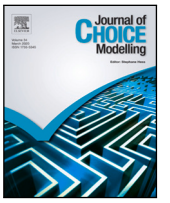
Journal of Choice Modelling 52 (2024) 100509

Contents lists available at ScienceDirect

Journal of Choice Modelling

journal homepage: www.elsevier.com/locate/jocm



The interdependence between hospital choice and waiting time — with a case study in urban China ☆

Joris van de Klundert [a,*], Roberto Cominetti [b], Yun Liu [c], Qingxia Kong [d]

[a] Business School Universidad Adolfo Ibáñez, Chile
[b] Faculty of Engineering, Universidad Adolfo Ibáñez, Chile
[c] School of Health Policy and Management, Erasmus University Rotterdam, Netherlands
[d] Rotterdam School of Management, Erasmus University Rotterdam, Netherlands

ARTICLE INFO

Keywords:
Hospital choice
Waiting time
Multinomial logit
Queuing theory
Urban china

ABSTRACT

Hospital choice models often employ random utility theory and include waiting time as a choice determinant. When applied to evaluate health system improvement interventions, these models disregard that hospital choice in turn is a determinant of waiting time. We present a novel, general model capturing the endogeneous relationship between waiting time and hospital choice, including the choice to opt out, and characterize the unique equilibrium solution of the resulting convex problem.

We apply the general model in a case study on the urban Chinese health system, specifying that patient choice follows a multinomial logit (MNL) model and waiting times are determined by M/M/1 queues. The results reveal that analyses which solely rely on MNL models overestimate the effectiveness of present policy interventions and that this effectiveness is limited. We explore alternative, more effective, improvement interventions.

1. Introduction

Long waiting time presents a significant barrier to healthcare access in various forms and in a variety of health services and settings across the globe (McIntyre and Chow, 2020). It often disadvantages patients of lower socioeconomic status and is negatively associated with patient outcomes such as mortality (McIntyre and Chow, 2020; Martinez et al., 2019; Jones et al., 2022).

For patients, waiting times are an important determinant of their choice of hospital and hospital level and may even cause them to avoid care and opt out (Victoor et al., 2012; Fischer et al., 2015; Liu et al., 2018). The significance of waiting time as a determinant of hospital (level) choice is evidenced by revealed preferences and by stated preferences obtained in a number of discrete choice experiments (DCEs) conducted across the globe (Brown et al., 2015; Berhane and Enquselassie, 2015; Zhu et al., 2019; Liu et al., 2020) (however not for all patient populations and contexts Smith et al., 2018; Liu et al., 2018).

Long waiting times can be viewed to signal a need for health system interventions that address underlying performance issues. In urban China, for instance, long waiting times have led to great discontent and caused undesired avoidance of care (Liu et al., 2020). In this setting, long waiting times especially arise at overutilized tertiary hospitals, as patients freely access hospitals at the level of their choice and tend to leave primary care underutilized (Liu et al., 2020; Arsenault et al., 2020). Both policy measures and modeling studies reported in the academic literature have sought to improve the persistent utilization problems by strengthening primary care (Li et al., 2017; Liu et al., 2020; National Health Commission of the People's Republic of China, 2020). Commonly

☆ **Funding:** The third author was supported by the Chinese Scholarship Council [grant number 201507720036].

* Corresponding author.
E-mail address: joris.vandeklundert@uai.cl (J. van de Klundert).

https://doi.org/10.1016/j.jocm.2024.100509
Received 26 May 2023; Received in revised form 28 June 2024; Accepted 23 July 2024
Available online 6 August 2024

applied models regard waiting time as a hospital (level) attribute, i.e., as an independent explanatory variable determining patient choice.

As observed by Lee and Cohen, waiting times may not be static, independent, hospital (level) attributes but typically vary with the choices made (Lee and Cohen, 1985; Marianov et al., 2008; Zhang and Atkins, 2019). Increased choice probabilities can cause congestion and result in longer waiting times. Thus, waiting time, which is typically presumed to be an independent variable in the aforementioned discrete choice models, is endogenously related to the dependent variable hospital choice. This form of endogeneity, known as simultaneity, has received considerable attention in econometric identification and estimation models using empirical data (see Train (2009), Guevara (2015) and the references therein). (Lu et al. (2013) estimated random utility models in which choice probability is a piece wise linear or quadratic function of queue length, in part to account for the simultaneity.) The empirical revealed preference data required to estimate such models may, however, be hard to obtain in the absence of natural experiments or when health policy interventions are complex and expensive to conduct.

Lacking revealed preference data, discrete choice experiments can provide stated preference data in which this endogeneity is not naturally expressed. Disregard of endogeneity in the corresponding (and other) discrete choice models can cause model inconsistency and incorrectness and cause the model to be ill suited for policy analysis (Train, 2009; Antonakis et al., 2010; Guevara, 2015). In this study we present and solve a novel, general, analytical (non-econometric) model which incorporates the aforementioned simultaneity and may facilitate consistent, correct, policy intervention assessment. It employs random utility theory to specify functions capturing how choice probabilities depend on utilities and how these utilities subsequently depend on waiting times. In addition, the model relies on a fairly general function to express how waiting times depend on choice probabilities. We show that, for any number of patient types (segments) and of hospital types (levels), the model yields unique equilibrium choice probabilities and waiting times, which can be characterized and found by convex optimization.

In the case of hospital choice in urban China, disregard of endogeneity may indeed explain why (evidence based) interventions to improve medical equipment and skills of physicians in primary care have not resolved the utilization problems (Meng et al., 2019; Ta et al., 2020; Li et al., 2017, 2020; Liu et al., 2018). For example, interventions to strengthen primary care can increase the probability of choosing primary care and reduce the probability to choose tertiary care. The revised choice probabilities translate to a tertiary care waiting time decrease that in turn increases its choice probability and thus may partially undo the intervention effects. A similar effect may occur when interventions to reduce the opt out probability translate into longer waiting times of hospitals, partially undoing the relative increase in attractiveness.

In addition to advancing the theoretical analysis of the endogenous relationship between waiting time and choice probability, we present a case study analyzing policy interventions in urban China (Marianov et al., 2008; Zhang and Atkins, 2019; Kucukyazici et al., 2020). For this case study, the presented model explicitly specifies the interdependence between waiting times and hospital choice, including the choice to opt out.

More specifically, the case study applies a multinomial logit (MNL) model to specify the choice probabilities as a function of waiting times (among other factors) while a queuing model specifies waiting time as a function of the choice probability (Marianov et al., 2008; Zhang and Atkins, 2019). Thus, the case study remedies the disregard of endogeneity in previously published preference and policy studies that consider waiting time to be exogenous, in pursuit of consistent assessments of the quantitative effects of health system interventions (such as interventions to strengthen primary care) that are more accurate than assessments obtained by previous MNL based models (Liu et al., 2020; Zhu et al., 2019). The analysis reports on intervention effects obtained with the special case model and on significance of differences in policy intervention effects obtained through models presented in previous studies.

In the discussion, we extensively consider future research on hospital choice behavior and models.

2. Models and equilibrium solutions

The model considers hospitals to belong to a finite set of types $i \in I = \{1, \dots, n\}$, each one characterized by a set of attributes such as skills of medical staff, equipment, price of service, and capacity. In case each hospital is of a unique type, the model regards hospital choice. The types might alternatively refer to hospital levels, such as primary, secondary, and tertiary hospitals, in which case the model regards choice of hospital level.

