Journal of Housing and the Built Environment
https://doi.org/10.1007/s10901-024-10120-x

ARTICLE

Rethinking the city resilience: COM-B model-based analysis of healthcare accessing behaviour changes affected by COVID-19

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Received: 31 August 2023 / Accepted: 15 March 2024

Abstract

The global pandemic of COVID-19 has been influencing people's lives and the cities. Not only people's physical and mental health have been threatened, but also the city operation has been profoundly affected from different perspectives (e.g., social and economic) permanently. How cities can efficiently react and response to improve city resilience is an urgent issue to be addressed. The healthcare system as a vital part of the city systems is confronting intense pressure and many challenges under this emergent public health crisis of COVID-19, which might cause huge impacts on the whole city's operation. Also, human beings as the direct victims of this public health crisis, their behaviour changes impacts on the healthcare system and the city could have been inevitable but have been neglected. In this context, this paper intends to study the citizen healthcare accessing behaviours changes in the post-pandemic era, and to unearth their impacts on the healthcare system and the city operation. For this purpose, first, a framework of influential factors for healthcare accessing was established based on a bidirectional "capability, opportunity, motivation, and behaviour" (COM-B) model and the comprehensive literature review. In which, 43 factors that would influence citizen healthcare accessing behaviour were identified and classified. Thus, based on the proposed framework, two cases (i.e., UK and China) were analysed in depth and compared based on a questionnaire survey to evaluate the factor importance and relationships under different scenarios. And the most influential factors based on analysis results are classified into 12 aspects (e.g., healthcare capability, policy support, information updating etc.). Further, a novel behaviour-healthcare system-city model based on the COM-B model was developed to rethink and indicate the relationships among citizen behaviour, healthcare system and city operation. The research results can be used by policymakers and researchers to improve the city resilience by enabling immediate responses to city systems and citizens behaviours confronting city emergencies.

Keywords COVID-19 · Behaviour change · Healthcare accessing · Healthcare system · City resilience · Public health crisis · COM-B model

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Published online: 26 March 2024

1 Introduction

Since the outbreak of COVID-19 in late 2019, the global sweeps of the pandemic have been causing massive social and economic impacts on people's lives and the cities (Batty, 2022). Because human beings' health has been threatened massively by this public health crisis, the healthcare system has been facing unprecedented challenges since the outbreak of the pandemic. Many countries (e.g., China, the U.S., the UK, Italy, France, and Japan) have reported a shortage of healthcare resources such as Intensive Care Unit (ICU) beds, ventilators, and trained personnel (Canas et al., 2021; Ceylan, 2020; Watanabe, 2020; White & Lo, 2020; Xie et al., 2020). Even worse, researchers have addressed the importance to focus on the physical and psychological health condition of medical practitioners under such a heavy workload caused by COVID-19, which increased the shortage of trained personnel (Shah et al., 2020). The scarcity of medical resources in the healthcare system has aggravated people's panic or anxiety (Qiu et al., 2020).

At city level, the healthcare system is an essential and vital component of the city as it relates closely to the stability of the city operation during the public health crisis of COVID-19. Moreover, studies have indicated that adequate management of the healthcare system was one of the top concerns in the city resilience framework (Feng et al., 2020; The Rockefeller Foundation & Arup, 2014), which drives the urgent need to rethink city resilience associating with the healthcare system affected by the public health crisis like COVID-19. In existing studies related to healthcare system accessibility, (Emanuel et al., 2020) discussed the fair allocation of scarce medical resources in the time of COVID-19 with recommendations from the healthcare system perspective. For example, the priority for limited resources should aim both at saving the most lives and at maximizing improvements in individuals' post-treatment length of life; prioritization guidelines should differ by intervention and should respond to changing scientific evidence (e.g., older persons and patients with chronic illness might need prioritization than younger patients) (Emanuel et al., 2020). Besides, the two-step floating catchment area (2SFCA) and enhanced 2SFCA (E2SFCA) methods were commonly used to analyse the spatial accessibility of healthcare with the consideration of demand–supply relationship (Mao & Nekorchuk, 2013; Wan et al., 2012). For instance, (Kang et al., 2020) used E2SFCA to optimise healthcare accessibility considering the bed-to-population ratio after the outbreak of COVID-19. (Ghorbanzadeh et al., 2021) researched on the spatial accessibility assessment of COVID-19 patients to healthcare facilities in Florida using the 2SFCA and E2SFCA. This study revealed many areas in the northwest and southern Florida have lower access compared to other locations, which provided provide valuable insights and information for state officials and decision makers (Ghorbanzadeh et al., 2021). Additionally, before the outbreak of COVID-19, individual characteristics (e.g., demographics, insurance status, needs, health status, car ownership and geographic distance) have been analysed for spatial healthcare accessibility (Comber et al., 2011; Litaker et al., 2005). However, the research gaps exist where, firstly, discussions were limited regarding the relationship between healthcare system and city operation/resilience involving multiple organisations and stakeholders, especially in the public health crisis; second, citizen reactions (i.e., the behaviour change of healthcare accessing) and the corresponding influences on the healthcare system and the city were overlooked.

As COVID-19 has directly threatened people's physical health, it has naturally caused people's intention of healthcare accessing behaviours, which potentially leads to the scarcity of medical resources. From the urban study perspective, a pattern of human behaviour-related influence for city systems and thus the cities have been addressed and studied in the post-pandemic era. For example, (Kato & Matsushita, 2021) revealed the speed increase of people's walking behaviour and more cyclists in a city of Japan, which suggested more walkable streets and bike lanes were needed in the city's transportation system. Travel-related behaviour changes have indicated different trends towards private and public transportation in different countries (Angell & Potoglou, 2022; Zhang et al., 2021). Also, the energy consumption patterns have been proved shifting during the pandemic because of lighting use changes (Rowe et al., 2022). To further explain how the behavioural changes can affect cities, Lu et al. proposed a bidirectional interaction between human and cities shown in Fig. 1 (Lu et al., 2021). Specifically, COVID-19 and the controlling strategies profoundly affected citizen behaviours (e.g., energy/transportation/culture related behaviours), and then the behaviours can affect city systems (e.g., energy/transportation/recreational systems) through actions on building systems and facilities, where city performance can be sequentially influenced by the alter of city system eventually and re-affect citizen behaviour (Lu et al., 2021). Therefore, it is reasonable and inevitable to concentrate on healthcare accessing behaviour changes and analyse their impacts on the healthcare system and the city facing city emergencies like COVID-19.

To understand the healthcare accessing behaviour change affected by COVID-19, it is necessary to figure out the influential factors hidden behind. Accept from the direct considerations of personal physical health, medical resources availability (e.g., physicians, equipment, ICU beds) (Emanuel et al., 2020), there have been several factors mentioned in existing studies. For example, (Giezendanner et al., 2021) has indicated the healthcare accessing change regarding healthcare provider choices (e.g., pharmacies, GPs, hospitals) and the potentials for telemedicine. Psychological distress or anxiety of the infection risk in the healthcare might be an influential factor (Bavel et al., 2020). And the COVID-19 policies such as keeping social distance, shutdown of transportation, quarantine requirements for infected people and close contacts might also stop people from accessing healthcare places (Bavel et al., 2020; Chen et al., 2020; Nikiforiadis et al., 2022). In addition, before the outbreak of COVID-19, many influential factors have been studied. For instance, (Nägga et al., 2012) studied the healthcare accessing factors like living environment, education background, assistance needs for elderly aged 85. (Lee et al., 2014) studied factors such as lack of money and transportation, no availability of appointment for disabilities in a Korea. (You, 2021) analysed factors regarding greening rate, time of completion, distance to the healthcare etc. However, the abovementioned factors were too scattered and isolated to be used as a theoretical framework to directly understand the behaviour changes facing COVID-19, which impeded the analysis of behaviour changes impacts on the healthcare system and the city.

