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Title

Public preferences for health care facilities in rural China: a discrete choice experiment

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Public preferences for health care facilities in rural China: a discrete choice experiment

Abstract

To successfully tackle the problems with the underutilization of primary care in rural China, it is important to align resource allocation with the preferences of the rural population. However, despite growing interest in the factors influencing the rural population's choice of facility, it is unclear how much weight should be placed on these factors, especially under different scenarios of disease severity. In the first study to elicit quantified trade-offs among influential factors in choosing health care facilities, we carried out a discrete choice experiment (DCE) in rural China. We used a Bayesian efficient design to construct 36 choice sets, and then divided them into three blocks. Each block formed one version of questionnaire that contained 12 choice questions. Each question was assigned a hypothetical perceived severity scenario of either minor or severe disease. 559 Rural residents completed the DCE through face-to-face interviews in December 2017 – March 2018. We used mixed logit models to analyze the choice data. The factors regarding the availability and affordability of a facility, such as visit time, travel time, and out-of-pocket cost, were highly valued. When the facilities changed simultaneously from the worst to the best case, a huge increase (from 4.8% to 66.5%) in the predicted choice probability of choosing to visit a facility was observed under perceived minor disease scenario, whereas there was no significant change under perceived severe disease scenario. Improvements to drug availability, medical professional skill and equipment in rural primary care system can induce potential medical care seeking, and redirect patient flow from higher level hospitals to primary level. Especially, township health centers, which provide service to the residents in rural communities, have great potential to be the ideal facilities for first-contact care.

Keywords

Discrete choice experiment; China; stated preferences; health-seeking behavior; rural health

1. Introduction

In China, health care facilities in rural areas are generally equipped with less qualified workforce and provide less comprehensive services compared to secondary or tertiary hospitals (Li et al., 2017; G. Liu et al., 2017), which are mostly concentrated in urban areas (Wang et al., 2018). Lack of competence is especially prominent in the rural primary care system. In this system, township health centers (THCs) act as the backbone, providing primary care and public health services to the population in rural communities (townships) (National Health and Family Planning Commission of the People's Republic of China, 2009; Wang et al., 2018). In addition, they also provide technical training to the doctors at village clinics (VCs) (Babiarz et al., 2012; Li et al., 2017). A study shows that 10% of the surveyed THCs could not perform routine medical diagnostics, such as blood or urine tests, while the percentage of VCs was even lower (Li et al., 2017). In less developed regions, over 30% of the medical professionals at THCs were unlicensed. The situation is even worse in VCs, where only 24% of the staffs hold licenses (Li et al., 2017). The education level of the staffs at these primary care facilities is also inadequate in that a large proportion hold diplomas below the required level (Li et al., 2017). As a result, the rural population – usually characterized by lower literacy and worse-off economic status than their urban counterparts (National Bureau of Statistics, 2017; Ren et al., 2018) – appear to benefit less from health services, especially primary care (Zhai et al., 2017).

Literature has confirmed that a good primary care system is essential for the overall wellbeing of population health (Starfield et al., 2005). Indeed, rural residents may choose to travel further to seek medical care, including primary care, at higher expense, since there is no gatekeeping role (Yip and Hsiao, 2014). Previous literature has shown that rural residents' visits to secondary and tertiary hospitals keep increasing over years, leading to low utilization of THCs and VCs (Yip and Hsiao, 2014). As a result, the primary care system may lose its significance in availing people to address community health problems by bringing the first level of contact as close as possible to where people live ("Primary Health Care:

Declaration of Alma-Ata," 1978). Underutilization of primary care facilities and the increasing demand for hospital care not only impair the availability of primary care to rural residents, but also undermines system efficiency, which in turn exacerbates the problem of overcrowded tertiary hospitals (G. Liu et al., 2017).

To improve the capacity of rural primary care facilities and alter the patient flow, the Chinese government has rolled out numerous policies, such as increased investment in the infrastructure of primary care facilities (Li et al., 2017; Yip and Hsiao, 2014) and financial incentives for both demand and supply sides (Timothy Powell-jackson, 2015; Yip et al., 2010). Unfortunately, as yet these policies have not shown any significant effect on improving the utilization of these facilities (National Health Commission of the People's Republic of China, 2018; Yip and Hsiao, 2014).

A series of factors are reported to influence health services utilization (Olenja, 2003). The impacts of these factors is not necessarily homogenous, but may be conditional on individual and contextual factors (Andersen and Davidson, 2007). Hence, scientific evidence to understand how influential factors exert an impact on rural residents' health-seeking behavior is essential for medical resource allocation to achieve the desired enhancement in utilization of rural facilities.

The issues regarding the influential factors and choice of care seeking have drawn considerable attention from researchers. Liu et al. synthesized such empirical studies on both rural and urban areas in a systematic review, which has shown that the factors influencing patients' choice can be categorized as individual, context, facility and composite factors (Liu et al., 2018a). Another study found that choice behavior also depended on perceived disease severity and stages in the health seeking process (Liu et al., 2018b). Various studies reported that both rural and urban patients regarded informal care or taking no action as alternatives to seeking medical care from a facility, especially for perceived minor disease (Liu et al., 2018b). Despite the growing recognition, the published studies have various limitations. First, no prior study is able to provide information on the relative weight of the factors that influence the rural residents' facility choices, although studies included both revealed and stated preference data (see Liu et al., 2018a for a summary of examples). Instead, respondents were asked only to evaluate the attributes independently (Jin et al., 2017; Wu et al., 2017). With those data, researchers cannot investigate the trade-offs among the attributes, nor can they simulate choice trends triggered by modifying certain factors of health care facilities. In addition, many studies recruited patients who were visiting a certain facility as the study sample, which means that they had already made a decision. The literature has well recognized that such sampling method may lead to skewed results on public preferences (e.g. Wu et al., 2017). Hence, there is a paucity of quantitative evidence for evaluation of the relative impacts of influential factors on facility choice behavior.

To bridge these gaps, this study aimed to elicit the Chinese rural public's preferences and trade-offs for first-contact health care facility in a discrete choice experiment (DCE). DCE is a stated preference technique widely used in health service research (Soekhai et al., 2018). Based on random utility theory, it assumes that respondents always prefer the alternative that offers the greatest utility, and its overall utility is decomposed by its attributes in DCE (Viney et al., 2002). By virtue of the theoretical basis of DCE, one can elicit the quantified importance of each attribute in the choice process as well as the trade-offs that the respondents are willing to make. Based on the findings in the literature, we incorporated the impact of perceived disease severity in preferences for health care facility, the option of opting out instead of seeking formal care from a facility, and individual factors into analysis. Also, any changes in the probability of choosing a facility brought by modifying its attribute levels can be predicted in DCE (Lancsar et al., 2007b), which allows us to estimate the impact of real-world decisions and analyze the implications for practice.

2. Methodology

Unlike other stated preference methods that frame abstract questions (Milte et al., 2018), DCE respondents are asked to make choices in hypothetical choice scenarios consisting of various levels of pre-defined attributes. Therefore, the choice is not made from certain types of goods in interest, but in essence aims to elicit the relative impact of generic attributes. This section describes the two systematic steps taken in conducting DCE: (1) design development and (2) DCE implementation. This is followed by a description of the data analysis method.

