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A quantifiable framework for ‘Covid-19 exposure’ to support the Vaccine prioritization and resource allocation for resource-constraint societies

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ABSTRACT

As the pandemic COVID-19 has severely affected the entire world, it became the utmost necessity of careful prioritization and utilization of limited medical resources, especially for the resource-constraint societies. This requirement along with the asymptomatic nature of COVID-19 in a significant proportion of the population, has prompted the need for a risk assessment tool-kit that can provide a rational behind prioritization and allocation of limited available medical resources. The purpose of this study is to compose a scientific-rationale-based ‘COVID-19-Self-Assessment-Test’ (C19SAT) framework, which helps develop a basis for measuring the risk of COVID-19 exposure with self-assessment. The study comprises of two major parts- (1) identification of key components of the C19SAT framework by studying various guidelines (WHO & CDC) and relevant literature, and (2) quantification of those components by assigning weight through the analysis of survey results and opinions from medical physicians and experts. A C19SAT framework is developed to measure the risk of covid-19 exposure, comprising a set of identified components (12 parameters and their corresponding attributes) and their corresponding weights. As the scientific rationale behind such assessment framework has not been reported to date in case of available mobile applications and web-based toolkit, the present study brings the novelty and reports the construction of such a framework. The study opens up untouched research and discussion on the composition of the COVID-19 exposure-measurement framework, which can help in vaccine prioritization and resource allocation. Further studies can be carried out on refining the framework for better understanding and effectiveness towards urban health governance.

1. Introduction

The pandemic ‘Coronavirus Disease’ or COVID-19 has claimed millions of death among the infected people across the world (Battineni, Chintalapudi & Amenta, 2020). A quick analysis of WHO data and situation report clearly indicates that the spread of COVID-19 cases is not uniform across nations. At some places, ‘imposing of early strict lockdown by the government’ has helped to contain the disease spread, as indicated by ‘Oxford Coronavirus Government Response Tracker’ (Aggarwal, 2020; Hale, Webster, Petherick, Phillips & Beatriz, 2020). However the fewer number or percentage of tests being conducted could also account for the lesser COVID-positive numbers (Aggarwal, 2020). A population of nearly 1.3 billion and a ranking of 145 among 195 countries in the ‘Global Healthcare Access and Quality Index’ (Fullman et al., 2018; Yadavar, 2018), are realities compelling India to wage a stringent war against COVID-19, as strict measures (Cohen & Kupferschmidt, 2020) are being followed to control disease transmis-

sion at some extent. Combined with limited available medical resources and infrastructure, there is a need to adopt a cautious approach and prioritize vaccine (De Hert, Mazereel, Detraux & Van Assche, 2021) and resource allocation based on severity of illness. The need for increasing COVID-19 diagnostic tests despite a severe shortage of testing kits (Shekhar, 2020), and lack of access to routine healthcare, generates a need for reliable self-assessment tool-kits that could help to pre-screen individuals, quantify their risk of being COVID-19 affected and help them decide if the COVID-19 diagnostic test is really mandated. As the researchers argued that the next decade will test the field of risk analysis (Greenberg et al.,), it is important the risk science should be built on strong knowledge base (Aven & Flage, 2020). The present study investigates the computes health-risk due to COVID-19 with the help of medical practitioners and existing literature, in order to form a framework to measure individual’s COVID risk.

As the internet has already become an essential medium for providing medical assistance (Brownstein, Freifeld & Madoff, 2009; Yusuf, Hafeez-Baig & Soar, 2020), several mobile technologies

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(Zhou et al., 2019) are invented for providing health services. There are many internet-based mobile applications (Wikipedia, 2020). ‘Aarogya Setu’ (GoI, 2020) is one of such app that informs millions of its users about the COVID-19 risks, best practices, and relevant advisories. Another similar type of app ‘Cova Punjab’ (GoP, 2020) provides preventive care information and advisories, such as quick self-screening, travel instructions, awareness, etc. Apart from mobile apps, there are plenty of web-apps as well. ‘Coronavirus Risk Scan’ (Apollo, 2020) is one of the popular risk scanner that predicts infection risk by analysing self-reported data gathered through a chat-box type interface. Similar type of web-app ‘COVID-19 Self-Assessment’ (GoO, 2020) helps in self-assessment by analysing data gathered from a conventional web interface with question-answer format. Another web-based tool ‘COVID-19 Symptom Checker’ (SoNJ, 2020) assists users about when to take medical care or when to get physical testing.