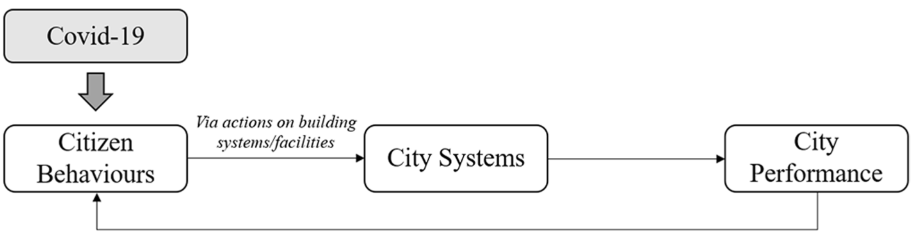

Fig. 1 The bidirectional interaction between human and cities based on (Lu et al., 2021)

In this sense, a capability, opportunity, motivation, and behaviour (COM-B) model from psychological science field is thus used in this study to provide a fundamental and bi-directional framework. The aim is to (1) establish a comprehensive framework of influential factors for healthcare accessing behaviour based on COM-B model, (2) using the framework, to analyse in depth and compare whether the healthcare accessing behaviour has been changed in pre- and post-pandemic era for the UK and China cases, and what are the key aspects affecting the changes, and (3) how the healthcare system and thus the city are influenced and what would be the responses regarding city operation and resilience.

The following of this study is structured as follows. Section 2 introduces the COM-B model in details and demonstrates its application in this study. Section 3 introduces the research methodology, data collection and data analysis. Section 4 illustrates establishment of the proposed framework of influential factors for healthcare accessing behaviour based on COM-B model. Section 5 shows the analysis and comparison results regarding multiple scenarios in the UK and China cases. Based on the results, Section 6 discusses the relationships among the healthcare accessing behaviour, healthcare system, and the cities, and proposes a novel model of the three components to improve city resilience towards public health crisis.

2 The bi-directional COM-B model and its related studies of healthcare

Healthcare accessing is a human behaviour, and it directly relates to the usage state of city's healthcare system. Many behavioural change interventions are potential to affect the stable operation of whole healthcare system. Examples are factors (i.e., interventions) such as personal health condition, transportation, healthcare medical capability that have been existing before the pandemic (Comber et al., 2011; Lee et al., 2014), and mask mandatory, social distance and vaccination requirements have occurred after the COVID-19 outbreak (Bavel et al., 2020; Chen et al., 2020; Nikiforiadis et al., 2022). In the psychological science research field, COM-B model has been well-established by (Michie et al., 2011) overcoming the limitations of the other 19 behaviour change frameworks (Perros et al., 2022). It has been widely employed for behaviour change studies such as diabetes, medication, energy saving behaviours (Handley et al., 2015; Jackson et al., 2014; Perros et al., 2022). After the outbreak of COVID-19, the COM-B model have also been implemented. For instance, they been used to explore pregnant women's understanding of the behavioural restrictions and their perceived ability to comply and the most concerning impacts of the measures in the post-pandemic time (Anderson et al., 2021). The British Psychological Society's Behavioural Science and Disease Prevention Taskforce advises using COM-B to understand and facilitate the enactment of preventative behaviours in the context of the pandemic (Chater et al., 2020; Michie & West, 2021; Michie et al., 2011). Therefore, there is great potential utility in applying COM-B for healthcare accessing behaviour study.

The COM-B model indicates that the human behaviour is influenced bi-directionally by capability, motivation, and opportunity and the interactions among them as shown in Fig. 2 (Michie et al., 2011). Besides, capability and opportunity contribute to motivation, so that having greater capability and opportunity can increase motivation and thus influence the behaviour more (Michie & West, 2021). The definitions of

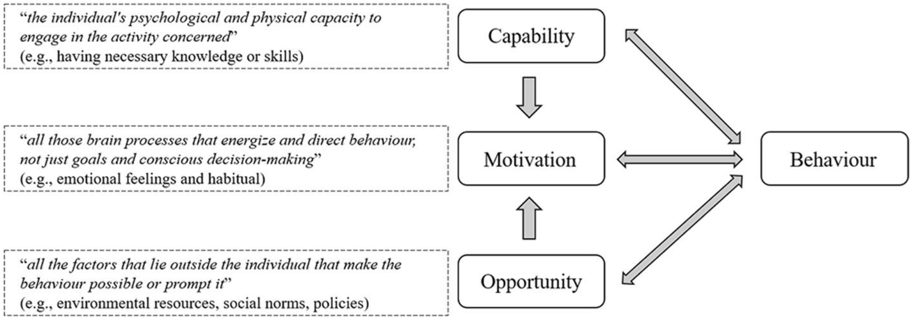

Fig. 2 The capacity, opportunity and motivation model based on (Anderson et al., 2021; Michie et al., 2011)

"capability", "opportunity", and "motivation" in the context of this study are explained and illustrated with existing studies as follows.

2.1 Capability

"Capability" was indicated as "*the individual's psychological and physical capability to engage in the activity concerned*", which represented having necessary knowledge or skills to achieve the activity (Anderson et al., 2021; Michie et al., 2011). In this study, it can be understood as the individual's capacity to access the healthcare system measured by his/her personal abilities (Michie et al., 2011). For example, in previous studies, personal physical health condition (e.g., severity and emergency of the illness, chronic illness history) relates directly to the healthcare accessing behaviour (Arora & Grey, 2020; Zanobetti et al., 2012). Other non-medical capability such as lack of driving ability and lack of public transportation accessing, financial affordability have been used to measure the healthcare accessibility (Lee et al., 2014; Litaker et al., 2005). Especially in the COVID-19 situation, a large amount of digital methods (e.g., self-checking of COVID-19 symptoms and remedy advice, QR codes scanning to ensure COVID-19 negative status, vaccination verification) were used to control the infections (Liu & Stern, 2021; Wang et al., 2020; Wymant et al., 2021), which have required the capability to learn and use these digital technology. However, this has also resulted in the capability from psychological aspect where people might be equipped with low acceptance or distrust of the digital technology (Troisi et al., 2022).

2.2 Opportunity

"Opportunity" was indicated as "*all the factors that lie outside the individual that make the behaviour possible or prompt it*" like societal norms and environmental resources (Anderson et al., 2021; Michie et al., 2011). For healthcare accessing behaviour, the opportunity factors can be diverse. For instance, previously, (Lu et al., 2019) have addressed the medical resources opportunity like ICU bed and COVID-specific equipment usage and transfer efficiency among different levels of healthcare. (Lee et al., 2014; You, 2021) have researched on the environmental measurements of healthcare accessibility such as congestion level, comfort level, service attitude etc. Moreover, the provision of the medical resources by the built environment, which could be the spatial distribution of healthcare and public transportation plan, has been constantly focused on regarding the healthcare accessibility topic (Ghorbanzadeh et al., 2021; Mao & Nekorchuk, 2013; You, 2021). In addition, several infection controlling policies during the COVID-19 pandemic have become important opportunity factors such as mask mandatory, social distance requirement are suggested and guaranteed by the policy to eliminate the infection and potentially influence healthcare accessing behaviour (Bavel et al., 2020; Michie et al., 2011; West et al., 2020).

2.3 Motivation

"Motivation" was indicated as "*all those brain process that energise the direct behaviour, not just goals and conscious decision-making*" like emotional feeling and habitual process (Anderson et al., 2021; Michie et al., 2011). For example, because of the high transmission feature of COVID-19 virus (especially with the Omicron variant), hospitals or general practices (GPs) were proved to have higher infection risk (Lai et al., 2020). In this context, motivation factors for healthcare accessing behaviour can associate with feelings and impulses (Michie et al., 2011) like anxiety or fear caused by COVID-19 infection risk (Bavel et al., 2020), potential quarantine risk by becoming close contact, traffic restriction by the lockdown policy (Serafini et al., 2020). (Giezendanner et al., 2021) has conducted the research to understand whether people's healthcare accessing behaviour have changed depending on the medical level of the healthcare provider after COVID-19 outbreak. Other factors that have been discussed previously like efficacy of general physicians' consultation, anxiety or fear of personal information exposure and low willingness to communicate can also be categorised as motivation factors (Lee et al., 2014; Serafini et al., 2020).

In general, previous studies have indicated that the healthcare accessing behaviour can be affected by a variety of factors. However, a comprehensive framework to overview and analyse the factors has lacked, which led to the difficulty to examine the healthcare behaviour change under public health crisis such as COVID-19 (which directly "attack" human beings). In this case, COM-B model provides a fundamental way to understand how human behaviours can be affected, and to analyse the influential factors that might cause the changes. Therefore, COM-B is employed as a theoretical framework for examining the healthcare accessing behaviour changes in the COVID-19 context in this study.