2.1 Study design development

2.1.1 Selection of attributes

It is critical to develop attributes and levels to establish the validity of a DCE (Determann et al., 2016). Due to task complexity and to ensure precision and reliability, only a few attributes and levels can be included. It thus requires a trade-off between the comprehensiveness of influential factors and cognitive manageability for respondents (Bridges et al., 2011). We selected the attributes and their corresponding levels through a systematic review (Liu et al., 2018a) and focus group interviews (Liu et al., 2018b). The focus group interviews identified a set of factors that influence facility choice for first contact. Among these factors, we selected those related to health care facilities and defined them as the attributes in the DCE. We then decided on the attribute levels based on the information we obtained from the focus group interviews and the systematic review. Table 1 shows the eight attributes included in the final design, comprising six provider factors and two composite factors conform the literature (Liu et al., 2018a). The hypothetical severity was differentiated as perceived minor or severe condition, hereafter referred to as "in a minor scenario" and "in a severe scenario", respectively.

2.1.2 DCE design

We used Ngene (ChoiceMetrics, version 1.1.1) to create the DCE design. Each choice set includes two facility alternatives in the generic form (Ryan et al., 2008) – facility A and facility B – with various attribute levels. Each choice set includes an opt-out option (Figure 1), which resembles the case when patients do not choose any facility but either go for informal care or do nothing. Compared to DCEs that do not present an opt-out option, DCEs that have opt-out options have lower risk of overestimating attribute influence (Louviere and Lancsar, 2009; Veldwijk et al., 2014). Each choice set specifies a hypothetical disease severity, which was consistent across the alternatives in each set. The severity was attributed to each choice set with the two-way interaction function in Ngene.

INSERT FIGURE 1 HERE

INSERT TABLE 1 HERE

The number of attributes and levels (6*3 levels+2*2 levels) leads to a very large number of choice tasks for a full-factorial design, which is deemed impractical (Johnson et al., 2013). Therefore we used Ngene to create an efficient design that maximized the D-efficiency. It generated a subset of the full design including 36 choice tasks which were divided into three blocks using design theory (blocked design). Each version of the questionnaire included 12 choice questions and they were evenly distributed among the respondents (Johnson et al., 2013).

We conducted a two-stage pilot to achieve the final version of the Chinese questionnaire. In the first stage, we carried out three interviews to check if respondents misunderstood or had difficulty in completing the questionnaire. After that, we refined the format and fine-tuned the expression according to the feedback. Then we applied the refined questionnaires in a formal pilot on 48 respondents. No signs of response fatigue were observed by the interviewers, and the respondents indicated that the task complexity and number of choices were manageable. The pilot data was also used as prior information to optimize the design for a multinomial logit model. To avoid frequently switching scenarios across the choice questions, which would bring cognitive burden, we grouped the questions according to disease severity. Intuitively, a severe condition could have bigger cognitive influence than a minor condition; we therefore presented the ones under minor conditions first, followed by the ones under severe conditions. Another part of the questionnaire collected 11 individual characteristics that were found to correlate with the choice of health care facility in literature (Liu et al., 2018a, 2018b) (Table 2).

2.2 Data collection

Chongqing is a city located in southwest China with a total population of 33.89 million, in which 17.53 million are rural residents in 2017. There were 38 counties, including 626 rural townships. The sample of this study were rural residents older than 18 years in Chongqing. The recruitment was supported by the local health bureau, who helped us select a study county and its five townships based on their staffs' availability. As in the study county there were in total 14 townships which were relatively homogenous, we did not impose any restriction on the township selection method. We calculated the sample size in R software by using the code proposed by de Bekker-Grob et al. (de Bekker-Grob et al., 2015). The result indicated that a sample size of 500 is sufficient. Stratified sampling method was used to ensure the sample representativeness. Specifically, the strata were pre-defined by gender (female or male) and age (18-45 years or >45 years) of the local population (National Bureau of Statistics of China, 2010). Table 2 lists the pre-defined sample quota and the respondents' characteristics.

The local health bureau assigned study coordinators to approach the respondents in each township. Before and during the pilot, the first author trained the study coordinators to administer the questionnaire. They first screened the residential registration databases to find eligible respondents and then collected the data with paper and pen through door-to-door visits, until the pre-defined sample quota was reached. Before administering the questionnaire, the study coordinators briefly explained the procedure and reminded respondents to answer each question in the indicated hypothetical severity scenario. They also made sure that the respondents understood the survey by giving further clarifications if necessary. Each respondent received a small token of reward (valued 2.5 US dollars) on completing the questionnaire. The rural respondents were recruited from five townships from December 2017 to March 2018.

2.3 Data analysis

2.3.1 Statistical analysis

Over the data collection period, 608 residents were invited to participate in the survey. Among them, 559 respondents answered at least one choice question. We included all the 559 questionnaires in the final analysis so as to include as much available preference information as possible. Our response rate is 91.9%. The questionnaires from 27 out of 559 respondents (4.8%) included missing choice data. The data was analyzed with Stata 15 software (StataCorp. 2017. Stata Statistical Software: Release 15. College Station, TX: StataCorp LLC). The interaction terms were constructed by interacting the disease severity term with each main attribute. Effects coding was used for all main attributes and dummy coding was used for opt-out and the interaction terms (Bech and Gyrd-Hansen, 2005). We estimated mixed logit models for the choice observations, which can capture the panel nature of the choice data in DCE (Clark et al., 2014; Hauber et al., 2016). We tried different combinations of ways to specify coefficients as random parameters or fixed parameters (Hensher et al., 2005). The final model was selected with the consideration of lower Akaike Information Criterion and the aim of arriving at a parsimonious model. To avoid divisions by zero and positive coefficients for cost, all cost-related attributes were modeled as fixed parameters (Bliemer and Rose, 2013). We used normal distributions for the random parameters. Formal testing showed no evidence of left-right bias between the opt-in alternatives (p=0.119).

INSERT TABLE 2 HERE

In the model results, the coefficients of each main attribute represent the effect size in the minor disease scenario compared to its grand mean. The coefficients of the interaction terms represent the changes in preferences when the hypothetical disease severity changes from minor to severe. Therefore, we conducted ex-post calculation of each main attribute’s coefficient in the severe disease scenario, by adding the corresponding coefficient under minor condition and its coefficient of the severity interaction term. The relative importance (RI) of each main attribute represents the relative weight of its impact on the decision making. It is calculated by dividing the difference between the highest and lowest utility of the levels of an attribute by the sum of such difference of all attributes (Lancsar et al., 2007b).

We built separate models to investigate the impact of demographic attributes on the respondents' preferences for health care facilities in the hypothetical minor and severe disease scenarios, respectively. For these two models, we created binary variables for the demographic attributes shown in Table 2 (see Table S1 for a list of the binary variables). We used those variables to interact with each main attribute. The main attributes were modeled as random effects except for the cost attributes, and all other interaction terms were treated as fixed effects.

Marginal willingness to pay (WTP) is the monetary amount that an individual is willing to pay for one unit change in the attribute of interest (Clark et al., 2014; Lancsar and Louviere, 2008). We calculated the WTP for the attributes with significant effects in the two hypothetical severity scenarios by taking the ratio of the coefficient of an attribute to the monetary attribute (Bridges et al., 2011). The WTP results can be found in Appendix 1.

2.3.2 Predicted choice probabilities

The overall utility score of an alternative is defined as the sum of all coefficients associated with its attribute levels (Hauber et al., 2016; Lancsar et al., 2007b). In DCE, the predicted choice probability of a facility is calculated based on the stated choice data, by taking the exponent of the alternative's utility divided by the sum of the exponent of all available alternatives in the choice set (Lancsar et al., 2007b). In this study, we calculated the predicted choice probabilities of choosing to visit any facility shown on the choice sets over opting out, and recorded the changes when one attribute was modified each time. In addition, the predicted choice probabilities of choosing to visit any facility for first-contact care, when it carried highest utility (best case) or lowest utility (worst case), were also calculated. As the variables were effect-coded, the modifications on attribute levels represent the estimates relative to the mean preferences, when each attribute carries its mean value (de Bekker-Grob et al., 2018; Lancsar et al., 2007a).

