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Understanding patients heterogeneity in healthcare travel and hospital choice - A latent class analysis with covariates

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ABSTRACT

Access to health care is key to well-being, and it is increasingly clear that aggregated accessibility analysis is hard to reflect people's actual healthcare behaviour. This paper employs a patient-based healthcare travel survey to obtain a nuanced picture of how healthcare travel varies across patients. The existing literature shows transportation is an essential factor in accessing health care; however, most studies focus on separate healthcare travel mode choices or hospital choices for certain segments of patients, making it difficult to derive clear profiles of patients. Also, the attitudinal factors in healthcare travel have long been neglected. This research explores the joint hospital choice and travel behaviour of patients. We conducted an online survey with patients in Shanghai to identify the heterogeneity in healthcare travel behaviour and hospital choice. A latent class model with covariates is adopted to identify different patient types that exhibited distinct hospital choices and healthcare travel behaviour. Attitudinal factors are included in our model to form clear-separated clusters. Four categories of patients are identified: public transit patients, car-oriented patients, near-hospital patients, and non-downtown hospital patients, which differ in sociodemographic characteristics, healthcare-seeking behaviour, and public transit accessibility. Our research shows that a substantial share of non-downtown hospital patients should not be underestimated in healthcare travel demand analysis. The behaviour of public transit and non-downtown patients requires improvement of quality and public transit accessibility in non-downtown tertiary hospitals. Our study contributes to a better understanding of the market segments of patients and tailored healthcare and transport policies to meet patient healthcare travel demand.

1. Introduction

Outpatient visits have experienced substantial growth since 1990 due to the expansion of universal health coverage and an ageing population (Moses et al., 2019). In China, outpatient visits have increased by 35% over the past decade, from 62.7 billion in 2011 to 84.7 billion in 2021 (National Health Commission of the P. R China, 2022). The urban growth and suburbanization are also characterized by an imbalance in the geographical distribution of health care resources. In response to the increasing demand for health care, new hospitals were built in non-central districts to relieve pressure on central hospitals. The growing demand for healthcare travel and the supply of facilities require a new understanding of where patients go and the determinants of their choices.

Transportation is an essential and necessary step in accessing health care. Studies have shown that poor transportation access to health care can lead to reduced health care utilization, missed medical appointments, and exacerbation of diseases. Furthermore, these effects may contribute to negative health outcomes and increase the burden on national health systems (Syed et al., 2013; Wallace et al., 2005; Wolfe et al., 2020). The Covid-19 pandemic has spurred the adoption of telemedicine and virtual care to treat remote patients, dramatically reducing the need for medical travel during this period. However, US evidence shows that in-person outpatient visits recovered to 74% of pre-pandemic levels within nine weeks (Patel et al., 2021). This evidence highlights the fact that travel for health care is necessary for individuals and difficult to replace remotely.

Traditional healthcare planning mainly relies on aggregated population characteristics in a given spatial unit to measure patient accessibility (Frew et al., 2017; Jin et al., 2022; Neutens, 2015). The heterogeneity of patients in healthcare travel decision-making has not been fully explored. This is partly due to the lack of healthcare travel

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information in large-scale urban travel surveys or custom surveys of healthcare providers (Demitiry et al., 2022). While previous literature has identified certain factors that influence hospital choice and medical travel patterns, most research focuses on only one segment of the whole population or one type of healthcare provider (Cao et al., 2022; M. Du et al., 2020; Li et al., 2020a; Mattson, 2011; Tai et al., 2004). Our paper attempts to consider as wide a range of travel attributes and hospital choices as possible. Indeed, the joint consideration of hospital choice and travel mobility is necessary because these choices are closely intertwined. People access the health care service either by finding a source of transportation or by finding an alternative arrangement, for instance, other hospitals with convenient transportation accessibility.

Healthcare in China is typically organized around public hospitals (Lu et al., 2019; The Lancet, 2019). Patients are free to choose different levels of hospitals depending on their intentions. Thereby they tend to go directly to a high-level hospital. The government issued a tiered health care system in 2015, with each level of healthcare facility (tertiary, secondary, and primary) providing care according to its designated functions (Li et al., 2020b). Besides, a referral reform was implemented to promote the attractiveness of primary care with a higher medical insurance reimbursement rate. According to the China Health Development Statistics Bulletin, 57.5% of patients seek high-level health care in tertiary hospitals, compared with 32.2% in secondary hospitals and 5.7% in primary hospitals (National Health Commission of the P. R China, 2022). Patients bypassing primary care are even more prevalent among the urban population (Li et al., 2020b; Luo et al., 2022). Therefore, the accessibility of health care services that account for the shortest distance or travel time may not reflect the actual choice of patients.

In view of the above discussion, this paper aims to link patient hospital choice and healthcare travel attributes using latent class analysis with covariates based on a dataset collected among patients in Shanghai. Latent class analysis is one of the most widely used approaches to deal with individual heterogeneity in decision-making toward various options (Ardeshiri and Vij, 2019; Everitt et al., 2011; Shabanpour et al., 2017). In order to improve our understanding of healthcare travel decision-making, we use multivariate statistics to explain the variation of personal and household sociodemographic, individual healthcare seeking and transportation accessibility attributes on typical healthcare travel patterns.

This paper is organized as follows. Section 2 presents an overview of research on hospital choice and health travel behaviour, followed by the data sources, descriptive analysis and methodology for modelling patient heterogeneity in Section 3. Section 4 presents the results of the latent cluster analysis with covariates, summary statistics of the model variables for each cluster, and the spatial distribution of each identified group. Section 5 summarises the paper and provides policy discussions. Finally, Section 6 concludes the paper and suggests a future research agenda.

2. Literature review

The interaction between treatment needs and supply raises questions of accessibility and utilization (Gatrell and Senior, 1999). In health care planning, scholars have proposed various approaches to assess the spatial accessibility of healthcare facilities. Among them, the floating catchments approach, which focuses on the spatial component of accessibility, has been widely adopted by scholars (Wang, 2012). The improvement in the floating catchments approach attempts to incorporate more realistic healthcare utilization behaviour factors, such as healthcare capacity, healthcare hierarchy, and level-of-service for different modes of transportation (Kanuganti et al., 2016; Ma et al., 2019; Wang, 2012). Despite these improvements, spatial factors such as the socioeconomic, demographic and mobility profiles of potential patients are rarely or only partially included in such aggregate assessments (Demitiry et al., 2022). Indeed, understanding the actual interplay between the demand and supply of health care requires a more nuanced picture of where patients go and how healthcare travel varies across patients. While there is a lack of studies that consider hospital choice and health travel characteristics together, awareness of active hospital choice, determinants of hospital choice and heterogeneity in health travel across different groups has increased over the past decade.

2.1. Patient choice of hospitals

Prior to the implementation of patient-driven healthcare reform, general practitioners (GPs) in many countries, such as the UK, Sweden and the Netherlands, are largely or solely responsible for choosing hospitals on behalf of patients (Hjelmgren and Anell, 2007; Lako and Rosenau, 2009; Sivey, 2012). In recent decades, there has been a steady trend toward greater patient involvement in healthcare decision-making. Previous research on hospital choice has provided insights into where patients go and how patient and provider characteristics may influence their choices.

For active hospital choice where its possible, socioeconomic status has been found to be important for hospital choice. Socioeconomic characteristics include age, gender, race, education level, income, employment status and place of residence. Based on US patient registry data, a multivariate conditional logit model was constructed by Tai et al. (2004) to estimate hospital choice for medicare beneficiaries aged 65 and older. The hospital choice set included the nearest rural hospital, other rural hospitals, urban non-teaching hospitals, and urban teaching hospitals. They found that unmarried men were more likely to choose an urban hospital than the nearest rural hospital. In contrast, rural beneficiaries aged 85 years or older were more likely to choose the nearest rural hospitals. Older rural patients preferred larger hospitals with more beds and hospitals offering more complex services. More highly educated patients were positively associated with selecting an urban teaching hospital. Tayyari Dehbarez et al. (2018) found that women with higher levels of education, higher incomes or who were active in the labour market were more likely to bypass the nearest hospital for up-specialization using a Danish women's hospital choice dataset between 2005 and 2014.

In addition, the severity and types of illnesses have also been found to influence patient hospital choices. For example, in the US case, Adams et al. (1991) concluded that the complexity of illness significantly increased the odds of choosing an urban hospital over a rural hospital, but it did not increase the odds of choosing a larger rural hospital over a smaller rural hospital. Another recent research by Liu et al. (2020) in the context of China adopted mixed logit models for surveyed people who perceived minor or severe conditions when choosing health care for their first visit. The model results reveal that people who perceived minor conditions valued quick consultation service most, followed by advanced equipment and doctors' medical skills; however, people who perceived severe conditions preferred large hospitals for advanced equipment and then less travel time. On the provider side, research has shown that patients are highly sensitive to hospital quality, size and affiliated facilities when choosing a hospital. Using individual-level survey data and a mixed logit choice model, Varkevisser et al. (2012) found that Dutch angioplasty patients were more likely to choose hospitals with a good reputation and low readmission rates. As a proxy for hospital size and service level, the number of beds and parking spaces had a positive association with hospital choice (Smith et al., 2018).

As for accessibility, proximity to health care providers, as measured by travel time or distance, significantly influences hospital choice (Smith et al., 2018; Tai et al., 2004; Tayyari Dehbarez et al., 2018; Victoor et al., 2012). For example, researchers have found that hospitals farther away from patients' homes are less attractive. A one-mile increase in the distance also reduced the likelihood of choosing a hospital by 1.4%. In comparison, an 8.7-mile standard deviation increase in travel distance reduced the likelihood of choosing a hospital by 12.2% (Baker et al., 2016). Tai et al. (2004) found a similar effect of distance decay (Tai et al., 2004). However, when it comes to surgery, patients may choose to bypass the nearest hospital for better care. For example, patients undergoing hepatectomy in California chose to travel the extra time to a distant high-volume hospital (Diaz et al., 2021). In other cases, travelling long distances to access health care may be an active choice for more affluent populations, while it may be a passive choice for rural residents to cope with a lack of accessibility (Jia et al., 2019).

In spite of the fact that the problem of transportation barriers to healthcare services has been identified, the actual travel behaviour of patients to health care is still neglected (Clarke, 2016; Mattson, 2011; Oluyede et al., 2022). For different travel modes, research on transportation barriers has found that patients without a car are more likely to have difficulty accessing health care (Syed et al., 2013). In contrast, living in areas with better access to public transport was positively associated with consulting a health professional at a hospital (Cui et al., 2020). In many urbanized areas, public transport is an important means of accessing health services, particularly for populations without access to a car (Palm et al., 2021; Sharma and Patil, 2021). However, the influence of public transport accessibility on hospital choice has received little attention. Furthermore, the joint consideration of hospital choice and healthcare travel behaviour is lacking.

2.2. Healthcare travel behaviour heterogeneity and influencing factors

Recognition of the heterogeneity of health travel behaviour is relatively new. Some research has paid special attention to the elderly group or compared elderly and non-elderly groups. Using GPS data and survey data from elderly patients in Kunming, Li et al. (2018) reported that elderly people are highly dependent on cars, including car passengers. After modelling the mode choice of patients, they concluded that elderly patients who were female had less travel time for medical care, were not accompanied by family, had shorter distances from bus stations and were more likely to choose public transport. Another study by Du et al. (2021) collected information on the travel behaviour of patients in nine first-class hospitals in Beijing. They found that a high proportion of the elderly (62.1%) used public transport for health care, despite having access to a car. They also conducted multinomial logit models to estimate the mode choice of elderly and non-elderly groups. They found that people with lower household income, more frequent health care visits, shorter trip lengths, direct access to public transport, and those without companions or access to a car were more likely to choose public transport over a car.