Further, we consider a finite set $K = \{1, \dots, m\}$ of patient types where each $k \in K$ represents a homogeneous patient population. The homogeneity refers to patient characteristics such as symptoms, insurance type, age, and occupation, that determine the utility U_i^k attached to hospital type i by patients of type k. If the locations of hospitals and patients are relevant choice determinants – as might be the case when considering travel time – each patient and hospital might have to form a separate type by itself.

We model utilities in terms of random variables. Namely, for each patient type $k \in K$ and hospital type $i \in I$, the utility is described by a random variable $U_i^k = u_i^k + \varepsilon_i^k$ where $u_i^k \in \mathbb{R}$ is the expected utility level, and ε_i^k is a random deviation that captures the variability within the kth patient population with $\mathbb{E}(\varepsilon_i^k) = 0$. The model also includes the possibility that patients choose to opt out. To this purpose, we introduce a fictitious opt-out hospital type $i = 0$ with utility $U_0^k = u_0^k + \varepsilon_0^k$ for patients of type $k \in K$ (Kucukyazici et al., 2020).

Following random utility theory, we assume patients choose the hospital that yields the maximal utility and hence the probabilities $\pi^k = (\pi_i^k)_{i\in I}$ of choosing hospital type i are given by the discrete choice model

$$\pi_i^k = \mathbb{P}(U_i^k \geq U_j^k, \forall j \in I \cup \{0\}).$$

For simplicity we assume that the random vector $\varepsilon^k = (\varepsilon_i^k)_{i\in I}$ has a continuous distribution. Denoting $u^k = (u_0^k, u_1^k, \dots, u_n^k)$ and considering the expected utility function

$$\Phi^k(u^k) = \mathbb{E}(\max\{u_0^k + \varepsilon_0^k, u_1^k + \varepsilon_1^k, \dots, u_n^k + \varepsilon_n^k\}),$$

we explicitly establish that:

Theorem 1. *$\Phi^k(\cdot)$ is smooth and convex, and its derivatives are precisely the choice probabilities, namely*

$$\pi_i^k = \pi_i^k(u^k) = \frac{\partial \Phi^k}{\partial u_i^k}(u^k) \qquad (\forall i \in I \cup \{0\}). \tag{1}$$

The proof is presented in Appendix A. We refer to Domencich and McFadden (1975), Sheffi and Daganzo (1978), Williams (1977) and Lee and Cohen (1985) for related (partial) results.

In the remainder, we adopt the common assumption that utility varies linearly with the waiting time and that an increase (decrease) in waiting time translates into a decrease (increase) in utility. More formally, we consider utilities of the form

$$u_i^k = \bar{u}_i^k - \alpha^k w_i \tag{2}$$

where $\bar{u}_i^k$ is a reference utility, w_i is the expected waiting time at hospital $i \in I$, and the parameter $\alpha^k > 0$ represents the sensitivity of patients of type $k \in K$ to waiting time. We reflect on this common assumption in the discussion section as a topic for future research.

Let us now turn to expressing how choice probabilities determine waiting times. To this purpose, we first define for each patient type $k \in K$ the arrival rate $I^k > 0$ as the number of patients of type k arriving per time unit. Then, for hospital type $i \in I$ and choice probabilities $\pi_i^k, k \in K$, and assuming Poisson arrivals, the total arrival rate at hospital type i can be expressed as

$$x_i = \sum_{k\in K} I^k \pi_i^k \qquad (\forall i \in I). \tag{3}$$

The waiting time is assumed to be zero when opting out, i.e., $w_0 \equiv 0$, whereas for $i \geq 1$ we assume that it is given by a strictly increasing continuous function $\theta_i : [0, \bar{x}_i) \to (0, \infty)$ of the arrival rates, namely

$$w_i = \theta_i(x_i) \qquad (\forall i \in I), \tag{4}$$

with $\bar{x}_i > 0$ a saturation level at which waiting times diverge, that is

$$\lim_{x\to\bar{x}_i} \theta_i(x_i) = \infty.$$

The saturation level $\bar{x}_i$ can serve to model the finite capacity of each of the hospital types and the infinitely long queues that can form when patient volumes are at or above capacity. However, the model allows for $\bar{x}_i = \infty$ at some or all hospital types (as in Lee and Cohen (1985)).

Given the exogenous rates $I^k > 0$ and the parameters $\bar{u}_i^k$ and α^k in the utilities (2), we look for w_i and x_i, $i \in I$, simultaneously satisfying the system of Eqs. (1)–(4). The Eqs. (3) and (4) extend the standard Eqs. (1), (2) in random utility based choice models, thus capturing the endogenous relationship between choice and waiting time.

Remark. From (3) it follows that any solution satisfies $x_i \geq 0$ and therefore $w_i \geq w_i^0$ where $w_i^0 \triangleq \theta_i(0)$. We observe that the equalities $x_i = 0$ and $w_i = w_i^0$ cannot be excluded at equilibrium. This will occur for a hospital type $i \in I$ whenever the choice probabilities are zero for all $k \in K$, that is $\pi_i^k = 0$, which is the case if the random terms ε_i^k have bounded support and the hospitals $j \neq i$ provide much higher utilities so that i is never optimal.

Let us consider a continuous and strictly increasing extension of $\theta_i(\cdot)$ to the negative reals with $\theta_i(x_i) \to -\infty$ for $x_i \to -\infty$. Since any equilibrium satisfies $x_i \geq 0$, the specific form of the extension of $\theta_i(\cdot)$ is irrelevant, and we may simply set $\theta_i(x_i) = \theta_i(0) + x_i$ for $x_i < 0$. This extended function has a well defined inverse $\theta_i^{-1} : (-\infty, \infty) \to (-\infty, \bar{x}_i)$ which is also strictly increasing and continuous. Thus, we can eliminate x_i from (3)–(4) and express these equations in terms of the variables w_i alone, namely

$$\theta_i^{-1}(w_i) = \sum_{k\in K} I^k \pi_i^k \qquad (\forall i \in I). \tag{5}$$

The equilibrium choice probabilities and waiting times can now be characterized as follows:

Theorem 2. *The system of Eqs. (1)–(4) has a unique solution. This equilibrium is the unique minimizer of the strictly convex smooth function* $\Theta : \mathbb{R}^d \to \mathbb{R}$ *given by*

$$\Theta(w) \triangleq \sum_{i\in I} H_i(w_i) + \sum_{k\in K} \frac{I^k}{\alpha^k} \Phi^k(\bar{u}_0^k, \bar{u}_1^k - \alpha^k w_1, \dots, \bar{u}_n^k - \alpha^k w_n) \tag{6}$$

where $H_i(w_i) = \int_{w_i^0}^{w_i} \theta_i^{-1}(z)\, dz$.

The proof is presented in Appendix A. We also present a refinement of Theorem 2 for the case in which there is no possibility to opt out:

Theorem 3. *Theorem 2 remains valid when there is no opt-out alternative, under the following non-saturation condition:*

$$\sum_{i\in I} \bar{x}_i > \sum_{k\in K} I^k. \tag{7}$$

The proof is presented in Appendix A.

Hence, we have established that the general model, which assumes that choice probabilities follow random utility theory and that waiting times at hospitals strictly increase with the corresponding total inflows, can be formulated as a strictly convex minimization problem. The model therefore has a unique solution describing the equilibrium choice probabilities and waiting times. The absence of alternative local minima reduces the interest to explore alternative (non-cooperative) game theoretical equilibria.

Let us now consider several specific elaborations to which these general results apply.