3. Results

3.1 DCE results

(1) Preferences under different hypothetical disease severities

Table 3 shows the coefficients for different hypothetical severity scenarios. The significance of the coefficients indicates that attribute level has a significant impact on the choice of health care facilities. The sign of a coefficient indicates the negative or positive impact of the attribute (level) on the utility of the alternative. In general, all attributes have significant impact in both scenarios, except drug availability in the severe disease scenario (p=0.077).

For both of the hypothetical severity scenarios, the positive signs of “time taken for a visit”, “OOP for a visit” and “travel time” indicate that respondents preferred facilities that consumed less time for a visit, less OOP, and shorter travel time, compared to those generating a longer time for a visit, higher OOP and longer travel time. Noteworthy, the middle level of travel time experienced a variation across the two hypothetical severity scenarios. In the minor scenario, only the shortest time generated utility gain, and the other two levels were attached with significant utility loss. However, the middle level showed no significance in the severe scenario, which suggests the respondents were more tolerant of a 1 hour long travel time as compared to the minor scenario. The positive signs of “medical equipment condition” and “drug availability” indicate that respondents preferred facilities that could offer advanced equipment and sufficient drugs. The positive signs of “personal connection in the facility” in both scenarios indicate that respondents preferred having personal connections compared to having no connection at all. For the two levels of personal connection, “know someone but not very familiar with them” was more preferred than “direct personal connection” in the minor scenario, while in the severe scenario, respondents did not significantly prefer either of these personal connection circumstances. The different signs and significance of the levels of “medical professionals’ skill” indicate that respondents’ preferred senior doctors most, followed by junior doctors and experts in the minor scenario; in the severe scenario, senior doctors were most preferred, followed by experts and junior doctors. Similarly, for facility size, under minor scenario respondents preferred small or mid-sized over large facilities, but found no difference between small and mid-sized. In the severe scenario, the mid-sized facilities were most favorable while the small ones were the least preferred. The different signs of opt-out in two severity scenarios indicate a strong preference to opt-out for perceived minor diseases, and to visiting a facility for perceived severe diseases.

The interaction terms in Table 3 indicate significant changes in utility between the two hypothetical severity scenarios. Most obviously, the respondents experienced large utility loss for opting out in the severe scenario in comparison to the minor scenario. They also attached less utility gain for OOP 25RMB and 1 hour visit time in the severe scenario, and perceived increased utility for available experts.

INSERT TABLE 3 HERE

The relative importance shown in Figure 2 indicates that in the minor disease scenario, respondents gave most importance to the time taken for a visit, followed by OOP, personal connection and travel time. In contrast, in the severe scenario, the respondents attached highest importance to the travel time, followed by OOP, visit time and medical skill.

INSERT FIGURE 2 HERE

(2) Preference heterogeneity

Results of the preference heterogeneity analysis in different hypothetical severity scenarios are in Table 4. In the minor disease scenario, five out of ten individual attributes played significant roles in decision making: age, number of family members, family income, insurance type, and facility experience. The negative coefficient of the interaction between opt-out and age indicated that the older the respondents were, the less utility they attached to opting out. Respondents who had more living-together family members, experienced utility loss from direct personal connection and sufficient drug but attached more utility to the one-hour travel time than those who had fewer family members. Respondents with higher family income valued a three-hour visit time and direct personal connection less than those from a lower-income family. Compared to those who contracted with URRBMI, respondents contracted with UEBMI placed less utility on 25 RMB OOP cost and opt-out. Respondents who used to visit higher level facilities in urban areas valued the shortest visit time, direct personal connection and shortest travel time more than those who had only visited village clinics or THC.

Four individual attributes had significant influence on the preferences in the severe disease scenario: employment status, marriage status, number of family members and health status. Employed respondents placed less utility on the lowest OOP cost than those who were unemployed or peasants. Married respondents attached more utility to opting out than their unmarried counterparts. The respondents with more family members valued the level of staff seniority “many senior doctors” more than those with fewer family members. The respondents who evaluated themselves as having average or better health status attached more utility to the middle level of OOP, but less utility to the lowest OOP level.

INSERT TABLE 4 HERE

3.2 Predicted choice probabilities of choosing to visit a facility vs. opting-out

Figure 3 shows the predicted choice probabilities of any facility (with different combinations of attribute levels) over opting out for first contact. The predicted choice probabilities of choosing to visit a reference facility are 25.0% and 99.95% in both the minor and severe disease scenarios, respectively. Change in one single level departing from the reference case could vary the probability of choosing to visit a facility from 16.8% to 33.4% in the minor disease scenario; while the range of the probability in the severe disease scenario was much smaller (from 99.94% to 99.97%). In the minor scenario, both the largest decrease and increase in the probability of choosing to visit any facility occurred when modifying the visit time. In the severe disease scenario, modifying the OOP to its highest level generated the largest decrease in the probability of choosing to visit any facility, while the largest increase was brought by shortening the travel time to 30 minutes. Figure 3-c shows the predicted choice probabilities of choosing to visit a worst-case, average-case, and best-case facility under both of the hypothetical scenarios. When a facility changes from its worst- to best-case, a huge increase (from 4.8% to 66.5%) in the probability of choosing any facility is observed in the minor scenario whereas there is not much change (from 99.80% to 99.99%) in the severe scenario.

INSERT FIGURE 3 HERE

4. Discussion

(1) Results interpretation

To the best of our knowledge, this is the first DCE which systematically assessed the impacts of factors influencing the stated choice of health care facilities for first-contact care in rural China. It expands the knowledge regarding the health-seeking behavior of rural residents for different disease severities. In the minor disease scenario, the predicted choice probability of choosing any facility over opting out rose dramatically from 4.8% to 66.5% if the available facilities were changed from the worst to the best case. This large increase reflects that the potential demand of health care depends on the factors identified in this study and that suppressed demand can be recovered when the available facilities improve (Levesque et al., 2013; Yu et al., 2015). In other words, it confirms the relevance of these factors with respect to the opt-out option.

All attributes in the model had a significant impact on the respondents' choices, except drug availability in the severe disease scenario. Interestingly, the residents generally considered the factors concerned with the availability and affordability of health care the most important (Levesque et al., 2013). In the minor scenario, visit time and OOP stood out with the largest impact on the preferences. In the severe scenario, travel time, followed by OOP, more influence on the preferences than the other attributes. In contrast, the provider factors directly related to the provision of care, such as medical skill and equipment, were never the most influential factors for both severity scenarios, although they gained utilities in the severe scenario compared to the minor. Such findings can be intuitively explained by people wanting quick and relatively cheap treatment as the ailment is usually easy to treat for minor diseases. For severe disease, the concern regarding the affordability can be associated with the worse-off economic status of rural residents, reflected by the high importance attached to cost. Drawing on other researches, factors pertaining to travel and visit time may relate to the high dependence on family caregivers in the Chinese culture (Qiu et al., 2018). In this situation, those factors represent convenience not only for the patient, but also for family caregivers who accompany the patient on facility visits. It merits further research, probably using qualitative methods, to gain insights to the underlying motives.