3 Research methodology

The research methodology consists of three phases. The first phase is to develop a framework of healthcare accessing influential factors based on COM-B model. To start with, a comprehensive literature review was conducted to find out the factors that have been addressed related to healthcare accessing (before and after the outbreak of COVID-19). Then, the factors were categorised based on the definitions and explanations of "capability" (coded with #C1, C2, C3 …), "motivation" (coded with #M11, M12, M13 …), and "opportunity" (coded with #O1, O8, O11 …) described in Section 2. Especially, this study used a behaviour change wheel which is a wider intervention development framework of the COM-B with suggested sub-categories under "capability", "motivation", and "opportunity", as a referencing framework to ensure a more comprehensive inclusion of the healthcare accessing factors (Michie et al., 2011; Perros et al., 2022).

The second phase is to conduct a Likert-scale form questionnaire survey to evaluate the importance of the factors for healthcare accessing based on the developed framework in

Phase 1 in the UK and China cases. There were three parts of the questionnaire for participants to fill in. The first part is demographic information including “gender”, “age group”,, “living location (i.e., the UK or China, specific location of city is not compulsory)”, and “current work/study mode (i.e., commute or work from home)”. The second and third parts asked for the degree of importance of each factor from “rare important” to “most important” in pre-pandemic scenario and post-pandemic scenario. For pre-pandemic, there were 31 factors to assess because multiple COVID-19 related factors were excluded. For post-pandemic, there were 43 factors were assessed. The data collection of the questionnaire survey is shown in Section 3.1. The collected data was analysed using Relative Importance Index (RII) method. Based on the results, different scenarios for the UK and China cases were created to analyse and compare the data in depth, i.e., (1) an overview of RII and RII rank of all factors, (2) top 15 influential factors in post-pandemic era for the UK and China case, (3) factors changing comparison between pre-pandemic and post-pandemic eras for the UK and China case, and (4) factor rank difference between the UK and China cases in the post-pandemic era. By analysis and comparison, the key aspects of concern were concluded based on the implications of factors. The data analysis details are described in Section 3.2

Lastly, based on the results of previous analysis, a novel behaviour-healthcare system-city model based on COM-B model was proposed to rethink and improve the city resilience by responding the healthcare requirements enlargement caused by the changed behaviour in the post-pandemic era. The discussions were conducted regarding the understanding of the changed healthcare accessing behaviour, impacts on the healthcare systems and city-level responses.

3.1 Data collection

The questionnaire was designed to be distributed in the UK and China. post for two weeks in March 2022. For the questionnaire distribution and data collection in China and the UK. These two countries were selected for their distinct healthcare systems, cultural backgrounds, and varied COVID-19 responses to public health crises, offering a comparative lens through which to explore the characteristics and changes of healthcare accessing behaviour. The UK, with its National Health Service (NHS), presents a model of a publicly funded healthcare system, whereas China’s mixed healthcare model reflects rapid evolution and reform (Grosios et al., 2010; Sun et al., 2021). This comparative analysis aims to uncover how systemic and cultural factors influence healthcare behaviour, providing insights with broad applicability beyond the specific contexts of the UK and China.

The questionnaire was post for two weeks in March 2022. For the questionnaire distribution and data collection in both countries, the web-based Wenjuanxing platform and Google Form platform were adopted respectively (Barbieri et al., 2020). There were 76 valid respondents from China case and 44 valid respondents from the UK case. The sample sizes were regarded as large sample tests for analysis because $N > 30$ in each case according to Central Limit Theorem. Therefore, it can be reasonable to conduct the following analysis and discussions based on the collected samples. The demographic distributions of “Gender”, “Age group” and “Current work/study mode” shows in Table 1. Based on Table 1, in both of the cases, it shows that both female (around 60%) and male (around 40%) respondents and more young and middle group (18–30, 31–45 age groups) respondents (added up over 85%) were surveyed. But the analysis of the age group distribution potentially indicates the surveyed samples are more representative for young and middle

Table 1 Demographic distribution of respondents from Chinese and the UK cities

Variants	China case respondents ($N=76$)	the UK case respondents ($N=44$)
Gender		
Female	49 (64.74%)	28 (63.64%)
Male	27 (35.53%)	16 (36.36%)
Age group		
18–30	41 (53.95%)	30 (68.18%)
31–45	25 (32.89%)	13 (29.55%)
46–65	8 (10.53%)	1 (2.27%)
Above 65	2 (2.63%)	0
Current work/study mode		
Commute	39 (51.32%)	22 (50.00%)
Work from home	37 (48.68%)	22 (50.00%)

age group populations. Based on the demographic distributions, it is also acquired that the distributions of each variant in the China and UK cases are very similar. For example, in the China case, the 18–30 age group (53.95%) and 31–45 age group (35.89%) take account for 89.84% of total respondents; in the UK case, the 18–30 age group (68.18%) and 31–45 age group (29.55%) take account for 97.73% of total respondents. The similar distributions of the age group variant (as well as gender and current work/study mode variants) indicates that the data can be analysed and compared between the China case dataset and the UK case dataset without compositional effects. Additionally, the specific living location were asked as an optional question. The top three specific locations of the total respondents were Guangdong Province (14.47%), Shanghai (13.16%), Shanxi Province (10.53%) in the China case; in the UK case, the respondents were mainly from London (15.91%), Loughborough (13.64%), and Cambridge (11.36%).

Table 2 presents the results of Cronbach's alpha for analysing the reliability of the survey before the survey data analysis. Cronbach's alpha for each factor category and factors overall in the post- and pre-pandemic scenarios in both the China and UK cases were calculated. The results were over 0.8, thereby indicating sufficient reliability and consistency of the survey data.

Table 2 The results of Cronbach's alpha

Case	Category	Cronbach's alpha			
		Post-pandemic		Pre-pandemic	
		Category	Overall	Category	Overall
China case	Capability	0.900	0.947	0.888	0.948
	Opportunity	0.867		0.909	
	Motivation	0.889		0.853	
UK case	Capability	0.823	0.913	0.844	0.931
	Opportunity	0.826		0.823	
	Motivation	0.830		0.835	

3.2 Data analysis

The data analysis method of RII is a common statistical analysis method for Likert-scale survey datasets. For example, RII method has been frequently employed in construction management research (Holt, 2014), where Gündüz et al. examined what were the delay factor for construction projects in Turkey (Gündüz et al., 2013). Rooshdi et al. used RII method to study the sustainable design and construction activities criteria for green highway (Rooshdi et al., 2018). This study adopted this analysis method innovatively to specify the ranks of the factors that have been surveyed through the Likert-scale questionnaire. Specifically, RIIs were calculated in for each factors using the Eq. (1) in IBM Statistical Package for the Social Sciences (SPSS) Statistics:

$$RII = \frac{\sum W}{(A * N)} \tag{1}$$

where RII is relative importance index; W is weighting given to each factor by respondents (ranging from 1 to 5, assign 1 to “rare important”, 2 to “low important”, 3 to “moderate important”, 4 to “very important”, and 5 to “most important”); A is highest weight, which is 5 in this study; N is total number of respondents.

With the calculated RII, the ranks of the factors were given for the Chinese case pre- and post-pandemic, the UK case pre- and post-pandemic respectively. Moreover, the rank comparisons between pre- and post-pandemic scenarios were conducted, where the changing rate “CR” was calculated:

Equation (2) is used if $R_{post} \leq T_f$:

$$CR = \frac{(R_{pre} - R_{post})}{T_f} \times 100\% \tag{2}$$

Equation (3) is used if $R_{post} > T_f$ (because the total factors in the post-pandemic scenarios is more than in the pre-pandemic scenario):

$$CR = \frac{((R_{pre} - F_d) - R_{post})}{T_f} \times 100\% \tag{3}$$

where R_{post} is the rank in post-pandemic scenario, R_{pre} is the rank in pre-pandemic scenario, F_d is the factor number difference between the post-pandemic and pre-pandemic (which is 13 for the China case and 12 for the UK case), T_f is the total number of the factors in pre-pandemic (which is 31 for the China case and 30 for the UK case).

Additionally, the rank difference of factors “D” between China and the UK cases in the post-pandemic scenario was calculated using Eq. (4):

$$D = \frac{((R_{post-CN} - R_{post-UK})}{T_{f2}} \times 100\% \tag{4}$$

where $R_{post-CN}$ is the rank in the China case, and $R_{post-UK}$ is the rank in the UK case, T_{f2} is the total number of factors in the post-pandemic scenario.