Different developers or groups might have adopted different approaches while building these mobile or web apps provide a quick self-assessment service to citizens regarding the chances of having COVID-19, but a scientific rationale-based quantifiable framework to measure the risk of COVID-19 exposure through self-assessment remains to be established. Several searches were attempted using ‘Google Scholar’ and ‘PubMed’, for published articles related to COVID-19 self-assessment test, exposure measurement, or relevant research thereof. The search terms are used with the combination of several keywords- covid 19, self, assessment, risk, reporting, exposure, measurement, evaluation, scanner, diagnostic and diagnosis. No relevant published articles were found that establishes the scientific rationale behind COVID-19 exposure measurement. The present study reports the development of a scientific rationale behind such framework and how to measure that. In this study, an investigation has been carried out to identify the components of ‘COVID-19 exposure measurement’ along with their weight distribution, which help develop a basis for measuring the risk of COVID-19 exposure with self-assessment.

2. Materials & methods

2.1. Study design

This study is an investigation into the scientific basis of the ‘COVID-19 self-assessment test’. The design to build the framework of the test involves two sections. The first comprises of identifying the components of the ‘COVID-19 Self-Assessment Test’. Here, the components are building blocks, which collectively form the skeleton of the model/framework. Second is the quantification process, i.e. to assign or understand the distribution of weights, which are essential to finalize the framework. The overall methodology followed in the study is shown in Fig. 1.

2.2. Understanding the components of “COVID-19 self-assessment test” framework

There are two types of components in the framework- parameters and attributes. The measurable factors namely those that define the ‘COVID-19 Self-Assessment Test’, are called “parameters.” The representative elements of each parameter are called the attributes of that specific parameter. For example- ‘symptom’ is a measurable factor for the ‘COVID-19 Self-Assessment Test’, and the ‘attributes’ of the parameter ‘symptom’ are fever, dry cough, tiredness, etc. The information provided on WHO website (WHO, 2020; 2020ab), Centers for Disease Control and Prevention (CDC) website (CDC, 2020a, 2020b), and other related scientific literature were thoroughly scrutinized to extract information on the parameters. This was followed by a discussion with physicians (who are medical doctors handling patients with COVID-19, pulmonary, and respiratory diseases) in order to finalize the set of parameters and their corresponding attributes, as expert opinion is a popular approach used to determine scientific parameters. The idea was to replicate the decision-

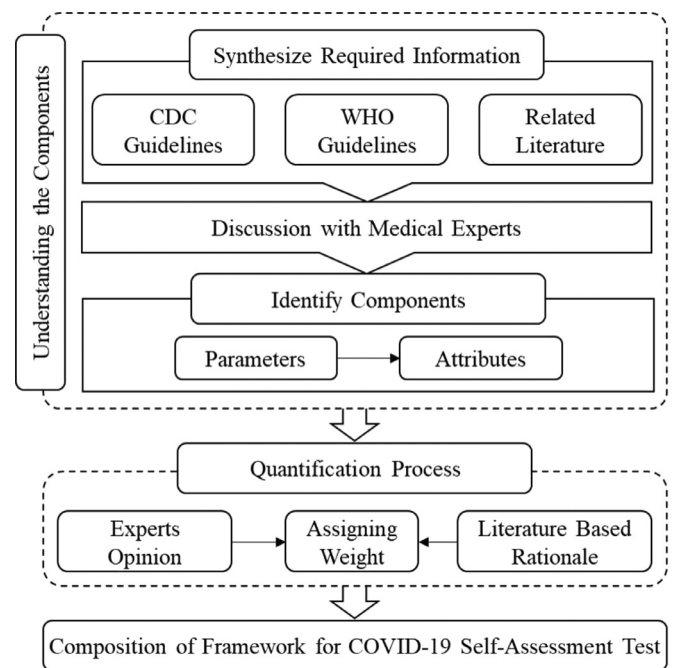


Fig. 1. Overall methodology.

making mechanism, based on which physicians advise their patient for a COVID-19 test.