More recently, Cao et al. (2022) conducted a health-seeking travel survey to identify the most likely travel mode and longest acceptable time to travel to primary care in Inner Mongolia. Their results show that walking was the most frequently chosen travel mode for primary health care, while the bus was rarely selected as a preferred travel mode. They also developed Bayesian statistical models to analyze the factors associated with travel mode choice. Their model results showed that males and people aged between the ages of 40 and 59 were less likely to use the bus for primary health care (Cao et al., 2022). However, individual attitudes, which are as important as traditional variables in influencing travel behaviour, were neglected in the above studies.

Previous studies have shown that healthcare travel behaviour is heterogeneous among different groups and that factors affect patient travel behaviour differently, but many studies do not control for hospital-level or provider-related factors. An exception is a study by Jin et al. (2022), which focused on the equity of access to multilevel health services. Using travel time estimation data generated from online maps, they found that tertiary-level hospitals had the most unbalanced distribution of accessibility compared to secondary and primary-level health care. Also, people living in central areas were well served by all levels of health care, while people living in peripheral areas suffered from both low access to higher-level health care and inefficient transportation systems (Jin et al., 2022). However, the online map data source could not capture the actual hospital and travel mode choices of patients.

Another study by Lippi Bruni et al. (2021) examined the joint influence of clinical quality, distance to the hospital and waiting time. They estimated mixed logit models using patient data on elective percutaneous transluminal coronary angioplasty in Italy. Their results show that younger and more severely ill patients are more likely to trade off clinical quality with travel distance and waiting times (Lippi Bruni et al., 2021). This highlights the need to consider hospital quality and travel mobility jointly.

Our research differs from the above studies in several ways. First, we use disaggregated patient survey data containing individual-level travel information, spatial distribution information and attitudinal factors for patients who received healthcare in the past twelve months. Second, given that hospital choice and travel mobility are known to be interrelated, we aim to assess patient heterogeneity by integrating indicators of hospital level, hospital location, healthcare travel behaviour, and attitudinal factors toward healthcare travel. Another unique feature of our study is the use of Latent Class Analysis (LCA) with covariates, which is a promising method in travel behaviour research to identify clusters with a combination of travel behaviour and attitudinal factors to explain the clustering by covariates.

3. Data and method

In this section, we describe the data set on which this study is based, the processing procedure, and our method of analysis.

3.1. Survey data

A survey was conducted to collect information on patient healthcare travel data. The main objective of the survey was to collect the reported hospital choice and healthcare travel behaviour of patients in the study area. Therefore, only subjects who reported using any of the three levels of healthcare services (tertiary, secondary, primary) in the 12 months prior to answering the survey were included.

The survey was an online travel survey that collected socioeconomic, hospital choice, pre-booking information, health travel characteristics, and patient attitudinal factors. Data was collected through an online platform Wen Juan Xing, a web-based survey company, between May 3 and July 2, 2021. When selecting the data collection period, we considered that no rigid restrictions on participating healthcare should be implemented, and outpatient visits should recover and become relatively stable. Since May 2020, one year before our survey was conducted, the number of outpatient visits in Shanghai had recovered to 70% of the pre-pandemic level (Bai, 2020). By 2021, outpatient visits to hospitals and community health centers in Shanghai had almost fully recovered to pre-pandemic levels, with 2.7 billion outpatient visits in 2021, compared to 2.4 and 2.8 billion in 2020 and 2019, respectively (Shanghai Municipal Bureau of Statistics, 2022). The survey randomly recruited samples from the commercial survey panel. A total of 1143 individuals aged 18 and older completed the survey.

The survey questionnaire was structured to collect information in four categories: Socioeconomic details include age group, gender, the highest level of education, personal income level, and household information, including household size and composition, car ownership, and dwelling location. Questions about the respondent's choice of hospital and scheduling of appointments are also included (whether the respondent booked the appointment on the same day of travel, two to three days in advance, one week in advance, or at least one month in advance). Travel characteristics questions include frequency of healthcare travel, travel time, travel mode, and seeking time to the reported hospital choice. We also asked attitudinal questions about whether the respondent considered certain factors important in healthcare travel. Responses to these questions are binary “agree” or “disagree”. We use dichotomous formats for attitudinal questions because the binary response format is significantly and substantially faster to complete, thus contributing to more reliable responses for long questionnaires

(Dolnicar and Grün, 2007). Even though a 5 or 7-point Likert scale may provide a higher degree of measurement precision, patients who agree or disagree with a statement are more of our concern.

Shanghai is a populous city with a population of 24.87 million (the Seventh National Population Census). By the end of 2021, Shanghai has 432 hospitals and 335 community health centers (Shanghai Municipal Bureau of Statistics, 2022). Among the 432 hospitals, 57 are tertiary hospitals (multi-site hospitals are counted as one), and 121 are secondary hospitals. Community healthcare centers were no longer counted in the number of hospitals since 2008; however, they are the essential primary health care in Shanghai. Therefore, in our study, primary healthcare includes primary-level hospitals and community healthcare centers.

In addition, we obtained the latitude and longitude of the hospital location by querying the Gaode API interface (Gaode map, 2022a). Respondents with valid hospital and home locations were retained for further analysis. Hospital-level information was obtained from the official website of the Shanghai Municipal Health Commission (Shanghai Municipal Health Commission, 2021). Travel distance (in kilometres) is also estimated using the Gaode map (2022b) as the fastest road line route from the residence of patients to the selected hospital. Reported travel times from the home location of patients to selected hospitals are collected from the survey in a defined four-level format. To ensure the quality of the collected data, we double-checked the reported travel time using the travel time estimate from the Gaode map (2022b) (see Appendix B). We use patient-reported travel times for further analysis due to that the perceived travel values may ultimately drive the choice-making process (Varotto et al., 2017). In the end, 961 responses remained for our further analysis. Jiedao, which is the basic administrative unit of Chinese cities, was used as the geocoded unit to display the spatial distribution of respondents in Fig. 1.

3.2. Descriptive statistics

The data collected was used to generate descriptive statistics as a first step. The descriptive statistics of the variables considered in this paper are summarized in Table 1.

The geographical distribution of the respondents in 16 administrative districts of Shanghai is similar to the population distribution of the 2020 census (National Bureau of Statistics, 2020). However, the central districts of Huangpu, Jingan, Changning, Putuo, Xuhui, and Yangpu are relatively highly representative of our sample. In contrast, the peripheral districts of Shanghai, including Chongming, Qingpu, Jiading, Pudong, and Songjiang, are slightly less representative. We did not control for gender in our survey recruitment process. The demographic characteristics of the samples have a higher proportion of females (60.7%) compared to the census data (48.2%). This may be due to the observed higher rate of female patient consultations at hospitals (Cui et al., 2020; Shen and Tao, 2022). Online surveys have been widely used in health travel research to obtain citywide patient travel information, although they have a bias toward underrepresentation of older age groups and less educated populations (Cao et al., 2022; Zhang et al., 2020). In terms of household size, the samples reported a higher proportion of three- and four-person households and a lower proportion of one- and two-person households. Therefore, we propose that appropriate caution should be used when applying the results to the general population in Shanghai.

The survey also collected the types of illnesses of the responding

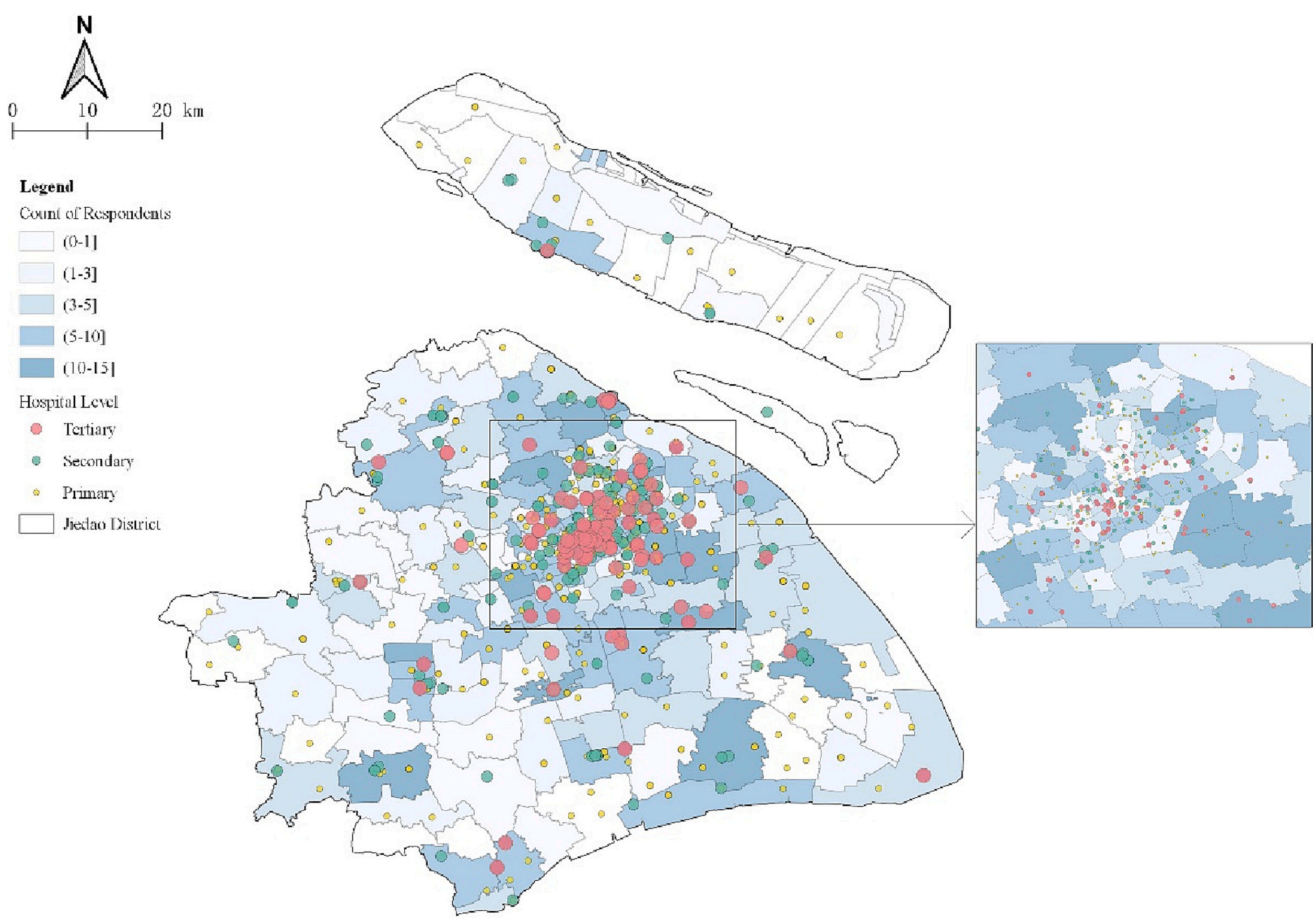

Fig. 1. Spatial distribution map of hospitals and respondents.

Table 1
Descriptive statistics of key socioeconomic attributes.