Table 3 The framework of influential factors for healthcare accessing behaviour in post-pandemic era

Capability Category				
Sub-category	Code	Factors	COVID-19 related	Reference
Physical Capability	C1	Go to the hospital on your own without a family member/friend		(Nägga et al., 2012)
	C2	Severity of the emergency illness (if not admitted to hospital immediately)		(Wong et al., 2020)
	C3	Severity of the chronic disease (e.g., high blood pressure, kidney failure, diabetes)		(Arora & Grey, 2020; Zanobetti et al., 2012)
Psychological Capability	C4	Level of psychological acceptance of going to the hospital by oneself without family or friends		(Barrutia & Echebarria, 2021)
	C5	Level of acceptance telemedicine/digital medical Apps/platforms (e.g., Google-based platforms, Dr. IQ mobile app in the UK)		(Dong & Bouey, 2020; Troisi et al., 2022)
Financial Capability	C6	Affordability of travel to the medical resources		(Riley, 2012)
	C7	Affordability of medical treatment		(Litaker et al., 2005; Riley, 2012)
	C8	Applicability of national medical insurance (only applicable in China)		(Yi, 2021)
Transportation Capability	C9	Accessibility by private vehicles (e.g., own a car or have a driver license)		(Comber et al., 2011; Saelens et al., 2003; You, 2021)
	C10	Accessibility by public transportation (e.g., live near a bus stop)		(Comber et al., 2011; Saelens et al., 2003; You, 2021)
Educational Capability	C11	Capability of using digital medical methods (e.g., telemedicine, Dingxiang Doctor App in China, Dr. IQ in the UK)		(Chivu et al., 2021; Troisi et al., 2022)
	C12	Capability of self-caring at home (e.g., COVID lateral flow test)	Yes	(Hsiao et al., 2021)

Table 3 (continued)

Capability Category				
Sub-category	Code	Factors	COVID-19 related	Reference
Opportunity Category				
Outside Built Environment Opportunity	O1	Availability of public transportation infrastructure (e.g., bus or subway stops)		(Lee et al., 2014)
	O2	Availability of walking/bicycling infrastructure (e.g., walking/bicycling lanes)		(Huang et al., 2020)
	O3	Availability of private vehicles infrastructure (e.g., easy parking, good driving lanes condition)		(Lovett et al., 2002)
	O4	Availability of shared cars services (e.g., taxi, uber)		(Mao & Nekorchuk, 2013; Su et al., 2022)
	O5	Neighbourhood connectivity to medical resources by walking/bicycling		(Mao & Nekorchuk, 2013)
	O6	Neighbourhood connectivity to medical resources by public transportation		(Comber et al., 2011; Mao & Nekorchuk, 2013)
Physical Opportunity	O7	Degree of congestion in the healthcare (e.g., long queue in hospital or GP)		(Lee et al., 2014; You, 2021)
	O8	Degree of comfort in the healthcare (e.g., attitude, atmosphere, decoration, greening etc.)		(Lee et al., 2014; You, 2021)
	O9	Real-time hospital bed capacity information		(Lu et al., 2019)
	O10	Transfer efficiency (among different levels of healthcare)		(Lu et al., 2019)
	O11	COVID-19 influenced real-time road condition information for arrival at target hospitals	Yes	(Liu & Stern, 2021)
	O12	Real-time hospital COVID-specific equipment capacity information	Yes	(IHME COVID-19 Health Service Utilization Forecasting Team and Murray, 2020)
	O13	Compulsory COVID-19 test before hospitalisation	Yes	(Yu et al., 2021)

Table 3 (continued)

Capability Category				
Sub-category	Code	Factors	COVID-19 related	Reference
Policy Regulation Opportunity	O14	Indoor mask-must requirement	Yes	(Bavel et al., 2020) (Qian & Jiang, 2020)
	O15	Full COVID-19 vaccination requirement	Yes	(Bai et al., 2021)
	O16	Social distance requirement	Yes	(Bavel et al., 2020)
	O17	Whether the healthcare take COVID-19 patients	Yes	(Powell et al., 2020)
Motivation Category				
Reflective Motivation	M1	Efficacy of general physicians' consultation		(Lee et al., 2014)
	M2	Availability of required pre-descriptive medicine		(Lee et al., 2014)
	M3	Availability of required non-COVID related life-sustaining equipment (e.g., Dialysis devices)		(Emanuel et al., 2020; Hsu et al., 2021)
	M4	Time spending on transportation		(Lee et al., 2014)
	M5	Waiting time in the healthcare		(You, 2021)
	M6	Medical services provided in grass root healthcare (China)/GPs (the UK)		(Giezendanner et al., 2021)
	M7	Medical services provided in Secondary-Tertiary hospitals (China)/Secondary-Tertiary care (the UK)		(Giezendanner et al., 2021)
	M8	Availability of required COVID related life-sustaining equipment (e.g., Ventilator and Extracorporeal circulation device)	Yes	(Emanuel et al., 2020)

Table 3 (continued)

Capability Category				
Sub-category	Code	Factors	COVID-19 related	Reference
Automatic Motivation	M9	Anxiety (fear) of personal health status being noticed by other people		(Serafini et al., 2020)
	M10	Low willingness to communicate		(Lee et al., 2014)
	M11	Anxiety (fear) of COVID-19 infection	Yes	(Serafini et al., 2020)
	M12	Anxiety (fear) of COVID-19 hospitalisation traffic restriction	Yes	(Serafini et al., 2020)
	M13	Anxiety (fear) of COVID-19 offsite control (cannot return to home)	Yes	(Serafini et al., 2020)
	M14	Anxiety (fear) of level of COVID-19 risk evaluation	Yes	(Serafini et al., 2020)

4 The framework of influential factors for healthcare accessing behaviour

According to the research methodology Phase 1 (Section 3), the framework of influential factors for healthcare accessing behaviour in the post-pandemic era is established based on COM-B model in Table 3. There are 43 factors for the China case (because the factor C8 is only applicable in China) and 42 factors for the UK case. Besides, the factors directly related to COVID-19 are noted (a total of 13 factors for both the UK and China cases). The factors' categories based on the COM-B model and sub-categories referred to the behaviour change wheel are illustrated as follows and labelled in Table 3 (Michie et al., 2011).

- Capability: refers to physical health condition of individuals (Physical Capability), the mental decision-making processes to engage or achieve the activity (Psychological Capability), the financial affordability to achieve the activity (Financial Capability), the transportation accessibility of individuals to fulfil the activity (Transportation Capability), knowledge and intellectual background to achieve the activity (Educational Capability);
- Opportunity: refers to the environmental resources (Outside Built Environment Opportunity), the physical environment of objects and events with which people interact (Physical Opportunity), the policy enactments that would affect human behaviour (Policy Regulation Opportunity);
- Motivation: refers to reflective intentions, evaluations and values (Reflective Motivation), and automatic habits, emotions and instincts that direct human behaviour (Automatic Motivation) (Perros et al., 2022).

For the classification of sub-categories, although the behaviour change wheel was used as the referencing framework to guarantee a full inclusion of the factors, the sub-categories in this study did not fully align with the subcategories in the behaviour change wheel because of the different research context. For example, the sub-category of financial capability of an individual would be an influential factor for one to access healthcare, but it has not been included in the original behaviour change wheel (Michie et al., 2011). Also, the sub-categories of "modelling" or "marketing" have been mentioned in the original wheel (Michie et al., 2011), no related factors for healthcare accessing were noticed in existing studies so they were excluded in the establishment of the framework in this study. Hence, the established framework in Table 3 is an innovative COM-B model-based framework for healthcare accessing behaviour that partially adopts the sub-categories of the original behaviour change wheel.