2.3. Quantification process

Once the components (i.e. parameters and attributes) are finalized, the next task was to assign weights, in order to quantify the Framework. An expert’ opinion based quantification process (Anonymous, 2019) is adopted here. A survey was conducted among specialized medical experts or physicians or practitioners who were asked to rate the parameters on a Likert Scale of 1–5 based on importance level, where ‘1’ represents ‘least important’ and ‘5’ represents ‘most important’. The physicians were asked to rate those parameters a second time where questions were kept in a different order. Though 15 respondents (De Villiers, De Villiers & Kent, 2005) are sufficient to conclude an experts’ opinion based study, there were 19 physicians who enunciated weight distribution from their expertise in both parts of our survey. The collected ratings were averaged to get the average score given by individual respondents. These average ratings are summarized for each parameter followed by a normalization. Those normalized scores are presented in a percentage form, and are the assigned weights for each of the parameters. The assigned weights of the parameters are further distributed among their respective attributes, based on a specific rationale identified through literature and physicians’ opinion, for a specific attribute of a specific parameter.

3. Result & discussion

3.1. Composition of framework: parameters & attributes

A set of 12 parameters are identified- symptoms, age, medical history, travel history, physical interaction with COVID-19 patient, stress, gender, precautionary measures, hygiene practice, food habits, exercise, and unawareness of COVID-19 related general information. The identified parameters (i) are demonstrated in Table 1. The average rating or weight for ‘i’th parameter, provided by ‘n’th expert, are denoted by ‘ R_{in} ’. These are summarized to get the aggregated score (S_i) for ‘i’th param-

Table 1
Weight distribution of the parameters as per the experts' opinion.

Parameters (i)	Average ratings provided by the experts ($R_{i,n}$)																			Aggregated Score (S_i)	Normalized Weight (P_i)
	$R_{i,1}$	$R_{i,2}$	$R_{i,3}$	$R_{i,4}$	$R_{i,5}$	$R_{i,6}$	$R_{i,7}$	$R_{i,8}$	$R_{i,9}$	$R_{i,10}$	$R_{i,11}$	$R_{i,12}$	$R_{i,13}$	$R_{i,14}$	$R_{i,15}$	$R_{i,16}$	$R_{i,17}$	$R_{i,18}$	$R_{i,19}$		
Symptoms	5	5	3	5	3	3	4+5	4	5	3	3	4+5	5	5	5	5	5	5	5	83	10*4600
Age	5	4+5	3+5	5	3	3+5	1	5	3	1+5	5	4+5	5	5	4	4	4+5	3	4	69	8*6957
Medical History	3+5	4	2+5	5	3	3+5	1	5	2	5	4	3+5	4	5	2	4	5	4	4	70	8*8217
Travel History	5	4+5	5	5	1	2	4	5	3	3	3	4+5	5	4	1	5	4	3	4+5	71+5	9*0107
Physical Interaction with COVID patient	5	5	5	5	3	5	5	5	3	5	5	4+5	5	5	1	5	5	4	5	85+5	10*7750
Stress	3	4	2+5	2	1	2	1	2	3	2	3	2+5	4+5	3	2	3+5	2+5	3	3+5	52	6*5532
Gender	2	3+5	3	2	1	2+5	3	5	2	4	1	2	4	4	1	2+5	3	3	3	52+5	6*6163
Precautionary Measures	4	5	4	5	2	5	2	5	3	5	4+5	3+5	4+5	4+5	5	4	3	4	76	9*5778	
Hygiene Practice	3+5	5	4	5	2+5	5	3	5	3	5	4+5	4+5	4+5	4+5	5	5	3	4	78+5	9*8929	
Food Habits	2	3+5	2+5	2	2	3	1	5	3	2+5	2+5	4	3	1	3+5	3	3	3	52+5	6*6163	
Exercise	3	3	2+5	2	1	2+5	1	5	2	3	2+5	3	4	2	1	3+5	1	3	3	47+5	5*9861
Unawareness of COVID related Information	1	4	2	1	2	5	1	5	2	2	2	4	4	3+5	3	4	3	3	55+5	6*9943	

ter (Eq. (1)).

$$S_i = \sum_{n=1}^{19} R_{i,n} \tag{1}$$

These aggregated scores (S_i) are normalized, and presented as percentages (P_i) in Eq. (2), which are the total weights allotted to each parameter.

$$P_i = \left(\frac{S_i}{\sum_1^{12} S_i} \right) * 100 \tag{2}$$

Each of the parameters are represented with several attributes. The normalized weights (mentioned in Table 1) are the maximum possible contribution for a parameter for measuring the chances of getting COVID. In other words, if a person takes the survey to know the chances of getting COVID, then the measured weight (as per the responses given against corresponding attributes by that person) for any of the parameter can either less than or equal to the normalized weight. The weights distribution among the attributes are rationalized based on available literature, experts' opinion, and authors' understanding.