Furthermore, choosing to visit a medical expert or a large-size hospital has never been the level the respondents preferred most for first-contact care, even in the severe disease scenario. This may be linked to the lower literacy level of the rural population, which was acknowledged in a previous study (Liu et al., 2018b). Rural residents usually found it difficult to navigate themselves and became frustrated when seeking help in tertiary hospitals. They also found that the medical experts were usually willing to devote very limited consulting time for each patient (Liu et al., 2018b). In respect of facility size, all other things being equal, the respondents were less likely to choose a big hospital than the facilities of any other in the minor disease scenario, whereas they were less likely to choose a small hospital than those of any other larger size in the severe scenario. However, although this attribute clearly indicates preferences in terms of facility size, it was ranked least important factor in the minor scenario and the third from last one in the severe scenario, respectively. While it has been observed that in practice, people tend to choose tertiary hospital (Wu and Lam, 2016; Yip and Hsiao, 2014), one can expect that the popular term “big hospital” used in health care related narrations in the Chinese health system may not represent physical size only, but other underlying factors commonly associated with size; in other words, the influence of the facility size is carried by other intrinsic attributes. Further qualitative studies are called for to explore the insights. Drug availability is the only attribute that lost significance under severe condition. One possible explanation for this finding is that patients are likely to rely on sophisticated diagnostic methods or interventions rather than medicine to diagnose or cure severe diseases, especially for first-contact care (Li et al., 2018; Yu et al., 2010).

We observed that the ideal facility that meets the respondents’ demands for first-contact care in both severity scenarios has the following attributes: in mid-sized, short distance from home, not too time-consuming for a visit, having some senior doctors, good enough equipment and sufficient drugs, with some personal connection, 25–76RMB as OOP per visit. Based on the functions of THCs in rural health system and their current capacity (National Health and Family Planning Commission of the People’s Republic of China, 2009; Wang et al., 2018), THCs have the potential to be the ideal facilities for first-contact care in terms of size, distance and visit time. It can be expected that with investment in staff upskilling and medical equipment, and improvements to drug availability of THCs, rural residents are very likely to choose THCs for first-contact care in both severity conditions.

The benefits of resource allocation favorable to primary level facilities have been well recognized (G. Liu et al., 2017). Moreover, scientific evidence also shows that diverting resources to encourage the competitions among tertiary hospitals may not bring benefits in health care, but enlarge the disparity between rural and urban areas in terms of health care availability (Cai et al., 2018; Lin et al., 2018). Building on the above findings, we conclude that resource allocation in favor of THCs may effectively guide patient flow to primary level in rural areas, and hence improve the system efficiency and population health. The findings in the current study can be cautiously compared with those in the literature. For example, one study that analyzed the data from a household survey (Qian et al., 2009) revealed that cost and distance were the most influential factors, but distance mattered less when health status was worse-off. In the current study, travel time was considered even more important when the disease was perceived as severe, although the middle level of travel time is more preferred than the other two levels. As in Qian et al. (2009) the stage of health-seeking behavior were not specified, and the disease severity was reflected by the number of bed-days, it is hard to judge if these results are comparable to those in current study.

(2) Study limitations and future research

As the first study that captures the quantitative impact of factors influential in choosing health care facilities, this study inevitably has its limitations that necessitate further investigation. For example, the DCE in this study focused on the first-contact facility only. Generalizing the results to overall health care seeking behavior or subsequent phases in the seeking process requires further investigation, as different sets of factors have been identified for consideration in different phases (Liu et al., 2018b). In addition, the results may gain credibility if they were compared with revealed preferences derived from the real-world data, such as visit records from health care facilities. Further, as we used fractional datasets to analyze the impacts of attributes under two disease severities, the results for the impact of demographic attributes should be interpreted cautiously. Mixed logit models can describe the impact of such attributes via interaction terms, but are unable to discover the underlying rationale in depth. Preference heterogeneities may be correlated to or mediated by profound attitudes to risk (N. Liu et al., 2017), or to uncertainty (Peyron et al., 2018), and can be better explained through qualitative interviews, for example, why older respondents attach less utility to opting out than younger respondents. Finally, as we grouped the questions by the severity scenario to lessen the cognitive burden for respondents, this may have generated ordering bias to the results under severe condition that were presented after minor disease. Similarly, due to practical reasons, we did not randomize the order of the attributes in the choice sets due to practical reasons, therefore ordering bias may also occur as consequence.

(3) Conclusion

Factors regarding the availability and affordability of a facility, such as visit time, travel, and OOP cost, are valued highly by rural residents when they choose a health care facility for first-contact care. In addition, rural residents attached different relative importance to these factors in the minor and severe disease condition. Improvements to drug availability, medical professionals' skill and equipment in rural primary care system can induce potential medical care seeking. Especially, such improvements on THCs may effectively direct patient flow from secondary or tertiary hospitals to the primary level. This study provides evidence for policy making on aligning health resource allocation with rural residents' preferences, a strategy aimed at motivating rational utilization of health care services in China.

References

Andersen, R.M., Davidson, P.L., 2007. Improving Access to Care in America: Individual and Contextual Indicators, in: Changing the US Health Care System: Key Issues in Health Services Policy and Management. pp. 3–31. https://doi.org/10.1186/s12914-015-0056-9

Babiarz, K.S., Miller, G., Yi, H., Zhang, L., Rozelle, S., 2012. China's new cooperative medical scheme improved finances of township health centers but not the number of patients served. Health Aff. 31, 1065–1074. https://doi.org/10.1377/hlthaff.2010.1311

Bech, M., Gyrd-Hansen, D., 2005. Effects coding in discrete choice experiments. Health Econ. 14, 1079–1083. https://doi.org/10.1002/hec.984

Bliemer, M.C.J., Rose, J.M., 2013. Confidence intervals of willingness-to-pay for random coefficient logit models. Transp. Res. Part B 58, 199–214. https://doi.org/10.1016/j.trb.2013.09.010

Bridges, J.F.P., Hauber, A.B., Marshall, D., Lloyd, A., Prosser, L.A., Regier, D.A., Johnson, F.R., Mauskopf, J., 2011. Conjoint Analysis Applications in Health—a Checklist: A Report of the ISPOR Good Research Practices for Conjoint Analysis Task Force. Value Heal. 14, 403–413. https://doi.org/10.1016/j.jval.2010.11.013

Cai, M., Liu, E., Tao, H., Qian, Z., Lin, X., Cheng, Z., 2018. Does Level of Hospital Matter? A Study of Mortality of Acute Myocardial Infarction Patients in Shanxi, China. Am. J. Med. Qual. 33. https://doi.org/10.1177/1062860617708608

Chongqing Municipal Human Resources and Social Security Bureau, 2018a. Chongqing Urban Employee Basic Medical Insurance Policy [WWW Document]. URL http://www.beibei.gov.cn/publicity_bbq/fgwj/zcjd__fgwj/zcjd/19182

Chongqing Municipal Human Resources and Social Security Bureau, 2018b. Chongqing Urban and Rural Residents Basic Medical Insurance [WWW Document]. URL http://www.dazu.gov.cn/tszf/publicity/zcjd/206393

Chongqing Municipal Human Resources and Social Security Bureau, 2017. Policy Interpretation of Cooperative Medical Insurance of Urban and Rural Residents in Chongqing [WWW Document]. URL http://www.cq.gov.cn/publicinfo/web/views/Show!detail.action?sid=4124875

Clark, M.D., Determann, D., Petrou, S., Moro, D., de Bekker-Grob, E.W., 2014. Discrete Choice Experiments in Health Economics: A Review of the Literature. Pharmacoeconomics 32, 883–902. https://doi.org/10.1007/s40273-014-0170-x

de Bekker-Grob, E.W., Donkers, B., Jonker, M.F., Stolk, E.A., 2015. Sample Size Requirements for Discrete-Choice Experiments in Healthcare: a Practical Guide. Patient 8, 373–384. https://doi.org/10.1007/s40271-015-0118-z

de Bekker-Grob, E.W., Veldwijk, J., Jonker, M., Donkers, B., Huisman, J., Buis, S., Swait, J., Lancsar, E., Witteman, C.L.M., Bonsel, G., Bindels, P., 2018. The impact of vaccination and patient characteristics on influenza vaccination uptake of elderly people: A discrete choice experiment. Vaccine 36, 1467–1476. https://doi.org/10.1016/j.vaccine.2018.01.054