Attributes	Survey sample (*N* = 961)		2020 census
	Count	Percentage	Percentage
Personal attributes			
Gender			
female	583	(60.7%)	(48.2%)
male	378	(39.3%)	(51.8%)
Age group			
18–30	334	(34.8%)	(17.8%)
30–39	364	(37.9%)	(20.3%)
40–49	172	(17.9%)	(14.6%)
50–59	63	(6.6%)	(14.1%)
60 and above	28	(2.9%)	(23.4%)
Highest education level			
bachelor's level and above	678	(70.6%)	(35.0%)
college	160	(16.6%)	(17.4%)
high school and below	123	(12.8%)	(47.6%)
Personal annual income (RMB)			
below 29,999	136	(14.2%)	
30,000-79,999	177	(18.4%)	
80,000-149,999	345	(35.9%)	–
150,000-299,999	232	(24.1%)	
300,000 and above	71	(7.4%)	
Types of illnesses			
common conditions	664	(69.1%)	
chronic conditions	193	(20.1%)	
acute conditions	32	(3.3%)	–
serious conditions	9	(0.9%)	
others	63	(6.6%)	
Household attributes			
Household size			
1	82	(8.5%)	(28.4%)
2	152	(15.8%)	(34.6%)
3	454	(47.2%)	(22.4%)
4	159	(16.5%)	(8.5%)
5 and above	114	(11.9%)	(6.2%)
Car ownership			
own	544	(56.6%)	–
not own	417	(43.4%)	
Household location (administrative districts)			
Pudong	176	(18.3%)	(22.8%)
Huangpu	64	(6.7%)	(2.7%)
Xuhui	72	(7.5%)	(4.5%)
Changning	32	(3.3%)	(2.8%)
Jingan	46	(4.8%)	(3.9%)
Putuo	74	(7.7%)	(5.0%)
Hongkou	28	(2.9%)	(3.0%)
Yangpu	79	(8.2%)	(5.0%)
Minhang	85	(8.8%)	(10.7%)
Baoshan	82	(8.5%)	(9.0%)
Jiading	42	(4.4%)	(7.4%)
Jinshan	38	(4.0%)	(3.3%)
Songjiang	68	(7.1%)	(7.7%)
Qingpu	22	(2.3%)	(5.1%)
Fengxian	41	(4.3%)	(4.6%)
Chongming	12	(1.2%)	(2.6%)

Note: Common conditions include illnesses such as cough, fever, rash and respiratory infections; Chronic conditions include illnesses such as cardiovascular, chronic respiratory, and diabetes. Acute conditions include illnesses such as heart attack, acute anaphylaxis, appendicitis, and bone fractures; Serious conditions include illnesses such as malignancy, stroke and other end-stage illnesses.

patients. The majority of respondents reported seeking care for common and chronic conditions, with 69.1% of respondents reported seeking care for common conditions, and 20.1% reported seeking care for chronic conditions. In the sample, 3.3% of respondents reported seeking medical care for acute conditions, while 0.9% reported for serious conditions. The low proportion of patients reporting serious or acute conditions could be due to the nature of data collection, which makes it difficult to reach a large proportion of the elderly and those with acute or severe illnesses.

Table 2 presents the hospital choice and health travel behaviour characteristics of the survey sample. The majority of respondents (62.2%) chose tertiary hospitals, while 21.6% and 16.1% sought health care at secondary and primary hospitals, respectively. The results are consistent with previous work, with patients in Shanghai tending to choose tertiary hospitals (Zhang et al., 2020). Similarly, 64.0% of respondents chose a downtown hospital, with lower proportions choosing suburban (20.8%) and outskirt (15.2%) hospitals. We also find a higher proportion of patients with serious or acute conditions chose tertiary hospitals than patients with chronic and common conditions (see Appendix A). Regarding preregistration, the percentage of respondents reporting same-day registration was 48.7%, with relatively fewer patients registering two to three days in advance. 27.2% of patients reported preregistering one week prior to their visit.

Respondents use multiple modes of transportation to access health care. Of the respondents, 25.0% drove or rode in a car to access health care, more respondents chose to walk or ride a bicycle (33.3%), and 34.3% chose public transport (including bus, metro, and integration of public transit and other modes). The remaining respondents (7.4%) reported taking a taxi or using other travel modes to get to the hospital. Travel time is a categorized variable into four levels (i.e., 0–15 min, 16–30 min, 31–60 min, and > 60 min) based on the common cutoff of 15 min. For access to motorized transportation, Weiss et al. (2020) reported

Table 2
Hospital choice and healthcare travel behaviour attributes.

Attributes	Survey sample (N = 961)	
	Count	Percentage
Hospital choice attributes		
Hospital level		
tertiary	598	(62.2%)
secondary	208	(21.6%)
primary	155	(16.1%)
Hospital location		
downtown	615	(64.0%)
suburb	200	(20.8%)
outskirts	146	(15.2%)
Preregister time		
same day	468	(48.7%)
two to three days in advance	232	(24.1%)
one week or more in advance	261	(27.2%)
Healthcare travel attributes		
Healthcare travel mode		
walk	133	(13.8%)
cycle	187	(19.5%)
bus	161	(16.8%)
metro	104	(10.8%)
public transit and others	64	(6.7%)
car	240	(25.0%)
taxi	58	(6.0%)
others	14	(1.4%)
Healthcare travel time (min)		
15 min and below	266	(27.7%)
16–30 min	424	(44.1%)
31–60 min	190	(19.8%)
above 60 min	81	(8.4%)
Healthcare travel distance (km)		
0–3 km	327	(34.0%)
3–5 km	133	(13.8%)
5–10 km	176	(18.3%)
10–15 km	113	(11.8%)
15km and above	212	(22.1%)
Healthcare travel frequency		
first time	508	(52.9%)
high (twice per week/weekly/biweekly)	54	(5.6%)
medium (monthly-bimonthly/seasonal)	152	(15.8%)
low (half yearly/yearly)	61	(6.3%)
no fixed time	186	(19.4%)
Seeking time		
weekday peak hour	348	(36.2%)
weekday nonpeak hour	305	(31.7%)
weekend	308	(32.0%)

that 82.6% of the population lived within 30 min of a hospital or clinic, and 91.1% lived within 60 min. Respondents in our sample reported travel time to health care within 30 and 60 min was 71.8% and 91.6%, respectively. This is reasonable because it considers non-motorized transportation and public transport. The majority of respondents (34.0%) travelled to hospitals within 3 km; however, 22.1% reported travel distances >15 km. Of the patients surveyed, 508 (52.9%) went to the hospital for a first-time check, 267 (27.7%) visited the doctor regularly, and the remaining 186 (19.4%) had no fixed time. The seeking time of respondents was almost evenly distributed between weekday peak hours, weekday off-peak hours, and weekends.

3.3. Methodology

A latent class analysis (LCA) was first conducted to probabilistically assign individuals to latent groups sharing relatively similar characteristics in hospital choice, travel behaviour and attitudinal attributes related to healthcare travel. Then we accommodated sociodemographic, healthcare seeking, and transportation accessibility factors as covariates in the model. The latent class including the covariates is then estimated simultaneously.

The latent class model is a finite mixture model that groups analysis variables into classes based on shared response patterns (Hagenaars and McCutcheon, 2002). The fundamental assumption in LCA is that cases are relatively homogeneous but are heterogeneous across classes with respect to the analytic variables. The observed variables are conditionally independent, given latent class membership. LCA can be used to examine multivariate input variables simultaneously. Unlike the traditional cluster analysis, latent class models allow the analyst to incorporate covariates, which are assumed to predict class membership (Vermunt, 2010). For a set of K categorical responses, let $\mathbf{Y}_{ik}$ represent the response of subject i to item k, and let t denote a particular category of $\mathbf{Y}_{ik}$. The probability of the full response pattern ($\mathbf{Y}_i$) can be formulated as follows:

$$P(\mathbf{Y}_i|X=t) = \prod_{k=1}^{K} P(Y_{ik}|X=t) = \prod_{k=1}^{K}\prod_{r=1}^{R_k} \theta_{ktr}^{I(Y_{ik}=r)} \tag{1}$$

The latent class model with covariates consists of two types of probabilities, the probabilities of belonging to a certain latent class given an individual's covariate values, $P(X=t|\mathbf{Z}_i)$; and the probabilities of particular responses on the indicator variables given latent class membership, as shown in Eq. (1).

$$P(\mathbf{Y}_i|\mathbf{Z}_i) = \sum_{t=1}^{T} P(X=t|\mathbf{Z}_i)P(\mathbf{Y}_i|X=t) \tag{2}$$

The probability of $P(X=t|\mathbf{Z}_i)$ will typically be parameterized by a multinomial logistic regression form:

$$P(X=t|\mathbf{Z}_i) = \frac{exp\left(\gamma_{0t} + \sum_{q=1}^{Q}\gamma_{qt}z_{iq}\right)}{\sum_{s=1}^{T} exp\left(\gamma_{0t'} + \sum_{q=1}^{Q}\gamma_{qs}z_{iq}\right)} \tag{3}$$

The parameters of interest γ and the multinomial parameters defining $P(X=t|\mathbf{Z}_i)$ are obtained by maximizing the following log-likelihood function.

$$logLL_{\mathrm{FIML}} = \sum_{i=1}^{N} logP(\mathbf{Y}_i|\mathbf{Z}_i) = \sum_{i=1}^{N} log\sum_{t=1}^{T} P(X=t|\mathbf{Z}_i)P(\mathbf{Y}_i|X=t) \tag{4}$$

One of the main reasons for choosing LCA with covariates is that LCA has been applied in the previous travel behaviour literature to identify market segments and has shown its strength in analyzing heterogeneity (Chang et al., 2021; Molin et al., 2016; Rafiq and McNally, 2021; Shah et al., 2021). Moreover, the use of LCA can complement the traditional use of behavioural theories by identifying holistic combinations or typologies, representing a variety of travel behaviour, destination choices, and attitudinal factors that cluster together. For example, to capture the heterogeneity of activity-travel patterns based on the trip and tour attributes of transit users (Rafiq and McNally, 2021), to identify long-distance tour types using multivariate tour characteristics (namely distance, purpose, duration, and destination region) (Davis et al., 2018), and to assess the heterogeneity of household travel and shopping patterns based on trip chaining, vehicle miles travelled (VMT) and trip frequency (Shah et al., 2021). In addition, LCA can be particularly useful for identifying subgroups of individuals who may benefit from an intervention based on their common characteristics.

Fig. 2 shows the model structure. We used nine indicator variables to classify patients based on their hospital and healthcare travel patterns. The indicators include healthcare travel time, healthcare travel mode, hospital level, hospital location, and five states of important perceptual factors for healthcare travel. The model in our study was estimated using the poLCA package in R programming (Linzer and Lewis, 2011).

We estimated models with incremental numbers of latent classes from one to six. Researchers typically use a combination of fit criteria in determining the number of latent classes, including likelihood ratio statistical test methods, information-theoretic methods, and the entropy-based criterion (Tein et al., 2013). Therefore, we compared different models based on the Bayesian Information Criterion (BIC), Akaike Information Criterion (AIC), Consistent Akaike Information Criterion (CAIC), Log-likelihood, entropy, and interpretability of results. Lower BIC, AIC, and CAIC values indicate a more parsimonious and correct model (Hagenaars and McCutcheon, 2002). Entropy, which measures the ability of a model to provide well-separated clusters, ranges from 0 to 1. An entropy >0.8 indicates a clear distinction between classes (Celeux and Soromenho, 1996).