3.1.1. Symptoms

Screening of vital symptoms is essential for COVID-19 exposure prediction (Dhanapal, Narayanamurthy, Shanmugam, Gangadharan & Magesh, 2020). A patient can either have one or multiple or no symptoms. Fever, dry cough, tiredness, shortness or difficulty in breathing, chest pain/pressure, and loss of speech or movement are reported as the most common and severe symptoms that require urgent medical assistance (WHO, 2020b). Aches and pains, sore throat, diarrhea, conjunctivitis, headache, loss of taste/smell, skin-rash or discoloration of fingers/toes, and nasal congestion or runny nose are reported as mild symptoms. A person can either have no symptoms, or mild, and/or severe symptom(s).

Due to the commonality and intensity, presence of any of the severe or common symptoms will attract the weight distribution with a ratio of 2:1 as compared to any of the mild ones. Having one or multiple severe or common symptoms, will attract the 2/3 wt of P_1 (i.e. 6.9036) to the measured weight for category symptoms (MP_1). Having one or more uncommon and mild symptoms, will add up 1/3 wt of P_1 (i.e. 3.4518) to the measured weight for category symptoms (MP_1). The collective measured weight for parameter 'symptom', will further contribute to the Final Measured Score (FMS), which represents the chances of getting COVID. Having no symptom will attract 'zero' or no contribution from the parameter P_1 toward the FMS.

3.1.2. Age

65 and higher aged adults (CDC, 2020b) are usually more prone towards COVID-19 due to lowered immunity. A case fatality-ratio (Verity et al., 2020) indicates adults having <49 age, are less prone towards COVID-19. The age-group is classified in to three categories (>=65, 49–65, and <=49), and followed a weight-distribution as 3:2:1 ratio based on the severity. A person can fall into either of these groups only. That means, there can be only one measured weight (MP_2) for this parameter 'Age'. Being 65 years old or more, will attract the whole weight of P_2 (i.e. 8.6957) to the measured weight (MP_2). Being aged between 49 and 65 years old, will attract 2/3 of weight of P_2 (i.e. 5.74) to the measured weight (MP_2). Being aged less than 49 years old, will attract 1/3 of weight of P_2 (i.e. 2.87) to the measured weight (MP_2). The measured weight for parameter 'Age', will further contribute to the Final Measured Score (FMS), which represents the chances of getting COVID.

3.1.3. Medical history

Patient with underlying 10 medical conditions (CDC, 2020b; WHO, 2020b), are prone towards a severe illness from COVID- Blood Pressure, Heart Problem, Diabetes, Lung Disease and Asthma, Cancer,

Kidney Failure, Liver Problem, Haemoglobin Disorder, Immunodeficiency, and Severe Obesity (BMI>40). A patient can either have one or multiple or no previous medical history. Having more medical conditions will increase the risk of getting COVID for a patient. The weight of P_3 is equally distributed across the history of medical conditions, so that these can be add up cumulatively based on selection, and contribute collectively towards the measured weight of parameter 'medical History' (MP_3), which will finally contribute to the FMS. Having each medical condition will add up 1/10 wt of P_3 (i.e. 0.8822). Not having a previous medical history attracts 'zero' or no contribution to the FMS.

3.1.4. Travel history

The disease was first detected in China and international travel helped it become a pandemic. It usually takes up to 14 days to generate symptoms from exposure to COVID-19 (WHO, 2020b). International travel, as well as the domestic and local travel in past 14 days during the pandemic can facilitate transmission of communicable disease (Ebrahim, Ahmed, Gozzer, Schlagenhauf & Memish, 2020). A patient can either have one or multiple or no travel history. The weights of P_4 are distributed equally. Each version of these three travels (international, domestic, and local), will attract 1/3 wt of P_4 (i.e. 3.0036). These will add up cumulatively based on the selection, and contribute collectively towards the measured weight of parameter 'Travel History' (MP_4), which will finally contribute to the FMS. No travel history attracts 'zero' or no contribution from the parameter P_4 toward the final score.