Determann, D., Lambooij, M.S., de Bekker-Grob, E.W., Hayen, A.P., Varkevisser, M., Schut, F.T., Wit, G.A. de, 2016. What health plans do people prefer? The trade-off between premium and provider choice. Soc. Sci. Med. 165, 10–18. https://doi.org/10.1016/j.socscimed.2016.07.022

Hauber, A.B., González, J.M., Groothuis-Oudshoorn, C.G.M., Prior, T., Marshall, D.A., Cunningham, C., IJzerman, M.J., Bridges, J.F.P., 2016. Statistical Methods for the Analysis of Discrete Choice Experiments: A Report of the ISPOR Conjoint Analysis Good Research Practices Task Force. Value Heal. 19, 300–315. https://doi.org/10.1016/j.jval.2016.04.004

Hensher, D.A., Rose, J.M., Greene, W.H., 2005. Applied choice analysis - A primer, Applied Choice Analysis. https://doi.org/10.1007/9781316136232

Jin, Y., Zhu, W., Yuan, B., Meng, Q., 2017. Impact of health workforce availability on health care seeking behavior of patients with diabetes mellitus in China. Int. J. Equity Health 16, 1–10. https://doi.org/10.1186/s12939-017-0576-0

Johnson, F.R., Lancsar, E., Marshall, D., Kilambi, V., Mühlbacher, A., Regier, D.A., Bresnahan, B.W., Kanninen, B., Bridges, J.F.P., 2013. Constructing experimental designs for discrete-choice experiments: Report of the ISPOR conjoint analysis experimental design good research practices task force. Value Heal. 16, 3–13. https://doi.org/10.1016/j.jval.2012.08.2223

Lancsar, E., Hall, J., King, M., Kenny, P., Louviere, J., Fiebig, D., Hossain, I., Thien, F., Reddel, H., Jenkins, C., 2007a. Using discrete choice experiments to investigate subject preferences for preventive asthma medication. Respirology 12, 127–136. https://doi.org/10.1111/j.1440-1843.2006.01005.x

Lancsar, E., Louviere, J., 2008. Conducting Discrete Choice Experiments to Inform Health Care Decision Making : A User's Guide 26, 661–677. https://doi.org/10.2165/00019053-200826080-00004

Lancsar, E., Louviere, J., Flynn, T., 2007b. Several methods to investigate relative attribute impact in stated preference experiments. Soc. Sci. Med. 64, 1738–1753. https://doi.org/10.1016/j.socscimed.2006.12.007

Levesque, J.F., Harris, M.F., Russell, G., 2013. Patient-centred access to health care: Conceptualising access at the interface of health systems and populations. Int. J. Equity Health 12, 1–9. https://doi.org/10.1186/1475-9276-12-18

Li, J., Shi, L., Liang, H., Ding, G., Xu, L., 2018. Urban-rural disparities in health care utilization among Chinese adults from 1993 to 2011. BMC Health Serv. Res. 18, 1–9. https://doi.org/10.1186/s12913-018-2905-4

Li, X., Lu, J., Hu, S., Cheng, K.K., De Maeseneer, J., Meng, Q., Mossialos, E., Xu, D.R., Yip, W., Zhang, H., Krumholz, H.M., Jiang, L., Hu, S., 2017. The primary health-care system in China. Lancet 390, 2584–2594. https://doi.org/10.1016/S0140-6736(17)33109-4

Lin, X., Cai, M., Fu, Q., He, K., Jiang, T., Lu, W., Ni, Z., Tao, H., 2018. Does Hospital Competition Harm Inpatient Quality? Empirical Evidence from Shanxi, China. Int. J. Environ. Res. Public Health 15, 2283. https://doi.org/10.3390/ijerph15102283

Liu, G., Vortherms, S.A., Hong, X., 2017. China's Health Reform Update. Annu. Rev. Public Health. https://doi.org/10.1146/annurev-publhealth-031816-044247

Liu, N., Finkelstein, S.R., Kruk, M.E., Rosenthal, D., 2017. When Waiting to See a Doctor Is Less Irritating: Understanding Patient Preferences and Choice Behavior in Appointment Scheduling. Manage. Sci. mnsc.2016.2704. https://doi.org/10.1287/mnsc.2016.2704

Liu, Y., Qingxia, K., Shasha, Y., Joris, van de K., 2018a. Factors influencing choice of health system access level in China – A systematic review. PLoS One 13, e0201887. https://doi.org/10.1371/journal.pone.0201887

Liu, Y., Zhong, L., Yuan, S., van de Klundert, J., 2018b. Why patients prefer high-level healthcare facilities: a qualitative study using focus groups in rural and urban China. BMJ Glob. Heal. 3, e000854. https://doi.org/10.1136/bmjgh-2018-000854

Louviere, J.J., Lancsar, E., 2009. Choice experiments in health: The good, the bad, the ugly and toward a brighter future. Heal. Econ. Policy Law 4, 527–546. https://doi.org/10.1017/S1744133109990193

Milte, R., Ratcliffe, J., Chen, G., Crotty, M., 2018. What Characteristics of Nursing Homes Are Most Valued by Consumers? A Discrete Choice Experiment with Residents and Family Members. Value Heal. 21, 843–849. https://doi.org/10.1016/j.jval.2017.11.004

National Bureau of Statistics, 2017. China Statistical Yearbook. China Statistics Press, Beijing.

National Bureau of Statistics of China, 2010. The 2010 Population Census.

National Health and Family Planning Commission of the People's Republic of China, 2009. What services can be provided by the primary health care institutions [WWW Document]. URL http://www.nhfpc.gov.cn/mohzcfgs/s9664/200904/39933.shtml (accessed 6.18.18).

National Health Commission of the People's Republic of China, 2018. National Medical Service Utilization from January to June in 2018 [WWW Document]. URL http://www.nhfpc.gov.cn/mohwsbwstjxxzx/s7967/201808/b9745940d99a4645b63afb6f5f8e1369.shtml

Olenja, J., 2003. Health Seeking Behaviour in Context. East Afr. Med. J. 61–62.

Peyron, C., Pélissier, A., Béjean, S., 2018. Preference heterogeneity with respect to whole genome sequencing. A discrete choice experiment among parents of children with rare genetic diseases. Soc. Sci. Med. 214, 125–132. https://doi.org/10.1016/j.socscimed.2018.08.015

Primary Health Care: Declaration of Alma-Ata, 1978. . Lancet 312, 1040–1041. https://doi.org/10.1016/S0140-6736(78)92354-1

Qian, D., Pong, R.W., Yin, A., Nagarajan, K. V., Meng, Q., 2009. Determinants of health care demand in poor, rural China: The case of Gansu Province. Health Policy Plan. 24, 324–334. https://doi.org/10.1093/heapol/czp016

Qiu, X., Sit, J.W.H., Koo, F.K., 2018. The influence of Chinese culture on family caregivers of stroke survivors: A qualitative study. J. Clin. Nurs. 27, e309–e319. https://doi.org/10.1111/jocn.13947

Ren, Q., Huang, Q., He, C., Tu, M., Liang, X., 2018. The poverty dynamics in rural China during 2000–2014: A multi-scale analysis based on the poverty gap index 28, 1427–1443.