Example 1 (*Multinomial Logit (MNL)*)**.** A popular discrete choice model, supported by Gnedenko's theorem on extremal value distributions, considers i.i.d. Gumbel variables $\{\varepsilon_i^k : i \in I\}$ centered at 0 and with scale parameter β^k, in which case

$$\Phi^k(u^k) = \tfrac{1}{\beta^k} \ln\Big(\textstyle\sum_{j=0}^n \exp(\beta^k u_j^k)\Big), \tag{8}$$

$$\frac{\partial \Phi^k}{\partial u_i^k} = \frac{\exp(\beta^k u_i^k)}{\sum_{j=0}^n \exp(\beta^k u_j^k)}. \tag{9}$$

Notice that the latter equation gives the choice probabilities as per (1).

Example 2 (*Nested Multinomial Logit*)**.** Nested Multinomial Logit models form a more flexible family of discrete choice models in which every population $k \in K$ classifies the alternatives $i = 0, \dots, n$ into disjoint buckets $\{B_\ell^k : \ell \in L^k\}$, and the random utilities are given by $U_i^k = u_i^k + \eta_\ell^k + \epsilon_{\ell,i}^k$ with $\{\eta_\ell^k : \ell \in L^k\}$ a family of independent Gumbel variables with parameter β^k, while each set $\{\varepsilon_{\ell,i}^k : i \in B_\ell^k\}$ is also a family of independent Gumbels with parameter β_ℓ^k. Using the tower property of conditional expectations we obtain the following expression for the expected utility function

$$\Phi^k(u^k) = \tfrac{1}{\beta 0^k} \ln\big(\textstyle\sum_{\ell\in L^k} \exp(\beta^k \Phi_\ell^k(u^k))\big)$$

where $\Phi_\ell^k(u^k)$ is the expected utility of the ℓth bucket given by

$$\Phi_\ell^k(u^k) = \tfrac{1}{\beta_\ell^k} \ln\big(\textstyle\sum_{j\in B_\ell^k} \exp(\beta_\ell^k u_j^k)\big).$$

As every expected utility function, the map $\Phi^k(\cdot)$ is convex. This can also be checked directly by noting that it is a composition of the convex and componentwise non-decreasing function $(y_\ell)_{\ell\in L^k} \mapsto \frac{1}{\beta^k} \ln\big(\sum_{\ell\in L} \exp(\beta^k y_\ell)\big)$, with the convex functions $u^k \mapsto \Phi_\ell^k(u^k)$ for $\ell \in L^k$. A straightforward chain rule shows that the choice probabilities $\pi_i^k = \frac{\partial \Phi^k}{\partial u_i^k}(u^k)$ can be expressed as

$$(\forall \ell \in L^k)(\forall i \in B_\ell^k) \quad \pi_i^k = \frac{\exp(\beta^k \Phi_\ell^k(u^k))}{\sum_{\ell'\in L^k} \exp(\beta^k \Phi_{\ell'}^k(u^k))} \cdot \frac{\exp(\beta_\ell^k u_i^k)}{\sum_{j\in B_\ell^k} \exp(\beta_\ell^k u_j^k)}$$

where the term $\exp(\beta^k \Phi_\ell^k(u^k))/\sum_{\ell'\in L^k} \exp(\beta^k \Phi_{\ell'}^k(u^k))$ represents the probability of choosing the ℓth bucket, whereas $\exp(\beta_\ell^k u_i^k)/\sum_{j\in B_\ell^k} \exp(\beta_\ell^k u_j^k)$ is the conditional probability of selecting the specific alternative $i \in B_\ell^k$.

In the setting of hospital choice, each bucket B_ℓ^k may represent a subset of hospitals grouped by geographic distribution, complexity level (primary, secondary, and tertiary care), public vs private, or other distinguishing attributes. Moreover, by a recursive argument one may handle multiple nesting levels, preserving the convexity of the function $\Phi^k(\cdot)$ and the convexity of the optimization problem in Theorem 2.

Example 3 (*Queuing Models*)**.** We can use any queuing model for the waiting time $w_i = \theta_i(x_i)$ as a function of the arrival rate x_i. The simplest one is an M/M/1 queue with $w_i = \frac{x_i}{\mu_i(\mu_i - x_i)}$. Similarly, for an M/M/$s$ queue (as also analyzed in Zhang and Atkins (2019)) we have $w_i = \frac{1}{\mu_i} Q_s\left(\frac{x_i}{\mu_i}\right)$ where

$$Q_s(z) = \left(\sum_{k=0}^{s-1} \frac{z^k}{k!} + \frac{z^s}{s!}\frac{s}{(s-z)}\right)^{-1} \frac{z^s}{s!}\frac{s}{(s-z)^2}.$$

Table 1
Hospital level attributes significantly affecting utility.

Hospital level	Primary	Secondary	Tertiary
Size	Small	Medium	Large
Out of pocket cost (RMB)	59	88	105
Typical skills level	Junior	Senior	Expert
Status of equipment	Outdated	Standard	Advanced
Travel time (min.)	15	15	15
Total visit time (h)	1	3	5

Our general result can also accommodate queues with finite capacity such as M/M/s/K queues and queues with different arrival distributions, such as M/G/s queues (see also Marianov et al. (2008) and Kucukyazici et al. (2020) and the references therein). The only restriction is that $\theta_i(\cdot)$ must be strictly increasing and continuous.

Example 4. Combining Examples 1 and 3 above, the model includes an MNL choice model and an M/M/1 queuing model for waiting times. The optimization problem of Theorem 2 then specifies the following equilibrium:

$$\min_{w} \sum_{i\in I} \left(\mu_i\, w_i - \ln(1+\mu_i\, w_i)\right) + \sum_{k\in K} \frac{I^k}{\alpha^k \beta^k} \ln\left(\sum_{j=0}^{n} \exp(\beta^k(\bar{u}_j^k - \alpha^k\, w_i))\right).$$

Once these waiting times w_i are found, e.g., by using standard convex minimization methods, the corresponding choice probabilities are computed as

$$\pi_i^k = \frac{\exp(\beta^k(\bar{u}_i^k - \alpha^k w_i))}{\sum_{j=0}^{n} \exp(\beta^k(\bar{u}_j^k - \alpha^k w_j))}. \tag{10}$$

This model combining an MNL choice model and an M/M/1 queuing model is applied in the case study presented below.

3. Case study in Urban China

3.1. Model specification

The case considers hospital choice in urban China. In line with the health system challenges and preceding research, the case study focuses on choice probabilities and waiting times per hospital level rather than per hospital. The indices $i \in \{1, 2, 3\}$ of hospital types therefore will represent the primary, secondary, and tertiary hospitals, and $i = 0$ refers to opting out.

The patient choice related health system challenges center around the perceived weakness of primary care. The low utility attached to the primary care level institutions by China's urban population – and to a lesser extent to the level of secondary hospitals (Liu et al., 2020) – causes (1) under-utilization of primary care, (2) over-utilization of tertiary care, and (3) undesirable avoidance of care, i.e., high opt-out rates (Meng et al., 2019; Ta et al., 2020; Li et al., 2017, 2020; Liu et al., 2018). This problematic situation has resisted large scale healthcare reforms which mainly aimed to change choice behavior by improving the skills level of the medical staff and the quality of the medical equipment at primary care hospitals. Such despite, skills level of medical staff and quality of medical equipment having been identified as the two main determinants of patient choice for the population of 24 million of Liu et al. (2020) and Natural Bureau of Statistics of China (2019). This case study uses the MNL model, data, and results obtained by the discrete choice experiment presented in Liu et al. (2020). To capture the endogeneity between choice probability and waiting time it additionally includes an M/M/1 queuing model. The case study thus advances on the policy analysis presented in Liu et al. (2020) which disregarded the endogeneity between choice probabilities and waiting times (but instead relies on exogenous waiting times). We thus aim to present a more accurate assessment of the policy interventions implemented to remedy the health system challenges and to present insight in the (lack of) effectiveness of these interventions. Moreover the case explores the possible effectiveness (efficacy) of alternative interventions.