3.1.5. Physical interaction with COVID-19 patient

A person can get infected very easily (WHO, 2020b), while coming in close contact with a COVID-19 patient without having protective and precautionary measures. One can either come in contact or not. Full weight of P_5 implies that the person came in contact, or no weight will be assigned for no contact, towards the measured weight of parameter 'physical interaction with COVID patient' (MP_5), which will finally contribute to the FMS.

3.1.6. Stress

There is a high risk for COVID-19 in those with stress (Zhang et al., 2020), as it reduces sleep. A five-point Likert-scale (Extremely Stressed, Highly Stressed, Moderately Stressed, Lightly Stressed, and Not At All Stressed) is used here to measure the severity of stress. The full weight of P_6 is distributed as 4:3:2:1 following the severity. No or 'zero' weight is assigned in case of no stress. A patient may be passing through a specific level of stress or may have no stress. If a person is highly stressed, then whole weight of P_6 (i.e. 6.5532) will contribute towards the measured weight of parameter 'stress' (MP_6), which will finally contribute to the FMS.

3.1.7. Gender

Higher case fatality is observed in male than female (Wadman, 2020; Walter & McGregor, 2020). The whole weight of P_7 is distributed between its attributes male and female as a ratio of 2:1 following chances of case fatality. Being a male, will attract whole weight of P_7 (i.e. 6.6163), will contribute towards the measured weight of parameter 'gender' (MP_7), which will finally contribute to the FMS.

3.1.8. Precautionary measures

Staying at home, maintaining social/physical distancing, and greeting method in daily life, are three important factors identified to stop COVID-19 (Alkhowailed et al., 2020; WHO, 2020b). These are collectively represented as precautionary measures. The whole weight of this precautionary measures (P_8) is distributed equally among these three factors. The allocated weight for each of these three factors become 3•1926. These are further distributed among the respective attributes as per the rationale. For example- a patient can either follow or ignore staying at home. If s(he) ignores, then a weight of 3•1926 will add up

towards the measured weight, otherwise it will attract 'zero'. Similar distribution will happen for not following social/physical distancing. In case of greeting-method, if s(he) follows unsafe approach (i.e. hand-shake and hug) that increases the risk of spread due to physical touch, the allotted weight of 3•1926 will add up towards the measured weight. All other safer method of greeting (i.e. wave, nod, and bow) attract 'zero' towards the measured weight. Measured weights from all the three factors collectively will become the measured weight for the parameter 'precautionary measures' (MP_8), which will finally contribute to the FMS.

3.1.9. Hygiene practice

Hygiene practices like avoiding face-touching, performing hand washing, and covering-up face (WHO, 2020b) or wearing mask (Yan, Guha, Hariharan & Myers, 2019) in public, are three important measures to stop the spread of COVID-19. The whole weight of this 'hygiene practice' (P_9) is distributed equally among these three measures. The allocated weight for each of these three measures become 3•2976. These are further distributed among the respective attributes as per the yes/no logic. If a patient often touches own face in daily life, it adds-up 3•2976 towards the measured weight, otherwise it attracts 'zero'. If a patient is unable to practice proper hand-washing, it will add-up a 3•2976, otherwise it will attract 'zero' towards the measured weight. Similar distribution also applies if a patient is unable to cover-up their own face. Measured weights from all the three measures collectively will become the measured weight for the parameter 'Hygiene Practice' (MP_9), which will finally contribute to the FMS.

3.1.10. Food habits

Poor diet (Shlisky et al., 2017), smoking (Walter & McGregor, 2020), and drinking alcohol (Szabo & Saha, 2015), can affect immunity. These food habits are important factors that can play crucial role in fight against COVID-19. The whole weight of this parameter 'food habit' (P_{10}) is distributed equally among these three factors. The allocated weight for each of these three factors become 2•2054. These are further distributed among the respective attributes as per the rationale. If a patient doesn't smoke or drink, it will attract 'zero' towards the final score, otherwise it will attract 2.2054. In case of the factor 'poor diet', if a patient is unable to take proper diet in a regular manner, it will add up 2•2054 to the measured weight. Measured weights from all the three factors collectively will become the measured weight for the parameter 'food habits' (MP_{10}), which will finally contribute to the FMS.