In terms of model fit, BIC, CAIC is the lowest in the four-class model, indicating the best fit to the data. Also, an entropy of 0.83 performed well under the four-class model specification (Table 3). Once the four-class model was selected, we presented the descriptive statistics and estimated coefficients of the covariates. The covariates included sociodemographic characteristics (i.e., gender, age group, income, car ownership, household size, disease type), healthcare seeking (seeking time, travel distance, seeking frequency) and transportation accessibility (bus station within 300 m and subway station within 1 km of the selected hospitals).

4. Results

This section presents the latent class model results with covariates. The class characteristics, spatial distribution of different patient clusters, and the estimation results for the class membership covariates are displayed.

4.1. Four identified types of patients: latent class model results

As stated in the above section, a comparison of the goodness of fit for various models showed that the four-class model indicates the best model fit for our data. The descriptive statistics of the four classes are presented in Table 4. The cluster share of the four-class model was 22.7%, 18.5%, 28.6%, and 30.2%, respectively. For each patient cluster, we first describe its class characteristics as measured by the hospital choice, healthcare travel behaviour, and perception indicators. This is followed by a description of the factors that influence cluster membership based on the within-cluster distributions of the covariate variables presented in Table 5.

The first class was identified as *public transit patients* (22.7% of the total correspondents), who mostly chose tertiary hospitals (82.7%) or selected hospitals in the downtown area (94.8%). None of the patients in this group chose outskirts hospitals. This group typically made a healthcare trip by metro (45.5%), bus (25.1%), or public transit modes

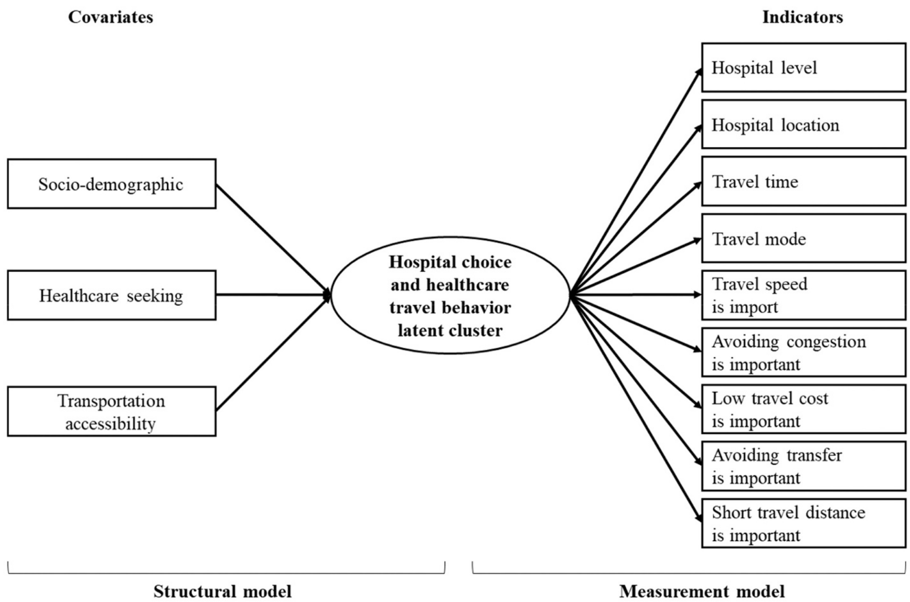

Fig. 2. Schematic diagram of the latent class model with covariates.

Table 3
LCA model fit statistics for one to six numbers of latent classes.

Model	Log-likelihood	Degrees of freedom	BIC	AIC	CAIC	Likelihood-ratio	Chi-square	Entropy
1-class	−7629.089	942	15,388.67	15,296.18	15,407.67	3350.833	11,711.72	–
2-class	−7389.537	922	15,046.92	14,857.07	15,085.92	2871.728	12,783.33	0.69
3-class	−7286.621	902	14,978.45	14,691.24	15,037.45	2665.897	14,504.97	0.84
4-class	−7201.185	882	14,944.94	14,560.37	15,023.94	2495.024	13,270.75	0.83
5-class	−7160.166	862	15,000.26	14,518.33	15,099.26	2412.986	11,913.87	0.82
6-class	−7125.95	842	15,069.19	14,489.9	15,188.19	2344.554	10,559.49	0.85

integrated with others (19.8%), and a higher proportion chose taxis to seek healthcare than the other three groups. Conversely, no patients in this group chose a car for healthcare travel. Unlike the other three groups, this group mostly spent long travel time accessing healthcare facilities, with 64.3% reporting travel times of >30 min and 25.3% reporting travel times of >60 min. Also, more patients in this group agreed with the three statements that '*avoiding congestion is important*', '*low travel cost is important*' and '*avoiding transfer is important*' compared to other groups. However, most of this group disagreed with the statement '*short distance to hospital is important*'.

The second group, *car-oriented patients,* with 18.5% of the total patients, mainly travelled by car (88.4%). In contrast to the first class, no patients in this group used bus, metro, or other public transport modes to access health care. Also, patients in this group rarely made non-motorized trips for health care. Additionally, patients in this group made more healthcare trips between 15 and 30 min for health care than patients in other classes. In terms of hospital choice, this group reported a relatively low proportion of seeking health care in tertiary hospitals compared to the first group (62.0%), whereas a higher proportion of using secondary (25.1%) and primary hospitals (12.9%). Most of this group chose downtown hospitals (80.1%), and 18.8% of patients made healthcare trips to suburban hospitals. In terms of attitudinal factors, most patients in this class agreed that '*travel speed is important*' (86.0%), while almost all disagreed with '*low travel cost is important*' (97.5%).

The third identified group was *near-hospital patients*. This class comprises 28.6% of the total patients. Most patients in this group travelled by active travel modes, including walking (36.3%) and cycling (36.2%). However, no patients reported travelling by car, and few reported travelling by public transit. In this group, 2.1% of patients made healthcare trips by other modes, which consisted of main e-bikes. 93.4% of patients in this group spent <30 min on healthcare travel, with 49.4% reporting a travel time below 15min. 96.1% of patients in this group chose downtown hospitals, the highest among the four groups; however, no patients selected outskirts hospitals. A higher fraction of patients in this group selected primary hospitals (18.4%), more than the first (4.3%) and the second identified class (12.9%). Moreover, unlike the first and second classes, most patients in this group agreed that '*short travel distance is important*'.

The final class of patients was deemed *non-downtown hospital patients*, who mostly made healthcare travel to suburbs (50.0%) and outskirts hospitals (49.7%). This class has the largest population share, with 30.2% of correspondents. Among all the groups, class 4 includes a higher percentage of patients travelling to primary (24.9%) and secondary hospitals (26.4%). Most members in this group travelled to hospitals by multi-travel modes, including driving a car, riding a bus, and cycling. Like class 3, this group typically reported a travel time of fewer than 30 min. Patients in this group held similar perceptions toward healthcare travel compared with the third identified class.

4.2. Spatial distribution map of the four identified groups of patients

To visualize the spatial distribution of the four identified clusters, we mapped the household location of patients, the percentage of patients within Jiedao spatial units for different groups, and the public transport network together in Fig. 3.

The *public transit patients* (22.7% of the sample): Most of the patients in this group are found in downtown and suburban districts. We also observe a high proportion of patients living in the Jiedao units along the metro network, and in the Jiedao units where the metro terminals are located. It initially reveals that good public transport accessibility may

Table 4
Class-conditional membersh'ip probabilities for indicator variables by each class ($N = 961$).

	Class 1: Public transit patients	Class 2: Car-oriented patients	Class 3: Near hospital patients	Class 4: Non-downtown hospital patients	Scale of indicators
Class share (%)	22.7%	18.5%	28.6%	30.2%	
Indicator variables					
Hospital choice: Hospital Level					
primary	0.043	0.129	0.184	**0.249**	1
secondary	0.130	0.251	0.213	**0.264**	2
tertiary	**0.827**	0.620	0.604	0.487	3
Hospital choice: Hospital Location					
downtown	0.948	0.801	**0.961**	0.004	1
suburb	0.052	0.188	0.039	**0.500**	2
outskirts	0.000	0.012	0.000	**0.497**	3
Healthcare Travel: Travel Mode					
walk	0.004	0.000	**0.363**	0.112	1
cycle	0.020	0.059	**0.362**	0.251	2
bus	**0.251**	0.000	0.153	0.222	3
metro	**0.455**	0.000	0.000	0.016	4
public transit + others	**0.198**	0.000	0.038	0.035	5
car	0.000	**0.884**	0.000	0.287	6
taxi	**0.073**	0.039	0.064	0.061	7
others	0.000	0.018	**0.021**	0.017	8
Healthcare Travel: Travel Time (min)					
below 15min	0.000	0.149	**0.494**	0.358	1
15-30min	0.357	**0.527**	0.440	0.453	2
30-60min	**0.390**	0.248	0.046	0.166	3
60min and above	**0.253**	0.076	0.020	0.022	4
Perception: Transportation speed is import					
disagree	0.312	0.141	**0.371**	0.320	1
agree	0.688	**0.860**	0.629	0.680	2
Perception: Avoiding congestion is important					
disagree	0.528	**0.684**	0.620	0.631	1
agree	**0.472**	0.316	0.380	0.369	2
Perception: Low travel cost is important					
disagree	0.758	**0.975**	0.764	0.760	1
agree	**0.242**	0.025	0.236	0.241	2
Perception: Avoiding transfer is important					
disagree	0.620	0.750	**0.873**	0.819	1
agree	**0.380**	0.250	0.127	0.181	2
Perception: Short travel distance is important					
disagree	**0.807**	0.701	0.420	0.541	1
agree	0.194	0.299	**0.580**	0.459	2

Numbers in bold indicate the highest value for each category among the four classes.

improve patient mobility to high-level health care in downtown districts.

The *car-oriented patients* (18.5% of the sample): Unlike the public transit patients, observations in this group are relatively dispersed in suburban and outskirts, specifically in outskirt units without metro available. An interesting finding from this group is that few patients live in Jiedao units along metro line 4, which is the circle line connecting branches extending outwards. We infer that a connected metro network may reduce car use when seeking medical care in downtown and suburban hospitals.

The *near-hospital patients* (28.6% of the sample): Near-hospital patients who mostly walk or ride a cycle to seek medical care are highly concentrated in downtown districts. This may be due to parking for downtown hospitals is difficult and expensive. Therefore, patients who could access health care within walking or biking distance would choose non-motorized transportation.

The *non-downtown hospital patients* (30.2% of the sample): Different from the other three groups, >99% of patients in this group were found to use suburbs or outskirts hospitals. No patients in this group live in the downtown districts. We also observe a higher percentage of the sample living in the outskirts than in the suburbs. This implies that outskirts patients are more dependent on suburban and outskirts hospitals than suburban residents. We further map this class and hospital location together in Fig. 4. An interesting finding is that a higher proportion of patients in this group are found to live in Jiedao units where there is at least one secondary or tertiary hospital. This indicates that the newly built or upgraded mid- or high-level hospitals in non-downtown areas are able to attract patients who live in the suburbs and outlying areas. However, some tertiary hospitals are found to attract fewer patients than others, such as the tertiary hospital in the north of the Pudong district. We suspect that the service quality of some high-level medical care may not meet the needs of people living nearby.