5 Comparison and analysis of two cases: UK and China

5.1 Calculated results in general

The calculated results of all factors in the proposed framework of healthcare accessibility influential factors have been presented in Table 4. In Table 4, the RIIs and ranks of pre- and post-pandemic scenarios in the UK and China case are demonstrated for the convenience

Table 4 Results of RIIs and rank in general

Category	Sub-category	Co-de	China case				the UK case			
			Post-pan-demic		Pre-pan-demic		Post-pan-demic		Pre-pan-demic	
			RII	R_{post}	RII	R_{pre}	RII	R_{post}	RII	R_{pre}
Capability	Physical Capacity	C1	0.700	20	0.639	19	0.640	26	0.591	25
		C2	0.803	1	0.803	2	0.813	1	0.747	3
		C3	0.768	4	0.792	3	0.733	7	0.698	8
	Psychological Capacity	C4	0.608	38	0.621	23	0.622	32	0.582	27
		C5	0.671	25	0.605	27	0.631	30	0.596	24
	Financial Capacity	C6	0.558	41	0.589	29	0.573	38	0.622	20
		C7	0.689	22	0.703	13	0.693	15	0.698	8
		C8	0.761	7	0.758	5	/	/	/	/
	Transportation Capability	C9	0.663	28	0.637	20	0.551	40	0.564	29
		C10	0.655	31	0.637	20	0.649	25	0.684	12
	Educational Capability	C11	0.674	24	0.616	26	0.640	26	0.587	26
		C12	0.668	26	0.621	23	0.716	10	0.676	16
Opportu-nity	Outside Built Environ-ment Opportunity	O1	0.639	35	0.666	15	0.733	7	0.707	6
		O2	0.524	42	0.574	31	0.529	42	0.547	30
		O3	0.703	19	0.661	16	0.618	34	0.582	27
		O4	0.661	30	0.687	14	0.613	35	0.618	21
		O5	0.589	40	0.605	27	0.560	39	0.609	22
		O6	0.605	39	0.650	18	0.640	26	0.662	18
	Physical Opportunity	O7	0.755	9	0.750	6	0.800	2	0.787	1
		O8	0.663	28	0.705	11	0.711	12	0.707	6
		O9	0.758	8	0.742	7	0.707	13	0.684	12
		O10	0.739	11	0.711	9	0.733	7	0.680	14
		O11	0.647	33	/	/	0.622	32	/	/
		O12	0.750	10	/	/	0.716	10	/	/
		O13	0.721	16	/	/	0.640	26	/	/
	Policy Regulation Opportunity	O14	0.766	6	/	/	0.680	18	/	/
		O15	0.689	22	/	/	0.738	6	/	/
		O16	0.734	14	/	/	0.684	17	/	/
		O17	0.784	2	/	/	0.671	20	/	/

Table 4 (continued)

Category	Sub-category	Co-de	China case				the UK case			
			Post-pan-demic		Pre-pan-demic		Post-pan-demic		Pre-pan-demic	
			RII	R_{post}	RII	R_{pre}	RII	R_{post}	RII	R_{pre}
Motiva-tion	Reflective Motivation	M1	0.784	2	0.808	1	0.742	4	0.778	2
		M2	0.739	11	0.761	4	0.702	14	0.716	5
		M3	0.716	18	0.705	11	0.671	20	0.698	8
		M4	0.666	27	0.658	17	0.671	20	0.680	14
		M5	0.721	16	0.708	10	0.796	3	0.747	3
		M6	0.655	31	0.618	25	0.676	19	0.667	17
		M7	0.768	4	0.742	7	0.742	4	0.693	11
		M8	0.726	15	/	/	0.658	24	/	/
	Automatic Motivation	M9	0.621	37	0.634	22	0.596	37	0.644	19
		M10	0.505	43	0.587	30	0.533	41	0.600	23
		M11	0.647	33	/	/	0.631	30	/	/
		M12	0.634	36	/	/	0.604	36	/	/
		M13	0.700	20	/	/	0.689	16	/	/
		M14	0.739	11	/	/	0.671	20	/	/

of comparison. For the factors that are only applicable in the post-pandemic scenario, the RIIs and ranks are presented with the null symbol "/".

In analysing the geographical distribution of the respondents, we observed a significant disparity. As noted in Section 3.1, the specific living location were asked as an optional question. The top three specific locations of the total respondents are Guangdong Province (14.47%), Shanghai (13.16%), Shanxi Province (10.53%) in the China case; in the UK case, the respondents are mainly from London (15.91%), Loughborough (13.64%), and Cambridge (11.36%). Although we attempted to analyse the impact of geographical distribution on healthcare access behaviours, no significant patterns emerged from the collected dataset. Therefore, subsequent analyses will focus on a more general comparison between the UK and China cases.

5.2 Top 15 influential factors in post-pandemic scenario

To further reveal the important factors affecting citizens' behaviour of healthcare system accessing, the top 15 factors sorted by the rank in the China case post-pandemic scenario (shown in Table 5) and in the UK case post-pandemic scenario (shown in Table 6) separately. In Tables 5 and 6, a column of "rank change" is attached to indicate whether the rank of the factor has been ascended "↑", descended "↓", or remained "-" comparing to the rank in pre-pandemic scenario.

Table 5 Top 15 factors of citizens' behaviour of healthcare accessing, sorted by the rank in post-pandemic China case

Code	China case					the UK case			
	Post-pandemic		Rank changing	Pre-pandemic		Post-pandemic		Pre-pandemic	
	RII	R_{post}		RII	R_{pre}	RII	R_{post}	RII	R_{pre}
C2	0.803	1	↑	0.803	2	0.813	1	0.747	3
O17	0.784	2	↑	/	/	0.671	20	/	/
M1	0.784	2	↓	0.808	1	0.742	4	0.778	2
C3	0.768	4	↓	0.792	3	0.733	7	0.698	8
M7	0.768	4	↑	0.742	7	0.742	4	0.693	11
O14	0.766	6	↑	/	/	0.680	18	/	/
C8	0.761	7	↓	0.758	5	/	/	/	/
O9	0.758	8	↓	0.742	7	0.707	13	0.684	12
O7	0.755	9	↓	0.750	6	0.800	2	0.787	1
O12	0.750	10	↑	/	/	0.716	10	/	/
O10	0.739	11	↓	0.711	9	0.733	7	0.680	14
M2	0.739	11	↓	0.761	4	0.702	14	0.716	5
M14	0.739	11	↑	/	/	0.671	20	/	/
O16	0.734	14	↑	/	/	0.684	17	/	/
M8	0.726	15	↑	/	/	0.658	24	/	/

Table 6 Top 15 factors of citizens' behaviour of healthcare accessing, sorted by the rank in post-pandemic the UK case

Code	China case				the UK case				
	Post-pandemic		Pre-pandemic		Post-pandemic		Rank changing	Pre-pandemic	
	RII	R_{post}	RII	R_{pre}	RII	R_{post}		RII	R_{pre}
C2	0.803	1	0.803	2	0.813	1	↑	0.747	3
O7	0.755	9	0.750	6	0.800	2	↓	0.787	1
M5	0.721	16	0.708	10	0.796	3	-	0.747	3
M1	0.784	2	0.808	1	0.742	4	↓	0.778	2
M7	0.768	4	0.742	7	0.742	4	↑	0.693	11
O15	0.689	22	/	/	0.738	6	↑	/	/
C3	0.768	4	0.792	3	0.733	7	↑	0.698	8
O1	0.639	35	0.666	15	0.733	7	↓	0.707	6
O10	0.739	11	0.711	9	0.733	7	↑	0.680	14
C12	0.668	26	0.621	23	0.716	10	↑	0.676	16
O12	0.750	10	/	/	0.716	10	↑	/	/
O8	0.663	28	0.705	11	0.711	12	↓	0.707	6
O9	0.758	8	0.742	7	0.707	13	↓	0.684	12
M2	0.739	11	0.761	4	0.702	14	↓	0.716	5
C7	0.689	22	0.703	13	0.693	15	↓	0.698	8

In Table 5 for post-pandemic scenario for the China case, it is observed that COVID-19 related factors have become respondents' primary considerations (6/15 factors) when considering healthcare accessibility. Amongst, the factor of whether the healthcare accept patients COVID-19 patients (i.e.O17), is the top concern. Following by that, COVID-19 related policy like indoor mask wearing and social distance keeping requirement (i.e., O14, O16), are very important to the respondents. Then, the factors regarding information updating (i.e., O12), psychological distress (i.e., M14), and medical capability (i.e., M8) are highly concerned by respondents in post-pandemic era. Further, the top 15 factors can be concluded to six aspects of concerns, which are (1) personal health condition (C2-rank 1, C3-rank 4), (2) healthcare capability (O17-rank 2, M1-rank 2, M7-rank 4, O7-rank 9, O10-rank 11, M2-rank 11, M8-rank 15), (3) policy regulation (O17-rank 2, O14-rank 6, O16-rank 14), (4) information updating (O12-rank 10), (5) policy support (financially) (C8-rank 7), (6) psychological distress (M14-rank 11).

In Table 6 for post-pandemic scenario for the UK case, it is observed that the COVID-19 related factors are less (3/15 factors) than the scenario in Chinese cities. Only factors of COVID-19 vaccination requirement, capability of self-caring at home (e.g., use COVID-19 lateral flow test), and COVID-19 equipment capability information. Similarly, we can also conclude the top 15 factors into seven aspects of concerns, which are (1) personal health condition (C2-rank 1, C3-rank 7), (2) healthcare capability (O1-rank 2, M5-rank 3, M1-rank 4, M7 rank 4, O10-rank 7, O8-rank 12, M2-rank 14), (3) policy regulation (O15-rank 6), (4) Transportation (O1-rank 7), (5) training (C12-rank 10), (6) information updating (O12-rank 10, O9-rank 13), and (7) financial support (C7-rank 15).