3.2. MNL model, parameters and data

The patient choice data were collected in a discrete choice experiment for which patients gave their consent and for which ethics approval was obtained from the Shanghai General Hospital Medical Ethical Review Committee (no 2017 KY207) (Liu et al., 2020).

Table 1 presents a first set of factors significantly affecting hospital level utility in the MNL model (*cf.* Liu et al. (2020)).

As the urban citizens of Shanghai typically live close to hospitals of each level and travel time is not among the most important factors determining hospital choice, Table 1 reflects an assumed generic travel time of 15 min.

The original discrete choice experiment in Liu et al. (2020) considered the total visit times to be exogenous and to equal 1, 3 and 5 h, for primary, secondary, and tertiary care, respectively, as presented in the bottom row of Table 1. The total visit time is defined by the time taken for a sequence of activities consisting of waiting, being serviced, waiting, being serviced, et cetera. Thus, the total visit time consists of a sum of waiting times and a sum of service times. In the remainder, we assume that the sum

Table 2
Data determining the utility per patient type.

Factor utilities	Mild	Severe
Opt out utility	2.499	−6.024
Waiting time sensitivities α^k	0.232	0.0995
Junior doctor utility	−0.277	−0.05
Senior doctor utility	0.199	−0.089
Expert doctor utility	0.078	0.139
Obsolete equipment utility	−0.275	−0.43
Advanced equipment utility	0.275	0.43

Table 3
Service and waiting time related hospital level attributes.

	Primary	Secondary	Tertiary
Service rate (patients/h)	10	10	12
Total service time (in min.)	34	88	87
Zero wait utility for mild patients	0.207	0.417	−0.259
Zero wait utility for severe patients	−0.257	0.089	0.773
Waiting time multipliers	3	5	7
Number of hospitals	1009	105	47
Number of Doctors per hospital	6.76	40.8	98.9
Doctor time allocated to first visits (%)	50	50	50

of the service times per hospital level is exogenous and constant (see also Table 3). More generally, this constant may include all exogenous parts of the visit time. The sum of the waiting times now forms the variable part of the total visit time of the original DCE and the total visit time sensitivities obtained in the original DCE now translate to the waiting time sensitivities α^k (see (2), (10)). In the remainder, waiting time refers to the aforementioned sum of the waiting times and its modeling will be further elaborated in Section 3.3.

For now, we correspondingly recast the expected utility functions to the form $u_i^k = \bar{u}_i^k - \alpha^k w_i$ (see (10)), in which the only explicit factor is the waiting time w_i and the reference utility $\bar{u}_i^k$ incorporates the utilities from all other factors, including service time. Thus, u_i^k represents the expected utility that patients of type $k \in K$ attach to hospitals of level $i \in I$.

Patients types are distinguished only by the evidence based factor perceived severity (Liu et al., 2018, 2020). More specifically, we consider two patient types: patients perceiving mild disease and patients perceiving severe disease.

The patient type-dependent utilities of factors obtained in the DCE and for which policy interventions are studied in Liu et al. (2020) and the scenarios below are presented in Table 2. The reader may notice the large difference in opt out utilities between the two severity types in Table 2.

The sensitivities to waiting time are independent of hospital level but vary with perceived disease severity. Utilities for doctors and equipment not only vary per patient type but also with skill and equipment levels. These levels vary across hospital levels as already depicted in Table 1.

3.3. M/M/1 model, parameters and data

Focusing the case study on patients who seek care for a first visit and hence without appointment with a pre-assigned physician, we assume the assignment of patients to physicians happens as soon as the patient is registered, *i.e.*, upon arrival at the hospital. Moreover, we assume that this causes patients to be evenly distributed among the doctors for each level. Thus, each registered patient joins a single server queue. More specifically, we assume arrivals and service rates are exponentially distributed and thus adopt an M/M/1 model and consider alternative queuing models in the discussion. The data required for the M/M/1 model are presented in Table 3.

As stated in Example 3 above, the M/M/1 model yields that expected waiting time equals $w_i = \frac{x_i}{\mu_i(\mu_i - x_i)}$ where x_i is the arrival rate of patients for a doctor at hospital level $i \in I$ and μ_i their service rate.

Data on the service rates μ_i were provided by four medical doctors, two from primary care hospitals, one from a secondary hospital, and one from a tertiary hospital in Shanghai in June 2019. The obtained data indicate that maximum service rates are normally around 12 patients per hour for each of the three hospital levels. As tertiary hospitals are especially known for long waiting times and short service times (Chao et al., 2017; Liu et al., 2018), the base service rates are set at 12 patients per hour for tertiary care hospitals and 10 patients per hour for primary and secondary level hospitals.

The same medical doctors also provided data on the average number of on duty doctors per day/and documentation on the total number of licensed medical doctors per hospital. The numbers of hospitals per level were obtained from Shanghai (2018).

The service capacity per level can then be determined by the number of hospitals, the number of physicians per hospital, and the fraction of physician time spent on first visit consults, which are all presented in Table 3. Moreover, we assume 261 working days of 8 h per year.

The incidence of patients who perceive to have an illness and consider visiting a hospital is taken from the national census (Laiyun et al., 2013). The division of these patients over the two severity types is determined by solving (1)–(4) for the base case model and data with the additional requirement that the solution yields the evidence based reference waiting times of the DCE as presented in Table 1. This yielded that 47.9 percent of the 160,432,700 patients in Shanghai per year who consider to visit a healthcare hospital or to opt out instead, perceive their disease as minor.

The parameter values for the queuing model presented in Table 3 additionally reflect that primary care consults typically require a follow up visit to the hospital pharmacy and the cashier, secondary hospitals typically perform diagnostic services such as imaging and lab tests, and tertiary hospitals have the most elaborate and time consuming pathways (Liu et al., 2018; Li et al., 2017; Zou et al., 2017). Correspondingly, we assume that patients will join additional queues for these follow-up services (*e.g.* at the pharmacy or for the lab test) as indicated by the waiting time multipliers depicted in Table 3.

3.4. Comparative intervention analysis methods

The case study evaluates the effects on choice probabilities and waiting times of policy interventions which are modeled through modifications of the (default) parameter values depicted in Tables 1, 2. Thus, each intervention is modeled by specifying a set of values for the utilities of all choice determinants with the exception of (the endogenous) waiting time and updating the reference utilities $\bar{u}_i^k$ accordingly.

The comparative analysis presents both the results from solving (1)–(4) with choice probabilities determined by an MNL model and waiting times determined by an M/M/1 queuing model as explained above, and the results obtained by using an MNL model only with the constant reference total visit times of 1, 3, and 5 h for primary, secondary and tertiary care respectively from the discrete choice experiment (Liu et al., 2020).

We compare the results for the base scenario and five policy interventions. The first three of these interventions aim to strengthen primary care and model the substantial efforts made as part of the national health reform to upgrade the medical skills of the physicians and to upgrade the equipment of primary care hospitals. Skill and equipment are the factors evidenced to impact choice probabilities most (Li et al., 2017; Liu et al., 2020; National Health Commission of the People's Republic of China, 2020).