4.3. Prediction of latent class membership

The sociodemographic, healthcare-seeking, and transport accessibility factors (covariates) that influenced a patient belonging to a specific class are shown in Table 5. The covariate coefficients for three classes are presented with reference to the second class, car-oriented patients. The car-oriented group was chosen with the goal of promoting sustainable healthcare travel and equitable access to health care.

The explanatory variables listed in our model have been investigated in the existing literature. However, each previous study only focuses on part of the determines, but very few consider them all together. This study is one of the few healthcare travel studies considering sociodemographic, healthcare-seeking, and public transport accessibility factors in the same model.

Females were more likely to belong to the public transit patient group (class 1) than the reference class. It may be because women living in higher-income areas are more inclined to bypass their closest hospital for better care (Bronstein and Morrisey, 1991) and are more likely to tolerate longer travel times for health care than men (Cao et al., 2022). Even though age was found to be positively related to choosing a nearby hospital for older people (Tai et al., 2004), our results showed limited effects of age group and income level on class membership. In contrast, disease type was found to affect class membership, with chronic disease patients more inclined to be non-downtown hospital patients and public transit patients. We also tested other disease types and found that patients with severe diseases were more likely to belong to car-oriented patients. This finding is similar to previous research, which measured the severity and types of illnesses from a diagonalized angle (Adams et al., 1991). However, in our sample, only nine patients are of serious diseases. Therefore, two disease types, acute and severe, were tested. The combination indicator was not statistically significant, probably because some acute conditions may not limit the mobility of patients to use public transport. Also, patients with more household members or

Table 5
Latent class model covariates [Reference category: Class 2 Car-oriented patients] ($N = 961$).

Class share (%)	Class 1: Public transit patients		Class 3: Near hospital patients		Class 4: Non-downtown hospital patients	
	22.7%		28.6%		30.2%	
Covariates	Coefficient	SE	Coefficient	SE	Coefficient	SE
Intercept	(17.690)***	0.491	(10.211)***	0.493	52.319***	2.365
Sociodemographic						
Gender: Female (dummy)	**0.772****	0.351	0.371	0.356	(0.525)	1.143
Age group: 60 and above (dummy)	(0.194)	1.229	(0.030)	1.375	(3.160)	4.392
Personal Annual Income: ≥ 150,000 RMB	(0.399)	0.366	(0.098)	0.346	(3.297)	2.138
Types of illnesses: chronic conditions (dummy)	**0.995****	0.449	0.219	0.446	**2.609***	1.505
Types of illnesses: serious or acute conditions (dummy)	(0.122)	0.699	(1.034)	0.872	(1.051)	6.318
Household size (continuous)	**(0.649)*****	0.176	**(0.623) *****	0.184	(0.621)	0.472
Car ownership (dummy)	**(26.965)*****	0.977	**(26.661)*****	0.986	**(26.649)*****	0.939
Household location (Ref: outskirts)						
downtown	0.297	1.089	**14.128*****	0.368	**(24.734)*****	2.271
suburb	(0.990)	1.020	**12.321*****	0.454	(0.526)	1.830
Healthcare travel						
Seeking time: weekday peak hour (dummy)	0.196	0.341	0.247	0.358	(1.725)	1.150
Pre-book appointment (Ref: same day)						
two to three days in advance	0.055	0.447	**(1.084)****	0.422	0.700	1.151
one week or more in advance	**0.790***	0.421	**(1.384)****	0.469	(0.596)	1.731
High travel frequency (dummy)	0.031	1.189	(1.327)	1.806	**(25.672)*****	0.965
Gender * High travel frequency	(0.235)	1.453	1.955	1.978	**24.587*****	0.965
Travel distance (Ref: 0-3km)						
3-5km	**1.838****	0.773	(0.749)	0.473	**(4.725)***	2.749
5-10km	**1.667****	0.764	**(2.270)*****	0.504	**(5.729)****	2.815
10-15km	**2.049****	0.804	**(2.106)*****	0.688	**(7.563)****	2.817
15km and above	**3.230*****	0.805	**(1.533)****	0.672	**(9.312)****	3.337
Transport accessibility						
No metro station in the household administration area (dummy)	(1.171)	1.015	(0.584)	0.973	0.062	1.556
At least one bus stop within 300m radius of the hospital (dummy)	**13.878*****	0.491	**10.978*****	0.493	**(9.059)*****	2.365
At least one metro station within 1km radius of the hospital (dummy)	**29.125*****	0.491	**15.083*****	1.844	**(8.041)****	2.708

*, **, and *** indicate statistical significance respectively at 10%, 5%, and 1% level.

who owned a car were more likely to belong to the reference group of car-oriented patients. This finding is consistent with the previous study, which showed that patients with companies or access to a car turn to choose car for health care (Du et al., 2021).

In addition, patients living in the outskirts area were a strong predicstor of non-downtown hospital patients than car-oriented patients. Since 2012, the government has promoted the construction of general tertiary hospitals and strengthened the secondary and primary care facilities in the suburbs and outskirts to balance the distribution of healthcare resources. Our results reveal that non-downtown hospitals can attract patients residing in outskirts. However, the findings also indicate that a higher proportion of non-downtown hospital patients choose primary and secondary hospitals compared to the other groups. In contrast, patients residing in the downtown and suburban area were more inclined to be near hospital patients than car-oriented patients. One possible reason could be that high-level healthcare facilities were concentrated in downtown and suburbs, patients living in downtown and suburban districts could access high-quality healthcare services nearby. This result further confirmed previous research which concluded that people living in central areas were well served by all levels of healthcare providers, while people living in periphery areas suffered from low access to upper-tier healthcare services (Jin et al., 2022).

We did not observe an apparent effect of patients seeking healthcare during weekday peak hours on class membership prediction. However, our results suggested that pre-booking patients were more inclined to directly go to high-level hospitals. Specifically, patients who booked appointments more than one week in advance were responsible for the prediction of public transit patients. Compared with same-day registered patients, patients who booked two to three days in advance or one week in advance were negatively associated with the near-hospital patient class. Regarding travel frequency, those with a high travel frequency of at least twice a week were less predictor of non-downtown hospital patients than car-oriented patients. However, when the interaction with gender was considered, female patients with high healthcare travel frequency were a key factor in distinguishing the non-downtown hospital classes from the car-oriented classes. Compared to patients with short healthcare travel distances (0-3km), those with longer travel distances were more likely to be public transit patients. This could be explained by a greater proportion of public transit patients chose tertiary downtown hospitals than their car-oriented counterparts. As expected, those with longer travel distances strongly predicted car-oriented patients compared to near-hospital or non-downtown hospital patients.

We also included indicators of public transport accessibility in our model. Results showed that bus stops and metro stations near selected hospitals were strong predictors of public transit and near-hospital patients. However, patients with good public transport accessibility to their chosen hospitals were less likely to belong to the class of non-downtown patients than car-oriented patients. This probably results from car-oriented patients mostly seeking health care in downtown hospitals, and hospitals located in the downtown area typically have better public transport accessibility than non-downtown hospitals. It also points to the need to promote public transport accessibility to non-downtown hospitals. We also tested the home-end public transport accessibility indicators and found a limited effect on membership prediction.

5. Policy discussion

Accessing health care is one of the most critical yet neglected aspects of healthcare planning in developing cities, such as in China. The equity in accessing health care is constrained not only by health care provision, but also by individual mobility. By investigating the heterogeneity of patients based on their hospital choice, travel behaviour and perceptional attributes, we could better understand the market segments of patients and tailor the healthcare and transport policy to meet their healthcare travel demand.

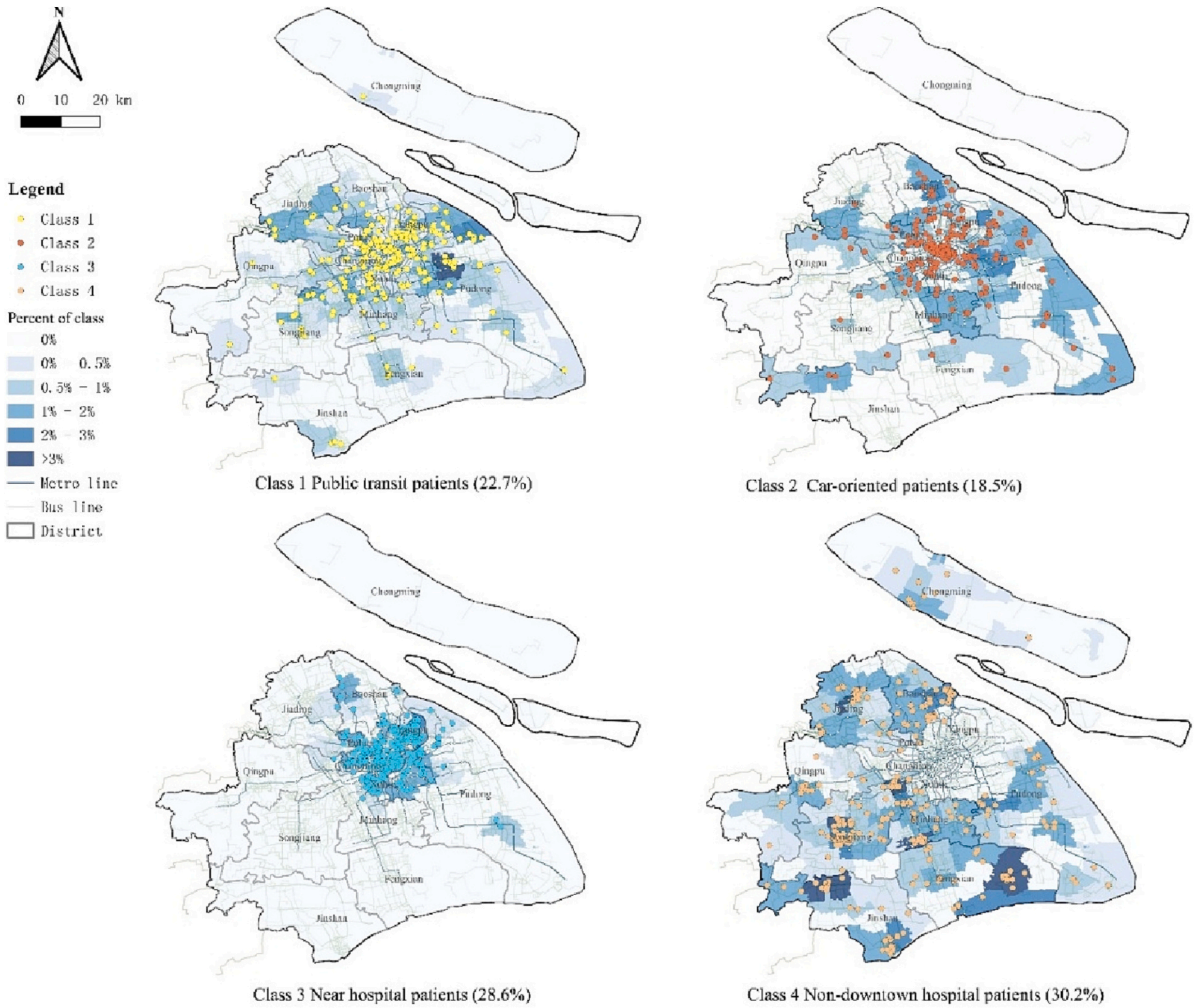

Fig. 3. Spatial distribution of the four identified groups of patients.