5.3 Factors changing between pre- and post-pandemic scenarios

To better understand the factors changing, we specify the factors that the ranks fluctuate over 16% (rank changing over or equal to ± 5). The rank change percentage and changing direction (i.e., whether the rank in post-pandemic scenario ascend, descend, or remain same comparing to the rank in pre-pandemic scenario) are presented in Table 7 and Table 8.

For the China case, there are 11 factors filtered and shown in Table 7. All the factors' ranks descend comparing to scenario before the COVID-19 outbreak, which can be

Table 7 The ranks of factors changing degree in the Chinese cities scenario

Code	Chinese cities						the UK cities			
	Post-pandemic		Changing direction	CR	Pre-pandemic		Post-pandemic		Pre-pandemic	
	RII	R_{post}			RII	R_{pre}	RII	R_{post}	RII	R_{pre}
M2	0.739	11	↓	-23%	0.761	4	0.702	14	0.716	5
M5	0.721	16	↓	-19%	0.708	10	0.796	3	0.747	3
M3	0.716	18	↓	-23%	0.705	11	0.671	20	0.698	8
C7	0.689	22	↓	-29%	0.703	13	0.693	15	0.698	8
C9	0.663	28	↓	-26%	0.637	20	0.551	40	0.564	29
O8	0.663	28	↓	-55%	0.705	11	0.711	12	0.707	6
O4	0.661	30	↓	-52%	0.687	14	0.613	35	0.618	21
C10	0.655	31	↓	-35%	0.637	20	0.649	25	0.684	12
M6	0.655	31	↓	-19%	0.618	25	0.676	19	0.667	17
O1	0.639	35	↓	-23%	0.666	15	0.733	7	0.707	6
O6	0.605	39	↓	-26%	0.650	18	0.640	26	0.662	18

Table 8 The ranks of factors changing degree in the UK case

Code	China case				the UK case					
	Post-pandemic		Pre-pandemic		Post-pandemic		Changing direction	CR	Pre-pandemic	
	RII	R_{post}	RII	R_{pre}	RII	R_{post}			RII	R_{pre}
M7	0.768	4	0.742	7	0.742	4	↑	23%	0.693	11
O10	0.739	11	0.711	9	0.733	7	↑	23%	0.680	14
C12	0.668	26	0.621	23	0.716	10	↑	20%	0.676	16
O8	0.663	28	0.705	11	0.711	12	↓	-20%	0.707	6
M2	0.739	11	0.761	4	0.702	14	↓	-30%	0.716	5
C7	0.689	22	0.703	13	0.693	15	↓	-23%	0.698	8
M3	0.716	18	0.705	11	0.671	20	↓	-40%	0.698	8
M4	0.666	27	0.658	17	0.671	20	↓	-20%	0.680	14
C10	0.655	31	0.637	20	0.649	25	↓	-43%	0.684	12
O6	0.605	39	0.650	18	0.640	26	↓	-27%	0.662	18
C4	0.608	38	0.621	23	0.622	32	↓	23%	0.582	27
C5	0.671	25	0.605	27	0.631	30	↓	-20%	0.596	24
O3	0.703	19	0.661	16	0.618	34	↑	17%	0.582	27
M9	0.621	37	0.634	22	0.596	37	↓	-20%	0.644	19
C6	0.558	41	0.589	29	0.573	38	↓	-20%	0.622	20
O5	0.589	40	0.605	27	0.560	39	↓	-17%	0.609	22
M10	0.505	43	0.587	30	0.533	41	↓	-20%	0.600	23

understood as "factors that are less important than before" from the respondents' perspective. The factors changed the most (changing over -30% to -50%) relates to transportation (i.e., C10, O4), which indicate less importance of public and shared transportation, and to degree of healthcare environmental and service comfort (i.e., O8). In general, the changed factors relate to aspects of concerns for (1) healthcare non-COVID-19 capability (i.e., M2, M3, M6), (2) healthcare environment and service comfort (i.e., M5, O8), (3) financial support (i.e., C7), (4) medical level of the healthcare provider (i.e., M6), (5) transportation (i.e., C9, O4, C10, O1, O6).

For the UK case, there are 17 factors filtered and shown in Table 8. There are 4 factors' ranks ascend (or "factors that are more important than before") and 13 factors' ranks descend (or "factors that are less important than before") comparing to scenario before the COVID-19 outbreak. The most changing factors (changing over -30% to -40%) relate to public transportation (i.e., M3, C10) and availability of required pre-descriptive medicine. The ascending factors are higher medical level of healthcare provider, transfer efficiency among different medical level providers, capability of self-caring at home, and availability of private transportation infrastructure. In general, the changed factors relate to aspects of concerns are (1) medical level of healthcare provider (i.e., M7, O10), (2) training (i.e., C12), (3) healthcare environment and service comfort (i.e., O8), (4) healthcare non-COVID-19 capability (i.e., M2, M3), (5) financial support (i.e., C7, C6), (6) transportation (i.e., M4, C10, O6, O3, O5), (7) companion and communication (i.e., C4, M10), (8) digital application (i.e., C5), (9) health data security (i.e., M9).

Table 9 Rank difference between the Chinese cities and the UK cities scenarios

Code	China case		the UK case		Rank differences (D)
	RII	R_{post}	RII	R_{pre}	
C1	0.700	20	0.640	26	-17%
C9	0.663	28	0.551	40	-31%
C12	0.668	26	0.716	10	36%
O1	0.639	35	0.733	7	64%
O3	0.703	19	0.618	34	-38%
O6	0.605	39	0.640	26	29%
O8	0.663	28	0.711	12	36%
O13	0.721	16	0.640	26	-26%
O14	0.766	6	0.680	18	-29%
O15	0.689	22	0.738	6	36%
O17	0.784	2	0.671	20	-43%
M5	0.721	16	0.796	3	29%
M8	0.726	15	0.658	24	-24%
M14	0.739	11	0.671	20	-24%

5.4 The ranks difference of factors between the Chinese and the UK cases

It is noted that some of the factors' ranks are very different between the two case. Table 9 displays the sorted 14 factors, ranks and the rank differences, where the factors are filtered if the rank difference is over 16% (rank difference over or equal to ± 5). If the rank difference value is positive, it indicates the factors rank higher in the UK cities scenario; If it is negative, it indicates the factors rank higher in the Chinese cities scenario.

The analysis reveals that COVID-19 related factors are valued differently (7 out of 14 factors) across countries, influenced by cultural differences. For instance, concerning factors such as whether healthcare facilities treat COVID-19 patients (O17), indoor mask mandates (O14), and the availability of public transportation infrastructure (O1), the rankings in the Chinese dataset (R_{post}) are 2, 6, and 19, respectively. In contrast, in the UK case, these rankings (R_{post}) are 20, 18, and 34, respectively. Additionally, regarding waiting times in healthcare facilities (M5), requirements for full COVID-19 vaccination (O15), the ability for self-care at home (C12), and the degree of comfort with medical services (O8), the Chinese case shows rankings (R_{post}) of 16, 22, 26, and 28, respectively. In contrast, the rankings (R_{post}) in the UK case are 3, 6, 10, and 12, respectively.

In general, the changed factors relate to aspects of concerns are related to (1) companion (i.e., C1), (2) training (i.e., C12), (3) transportation (i.e., O1, O3, O6), (4) healthcare environment and service comfort (i.e., O8, M5), (5) policy regulation (i.e., O13, O14, O15, O17), (6) healthcare capability (i.e., M8), and (7) psychological distress (i.e., M14). To conclude, the rank and the changes of the rank before and after COVID-19 indicate that that influence the healthcare accessing behaviour are affected by the cultural background in different countries.