- **Upskill:** Maximally upskill primary care physicians from the *mostly junior* level to the *mostly expert* level of tertiary care physicians. To avoid secondary care having less skilled physicians than primary care, the secondary care physicians are upskilled to the *mostly expert* level as well. The required upskilling effort can be considered to be unrealistically ambitious. Hence, the relevance of the intervention results is not to model the effectiveness of actual interventions but rather to estimate the maximum effect attainable by these actively practiced upskilling interventions.
- **Upgrade:** Maximally upgrade primary care equipment from the level *obsolete* to the *advanced* level of tertiary care. To avoid secondary care having poorer equipment than primary care, the secondary care equipment is upgraded to *advanced* as well. Again, the required upgrading effort can be viewed as unrealistic, *e.g.*, for being too costly, and the relevance of the analysis is to provide insight into the maximum effectiveness of the on going equipment upgrading interventions.
- **Upskill and Upgrade:** The third intervention combines the previous two and therefore gives insight into the maximum effect attainable by combined upskilling and upgrading.

As both evidence from practice and the comparative analysis results below illustrate, the (maximum) effectiveness of upskilling and upgrading interventions is limited. A first main underlying cause appears to be the high utility patients perceiving a mild disease attach to opting out (self care). Patients perceiving a mild disease attach a utility difference between opting out and a zero wait primary care visit of 2.3, more than twice the utility gain from maximum upskilling and upgrading (0.903) and equivalent to 10 h of waiting time reduction (0.232 per hour) (see Tables 2 and 1). As a result more than three out of four such patients opt out in expectation, and this choice probability is only weakly impacted by upskilling and upgrading. Intervention four therefore models a health promotion campaign that reduces the utility of self care (opting out) by half.

A second important underlying cause is that utility is quite insensitive to waiting times for patients perceiving a severe disease. One hour of waiting time reduction reduces the utility of a hospital by 0.1 (approximately), while the utility difference between primary and tertiary care is more than ten times larger for these patients. For realistic waiting times which correspond to being serviced on the day of visiting, the probability of choosing primary care therefore remains low and the probability to choose tertiary care remains high for these patients.

One may argue that the utility of waiting should only depend on the person and not on the severity of the illness. Then, the current difference between the waiting time utilities for perceiving mild and severe disease are an artifact that may reflect other more lowly valued characteristics of primary and secondary care not already captured by the utility factors presented in Table 1. Uniform waiting time sensitivities, which disregard perceived disease severity, then more realistically reflect waiting time sensitivities and may apply to the aspired future state of the health system in which it provides balanced access to care.

Table 4
Baseline choice probabilities and waiting times.

Baseline	MNL	1–4	μMNL	μ 1–4	Sign test	Nonzero
$\mathbb{P}(OO\|M)$	0.7757	0.7759	0.7757	0.7740	– –	
$\mathbb{P}(1\|M)$	0.0784	0.0784	0.0784	0.0783	– –	
$\mathbb{P}(2\|M)$	0.0967	0.0966	0.0967	0.0972	+ +	
$\mathbb{P}(3\|M)$	0.0492	0.0491	0.0492	0.0505	+ +	
$\mathbb{P}(OO\|S)$	0.0006	0.0006	0.0006	0.0006	– –	
$\mathbb{P}(1\|S)$	0.1917	0.1918	0.1917	0.1906	– –	
$\mathbb{P}(2\|S)$	0.2709	0.2709	0.2709	0.2701	– –	
$\mathbb{P}(3\|S)$	0.5368	0.5367	0.5368	0.5387	+ +	
$W(1)$	0.43	0.43	0.43	0.43	– –	
$W(2)$	1.53	1.52	1.50	1.48	– –	
$W(3)$	3.54	3.54	3.58	3.43	+ +	

Thus we have two more interventions:

- **Health Promotion Campaign:** This campaign discourages self care for patients perceiving a mild disease and halves the utility of opting out from 2.499 to 1.250.
- **Uniform Waiting Time Sensitivity:** This intervention does not reflect a health reform but rather adjusts the model assuming that the current long waiting times may no longer be valid in the future and adjust the present low sensitivities to waiting time for patients perceiving severe disease to become equal to the waiting time sensitivity of patients perceiving mild disease, 0.232.

Appendix B additionally presents analysis results for an intervention in which upskilling is only for primary care physicians and thus from *mostly junior* to *mostly senior*, which is the skills level for secondary care. Moreover, the same appendix presents results obtained when combining the upskilling and upgrading interventions with interventions four and five.

As the data on service use and hospital capacity are not based on strong evidence, we conducted a sensitivity analysis for each of the interventions studied. For each intervention study, we generated 1000 problem instances in which, for each of the hospital levels, the waiting time multipliers (demand) and fraction of on duty doctors per day (supply) experience a uniformly distributed random perturbation of between −10% and 10%.

This sensitivity analysis provides insights into the robustness of the results. Moreover, it allows to test whether the differences between the results obtained by solving (1)–(4) are significantly different from the solutions obtained when solving the MNL model only. We present results on two statistical tests for the significance of difference. First, we conducted a sign test, testing the null hypothesis that there are no differences in choice probabilities and waiting times between the two models. For each of these parameters and for 1000 instances, this hypothesis is rejected if the number of instances for which the difference is positive (negative) is at least 526 (at most 473) because this number has a probability of less than 0.05. These results are indicated with '+' and '–', in case of rejection. A stronger variant of the same test rejects the hypothesis if the number of instances for which the difference is positive (negative) is at least 537 (at most 462), which has a probability of less than 0.01 under the null hypothesis.

Even though the service use and capacity perturbations are sampled from uniform distributions which are symmetric around the mean values of the base scenario, the effects on waiting time can be highly nonlinear and asymmetric, if only because M/M/1 waiting time is superlinear in the arrival rate per doctor ($w_i = \frac{x_i}{\mu_i(\mu_i - x_i)}$). Thus, a second test rejects the null hypothesis of zero difference for choice probability or waiting time, if the value is outside of a 95% confidence interval around the mean of the variable under consideration. This occurs when at most 25 of the 1000 problem instances report a difference below zero or above zero. Notice that this second test is much more demanding. Both tests are robust as they make no assumptions about the distributions of the (differences between) outcome parameters.

The Python code used for the computational studies is available on Github (Cominetti and Van de Klundert, 2023).

3.5. Comparative intervention analysis results

Table 4 presents the results of the base case with the originally collected data and the results of 1000 perturbed model instances. Columns two and three present the choice probabilities and waiting times for the MNL model and for model (1)–(4) respectively for the unperturbed base instance. These columns present the choice probabilities $\pi_i^k = \mathbb{P}(i|k)$ denoted in column 1, starting with the probability of opting out by patients perceiving mild disease $\mathbb{P}(OO|M)$, to primary care for patients perceiving mild disease $\mathbb{P}(1|M)$, et cetera, to tertiary care for patients perceiving severe disease $\mathbb{P}(3|S)$. These probabilities confirm that the calibrated base instance of model (1)–(4) accurately models the empirical data on which the discrete choice experiment is based. This is further confirmed by the virtually equal waiting times reported by both models for each of the three hospital levels in the corresponding bottom rows of columns two and three.

Columns four and five of Table 4 present the average values over 1000 randomly perturbed problem instances for the MNL model and model (1)–(4) respectively. The choice probabilities in column four are identical to the choice probabilities in the second

Table 5
Choice probabilities and waiting times after upskilling and upgrading interventions.