Ryan, M., Gerard, K., Amaya-Amaya, M., 2008. Using Discrete Choice Experiments to Value Health and Health Care, The Economics of Non-Market Goods and Resources. https://doi.org/10.1007/978-1-4020-5753-3

Soekhai, V., de Bekker-Grob, E.W., Ellis, A., Vass, C.M., 2018. Discrete Choice Experiments in Health Economics: Past, Present and Future. Pharmacoeconomics. https://doi.org/10.1007/s40273-018-0734-2

Starfield, B., Shi, L., Macinko, J., Milbank, Q., 2005. Contribution of primary care to health systems and health. Milbank Q. 83, 457–502. https://doi.org/10.1111/j.1468-0009.2005.00409.x

Timothy Powell-jackson, 2015. Realigning demand and supply side incentives to improve primary health care seeking in rural China. Health Econ. 24, 755–772. https://doi.org/10.1002/hec

Veldwijk, J., Lambooij, M.S., De Bekker-Grob, E.W., Smit, H.A., De Wit, G.A., 2014. The effect of including an opt-out option in discrete choice experiments. PLoS One 9. https://doi.org/10.1371/journal.pone.0111805

Viney, R., Lancsar, E., Louviere, J., 2002. Discrete choice experiments to measure consumer preferences for health and healthcare. Expert Rev. Pharmacoecon. Outcomes Res. 2, 319–326. https://doi.org/10.1586/14737167.2.4.319

Wang, X., Yang, H., Duan, Z., Pan, J., 2018. Spatial accessibility of primary health care in China: A case study in Sichuan Province. Soc. Sci. Med. 209, 14–24. https://doi.org/10.1016/j.socscimed.2018.05.023

Wu, D., Lam, T.P., 2016. Underuse of Primary Care in China: The Scale, Causes, and Solutions. J. Am. Board Fam. Med. 29, 240–7. https://doi.org/10.3122/jabfm.2016.02.150159

Wu, D., Lam, T.P., Lam, K.F., Zhou, X.D., Sun, K.S., 2017. Health reforms in China: The public's choices for first-contact care in urban areas. Fam. Pract. 34, 194–200. https://doi.org/10.1093/fampra/cmw133

Yip, W., Hsiao, W., 2014. Harnessing the privatisation of China’s fragmented health-care delivery. Lancet 384, 805–818. https://doi.org/10.1016/S0140-6736(14)61120-X

Yip, W.C.M., Hsiao, W., Meng, Q., Chen, W., Sun, X., 2010. Realignment of incentives for health-care providers in China. Lancet 375, 1120–1130. https://doi.org/10.1016/S0140-6736(10)60063-3

Yu, B., Meng, Q., Collins, C., Tolhurst, R., Tang, S., Yan, F., Bogg, L., Liu, X., 2010. How does the New Cooperative Medical Scheme influence health service utilization? A study in two provinces in rural China. BMC Health Serv. Res. 10. https://doi.org/116\r10.1186/1472-6963-10-117

Yu, W., Li, M., Ge, Y., Li, L., Zhang, Y., Liu, Y., Zhang, L., 2015. Transformation of potential medical demand in China: A system dynamics simulation model. J. Biomed. Inform. 57, 399–414. https://doi.org/10.1016/j.jbi.2015.08.015

Zhai, S., Wang, P., Dong, Q., Ren, X., Cai, J., Coyte, P.C., 2017. A study on the equality and benefit of China’s national health care system. Int. J. Equity Health 1–11. https://doi.org/10.1186/s12939-017-0653-4

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Table 1. DCE attributes and attribute levels.

Scenario variable	**Levels**	**Explanation**
Hypothetical perceived disease severity	▪ Minor (reference) ▪ Severe	The examples given to help understand the perceived minor disease were: catching a cold, coughing, sore throat. The perceived severe disease was described as a situation that was very likely to cause the respondent worry and anxiety. No exact examples were given in the severe scenario because aversion to and taboo against severe disease might have harmed the respondents' willingness to continue the survey.
Attributes	**Levels**	**Explanation**
1. Time taken for a visit (h)	▪ 5 (reference) ▪ 3 ▪ 1	Time taken for a visit describes the total time to finish one visit from the point the patient steps into the facility. It generally includes physician consulting time and waiting time. This attribute was varied in three possible levels elicited from the focus group discussions (Liu et al., 2018b)
2. Out-of-pocket expense (OOP) for a visit (RMB)	▪ 118 (reference) ▪ 76 ▪ 25	OOP has three levels, which were calculated based on the reimbursement policy and average cost per outpatient visit in Chongqing.* The values were further validated in the pilot study.
3. Medical professionals' skill	▪ Mostly junior doctors (reference) ▪ Many senior doctors; not much experts ▪ Experts are available	Medical professionals' skills were described by the seniority of the individual in the facility.
4. Personal connection in the facility	▪ Know nobody in person (reference) ▪ Know somebody but are not very familiar ▪ Direct personal connection	As there is not much literature on this attribute, we aimed to differentiate personal connection by three levels. It was validated in our pilot study.
5. General condition of medical equipment	▪ Obsolete (reference) ▪ Advanced	The focus group discussions led us to differentiate two levels for the general condition of medical equipment.
6. Drug availability	▪ Deficient (reference) ▪ Sufficient	General condition of the availability of commonly-used medicine.
7. Travel time (min)	▪ 2.5 hours (reference) ▪ 1 hour ▪ 0.5 hour	The travel time was described by the time taken to go to the facility from home (one way travel). It was varied by three levels, based on interviews with the representative respondents.
8. Facility size	▪ Small (reference) ▪ Medium ▪ Large	This attribute can be assessed simply by the physical size of a facility, such as its land's area; or by the number of hospital beds.

Notes:
*Average OOP for one outpatient visit was estimated according to the local health insurance policy (Chongqing Municipal Human Resources and Social Security Bureau, 2017) and interviews with local residents.

Table 2. Respondents' characteristics (n=559).

Characteristics		Sample (%)	Pre-defined quota (%) [a]	Nationwide census (%) [a]
Gender	Female	52.33	51.00	51.02
	Male	47.67	49.00	48.98
Age [b]	18-45 years	39.71	43.00	42.86
	45+ years	59.75	57.00	57.14
Education	Primary school or below	30.77		
	Middle school	36.67		
	High school	19.50		
	College or above	13.06		
Marriage	Married	86.76		
	Not in a marriage	13.24		
Employment status	No job	11.63		
	Employed	16.99		
	Peasant	71.38		
Have children	No	9.84		
	Yes	90.16		
Number of family members [c]	1	7.33		
	2	23.26		
	3 to 4	53.49		
	>5	15.92		
Family annual income [c] **(US dollar)**	≤ 4,500	51.34		
	> 4,500 and ≤ 7,500	27.37		
	> 7,500 and ≤ 15,000	13.95		
	> 15,000 and ≤ 22,400	5.37		
	> 22,400	1.97		
Insurance type [d]	URRBMI	77.99		
	UEBMI	19.68		
	No insurance	2.33		
Facility visiting experience	Only have visited primary level facilities [e]	55.20		
	Only have visited higher level hospitals [f]	9.32		
	Have visited both above two types of facilities	35.48		
Self-rated health condition	Worse than average	16.13		
	Average	68.46		
	Better than average	15.41		

Notes:

[a] Pre-defined quota were calculated by referring the data from the 2010 National Population Census (National Bureau of Statistics of China, 2010).
[b] Not all respondents answered.
[c] These terms represent the number of family members and total annual income pertaining to all family members living together.
[d] UEBMI: Urban Employee Basic Medical Insurance; URRBMI: Urban and Rural Resident Basic Medical Insurance. Compared to URRBMI, UEBMI has higher premium, higher reimbursement rate, and covers more comprehensive service packages (Chongqing Municipal Human Resources and Social Security Bureau, 2018a, 2018b).
[e] Primary level facilities include township health centers and village clinics in rural areas.
[f] Higher level hospitals include secondary and tertiary hospitals.