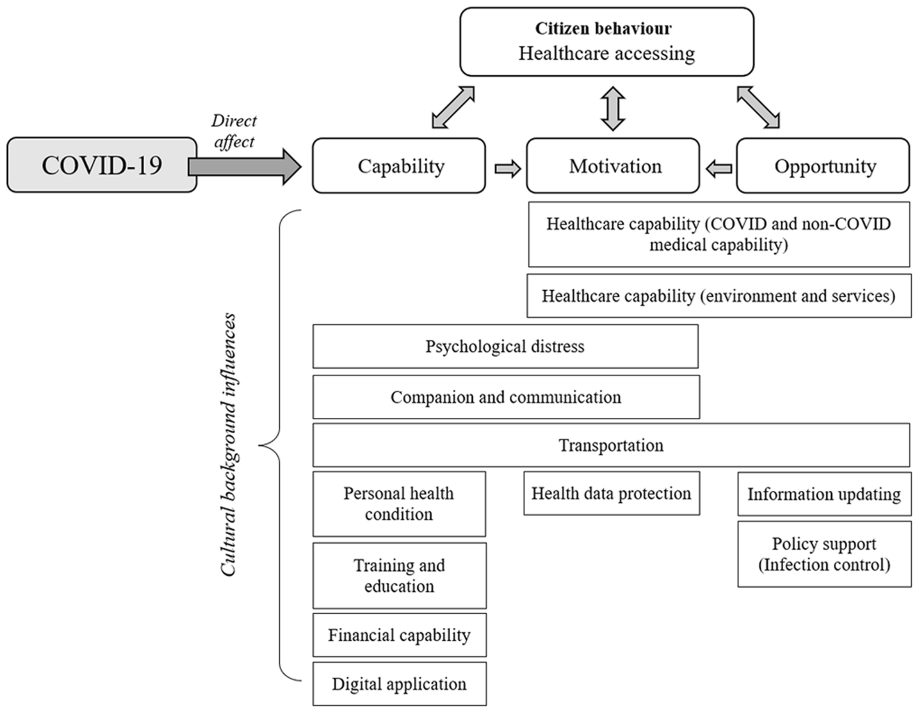

Fig. 3 Summarised critical aspects of concerns for healthcare accessing, mapped in the COM-B model

6 Discussion of the behaviour-healthcare system-city

6.1 Citizen behaviours—changing

This study addressed the citizen behaviour change towards healthcare accessing after the COVID-19 outbreak by comparing the RII of the factors, which indicates that the changes are shaping. Moreover, based on the analysis and comparisons in the UK and China cases in Section 5, the total of 12 aspects of concerns for healthcare accessing in the post-pandemic era can be revealed and summarised in Fig. 3. According to the factors that each aspect contains, they are mapped in the COM-B model to illustrate the critical contributions in terms of capability, motivation, and opportunity.

In Fig. 3, COVID-19 regarded as a global public health crisis, has directly affected human beings, which has potentially stimulated interventions (i.e., factors) that have been studied in this research. According to the feature of the original COM-B model, capability, motivation, and opportunity can all influence behaviour and vice versa (Michie et al., 2011). This indicates that the healthcare accessing behaviour can probably be managed to achieve the desired usage state of the healthcare system by considering the 12 aspects. Especially, given capability and opportunity can have the single-headed arrow for motivation (Michie et al., 2011), which implies the enabling of capability and opportunity aspects can potentially accelerate the healthcare behaviour change influenced by motivation. For example, the effective and real-time information updating of the medical resources in the healthcare in opportunity category can possibly affect citizens' emotional feelings (which is a partial explanation of motivation) and better influence the healthcare accessing behaviour (Anderson et al., 2021; Holmes et al., 2020). Additionally, the detailed factors in the 12 aspects affecting the healthcare accessing behaviour might vary depending on different cultural background (Section 5.4). Ideally, the cultural background influences might indicate diverse perspectives such as healthcare system differences, values, beliefs, knowledge etc. (Napier et al., 2014), which require sophisticated studies in the future.

It should be noted that motivation as a key component among all the others, most aspects under it can be enabled to some extent at the healthcare system level. For example, the medical resources regarding equipment and physicians can be re-allocated within the management of the healthcare (Emanuel et al., 2020). However, several aspects especially in capability and opportunity categories (e.g., transportation, training and education, financial capability, digital application, information updating, policy support) cannot be fully achieved solely relying on efforts at the healthcare system level. For instance, the policy support aspect for COVID-19 has been enacted at the city level and even national level so that the infection can be controlled effectively (Bavel et al., 2020). Therefore, it is revealed that, in order to gradually guide the healthcare accessing behaviour while not causing dramatic increase of healthcare usage in public health crisis, reactions should be made not only from the system-level but also from the city-level perspective.

6.2 Healthcare systems—requirements

To further unearth how the healthcare system has been influenced based on the 12 critical aspects of concerns, we figure out that the factors related to the healthcare accessing behaviour change have shown that the citizens' requirements for the healthcare system are altering in the post-pandemic era. Specifically, the requirements can be discussed in the following 7 aspects.

Increase healthcare capability The study results implied that citizens have been paying a lot more attention to the importance of healthcare capability, which transforms to a higher requirement for the healthcare system. First, the medical resources such as physicians, equipment, hospitalisation spaces for both COVID-19 and non-COVID-19 are highly required (i.e., the resources sufficiency is guaranteed) under the public health crisis. One evidence could be the increasing importance rank of the secondary-tertiary level of the healthcare provider (M7) and decreasing importance rank of low threshold level of healthcare providers like community hospitals and GPs (M6) in both the Chinese and the UK case. Then, the healthcare capability of the environment and services provided is still important to citizens despite of the slight rank drop in the pandemic, such as the degree of congestion (O7). In general, a more efficient and medical resources sufficient healthcare system would be urgently anticipated by citizens after the outbreak of the public health crisis.

Enact policy support The public's emphasis on the COVID-19 related policy regulation (O14-O17) in the healthcare system indicates the immediate system level or city level policy support made by policy makers is required for the citizens. From a short-term perspective, the policies are needed to control the infection while ensuring the regular operation of the healthcare system. From a long-term perspective, more comprehensive policy supports including but not limited to health protection, financial aid and insurance coverage, special care needed group support are required to confront the public health crisis.

Enable transportation adaptation While the public transportation is still the important factor for healthcare accessing (O1), the decreasing importance of the public transportation and shared cars connectivity to the healthcare reflects the worry of getting infected. To ensure the stability of safe accessibility to the healthcare, proper adaptation strategies on the transportation system are required and should be enabled in time for the public's health and welfare. In addition, abrupt traffic control and shutdown of the public transportation might cause inconvenient for healthcare accessing, where the proactive transportation plans can be highly required.

Share real-time information The information updating of the medical resources in the healthcare system has been valued very important in this study, which required the healthcare system or even the city-level organisations to take efforts together. This can allow the public to make moves in advance and increase the public's confidence confronting the crisis. It is extremely important as experts have indicated in the journal of *The Lancet Psychiatry* that "*Increasing people's confidence and clarity in what they need to do fosters adherence to health behaviours, and can help people to manage psychological distress*" (Holmes et al., 2020).

Require education and training The study results have indicated that the capability of self-caring at home (C10) has been considered as an important factor, especially in the UK cities scenario. This required proper educational information distribution and training provision from the healthcare system such as how to conduct COVID-19 lateral flow test at home and COVID-19 home treatment plans. needed. Because as the survey results have shown that the current acceptance of digital platform (C5) was still high enough for the public to rely on. The instructions notice about how to use the digital platforms for medical advice (C11) and their credibility are also important. Additionally, given the high infection risks of COVID-19 (Murray, 2022), people might consider home treatment plans for other common illnesses (e.g., influenza) and chronic illnesses (e.g., kidney failure (Hsu et al., 2021)), which require more professional instructions and trainings from the healthcare system.

Provide companion and communication assist Although the factor of low willingness to communicate (M10) had an obvious drop in the post-pandemic scenario, it is meaningful to address it in the long-term run to improve the healthcare services, especially under the extreme circumstances for people with special needs (e.g., disability, pregnancy, elderly). Besides, the companion for patients (C1, C4) is still preferred if the infection can be prevented. Hence, more diverse methods supporting companion and communication would be expected.

Concern health data protection in the long-term run Based on the questionnaire result, it indicated that people would partially give up the personal health information (M9) facing the public health crisis. However, the data protection is always a vital and ethical issue in the healthcare system to be addressed. In the early and middle stages of the pandemic, COVID-19 patients health status and related personal information (e.g., mobility, behaviour) were used to track close contacts for infection control (Mbunge, 2020). And as the

QR codes scan for COVID-19 negative or vaccine confirmation was required, it is concerned about the data ownership and sharing among organisations, data usages etc. Therefore, more strict health data protection would be expected by citizens.