Upskill	MNL	1–4	μMNL	μ1–4	Sign test	Nonzero
$\mathbb{P}(OO\|M)$	0.7587	0.7545	0.7587	0.7526	−−	
$\mathbb{P}(1\|M)$	0.1094	0.1080	0.1094	0.1079	−−	
$\mathbb{P}(2\|M)$	0.0838	0.0814	0.0838	0.0822	−−	
$\mathbb{P}(3\|M)$	0.0481	0.0560	0.0481	0.0573	++	×
$\mathbb{P}(OO\|S)$	0.0005	0.0005	0.0005	0.0005	−−	
$\mathbb{P}(1\|S)$	0.2087	0.2020	0.2087	0.2009	−−	×
$\mathbb{P}(2\|S)$	0.3068	0.2949	0.3068	0.2944	−−	×
$\mathbb{P}(3\|S)$	0.4840	0.5026	0.4840	0.5042	++	×
$W(1)$	0.47	0.46	0.47	0.46	−−	×
$W(2)$	1.77	1.62	1.72	1.57	−−	×
$W(3)$	2.41	2.85	2.36	2.76	++	×
Upgrade	MNL	1–4	μMNL	μ1–4	Sign test	Nonzero
$\mathbb{P}(OO\|M)$	0.7129	0.7046	0.7129	0.7029	−−	×
$\mathbb{P}(1\|M)$	0.1249	0.1194	0.1249	0.1193	−−	×
$\mathbb{P}(2\|M)$	0.1170	0.1110	0.1170	0.1110	−−	
$\mathbb{P}(3\|M)$	0.0452	0.0650	0.0452	0.0657	++	×
$\mathbb{P}(OO\|S)$	0.0004	0.0004	0.0004	0.0004	−−	×
$\mathbb{P}(1\|S)$	0.3220	0.3003	0.3220	0.2994	−−	×
$\mathbb{P}(2\|S)$	0.2960	0.2752	0.2960	0.2755	−−	×
$\mathbb{P}(3\|S)$	0.3816	0.4241	0.3816	0.4247	++	×
$W(1)$	0.62	0.58	0.61	0.57	−−	×
$W(2)$	2.03	1.69	1.98	1.65	−	×
$W(3)$	1.49	1.91	1.46	1.86	++	×
Upskill & Upgrade	MNL	1–4	μMNL	μ1–4	Sign test	Nonzero
$\mathbb{P}(OO\|M)$	0.6856	0.6791	0.6856	0.6776	−−	×
$\mathbb{P}(1\|M)$	0.1713	0.1611	0.1713	0.1611	−−	×
$\mathbb{P}(2\|M)$	0.0997	0.0927	0.0997	0.0938	−−	×
$\mathbb{P}(3\|M)$	0.0435	0.067	0.0435 1	0.0676	++	×
$\mathbb{P}(OO\|S)$	0.0003	0.0004	0.0004	0.0004	−−	×
$\mathbb{P}(1\|S)$	0.3403	0.3158	0.3403	0.3151	−−	×
$\mathbb{P}(2\|S)$	0.3254	0.3005	0.3254	0.3011	−−	×
$\mathbb{P}(3\|S)$	0.3339	0.3833	0.3339	0.3834	++	×
$W(1)$	0.72	0.66	0.71	0.65	−−	×
$W(2)$	2.26	1.79	2.20	1.73	-	×
$W(3)$	1.26	1.61	1.24	1.50	++	×

column as the MNL model does not consider effects of any changes in waiting time on the choice probabilities. The bottom rows show that the average waiting times differ slightly from the unperturbed base instance. However, one might argue that the column two and four waiting times should be disregarded as the MNL model assumes there is no change in the utility from waiting times and hence no change in waiting times. Thus, below we focus on the choice probabilities in the model comparison. Column five shows that the choice probabilities and waiting times differ slightly from those of column three when using model (1)–(4).

Column six of Table 4 shows the result of the sign test, where '++' and '−−' mean that the null hypothesis of zero difference holds with probability less than 0.01 and single '+', '−' indicate the same yet with probability at most 0.05. Thus '(+)+'s indicate that (1)–(4) results are significantly higher than MNL results and '(−)−'s indicate that these are significantly smaller. Empty cells in column six indicate that there are no significant differences. Even for this base case for which the model (1)–(4) is calibrated to reproduce the MNL outcomes and evidence-based DCE assumptions, the perturbations lead to differences in outcomes between the two models that cause the sign test to reject that hypothesis of equal outcomes ($p \leq 0.01$) for all choice probabilities and waiting times.

An 'X' in column seven of Table 4 indicates that the second test described in the methods section is rejected and any empty cell indicates it is not rejected, which is the case for all outcome variables in this base scenario.

Next, we turn to considering the model results for the upskilling and upgrading interventions. These results are presented in Table 5.

The most notable policy observation from these three modeled intervention studies might be that even full upskilling and upgrading only reduces the opt out probability of mild patients from 0.78 to 0.67 (or to 0.68 according to the MNL model which ignores waiting time effects). However, the relative changes in choice probabilities among the hospital levels tend to be larger. For instance, the original probability of patients perceiving severe disease to choose tertiary care was 0.54 and decreases to 0.50 (upskill), to 0.42 (upgrade), and to 0.38 (upskill and upgrade) for the successive interventions studied. The MNL model finds this probability to be as low as 0.33 and both significance tests reveal that this reduction appears significantly overestimated.

Table 6
Choice probabilities and waiting times after intervening on opt out utility and waiting time sensitivity.

Health Promotion	MNL	1–4	μMNL	μ1–4	Sign test	Nonzero
$\mathbb{P}(OO\|M)$	0.4980	0.5405	0.4980	0.5348	++	×
$\mathbb{P}(1\|M)$	0.1755	0.1859	0.1755	0.1844	++	×
$\mathbb{P}(2\|M)$	0.2164	0.1818	0.2164	0.1851	−−	×
$\mathbb{P}(3\|M)$	0.1101	0.0917	0.1101	0.0957	−−	
$\mathbb{P}(OO\|S)$	0.0006	0.0006	0.0006	0.0006	++	×
$\mathbb{P}(1\|S)$	0.1917	0.2079	0.1917	0.2053	++	×
$\mathbb{P}(2\|S)$	0.2709	0.2661	0.2709	0.2656	−−	
$\mathbb{P}(3\|S)$	0.5368	0.5254	0.5368	0.5285	−−	
$W(1)$	0.51	0.54	0.51(739)	0.53	++	×
$W(2)$	4.08	2.62	4.19(739)	2.50	−−	×
$W(3)$	6.92	4.66	5.24(739)	4.46	−−	
Uniform Waiting time Sensitivities	MNL	1–4	μMNL	μ1–4	Sign test	Nonzero
$\mathbb{P}(OO\|M)$	0.7757	0.7697	0.7757	0.7678	−−	×
$\mathbb{P}(1\|M)$	0.0784	0.0773	0.0784	0.0773	−−	×
$\mathbb{P}(2\|M)$	0.0967	0.0951	0.0967	0.0961	−−	
$\mathbb{P}(3\|M)$	0.0492	0.0577	0.0492	0.0588	++	×
$\mathbb{P}(OO\|S)$	0.0006	0.0007	0.0006	0.0007	++	×
$\mathbb{P}(1\|S)$	0.1917	0.2252	0.1917	0.2227	++	×
$\mathbb{P}(2\|S)$	0.2709	0.2753	0.2709	0.2750	++	
$\mathbb{P}(3\|S)$	0.5368	0.4986	0.5368	0.5015	−−	×
$W(1)$	0.43	0.46	0.43	0.45	++	×
$W(2)$	1.52	1.55	1.48	1.50	++	
$W(3)$	3.54	2.80	3.55	2.72	−−	

More generally we can observe that differences between the policy effects obtained by the models are always significant according to the sign test, and significant for the far majority on the second test as well. As a rule, the MNL model significantly overestimates the policy effects. There are some irregularities, for instance, because the utility severe patients attach to physicians is not increasing with the skills level. They value senior doctors the least. The results also indicate that the combination of full upskilling and upgrading goes a long way to balance the flow of patients perceiving severe disease but is hardly effective to prevent patients perceiving mild disease from opting out.