Table 3. Results of the interaction model in hypothetical minor disease and severe disease scenarios

		Mixed logit model estimates (perceived minor disease)				**Post-hoc estimates (perceived severe disease)** [f]	
Attribute	**Attribute level**	**Coefficient**[a,b]	**SE**	**SD** [c]	**SE** [c]	**Coefficient**[a,b]	**SE**
Time taken for a visit (h)	5 (reference)	-0.499***	0.077			-0.252***	0.067
	3	0.090	0.057			0.062	0.059
	1	0.409***	0.066	-0.391***	0.059	0.190***	0.066
OOP for a visit (RMB) [d]	118 (reference)	-0.443***	0.061			-0.317***	0.057
	76	0.043	0.058			0.090	0.052
	25	0.400***	0.058			0.226***	0.060
Medical professionals' skill	Junior doctors (reference)	-0.009	0.054			-0.190***	0.058
	Many senior doctors	0.162**	0.065	0.101	0.112	0.157***	0.057
	Experts available	-0.153**	0.070			0.033	0.051
Personal connection in the facility	Know nobody (reference)	-0.238***	0.067			-0.127**	0.063
	Know somebody but not very familiar	0.187***	0.063			0.076	0.056
	Direct personal connection	0.051	0.067			0.052	0.053
Medical equipment condition	Obsolete (reference)	-0.103***	0.040			-0.165***	0.038
	Advanced	0.103***	0.040	0.176***	0.063	0.165***	0.038
Drug availability	Deficient (reference)	-0.189***	0.046			-0.073	0.041
	Sufficient	0.189***	0.046	-0.109	0.084	0.073	0.041
Travel time (min)	150 (reference)	-0.114**	0.553			-0.266***	0.061
	60	-0.146**	0.065	0.154	0.098	-0.037	0.049
	30	0.260***	0.062	0.204***	0.077	0.303***	0.052
Facility size	Small (reference)	0.076	0.066			-0.170**	0.080
	Medium	0.044	0.069			0.138***	0.051
	Large	-0.121**	0.057	-0.396***	0.062	0.032	0.072
Opt-out		1.793***	0.229	4.400***	0.277	-7.076***	0.591
Interaction: attribute × severity [e]	OOP 25 RMB × severity	-0.173**	0.082				
	1 hour visit time × severity	-0.219**	0.091	-0.503***	0.092		
	Expert doctor × severity	0.186**	0.087	0.113	0.090		
	Not visiting a facility × severity	-8.869***	0.595	6.133***	0.408		
Model fit	Akaike Information Criterion	9910.681					
	Log likelihood	-4905.340					
Observations = 6,642	Respondents = 559						

Notes:

[a] Coefficients of the reference levels are calculated as the negative sum of the coefficients of the other levels of the attribute.
[b] **, *** denote significance at the 0.05 and 0.01 level, respectively.
[c] SD: the standard deviations of random coefficients and standard errors.
[d] OOP: out-of-pocket cost for a visit.
[e] For conciseness, only the significant interaction terms at 5% level are listed in the table. The reference level of severity is perceived minor disease.
[f] Each main attribute's coefficient in the severe disease scenario was calculated by adding the corresponding coefficient in the minor scenario and its coefficient of the severity interaction term.

Table 4. Results of the preference heterogeneity analysis.

		Estimates in the minor disease scenario				Estimates in the severe disease scenario			
Attribute	**Attribute level**	**Coefficient [a,b]**	**SE**	**SD [c]**	**SE [c]**	**Coefficient [a,b]**	**SE**	**SD [c]**	**SE [c]**
Time taken for a visit (h)	5 (reference)	-0.493	0.573			-0.323	0.462		
	3	0.410	0.417	0.043	0.243	0.656	0.433	-0.467***	0.096
	1	0.083	0.514	0.480***	0.102	-0.333	0.457	0.669***	0.087
OOP for a visit (RMB) [d]	118 (reference)	-0.994**	0.459			-0.761	0.395		
	76	0.074	0.422			-0.062	0.358		
	25	0.920**	0.428			0.823**	0.406		
Medical professionals' skill	Junior doctors (reference)	0.502	0.382			-0.132	0.407		
	Many senior doctors	-0.119	0.480	-0.024	0.461	-0.385	0.413	0.491***	0.112
	Experts available	-0.383	0.504	0.012	0.155	0.516	0.358	0.008	0.135
Personal connection in the facility	Know nobody (reference)	-0.054	0.496			-0.769	0.439		
	Know somebody but not very familiar	0.270	0.468	0.003	0.118	0.329	0.379	-0.028	0.101
	Direct personal connection	-0.216	0.496	-0.059	0.139	0.440	0.377	0.271*	0.136
Medical equipment condition	Obsolete (reference)	0.077	0.296			-0.261	0.265		
	Advanced	-0.077	0.296	0.214*	0.092	0.261	0.265	0.345***	0.064
Drug availability	Deficient (reference)	-0.602	0.341			-0.206	0.300		
	Sufficient	0.602	0.341	-0.112	0.158	0.206	0.298	-0.281***	0.081
Travel time (min)	150 (reference)	0.204	0.414			-0.154	0.425		
	60	-0.319	0.496	0.251	0.167	-0.362	0.357	0.259	0.139
	30	0.114	0.459	0.264	0.138	0.516	0.353	0.133	0.189
Facility size	Small (reference)	-0.228	0.471			-0.045	0.558		
	Medium	0.051	0.497	0.049	0.268	-0.243	0.361	-0.089	0.346
	Large	0.176	0.420	-0.389***	0.105	0.287	0.505	0.957***	0.103
Opt-out		6.813***	1.849	5.630***	0.432	-3.888***	1.290	3.580***	0.310
Interaction: attribute x demographic attributes [e]	Opt-out × age	-0.072***	0.024						
	OOP25 × employment					-0.472**	0.184		
	Opt-out × marriage status					1.771**	0.722		
	Many senior doctors × family members					0.327**	0.155		
	Direct personal connection × family members	-0.581***	0.200						
	Sufficient drug × family members	-0.392***	0.141						
	Travel 1 hour × family members	0.535***	0.206						
	Visit 3hrs × family income	-0.331**	0.167						
	Direct personal connection × family income	-0.421**	0.198						
	OOP25 × insurance type	-0.350**	0.168						

	Opt-out × insurance type	-2.886***	0.820		
	Visit 1hr × experience [f]	0.352**	0.163		
	Direct personal connection × experience [f]	0.610***	0.166		
	Travel 30 min × experience [f]	0.322**	0.148		
	OOP76 × health status			0.368**	0.161
	OOP25 × health status			-0.422**	0.177
Model fit	Akaike Information Criterion	4254.254		5445.835	
	Log likelihood	-1949.127		-2544.917	

Notes:
[a] Coefficients of the reference levels are calculated as the negative sum of the coefficients of the other levels of the attribute.
[b] **, *** denote significance at the 0.05 and 0.01 level, respectively.
[c] SD: the standard deviations of random coefficients and standard errors.
[d] OOP: out-of-pocket cost for a visit.
[e] For conciseness, only the significant interaction terms at 5% level are listed in the table.
[f] Experience represents the “facility visiting experience” in Table 2. It varies in three levels – “visited primary level facilities only”, “visited higher level hospitals only”, and “visited both above two types of facilities”. The reference level is “visited primary level facilities only”.

