, 18, 34, 38, 40, 41)		Forced choice	Qualifier value	764868004
Gender (2, 4, 9, 10, 12, 15, 21, 36, 40, 41)	M:1 F:0	Binary	Clinical finding	703118005
National ID number (4, 6, 9, 13, 18, 34, 40)	xxx-xxxxxx-x	Numerical	Observable entity	422549004
Citizenship (2, 15, 18, 21, 34, 36, 39, 41)	Iranian; Non-Iranian	Binary	Social concept	275595001
Medical record number (4, 5, 7, 12, 13, 16, 18, 21, 31, 40)	xx-xx-xx	Numerical	Observable entity	398225001
Level of education (5, 10, 12, 13, 15, 18, 36, 39, 41)	Primary; Secondary; Tertiary	Forced choice	Observable entity	224300008
Marital status (5, 7, 9, 12, 13, 16, 18, 34, 36, 39, 40)	Single; Married; Widow; Other	Forced choice	Clinical finding	87915002
Monthly income (3, 5, 6, 9, 13, 16, 21, 34, 36, 39, 41)	Low: < 120\$; Medium: 120\$ - 250\$; High: > 250\$	Forced choice	Clinical finding	424860001
Family relationship to index cases (5, 6, 9, 15, 34)	Nuclear family; Extended family	Binary	Social concept	394568007
Phone number (4-6, 9, 13, 15, 16, 40)	+98 xxx xxx xxxx	Numerical	Observable entity	398198004
Healthcare facility unique ID (5, 6, 15, 18, 21, 40)	xxxxx	Numerical	Observable entity	713578002
Frontline health worker ID (4-6, 9, 10, 13, 15, 16, 36)	xxxxx	Numerical	Observable entity	713578002
Relationship with the source case (5, 6, 12, 14, 15, 18, 21, 34, 40, 41)	Partner / spouse; Family member; Other	Forced choice	Clinical finding	852071000000103
Geolocation Data				
Place of birth (6, 14, 15, 18, 21, 40, 41)	Geographical location: Province, city, village	String	Environment/ location	315446000
Resident situation (5, 6, 8, 15, 40)	Tenant; Owner; Other	Forced choice	Environment/ location	184097001
Residential address (3, 4, 6, 8, 9, 14, 36, 40)		String	Observable entity	433178008
Postal code / zip code (3, 6, 8-10, 15, 36, 41)	xxxxx-xxxxx	Numerical	observable entity	184097001
Place of contact (3-6, 10, 11, 14-16, 36, 41)	Workplace; Home; Public place; Other; Unknown	Forced choice	Environment/ location	257710009
Location case identified (4, 6, 11, 13, 15, 21, 40)	Geographical location	String	Environment/ location	706956001
Origin of travel (5, 6, 15, 16, 34, 41)	Geographical location	String	Environment/ location	224803003
Travel destination (6, 10, 13, 16, 36, 39)	Geographical location	String	Environment/ location	224807002
Address of healthcare organization (3, 6, 13, 21, 39-41)		String	Observable entity	184097001
Isolation/quarantine location (6, 13, 16, 40)	Self-isolation at home; Hospital; Long term care facilities; Other	Forced choice	Procedure	1321131000000109
Clinical Characteristic				

Symptom incidence (3, 4, 6, 7, 10, 12, 16, 31, 39, 40)	Asymptomatic; Pre symptomatic	Forced choice	Qualifier value	264931009
Date of symptom onset (6, 9, 12, 13, 15, 31, 36, 39, 40)	yyyy/mm/dd	Integer	Observable entity	520191000000103
Days from exposure to symptom onset (8-10, 12, 13, 15, 36, 38, 39)	xx	Numerical	Qualifier value	307474000
Days from illness onset to first admission (5, 6, 10, 12, 15, 18, 38)	xx	Numerical	Qualifier value	307474000
Days from diagnosis to treatment (8, 12, 14, 40)	xx	Numerical	Qualifier value	432213005
Date of diagnosis (10, 12, 14, 18, 40, 41)	yyyy/mm/dd	Integer	Observable entity	432213005
Covid-19 classification (10, 12, 18)	Confirmed; Probable; Unknown	Forced choice	Situation	395098000
Covid-19 status (9, 14, 18)	Active; Inactive; Recovered	Forced choice	Clinical finding	110278006
Case finding approaches	Random screening; Symptomatic case referral; Contact tracing; Other	Forced choice	Clinical finding	Country, Province/ State, City,
Prior hospitalization (3, 5, 9, 10, 12, 14, 34, 38)	Yes; No	Numerical	Clinical finding	314503007
Self Reported Clinical Manifestation				
Fever/chill (4-7, 10, 13, 18, 21, 31, 40)	Yes; No	Binary	Qualifier value	14732006
Cough (4, 6, 9, 10, 13, 18, 41)	Yes; No	Binary	Clinical finding	314503007
Dyspnea (6, 10, 12, 14, 18, 31, 38, 39)	Yes; No	Binary	Qualifier value	385432009
Respiratory distress (10, 12, 21, 38, 39)	Yes; No	Binary	Clinical finding	386661006
Myalgia (9, 12, 18, 38)	Yes; No	Binary	Clinical finding	36523521
Headache (10, 14, 18, 38, 39)	Yes; No	Binary	Clinical finding	43724002
Nausea/vomiting (4, 9, 14, 18, 21, 36)	Yes; No	Binary	Clinical finding	65124004
GI symptoms (4, 10, 15, 16, 39, 40)	Yes; No	Binary	Clinical finding	664563201
Anosmia (12, 16, 21, 34)	Yes; No	Binary	Situation	162298006
Runny nose (12, 13, 15, 34, 39, 41)	Yes; No	Binary	Situation	162062008
Sore throat (4, 12, 13, 16, 21, 34, 40, 41)	Yes; No	Binary	Situation	162104009
Unexpected fatigue (12, 13, 15, 16, 40)	Yes; No	Binary	Clinical finding	93559003
Real-Time Vital Sign Monitoring				
Oxygen saturation (SO₂) (13, 18, 34)	75 < mmHg; 75 - 100 mmHg; 100 > mmHg	Forced choice	Clinical finding	448225001
Heart rate (bit per minute) (10, 12, 13, 18, 34, 36, 41)	< 60 bps; 60-100 bps; > 100 bps	Forced choice	Clinical finding	76863003
Blood pressure (mmHg) (10, 12, 14, 16, 31, 39)	< 120; 120-139; > 140	Forced choice	Clinical finding	2004005
Body temperature (°C) (2, 3, 12-14, 16, 21)	< 37.3; 37.3 - 39; > 39.0	Forced choice	Clinical finding	50177009
Respiratory rate (breaths per min) (2, 3, 12, 16, 21)	≤ 24; > 24	Forced choice	Clinical finding	289100008
Occupational Criteria				
Employment status (5, 7, 8, 18, 34, 41)	Unemployed; Employed	Forced choice	Clinical finding	224363007
Working status (7, 16)	Full time; Part time	Forced choice	Clinical finding	160903007
If employed, occupation risks (3, 8, 13, 31, 34, 38, 39)	High risk; Medium risk; Low risk	Forced choice	Event	16090731000119102