3.1.11. Exercise

As regular exercise (Nieman, 2011; Shlisky et al., 2017) can build up better immunity, it is considered as an important parameter against COVID-19. The whole weight of the parameter 'exercise' (P_{11}) is distributed across its attributes as per the regularity/frequency of exercise. A yes/no logic is used here to measure regularity of exercise. No or 'zero' weight is assigned in case of daily or regular exercise, otherwise it will attract the whole weight of P_{11} (i.e. 5.9861). This will contribute towards the measured weight of parameter 'exercise' (MP_{11}), which will finally contribute to the FMS.

3.1.12. Unawareness of COVID-19 related general information

Being unaware about the necessary information of an epidemic/pandemic and its seriousness (Johnson & Hariharan, 2017), may lead to serious illness. The unawareness is considered as one of the key parameters. The whole weight of parameter 'unawareness' (P_{12}) is distributed among its attributes with yes/no logic. If a person unaware about the guidelines or general information about the pandemic, then whole weight of P_{12} (i.e. 6.9943) will contribute towards the measured weight of parameter 'unawareness' (MP_{12}), which will finally contribute to the FMS. Otherwise it will attract 'zero'.

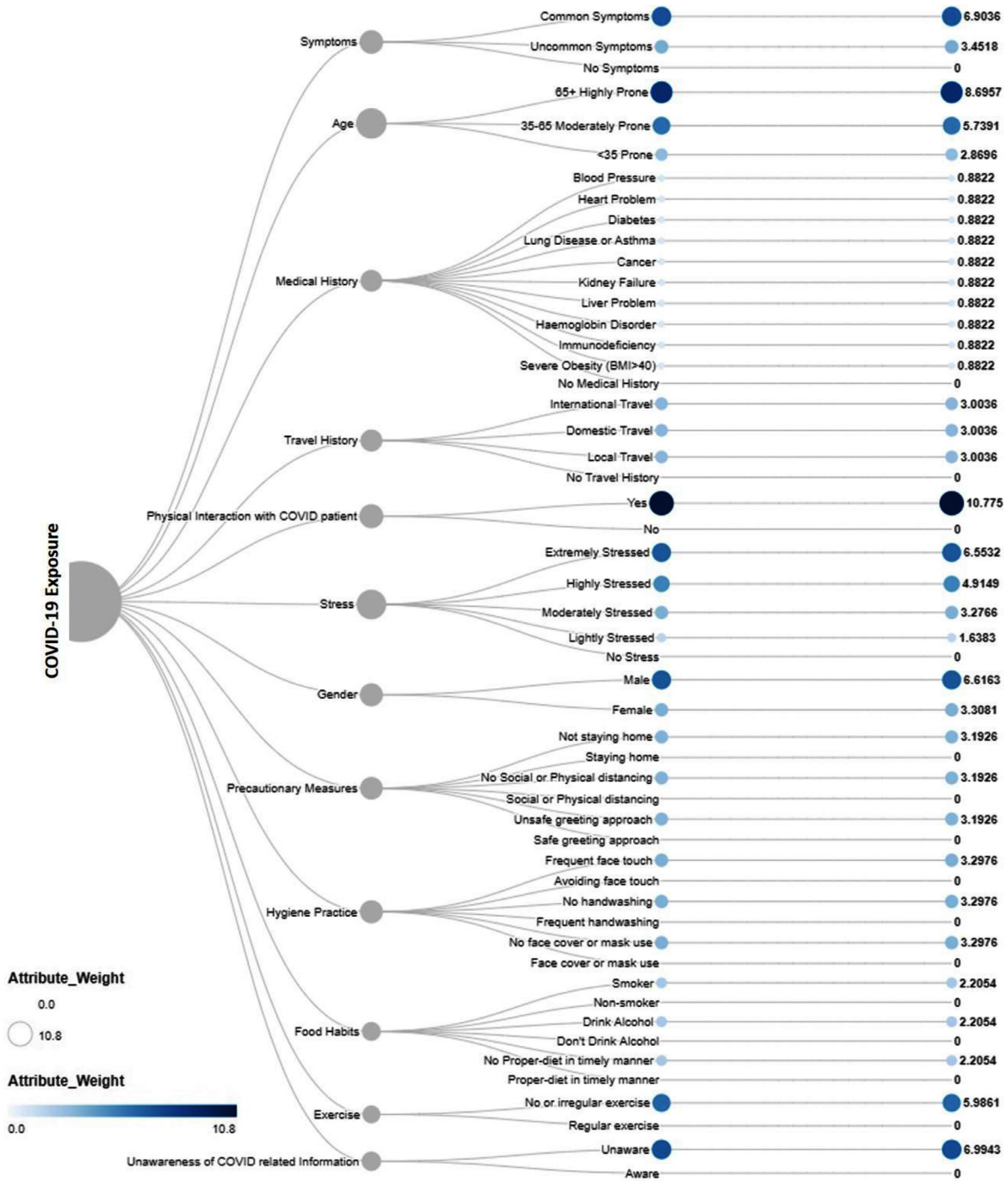


Fig. 2. Graphical representation of weight distribution.

3.2. Measuring the framework

The framework comprises of 12 parameters and their corresponding attributes. The graphical weight distribution is shown in Fig. 2. These are discussed in details in the previous Section 3.1, along with their rationale for measuring them. The framework is evaluated with a Final Measured Score (FMS), which is the sum of measured weight of every parameter (MP_i) shown in Eq. (3).

$$FMS = \sum_{i=1}^{12} MP_i \quad (3)$$

Where MP_i is calculated based on user response, recorded against a set of corresponding attributes.

A higher FMS reflects a high chance of getting COVID-19. Higher the chance of COVID-19 exposure means more priority to be given for vaccine and resources allocation. The maximum possible value of FMS is 100, which represents highest chance of getting COVID-19.

3.3. Implications

As the world faces a massive disruption due to the COVID-19 pandemic, careful resource utilization as part of better urban governance,

became necessary for resource-constraint nations. Deciding the rationale or the basis, emerged as one of the major challenges while doing so. The present study addresses this challenge, by composing a quantifiable framework to measure ‘Covid-19 exposure’ at the individual level. It will not only help individuals to know their own COVID-risk, but will also help the authorities to identify the populations with higher COVID-exposure who should be given priority in vaccination, medical assistance, or distributing any other form of limited resources, given the pandemic situation in place.