In our study, we identified four categories of patients: public transit patients (22.7%), car-oriented patients (18.5%), near-hospital patients (28.6%), and non-downtown hospital patients (30.2%). Descriptive statistical results show that the four classes differ in terms of the selected hospital level, hospital location, healthcare travel time, healthcare travel mode, and the perception of essential factors related to healthcare travel. There is also a clear difference in the spatial distribution of the four patient groups. It is not surprising that public transit patients are located closer to the public transport network, while the residents of car-oriented patients are relatively dispersed in suburbs and outskirts. Observations of near-hospital patients are clustered downtown, where non-motorized transport is widely adopted, whereas non-downtown hospital patients are found only in the suburbs and outskirts. Possible targeted measures for each group of patients are suggested.

Public transit patients were more inclined to choose tertiary hospitals in downtown districts. We found that female patients with chronic conditions, patients who made appointments at least one week in advance, and those who chose hospitals with good public transport accessibility were more inclined to be public transit patients. Patients with chronic conditions require long-term prescriptions and are found to make frequent visits for routine treatment (Zeng et al., 2020). Contrary to previous findings in the US, where routine check-ups for chronic patients mainly occur in local clinics (Mattson, 2011), female chronic patients in Shanghai were more likely to travel long distances to seek health care in tertiary hospitals. A shift from the current tertiary hospital-dominated healthcare system to a hierarchy-based one with a more rigid referral system could be considered. Also, introducing skilled doctors to primary hospitals on a monthly or seasonal basis to meet the demand for routine check-up of chronic patients may reduce outpatient pressure on downtown hospitals.

Moreover, good public transport links to downtown tertiary hospitals seems to encourage patients to bypass the closest hospitals. Currently, for the hospitals selected by respondents, 99% of the downtown hospitals have at least one metro station within 1km, compared to 55% in suburbs, and only 5% in outskirts. This may partly explain why the spatial distribution of public transport users in non-downtown areas is located close to the metro network and drives patients to downtown hospitals. Much effort has been put into public transport planning to promote connections between the outskirts and suburbs to central districts, but public transport connections from the outskirts to suburban or outskirts hospitals are also needed. Public transport accessibility should also be included in the hospital siting process, which currently favours the car. Solutions could include a reliable timetable, direct routes, better integration between the bus and metro systems, a short distance from the station or bus stop to the hospital entrance, and a safe walking environment around the hospitals.

The second class, car-oriented patients had higher car use for healthcare travel. Car-oriented patients did not consider travel costs to be essential. Most patients in this class chose downtown and suburb hospitals, booked in advance, and considered travel to be critical for

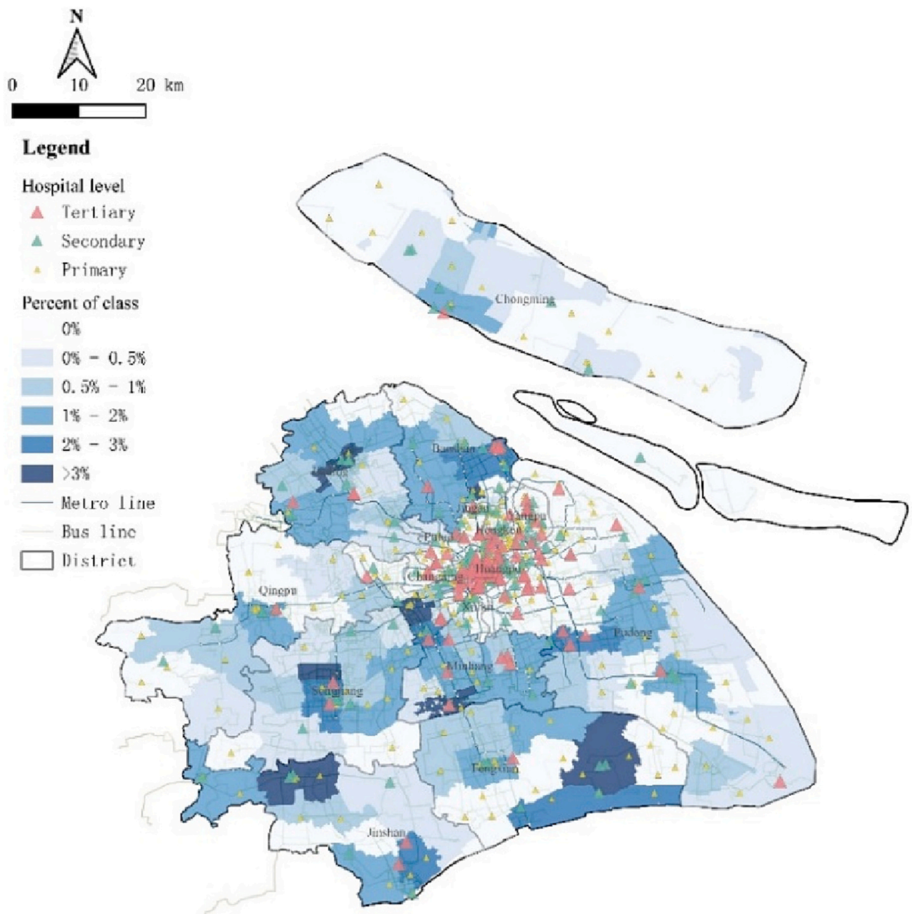

Fig. 4. Spatial distribution of the non-downtown hospital patients and hospital location in Shanghai.

health care. Patients who owned a car, had more family members, lived in the outskirts, and chose hospitals that were not near metro stations or bus stops were more likely to belong to this class. Nowadays, downtown hospitals suffer from severe parking problems (Ji et al., 2022). Promoting access to public transport in their chosen downtown and suburban hospitals may be essential to alleviate the parking pressure and reduce the disparity between car owners and non-owners living in the outskirts. In addition, as patients in this group have pre-booking habits, a pre-booking parking system could be used to reduce car dependency.

The third identified group was near-hospital patients, who were more likely to choose downtown hospitals and access healthcare by active travel modes. For most of them, short travel distances to health care were important. Moreover, patients living in downtown or suburbs and those registered on the same day as their healthcare visit were strong predictors of this group. Previous research has shown that people who live close to a hospital have a lower threshold for attendance at healthcare facilities (Smith et al., 2018). Our study also found that patients living close to a hospital were able to access health care without making an effort to preregister days or weeks in advance. To our knowledge, no previous studies have considered the appointment seeking factor in healthcare travel. Transport policies to increase active and sustainable travel have been widely adopted worldwide (Pucher and Buehler, 2010). Promoting walking and cycling to health care could also benefit health. Improving the accessibility and connectivity of walking and cycling to health facilities and creating traffic-calmed neighbourhoods around hospitals would help to encourage more active travel to health care.

The non-downtown hospital patient class has the largest population share. The rapid suburbanization of the population may contribute to the large share of this market segment. Patients in this class were characterized by a higher proportion of primary and secondary hospital choices in suburban and outskirts. Multiple modes of transport were used in this class, with patients almost evenly split between car, cycle, and bus; however, relatively few patients in this group walked to health care. Most patients travelled to hospitals within 30 min. Patients with chronic conditions, female patients with a high frequency of health care, and those living in the outskirts were more likely to be in this group. The inverse effect of public transport accessibility on predicting this class may be due to poor public transport services in non-downtown areas. Even with public transport, infrequent services and poor transfers between metro stations and bus stops between suburban and outskirts hospitals by public transport need to be further investigated in future studies.

During the pandemic and post-pandemic, we have seen major reforms in healthcare decentralization to promote health system resilience (Ewert et al., 2023). This emphasizes the need to improve public transport and active travel access to secondary and primary health care close to patient homes. Using the model results as a baseline scenario, we include three scenarios to compare the market share of patients after improving public transport accessibility in the outskirts. The results show a decreasing trend in the share of car-oriented patients and the share of non-downtown patients, while the share of patients close to the hospital increases. For example, if all outskirt hospitals had access to at least one metro station within 1km, the market share of car-oriented patients would drop by 10.6%. The decline in the proportion of car-oriented patients is greater for measures to improve accessibility at the hospital end than at the home end (see Table 6).

Other than that, local governments should also pay more attention to improving the quality of health care services. We found that tertiary hospitals in the suburbs and outskirts have a limited attraction range

Table 6
Class share and relative change of class share for different scenarios.

Class share (%)	Class 1: Public transit patients	Class 2: Car-oriented patients	Class 3: Near hospital patients	Class 4: Non-downtown hospital patients
Base	22.7%	18.5%	28.6%	30.2%
Scenario A *(All outskirt residents Jiedao with metro)*	22.3% (−1.8%)	18.3% (−0.8%)	29.3% (+2.2%)	30.1% (−0.2%)
Scenario B *(All outskirt hospitals with the bus within 300m)*	22.8% (+0.3%)	18.2% (−1.7%)	30.1% (+5.1%)	29.0% (−3.9%)
Scenario C *(All outskirt hospitals with metro within 1km)*	22.6% (−0.8%)	16.5% (−10.6%)	32.1% (+11.9%)	28.9% (−4.2%)

compared to downtown tertiary hospitals, as shown in Fig. 5. Additionally, the decaying trend of the curve for outskirt secondary hospitals is relatively flat than the outskirts tertiary hospitals. On the one hand, new facilities should be prioritized in areas with much lower facilities, as suggested by Jin et al. (2022). On the other hand, the reputation and quality of the hospital in non-downtown areas, even at the same level, may be inferior to that of downtown hospitals. Suburban and outskirts hospitals can improve the supply of physicians by involving regularly scheduled specialists from downtown hospitals, thus providing favourable service to nearby patients.

6. Conclusion

In summary, this study contributes to the literature from the perspective of joint hospital choice and healthcare travel behaviours in healthcare decision-making by latent class analysis with covariates.

First, using survey data containing patient-reported information on hospital choice and healthcare travel in Shanghai, our study identified patient healthcare travel behaviour patterns and their different spatial distribution. Second, we assessed the heterogeneity of patients based on their hospital choice, healthcare travel behaviour and their attitudinal statements toward healthcare travel. The inclusion of attitudinal factors provides better well-separated clusters measured by entropy. Based on the introduced method, our study identified four categories of patients: public transit patients, car-oriented patients, near-hospital patients, and non-downtown hospital patients. Obviously, it can be stated that patients are not homogeneous in hospital choice and healthcare travel behaviour. The four categories of patients exhibited distinct hospital choice and healthcare travel behaviour. Based on the revealed