The Health Promotion intervention models the reduction of the opt out utility for patients perceiving mild disease. The modeled intervention results are presented in Table 6. Columns three and five show the effectiveness of this intervention to reduce opting out among patients perceiving mild disease from 0.78 to around 0.54. The increased opting in leads to considerable increases in waiting times, especially for secondary and tertiary for which patients arrival rates were already close to hospital level capacity.

For this health promotion intervention, the limitations of the MNL model again cause an overestimation of the effectiveness. Moreover, Table 6 reveals another main shortcoming of the MNL model. It may yield choice probabilities that cause patient flows above capacity and thus unstable queues with infinite waiting times. Column four shows that only 739 out of the 1000 perturbed instances had feasible solutions. In fact, the feasibility limit applied is slightly more restrictive than requiring finite waiting times. All instances with a waiting time of more than ten hours are considered as infeasible. Such because regular hospital opening hours are limited to 10 h and longer waiting might imply waiting until the next day. The estimated sensitivities of the DCE are unlikely to be valid for such situations, despite the fact that such exceptionally long waiting has occurred in Chinese urban health systems in the recent past. Appendix B shows that when combining the interventions of upgrading equipment and health promotion, even the undisturbed results (column two) are infeasible.

Finally, the same table shows the effects of changing the waiting time sensitivities of patients perceiving severe disease to equalize the sensitivities of mild patients. These effects are comparable to the effect of complete upskilling. Hence, they are relatively modest, with the exception of a substantial reduction in the choice probabilities of tertiary care by patients perceiving severe disease and the corresponding tertiary care waiting times. Because the MNL model assumes waiting times to be fixed, it fails to register any effects of modified waiting time sensitivities on choice probabilities.

For both these additional interventions, the sign test qualifies all differences between the outcomes of the two models as highly significant, as is mostly confirmed by the stricter second test.

4. Discussion and conclusion

We discuss the results in the reverse order of presenting them, first interpreting case study results from urban China and then zooming out to the presented models, as well as present and future theoretical contributions on the relationship between patient choice and waiting time.

The inclusion of the mutual dependence between choice probabilities and waiting time in the modeling of health policy intervention effects strongly suggests that the ongoing efforts to upskill doctors and upgrade equipment can contribute to alleviating the persistent problems of underutilization of primary care and overutilization of tertiary care. At the same time, the analysis reveals that these interventions likely fall short of resolving these problems. In comparison to the previous MNL based policy analyses, the increase in utility of primary and secondary care hospitals – and thus the probability to choose hospitals at these levels instead of opting out – that results from these interventions are significantly smaller when accounting for endogeneity between waiting time and choice probability by solving (1)–(4). An intuitive interpretation is that the utility increases caused by the interventions yield higher choice probabilities, which in turn imply longer waiting times that partially undo the initial utility increases.

While the opt in probabilities remain low for patients perceiving mild disease for both models, the differences in effects of the intervention to upgrade equipment and upskill medical doctors are highly significant and larger in relative terms. For example, the MNL model estimates their probability to attend tertiary care is 0.0435 while solving (1)–(4) yields a 0.0241 higher probability. Thus, the relative difference is more than 50 percent.

The patients perceiving severe disease almost all opt in and the equally significant differences between model outcomes of upgrading and upskilling now also translate into larger absolute differences in the choice probabilities. For example, the MNL model estimates their probability to attend tertiary care after upgrading and upskilling is 0.3339 while solving (1)–(4) gives a probability of 0.3833. This difference translates to around 4 million first visits to tertiary care per year.

Based on the above observations, we analyzed two alternative interventions. The first suggestion is a health promotion campaign that diminishes the utility attached to self care and opting out. Our analysis reveals that such a campaign has much more efficacy potential than upskilling and upgrading. Moreover, our findings suggest that MNL based analysis significantly errs on the resulting choice probability changes and that its disregard of endogeneity can even yield choice probabilities that are infeasible because they violate hospital capacity limits.

The MNL model is incapable of evaluating interventions which cause changes in waiting time sensitivities as it assumes waiting times to be constant. Hence, the newly developed model is a welcome advancement to provide insight into the effect of remedying the waiting time insensitivity reported for patients perceiving severe disease (Liu et al., 2020). The analysis shows that the effects of interventions to adjust waiting time sensitivities of patients perceiving severe disease to those of patients perceiving mild disease, resulting in uniform patient dependent sensitivities, are comparable to those obtained by full upskilling of physicians. This intervention follows the universal health coverage principles of the WHO which reaffirm the importance of access to strong primary care hospitals for all and referral to higher levels as needed (Ghebreyesus et al., 2018). Further research into the determinants of waiting time (in)sensitivity and interventions to resolve the insensitivity is called for.

The case study analysis and in particular the analysis comparing the results obtained by the newly developed model with the results obtained by the MNL model only shows that the newly presented model can significantly more accurately capture the effects of interventions aimed at altering patient choice and corresponding health system utilization and performance. This confirms the importance of capturing the endogeneous relationships in the model for intervention analysis (Train, 2009; Antonakis et al., 2010).

Regarding the data considered in the case study at hand, one may wonder whether revealed preference data would have yielded more accurate results. The choice set of the DCE limited waiting times to 1, 3, and 5 h when eliciting stated preferences. As policy interventions advance, empirical revealed preference data can include a wider variety of combinations of choices and waiting times, which naturally capture the simultaneity. This enables to identify and estimate econometric models (Train, 2009; Guevara, 2015), and specifically to improve the validity of the waiting time coefficients used in our study which assumes the stated preferences from the DCE are valid beyond the presented choice sets.

A difficulty with collecting revealed preference data may, however, lie in the collection of an unbiased set of opt out choices. Another possible difficulty with revealed preference data is that the attributes (independent variables) equipment, skills level, out of pocket costs, and hospital size, are highly correlated in practice as these are regulated to vary among hospital levels but not between hospitals of the same level. This may render the data to be unsuited for the analysis of policy interventions targeting the individual attributes considered in our study. Combined with earlier evidence that stated preferences can predict revealed choices with a high degree of confidence for healthcare choices, we hope the presented models promote the use of stated preferences elicited through appropriately designed (MNL) models and corresponding choice sets for policy intervention studies in which waiting time and choice interact (de Bekker-Grob et al., 2020).

Regarding the choice of queuing model for the case study at hand, one may argue that the M/M/1 queuing model which assumes patients distribute uniformly over the physicians per level has limited validity and moreover limits generalization of the results to other settings. Indeed, service rates or arrival rates may not be exponentially distributed and the service regime may be different in other settings. Example 3 of the modeling section already discusses the alternatives of M/M/s, /M/M/s/K and M/G/s queuing models. These examples illustrate that the proposed mathematical model is much more general than the specific model of the case study. It accommodates all queuing regimes in which waiting times are increasing in the choice probabilities, in combination with a variety of random utility based choice models. Theorem 3 extends the model to contexts in which opting out is not permitted.