Imagine you have a mild symptom, such as a cough, fever, or runny nose…Which health care facility would you prefer to visit for first-contact care?				
□ Facility A		**□ Facility B**		**□ Will not visit any facility**
▪ 1 hour to complete the visit		▪ 5 hours to complete the visit		▪ Stay at home or go to a pharmacy to get some medicine
▪ Pay RMB 118 out-of-pocket		▪ Pay RMB 25 out-of-pocket		
▪ Most health professionals are junior doctors		▪ Medical experts are available on call		
▪ You know someone there but are not very familiar with them		▪ You know nobody personally		
▪ General condition of medical equipment is obsolete		▪ General condition of medical equipment is advanced		
▪ 1 hour travel time from home		▪ 2.5 hours travel time from home		
▪ Large-size facility		▪ Small-size facility		

Figure 1. Example of choice set

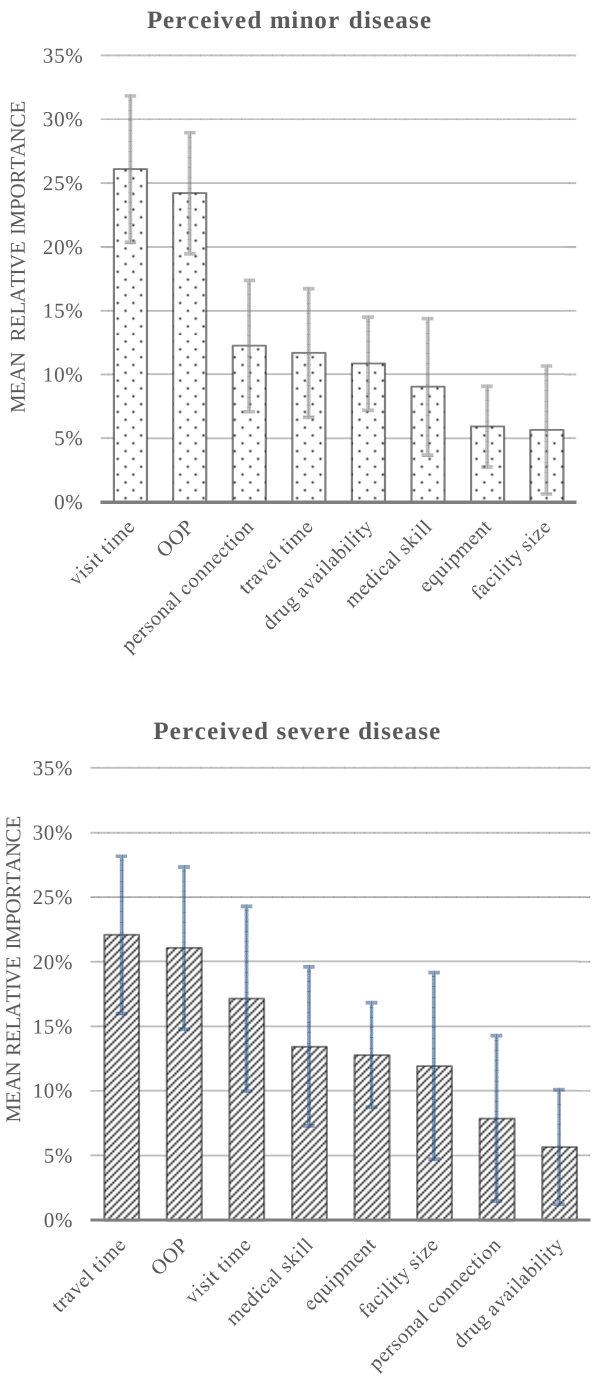

Figure 2. Relative importance of the attributes in the hypothetical minor and severe scenarios with 95% CI. (OOP: out-of-pocket cost for a visit)

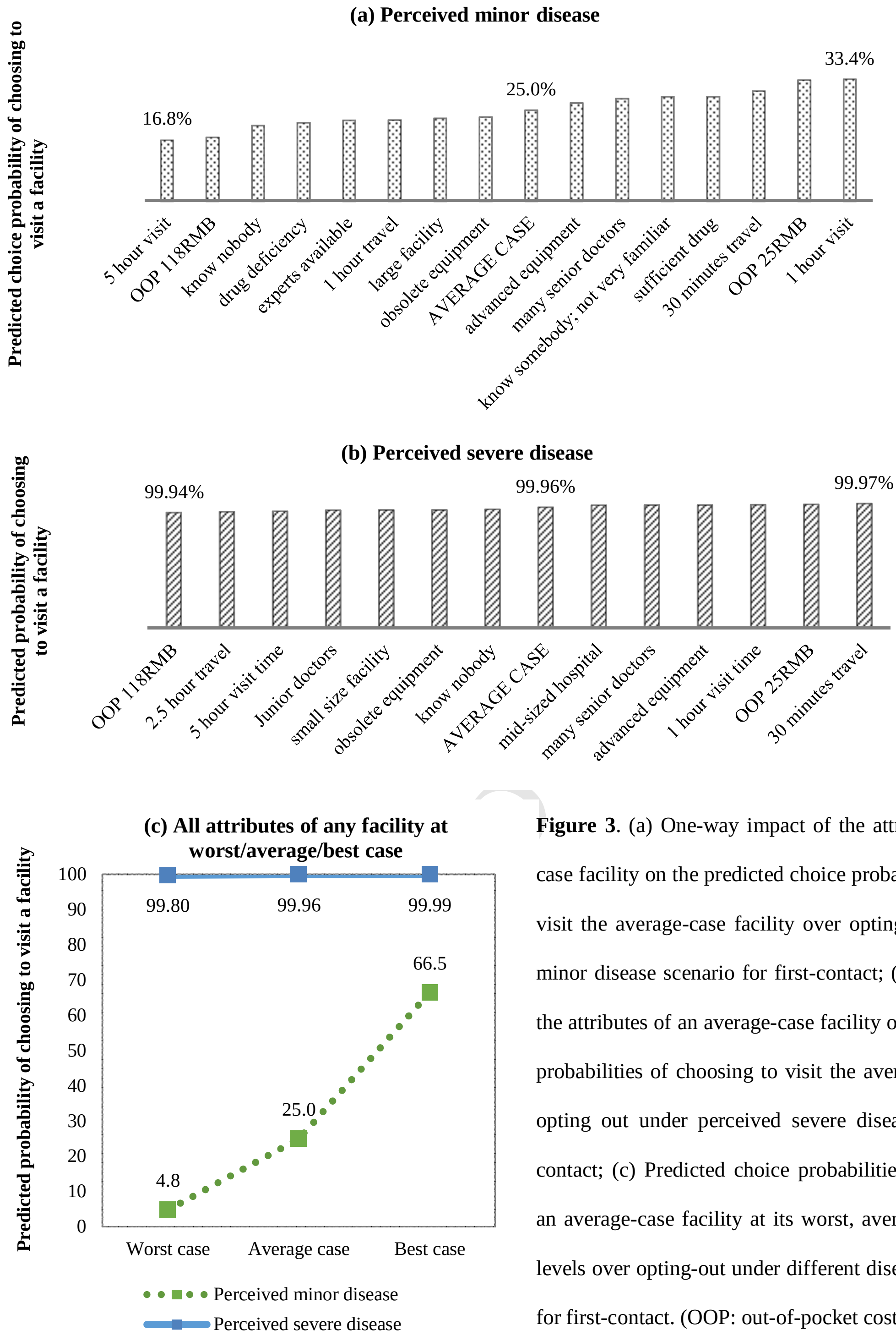

Figure 3. (a) One-way impact of the attributes of an average-case facility on the predicted choice probabilities of choosing to visit the average-case facility over opting out under perceived minor disease scenario for first-contact; (b) one-way impact of the attributes of an average-case facility on the predicted choice probabilities of choosing to visit the average-case facility over opting out under perceived severe disease scenario for first-contact; (c) Predicted choice probabilities of choosing to visit an average-case facility at its worst, average and best attribute levels over opting-out under different disease severity scenarios for first-contact. (OOP: out-of-pocket cost for a visit.)

Highlights

- First DCE to study the relative importance of facility factors in rural China.
- Rural residents highly valued the availability and affordability of a facility.
- Factors' relative importance varied between minor and severe disease scenarios.
- Improving available facilities could induce the demand for health care.