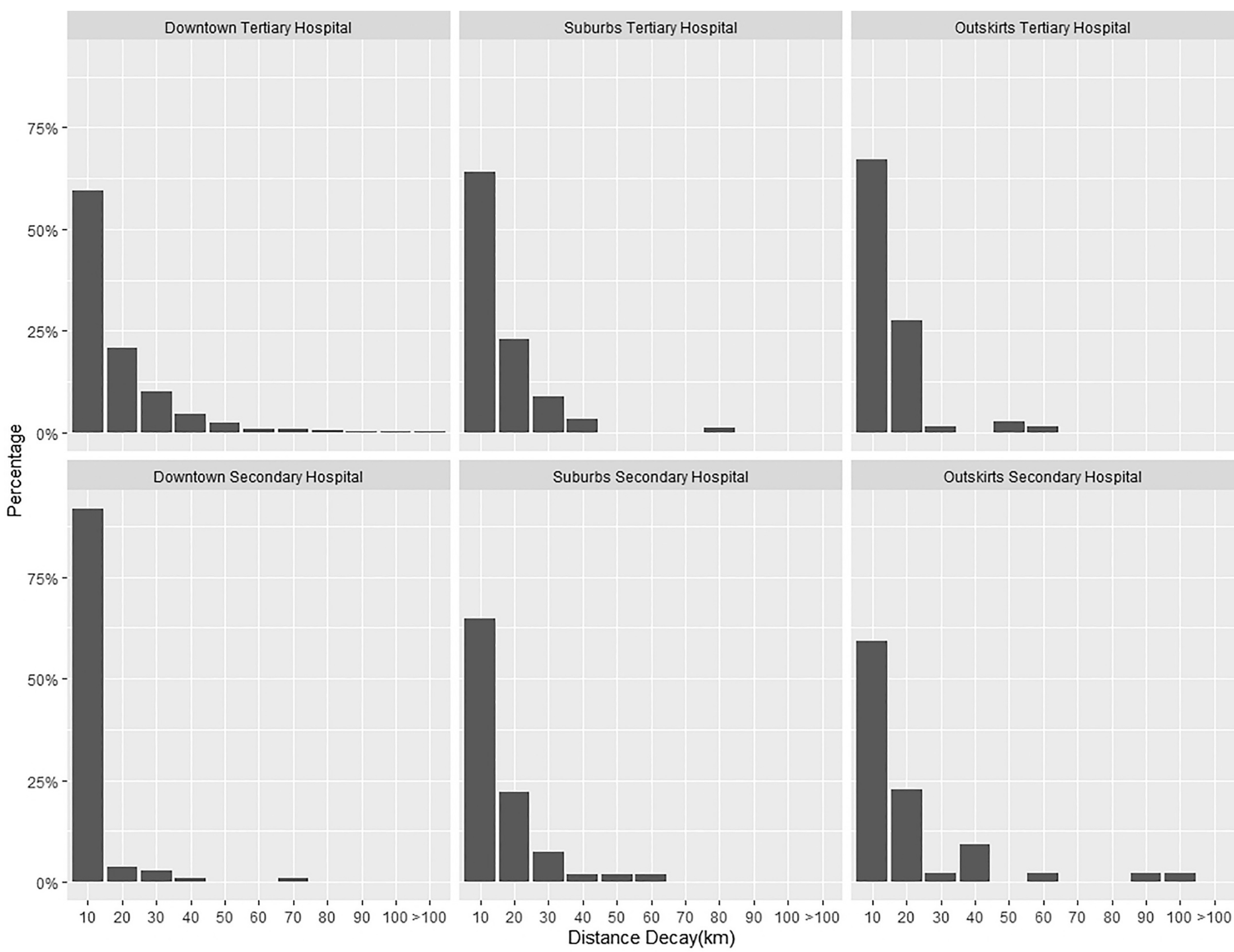

Fig. 5. Hospital location, hospital level and distance decay.

healthcare travel behaviour of patients, we observed a great share of public transit patients bypassing the closest hospitals, which may be underestimated in previous healthcare travel demand analyses.

Thirdly, we controlled for sociodemographic, healthcare seeking, and public transportat accessibility covariates to the clustering prediction in our model. Model results show that car ownership, household location and public transport accessibility of selected hospitals have strong effects on a patient belonging to a specific class. Patients owning a car were more likely to belong to the car-oriented patients' group, while those residing in the downtown or suburbs have a greater tendency to be near hospital patients. High public transport accessibility in the hospital end is positively associated with public transit patients. However, poor bus and metro connectivity to selected hospitals strongly predicts belonging to the non-downtown hospital patients. The results point to a need for promoting public transport accessibility to non-downtown hospitals to reduce the disparities in tertiary hospitals vary by geographic location.

The results of this study are subject to several limitations. The nature of online surveys makes it hard to reach older people and those with acute or severe conditions. A hospital survey integrated with an online survey was recommended to better represent patients. In addition, only selected indicators in our framework are examined to identify the heterogeneity of patients and predictions of class membership, meaning that some factors may be left unexplained. For example, the travel companion of patients, which has been found to influence the patient healthcare travel mode choice, was not included in our data collection (M. Du et al., 2020). Further investigation may also include the factors of household composition, hospital reputation and equipment, treatment time and patient complexity of illness. Different public transport accessibility solutions, such as on-demand services, radial routes, and reduced waiting time, could also be tested. For the attitudinal statements of patients, it would be preferable to consider statements toward both healthcare travel and hospital choice in a Likert format in the future. Last, more complex spatial models that incorporate patient socioeconomic, demographic and mobility profiles and preferences are expected.

Author contribution statement

The authors confirm their contribution to the paper as follows: study conception and design: Ya Gao, Haixiao Pan, Khandker Nurul Habib; data collection: Zhilin Xie, Ya Gao; analysis and interpretation of results: Ya Gao; draft manuscript preparation: Ya Gao, Haixiao Pan, Khandker Nurul Habib. All authors reviewed the results and approved the final version of the manuscript.

Data availability

The authors do not have permission to share data.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jtrangeo.2023.103608.

References

Adams, E.K., Houchens, R., Wright, G.E., Robbins, J., 1991. Predicting hospital choice for rural Medicare beneficiaries: the role of severity of illness. Health Serv. Res. 26 (5), 583–612. http://www.pubmedcentral.nih.gov/articlerender.fcgi?artid=PMC1069844.

Ardeshiri, A., Vij, A., 2019. Lifestyles, residential location, and transport mode use: a hierarchical latent class choice model. Transp. Res. A Policy Pract. 126 (June), 342–359. https://doi.org/10.1016/j.tra.2019.06.016.

Bai, J.Y., 2020. Speed Up the Recovery of the Health Care in Shanghai. Chinanews. March 27. https://m.chinanews.com/.

Baker, L.C., Bundorf, M.K., Kessler, D.P., 2016. The effect of hospital/physician integration on hospital choice. J. Health Econ. 50, 1–8. https://doi.org/10.1016/j.jhealeco.2016.08.006.

Bronstein, J.M., Morrisey, M.A., 1991. Bypassing rural hospitals for obstetrics care. J. Health Polit. Policy Law 16 (1), 87–118. https://doi.org/10.1215/03616878-16-1-87.

Cao, W.R., Huang, Q.R., Zhang, N., Liang, H.J., Xian, B.S., Gan, X.F., Xu, D.R., Lai, Y.S., 2022. Mapping the travel modes and acceptable travel time to primary healthcare institutions: a case study in Inner Mongolia Autonomous Region, China. J. Transp. Geogr. 102 https://doi.org/10.1016/j.jtrangeo.2022.103381.

Celeux, G., Soromenho, G., 1996. An entropy criterion for assessing the number of clusters in a mixture model. J. Classif. 13, 195–212.

Chang, M.-C., Kahn, R., Li, Y.-A., Lee, C.-S., Buckee, C.O., Chang, H.-H., 2021. Variation in human mobility and its impact on the risk of future COVID-19 outbreaks in Taiwan. BMC Public Health 21 (1). https://doi.org/10.1186/s12889-021-10260-7.

Clarke, J., 2016. Difficulty accessing health care services in Canada. Health Glance 82, 11.

Cui, B., Boisjoly, G., Wasfi, R., Orpana, H., Manaugh, K., Buliung, R., Kestens, Y., El-Geneidy, A., 2020. Spatial access by public transport and likelihood of healthcare consultations at hospitals. Transp. Res. Rec. 2674 (12), 188–198. https://doi.org/10.1177/0361198120952793.

Davis, A.W., McBride, E.C., Goulias, K.G., 2018. A latent class pattern recognition and data quality assessment of non-commute long-distance travel in California. Transp. Res. Rec. 2672 (42), 71–80. https://doi.org/10.1177/0361198118787362.

Demitiry, M., Higgins, C.D., Páez, A., Miller, E.J., 2022. Accessibility to primary care physicians: comparing floating catchments with a utility-based approach. J. Transp. Geogr. 101 (March) https://doi.org/10.1016/j.jtrangeo.2022.103356.

Diaz, A., Cloyd, J.M., Manilchuk, A., Dillhoff, M., Beane, J., Tsung, A., Ejaz, A., Pawlik, T. M., 2021. Travel patterns among patients undergoing hepatic resection in California: does driving further for care improve outcomes? J. Gastrointest. Surg. 25 (6), 1471–1478. https://doi.org/10.1007/s11605-019-04501-9.

Dolnicar, S., Grün, B., 2007. How constrained a response: a comparison of binary, ordinal and metric answer formats. J. Retail. Consum. Serv. 14 (2), 108–122. https://doi.org/10.1016/j.jretconser.2006.09.006.

Du, M., Cheng, L., Li, X., Yang, J., 2020. Factors affecting the travel mode choice of the urban elderly in healthcare activity: comparison between core area and suburban area. Sustain. Cities Soc. 52 (September 2019), 101868 https://doi.org/10.1016/j.scs.2019.101868.

Du, F., Mao, L., Wang, J., 2021. Determinants of travel mode choice for seeking healthcare: a comparison between elderly and non-elderly patients. J. Transp. Geogr. 92 (October 2020) https://doi.org/10.1016/j.jtrangeo.2021.103023.

Everitt, B.S., Landau, S., Leese, O., Stahl, D., 2011. Cluster Analysis (5th Edition). Wiley.

Ewert, B., Wallenburg, I., Winblad, U., Bal, R., 2023. Any lessons to learn? Pathways and impasses towards health system resilience in post-pandemic times. Health Econ. Policy Law 18 (1), 66–81. https://doi.org/10.1017/S1744133122000238.

Frew, R., Higgs, G., Harding, J., Langford, M., 2017. Investigating geospatial data usability from a health geography perspective using sensitivity analysis: the example of potential accessibility to primary healthcare. J. Transp. Health 6, 128–142. https://doi.org/10.1016/j.jth.2017.03.013.

Gaode map, 2022a. Geocoding and Reverse Geocoding Manual. Accessed July 31 2022. https://lbs.amap.com/api/webservice/guide/api/georegeo.

Gaode map, 2022b. Route Planning Manual. Accessed July 31 2022. https://lbs.amap.com/api/webservice/guide/api/newroute.

Gatrell, A., Senior, M., 1999. Health and Health Care Applications. Geographical Information systems: Principles, Techniques, Applications and Management.

Hagenaars, J.A., McCutcheon, A.L., 2002. Applied Latent Class Analysis. Cambridge University Press. https://doi.org/10.1017/CBO9780511499531.

Hjelmgren, J., Anell, A., 2007. Population preferences and choice of primary care models: a discrete choice experiment in Sweden. Health Policy 83 (2–3), 314–322. https://doi.org/10.1016/j.healthpol.2007.02.006.

Ji, Y., Dong, J., Lai, Z., Feng, Q., 2022. Optimal allocation of shared parking spaces for hospital parkers considering parking choice behavior under bounded rationality. Transp. Lett 00 (00), 1–12. https://doi.org/10.1080/19427867.2022.2048226.

Jia, P., Wang, F., Xierali, I.M., 2019. Differential effects of distance decay on hospital inpatient visits among subpopulations in Florida, USA. Environ. Monit. Assess. 191 (381), 1–16. https://doi.org/10.1007/s10661-019-7468-2.

Jin, T., Cheng, L., Wang, K., Cao, J., Huang, H., Witlox, F., 2022. Examining equity in accessibility to multi-tier healthcare services across different income households using estimated travel time. Transp. Policy 121 (March), 1–13. https://doi.org/10.1016/j.tranpol.2022.03.014.