4. Conclusion

The pandemic COVID-19 that has infected millions and caused millions of deaths globally till date, has varied presentations ranging from symptomatic patients with completely asymptomatic individuals. It is necessary to optimize vaccine allocation and resource utilization to prioritize limited resources, especially in the low or lower-middle-income countries. In this scenario a COVID-19 exposure-measurement can help pre-screen individuals by quantifying their risk of COVID-19 and helping them prioritize medical assistance for a COVID-19 diagnostic test if the risk was high. This has potential to play a crucial role in an overwhelmed healthcare system. Numerous mobile applications and web platforms across the globe have provided such a service, however the scientific rationale behind the development of such applications has not been elaborated. The present study was designed to elucidate the scientific basis of the COVID-19 exposure-measurement.

The study synthesized the WHO and CDC guidelines along with relevant literature, to identify the basic components of a “COVID-19 Exposure Measurement” i.e. ‘parameters’ and ‘attributes’ of each parameter. A set of 12 parameters and their corresponding attributes are identified. In order to quantify the framework, a survey was conducted among the physicians and the recorded insights are analyzed, which eventually helped in weight-distribution among the components. The parameters, attributes and their weight-distributions together form such quantifiable framework. This can be easily associated with web-based or cell-phone based platform.

The study opens up room for a new research discussion among the scientific community on the composition of a ‘COVID-19 Exposure Measurement’ framework. It provides a scientific basis that may be utilized to develop any platform, application or toolkit to be used by individuals to measure their COVID-19 risk through self-assessment. The developers, medical service providers and administrators can adopt this framework while designing or developing such a system that can help in prioritizing vaccine and resource allocation. This is the first of its kind study that describes a rationale-based framework for ‘COVID-19’ exposure measurement. Future research on improvising the framework for better functioning and effectiveness, by consulting with more number of experts or exploring alternate components or deciding data-analytics based weight distribution or updating with emerging scientific-evidence on COVID-19, will definitely advance the results of this study.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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