In general, the behaviour changes can possibly imply an expanded requirements in diverse categories for the healthcare system. Particularly, the categories are interrelated instead of independent, which aligns with the original behaviour change wheel framework developed based on COM-B model (Michie et al., 2011). For instance, one of the results in this study indicated the increasing importance of secondary-tertiary hospitals and the decreasing importance of community hospitals/GPs. However, Giezendanner et al. concluded that individuals seemed to change their provider choice towards more easily accessible and low-threshold medical services facing COVID-19 pandemic in Switzerland (Giezendanner et al., 2021). In this case, the real-time information sharing of medical resources, scientific facts or governmental initiatives might be contributed to remedy the psychological distress (Holmes et al., 2020; Ting et al., 2020), so that the health capability requirement expansion can be limited. Nevertheless, the enlarged comprehensive requirements for the healthcare system cannot be realised efficiently and effectively based only on system-level actions (e.g., individual hospitals' improvements of medical capability), higher-level responses and reactions are needed beyond the system-level actions.

6.3 Cities – resilience

Rethinking the influential factors of the behaviour changes and requirements impact on the healthcare system, the city level responses and reactions are in urgent need to improve the resilience of a city confronting the public health crisis like COVI-19, or other emergent incidents. To further explain the reciprocal relationships among the citizen behaviour, healthcare system and the city operation, and illustrate how the city resilience can be

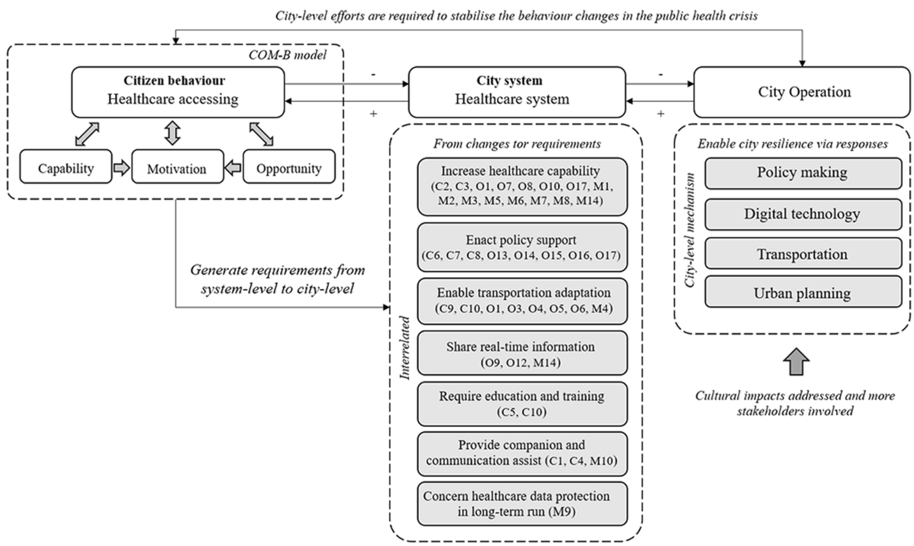

Fig. 4 A novel behaviour-healthcare system-city model based on COM-B model

Table 10 Potential city-level responses for healthcare system requirements (Emanuel et al., 2020; Ting et al., 2020)

City-level responses	Contents	Corresponding healthcare system requirements
Policy making	• Healthcare resources allocation and collaboration within systems (especially among different level of healthcare providers) and among regions • Non-medical infection control strategies for the city Financial support strategies for COVID-19 related incidents • City/nation level information sharing strategies • Long-term open data and data protection policy	• Increase healthcare capability • Share real-time information • Enact policy support • Concern healthcare data protection in long-term run
Digital technology	• Real-time information updating via media press and social network APPs distributing accurate information about COVID-19 and government initiatives • IoT and AI technologies can be used to track and recognise people that has elevated temperature (e.g., thermal imaging–enabled facial recognition), and predict the vicinity at risk and potential infection sizes in the future (e.g., statistical models and algorithms) • Using city/national datasets that were built up during COVID-19 for city emergencies in the future • Adopting blockchain for insurance claims from COVID-19 related illness and death	• Require education and training • Share real-time information • Policy support (financial)
Transportation	• Infection control strategies (e.g., disinfection of public transportation infrastructure, mobility restriction) • Traffic control strategies for emergent/special needs patients • City-level transport and lockdown plans for public health crisis	• Enable transportation adaptation
Urban planning	• Long-term considerations for more advanced and resilient healthcare spatial design plans • Alternative connectivity design for healthcare system (e.g., quick switching plans between normal and public health crisis periods for public and private transportation) • More convenient infrastructure for special care needed groups	• Increase healthcare capability • Enable transportation adaptation

enabled, a novel behaviour-healthcare system-city model based on COM-B model has been proposed (Fig. 4).

As shown in Fig. 4, first, to understand the healthcare accessing behaviour changes facing the global pandemic of COVID-19, the COM-B model originated from behavioural science field are adopted as the foundation. Key aspects of concerns behind the behaviour changes have been identified based on analysis and comparison, where it is realised that city-level efforts are required to stabilise the behaviour changes in the public health crisis. Then, to further discuss and reveal the essence of the changed aspects, we propose that the factors changing of the healthcare accessing behaviour potentially imply citizens' requirements changing for the healthcare system as discussed in Sect. 5.2. Supporting factors of each requirement category are summarised in Fig. 4. Third, the requirements for the healthcare system can only be better fulfilled from a city level perspective (i.e., the cities responses to city system's requirements changing). Examples are given in Table 10.

Additionally, at the city level, people with diverse background and difference opinions or feedback could be involved. Hence, the decision-making on the healthcare system can be more deliberated forming policies and strategies for city emergencies. Also, for all the city level responses mentioned above, multiple stakeholders (e.g., governors, engineers, researchers, architects, urban planners) and organisations (e.g., diverse governmental departments, research institute, technology companies, design firms and construction enterprises) in cities other than healthcare related personnel could be involved to assist decision making for the healthcare system. And each category of response is interrelated and interdependent to some extent. Therefore, a city level emergency response mechanism involving multi-stakeholders can be established to answer the sharply increase requirements of the city system. In this sense, we argue that emergencies usually negatively ("-" in Fig. 4) influence citizen behaviours and city systems. On the opposite, if the changed behaviours and requirements can be well responded at the city level, the city systems and citizens would be positively ("+" in Fig. 4) in terms of the healthcare system operation stability and human being health and wellness in this study. Hence, the city resilience can be greatly improved.

7 Conclusion

This research addressed the citizen healthcare accessing behaviours changes based on a well-established COM-B model from behavioural science field in the post-pandemic era, and revealed their impacts on the healthcare system and the city operation. Consequently, the comprehensive framework of influential factors for healthcare accessing behaviour has been established (Table 1), which can be used to examine behaviour changes in the public health crisis like COVID-19 and potentially in other behaviour-related healthcare research in the future. Based on the framework, a questionnaire survey was conducted to assess the importance of the influential factors to the respondents in the China and the UK cases. A total number of 120 surveyed questionnaires (76 from the China case and 44 from the UK case) were collected and analysed with RII method. Analysis and comparisons were conducted in different scenarios, where the key aspects of concerns regarding healthcare accessing behaviour changes were revealed. Based on the findings, we discussed the implications of the healthcare accessing behaviour changes, and the influences on the healthcare system and the city. Specifically, we proposed city-level efforts should be encouraged tremendously. Further, the important influential factors causing the citizens' behaviour change have become the expanded requirements for the healthcare system, which required immediate responses at the city level confronting city emergencies like COVID-19. Finally, a novel behaviour-healthcare system-city model based on COM-B model has been proposed and discussed. The study's limitation lies in the inability to determine the specific impacts of geographical locations, as the number of respondents from each location was very limited in the datasets of both countries. Ultimately, this model can be employed to "predict the unpredictability" (Batty, 2022) by city level stakeholders in the post-pandemic era to rethink how the city resilience can be better realised combing citizen behaviour changes and city systems.

Author contribution Jiayi Yan: Writing – Original Draft, Investigation, Visualization; Zigeng Fang: Writing – Original Draft, Investigation, Visualization; Qiuchen Lu: Conceptualization, Methodology, Writing – Review & Editing, Supervision, Project administration, Funding acquisition; Junqing Tang: Conceptualization, Methodology, Writing – Review & Editing, Supervision, Project administration, Funding acquisition; Long Chen: Conceptualization, Methodology, Writing – Review & Editing, Supervision; Xuhui Lin: Writing – Original Draft, Investigation, Visualization;

Funding This project was funded the UCL-Peking University Strategic Partner Funds 2021/22.

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