Kanuganti, S., Sarkar, A.K., Singh, A.P., 2016. Evaluation of access to health care in rural areas using enhanced two-step floating catchment area (E2SFCA) method. J. Transp. Geogr. 56, 45–52. https://doi.org/10.1016/j.jtrangeo.2016.08.011.

Lako, C.J., Rosenau, P., 2009. Demand-driven care and hospital choice. Dutch health policy toward demand-driven care: results from a survey into hospital choice. Health Care Anal. 17 (1), 20–35. https://doi.org/10.1007/s10728-008-0093-9.

Li, X., Zhang, Y., Du, M., 2018. Analysis of travel decision-making for urban elderly healthcare activities under temporal and spatial constraints. Sustainability (Switzerland) 10 (5). https://doi.org/10.3390/su10051560.

Li, S., Zhang, Y., Ruan, H., Guerra, E., Burnette, D., 2020a. The role of transportation in older adults' use of and satisfaction with primary care in China. J. Transp. Health 18. https://doi.org/10.1016/j.jth.2020.100898.

Li, X., Krumholz, H.M., Yip, W., et al., 2020b. Quality of primary health care in China: challenges and recommendations. Lancet 395 (10239), 1802–1812. https://doi.org/10.1016/S0140-6736(20)30122-7.

Linzer, D.A., Lewis, J.B., 2011. poLCA: an R package for polytomous variable latent class analysis. J. Stat. Softw. 42 (10 SE-Articles), 1–29. https://doi.org/10.18637/jss.v042.i10.

Lippi Bruni, M., Ugolini, C., Verzulli, R., 2021. Should I wait or should I go? Travelling versus waiting for better healthcare. Reg. Sci. Urban Econ. 89 (February 2020), 103697 https://doi.org/10.1016/j.regsciurbeco.2021.103697.

Liu, Y., Kong, Q., Wang, S., Zhong, L., van de Klundert, J., 2020. The impact of hospital attributes on patient choice for first visit: evidence from a discrete choice experiment in Shanghai, China. Health Policy Plan. 35 (3), 267–278. https://doi.org/10.1093/heapol/czz159.

Lu, C., Zhang, Z., Lan, X., 2019. Impact of China's referral reform on the equity and spatial accessibility of healthcare resources: a case study of Beijing. Soc. Sci. Med. 235 (April), 112386 https://doi.org/10.1016/j.socscimed.2019.112386.

Luo, L., Zhang, Y., Zhang, Y., Feng, C., Zhang, X., 2022. Large hospitals' outpatient diversion system in China: following individual intention and referral. Int. J. Health Plann. Manag. 10, 1973–1989. https://doi.org/10.1002/hpm.3436.

Ma, X., Ren, F., Du, Q., Liu, P., Li, L., Xi, Y., Jia, P., 2019. Incorporating multiple travel modes into a floating catchment area framework to analyse patterns of accessibility to hierarchical healthcare facilities. J. Transp. Health 15 (May), 100675. https://doi.org/10.1016/j.jth.2019.100675.

Mattson, J., 2011. Transportation, distance, and health care utilization for older adults in rural and small urban areas. Transp. Res. Rec. 2265, 192–199. https://doi.org/10.3141/2265-22.

Molin, E., Mokhtarian, P., Kroesen, M., 2016. Multimodal travel groups and attitudes: a latent class cluster analysis of Dutch travelers. Transp. Res. A Policy Pract. 83, 14–29. https://doi.org/10.1016/j.tra.2015.11.001.

Moses, M.W., Pedroza, P., Baral, R., et al., 2019. Funding and services needed to achieve universal health coverage: applications of global, regional, and national estimates of utilisation of outpatient visits and inpatient admissions from 1990 to 2016, and unit costs from 1995 to 2016. Lancet Public Health 4 (1), e49–e73. https://doi.org/10.1016/S2468-2667(18)30213-5.

National Bureau of Statistics, 2020. China Population Census Yearbook 2020. Accessed July 31 2022. http://www.stats.gov.cn/tjsj/pcsj/rkpc/7rp/zk/indexce.htm.

National Health Commission of the P. R China, 2022. China Health Statistics Yearbook (2010, 2022). Accessed July 31 2022. http://www.nhc.gov.cn/wjw/gongb/list.shtml.

Neutens, T., 2015. Accessibility, equity and health care: review and research directions for transport geographers. J. Transp. Geogr. 43, 14–27. https://doi.org/10.1016/j.jtrangeo.2014.12.006.

Oluyede, L., Cochran, A.L., Prunkl, L., Wang, J., Wolfe, M., McDonald, N.C., 2022. Unpacking transportation barriers and facilitators to accessing health care: interviews with care coordinators. Transp. Res. Interdiscip. Perspect. 13, 100565 https://doi.org/10.1016/j.trip.2022.100565.

Palm, M., Sturrock, S.L., Howell, N.A., Farber, S., Widener, M.J., 2021. The uneven impacts of avoiding public transit on riders' access to healthcare during COVID-19. J. Transp. Health 22 (June), 101112. https://doi.org/10.1016/j.jth.2021.101112.

Patel, S.Y., Mehrotra, A., Huskamp, H.A., Uscher-Pines, L., Ganguli, I., Barnett, M.L., 2021. Trends in outpatient care delivery and telemedicine during the COVID-19 pandemic in the US. JAMA Intern. Med. 181 (3), 388–391. https://doi.org/10.1001/jamainternmed.2020.5928.

Pucher, J., Buehler, R., 2010. Walking and cycling for healthy cities. Built Environ. 36 (4), 391–414.

Rafiq, R., McNally, M.G., 2021. Heterogeneity in activity-travel patterns of public transit users: an application of latent class analysis. Transp. Res. A Policy Pract. 152 (August), 1–18. https://doi.org/10.1016/j.tra.2021.07.011.

Shabanpour, R., Golshani, N., Derrible, S., Mohammadian, A., Miralinaghi, M., 2017. Joint discrete-continuous model of travel mode and departure time choices. Transp. Res. Rec. 2669, 41–51. https://doi.org/10.3141/2669-05.

Shah, H., Carrel, A.L., Le, H.T.K., 2021. What is your shopping travel style? Heterogeneity in US households' online shopping and travel. Transp. Res. A Policy Pract. 153, 83–98. https://doi.org/10.1016/j.tra.2021.08.013.

Shanghai Municipal Bureau of Statistics, 2022. Shanghai Economic and Social Development Statistics Bulletin (2021), 2022. Accessed July 31 2022. http://tjj.sh.gov.cn/tjgb/20220314/e0dcefec098c47a8b345c996081b5c94.html.

Shanghai Municipal Health Commission, 2021. Accessed July 31 2022. https://wsjkw.sh.gov.cn/fwjg/20180601/0012-55891.html. https://wsjkw.sh.gov.cn/fwjg/20180815/0012-61976.html.

Sharma, G., Patil, G.R., 2021. Public transit accessibility approach to understand the equity for public healthcare services: a case study of Greater Mumbai. J. Transp. Geogr. 94 https://doi.org/10.1016/j.jtrangeo.2021.103123.

Shen, Y., Tao, Y., 2022. Associations between spatial access to medical facilities and health-seeking behaviors: a mixed geographically weighted regression analysis in Shanghai, China. Appl. Geogr. 139, 102644 https://doi.org/10.1016/j.apgeog.2022.102644.

Sivey, P., 2012. The effect of waiting time and distance on hospital choice for english cataract patients. Health Econ. 21, 444–456. https://doi.org/10.1002/hec.

Smith, H., Currie, C., Chaiwuttisak, P., Kyprianou, A., 2018. Patient choice modelling: how do patients choose their hospitals? Health Care Manag. Sci. 21 (2), 259–268. https://doi.org/10.1007/s10729-017-9399-1.

Syed, S.T., Gerber, B.S., Sharp, L.K., 2013. Traveling towards disease: transportation barriers to health care access. J. Community Health 38 (5), 976–993. https://doi.org/10.1007/s10900-013-9681-1.

Tai, W.T.C., Porell, F.W., Adams, E.K., 2004. Hospital choice of rural medicare beneficiaries: patient, hospital attributes, and the patient-physician relationship. Health Serv. Res. 39 (61), 1903–1922. https://doi.org/10.1111/j.1475-6773.2004.00324.x.

Tayyari Dehbarez, N., Gyrd-Hansen, D., Uldbjerg, N., Søgaard, R., 2018. Does free choice of hospital conflict with equity of access to highly specialized hospitals? A case study from the Danish health care system. Health Policy 122 (7), 722–727. https://doi.org/10.1016/j.healthpol.2018.04.006.

Tein, J., Coxe, S., Cham, H., Tein, J., Coxe, S., Cham, H., 2013. Statistical power to detect the correct number of classes in latent profile analysis. Struct. Equ. Model. Multidiscip. J. 20 (4), 640–657. https://doi.org/10.1080/10705511.2013.824781.

The Lancet, 2019. A tieredhealthcare delivery system for China. Lancet 393 (10177), 1178. https://doi.org/10.1016/S0140-6736(19)30730-5.

Varkevisser, M., van der Geest, S.A., Schut, F.T., 2012. Do patients choose hospitals with high quality ratings? Empirical evidence from the market for angioplasty in the Netherlands. J. Health Econ. 31 (2), 371–378. https://doi.org/10.1016/j.jhealeco.2012.02.001.

Varotto, S.F., Glerum, A., Stathopoulos, A., Bierlaire, M., Longo, G., 2017. Mitigating the impact of errors in travel time reporting on mode choice modelling. J. Transp. Geogr. 62, 236–246. https://doi.org/10.1016/j.jtrangeo.2017.05.016.

Vermunt, J.K., 2010. Latent class modeling with covariates: two improved three-step approaches. Polit. Anal. 18 (4), 450–469. https://doi.org/10.1093/pan/mpq025.

Victoor, A., Delnoij, D.M., Friele, R.D., Rademakers, J.J., 2012. Determinants of patient choice of healthcare providers: a scoping review. BMC Health Serv. Res. 12, 272. https://doi.org/10.1186/1472-6963-12-272.

Wallace, R., Hughes-Cromwick, P., Mull, H., Khasnabis, S., 2005. Access to health care and nonemergency medical transportation: two missing links. Transp. Res. Rec. 1924, 76–84. https://doi.org/10.3141/1924-10.

Wang, F., 2012. Measurement, optimization, and impact of health care accessibility: a methodological review. Ann. Assoc. Am. Geogr. 102 (5), 1104–1112. https://doi.org/10.1080/00045608.2012.657146.

Weiss, D.J., Nelson, A., Vargas-Ruiz, C.A., et al., 2020. Global maps of travel time to healthcare facilities. Nat. Med. 26 (12), 1835–1838. https://doi.org/10.1038/s41591-020-1059-1.

Wolfe, M.K., McDonald, N.C., Holmes, G.M., 2020. Transportation barriers to health care in the United States: findings from the National Health Interview Survey, 1997-2017. Am. J. Public Health 110 (6), 815–822. https://doi.org/10.2105/AJPH.2020.305579.

Zeng, Y., Xu, W., Chen, L., Chen, F., Fang, Y., 2020. The influencing factors of health-seeking preference and community health service utilization among patients in primary care reform in xiamen, china. Patient Prefer. Adher. 14, 653–662. https://doi.org/10.2147/PPA.S242141.

Zhang, Y., Li, W., Deng, H., Li, Y., Liu, T., 2020. Evaluation of public transport-based accessibility to health facilities considering spatial heterogeneity. J. Adv. Transp. 2020 https://doi.org/10.1155/2020/7645153.