Work situation during general quarantine (7, 16, 34, 38)	Not working; Working at usual place; Teleworking; Other	Forced choice	Clinical finding	302201002
Work in a patient care setting (3-5, 7, 9, 13, 16, 21, 39-41)	Yes; No	Binary	Clinical finding	302201002
Attending work at the time of symptom occur (4, 9, 10, 14, 34, 40)	Yes; No	Binary	Clinical finding	83408003
Travel/Relocation Data				
Recent travel / relocation (4, 6, 8, 10, 13, 15, 18, 34, 36, 40)	Yes; No	Binary	Situation	473087005
Reason for travel (6, 9, 15, 36, 41)	Holiday business; Pilgrimage other	Forced choice	clinical finding	161091009
Travel type (4, 6, 8, 18)	Domestic travel; Foreign travel	Binary	Observable entity	441969007
Date of departure (3-6, 8, 9, 14, 34, 40)	dd/mm/yy	Integer	Observable entity	810811000000107
Number of travels in the last 7 days (5, 6, 8, 9, 11, 16, 36, 40)	None; One - two times a week; Two - four times a week; More than five times a week	Forced choice	Qualifier value	259083004
Travel to epidemic places (2, 5, 7, 9, 18, 21, 36, 40)	Yes; No	Binary	Clinical finding	506931000000109
Relocation / transfer method (3, 5, 9-11, 13, 16, 36)	Public transportation; Personal transportation	Binary	Procedure	715957006
Duration of travel (3, 7, 13)	Daily travel (1 day <); 1 day ≥	Binary	Qualifier value	69620002
Contact Tracing Data				
Prior contact tracing experience (10, 15-18, 22, 25)	Yes; No	Binary	Procedure;	225368008
If yes, prior contact tracing approach (2, 3, 7, 13)	Conventional; Automatic	Binary	Clinical finding;	52669001
If Automatic, contact tracing technology (2, 3, 5-11, 14, 18, 31, 34, 40, 41)	Mobile phone; Implant tools other microcomputers	Forced choice	Qualifier value	723991000000105
Contact tracer ID (3, 5, 6, 9, 11, 14, 34, 38, 39)	XXXX	Forced choice	Qualifier value	118522005
Notification ID (3, 5, 6, 9, 10, 34, 39)	XXX /XXXX -X	Forced choice	Observable entity	895571000000108
Contact Data				
Contact type (4, 10, 12, 13, 18, 36, 38)	Primary: Person-to-person; Secondary: Person-to-surface / animal	Binary	Social concept	70862002
Contact category (2-4, 14, 21, 31)	No contact; Family members; Social contact; other	Forced choice	Clinical finding	381441000000103
Contact risk level (13, 15, 34, 36, 41)	Living with an infected/suspected case in the past 14 days; Prolonged direct contact in the past 14 days; Casual and indirect contact in the past 14 days; Not in contact	Forced choice	Situation	76906009
Contact with care facility	Yes; No	Binary	Situation	136569214
Contact frequency (3, 8, 16, 18)	Sometimes: ≥ 2 times a day; Always: 2 - 4 times a day; Repeatedly: < 4 times a day	Forced choice	Qualifier value	735269004
Contact list (person) (7, 13, 34)	5 >; 5 - 10; 10 - 30; 30 <	Forced choice	Social context	125676002
Minimal distance of contact (meters) (2-4, 14, 21, 36, 41)	2 >; 2 <	Binary	Qualifier value	421669002
Date of last contact (6, 12, 14, 16, 18, 21, 36, 41)	yyyy /mm/ dd	Integer		
Time between contact and diagnosis (10, 15, 16, 18, 41)		Numerical	Qualifier value	305698526

Total duration of contact (minutes) (3, 7, 8, 13, 34, 36)	$\geq 15; < 15$	Binary	Qualifier value	356624006
Total duration of contact (day) (3, 7, 8, 13, 34, 36)	$\geq 14; < 14$	Binary	Qualifier value	258703001