The general model presented still offers a variety of research directions worthwhile pursuing to strengthen and extend it. A main area of improvement lies in the assumption that hospital utility is a linear function of expected waiting time. We are not aware of evidence supporting this assumption, which is implied by the MNL model. On the contrary, there is evidence of piece wise linear

and quadratic relations between travel time and observed queue length with choice probability (Varkevisser et al., 2010; Lu et al., 2013). More generally, it may appear incorrect that a waiting time increase from 15 min to 45 min has the same effect on utility as a waiting time increase from 5 h and 15 min to 5 h and 45 min. Thus generalizations of the proofs of Theorem 2 and 3 to such alternative models, possibly with multiple equilibrium solutions, are called for.

On the same thread, the utility of waiting time likely not only depends on expected waiting time but also on other moments such as the variance, or on the probability of long waiting. This is especially important as waiting times may vary considerably in practice for reasons of variability in demand and capacity as modeled in the perturbed instances of the computational study. Thus, we call for studies which include uncertainty of waiting time and nonlinear relations between expected waiting time and utility, for example using prospect theory based value functions which have been recently explored in a variety of studies on patient preferences (Rouyard et al., 2018; Stolk-Vos et al., 2022).

Among the interesting extensions of the general model, choices and queuing beyond the first visit are of interest, as well as models in which service tasks and times vary depending on patient type (severity). Such extensions may also create further interest in nested choice processes, as already considered in Example 2.

Another valuable direction for extension is formed by the modeling of the learning dynamics of patients. We have assumed that equilibrium choice and waiting time will materialize but policy interventions intend to disturb the equilibrium, for instance, to reduce waiting times. To analyze the effectiveness of interventions, it is therefore also of interest to know how patients learn about waiting times and how newly learned waiting times translate into updated utilities and choices. This matter is especially challenging as the expected waiting time is not easy to observe. The queue length at a given moment in time may be observable, but this does not easily translate into an accurate assessment of expected queue length or subsequent expected waiting time. Moreover, patients may typically have few waiting time observations from personal visits. Added to the fact that learning processes may be slow and not fully rational, the envisioned equilibrium effects of policy interventions may not be realized until much later, if at all (Erev and Roth, 1998). Further research into the underlying strategic learning dynamics of hospital choice and how they can be promoted is thus an important area of future research (Young, 2004; Hart, 2005). This research can borrow from related research in transportation science (see for instance Cominetti et al. (2010) and references therein).

Funding

The third author was supported by the Chinese Scholarship Council [grant number 201507720036]

CRediT authorship contribution statement

Joris van de Klundert: Writing – review & editing, Writing – original draft, Validation, Supervision, Software, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Roberto Cominetti:** Writing – review & editing, Writing – original draft, Software, Methodology, Investigation, Formal analysis, Conceptualization. **Yun Liu:** Writing – original draft, Project administration, Methodology, Investigation, Funding acquisition, Data curation, Conceptualization. **Qingxia Kong:** Writing – review & editing, Validation, Supervision, Software, Methodology, Investigation, Conceptualization.

Declaration of competing interest

None.

Data availability

Data will be made available on request.

Appendix A. Proofs

Proof of Theorem 1. Let $U_i = u_i + \varepsilon_i$. For each realization of the random variables ε_i, the expression

$$\varphi(u, \varepsilon) = \max\{u_1 + \varepsilon_1, \dots, u_n + \varepsilon_n\}$$

is a maximum of linear functions of u, hence it is a convex polyhedral function. Therefore its expectation, being an average of these, is also convex

$$\Phi(u) = \int_{\mathbb{R}^n} \varphi(u, \varepsilon)\, d\mathbb{P}(\varepsilon).$$

Now, let e_i be the ith canonical vector in $\mathbb{R}^n$. Then, when $t \to 0$ with $t > 0$ one can readily check that the differential quotients of $\varphi(\cdot, \varepsilon)$ converge monotonically towards an indicator function, namely

$$\frac{\varphi(u + te_i, \varepsilon) - \varphi(u, \varepsilon)}{t} \to \begin{cases} 1 & \text{if } u_i + \varepsilon_i \geq u_j + \varepsilon_j, \forall j \\ 0 & \text{otherwise,} \end{cases}$$

and therefore Lebesgue's monotone convergence theorem yields

$$\lim_{t \to 0^+} \frac{\Phi(u + te_i) - \Phi(u)}{t} = \int_{\mathbb{R}^n} \mathbb{1}_{\{u_i + \varepsilon_i \geq u_j + \varepsilon_j, \forall j\}} \, d\mathbb{P}(\varepsilon) = \mathbb{P}(U_i \geq U_j, \forall j).$$

Similarly, for $t \to 0$ with $t < 0$ we have

$$\lim_{t \to 0^-} \frac{\Phi(u + te_i) - \Phi(u)}{t} = \int_{\mathbb{R}^n} \mathbb{1}_{\{u_i + \varepsilon_i > u_j + \varepsilon_j, \forall j\}} \, d\mathbb{P}(\varepsilon) = \mathbb{P}(U_i > U_j, \forall j).$$

Since the random variables ε_i are assumed continuous these two limits coincide and then

$$\frac{\partial \Phi}{\partial u_i}(u) = \mathbb{P}(U_i \geq U_j, \forall j) = \mathbb{P}(U_i > U_j, \forall j).$$

As every convex function which is Gateaux differentiable is automatically of class C^1 (Rockafellar, 1997), this completes the proof. □

Proof of Theorem 2. Since the expected utilities $\Phi^k(\cdot)$ are smooth and convex, while the functions $\theta_i^{-1}(\cdot)$ are strictly increasing, it follows that $\Theta(\cdot)$ is strictly convex and smooth, with

$$\frac{\partial \Theta}{\partial w_i}(w) = \theta_i^{-1}(w_i) - \sum_{k \in K} I^k \frac{\partial \Phi^k}{\partial u_i^k}(\bar{u}_0^k, \bar{u}_1^k - \alpha^k w_1, \ldots, \bar{u}_n^k - \alpha^k w_n). \tag{11}$$

Using (1)–(2) it follows that (5) is equivalent to $\nabla \Theta(w) = 0$, and therefore the equilibria coincide with the minimizers of $\Theta(\cdot)$. 0 Since $\Theta(\cdot)$ is strictly convex it has at most one minimizer, and therefore it remains to establish that the minimum is attained. This follows by showing that the recession function satisfies $\Theta^\infty(d) > 0$ for all $d \in \mathbb{R}^n \setminus \{0\}$. Indeed, let us take $d \neq 0$. From Lebesgue's monotone convergence theorem, we have

$$(\Phi^k)^\infty(d) = \max\{0, -\alpha^k d_1, \ldots, -\alpha^k d_n\} = -\alpha^k \min\{0, d_1, \ldots, d_n\},$$

and then using standard rules for computing recession functions we get

$$\Theta^\infty(d) = \sum_{i \in I} H_i^\infty(d_i) - \sum_{k \in K} I^k \min\{0, d_1, \ldots, d_k\}$$

with

$$H_i^\infty(d_i) = \lim_{t \to \infty} \theta_i^{-1}(td_i) d_i = \begin{cases} \bar{x}_i d_i & \text{if } d_i > 0 \\ 0 & \text{if } d_i = 0 \\ +\infty & \text{if } d_i < 0. \end{cases}$$

It follows that $\Theta^\infty(d) = +\infty$ whenever $d_i < 0$ for some $i \in I$. Otherwise, when $d_i \geq 0$ for all $i \in I$, we get $\Theta^\infty(d) = \sum_{i \in I} \bar{x}_i d_i > 0$ which follows since $\bar{x}_i > 0$ for all $i \in I$ and $d \neq 0$. This completes the proof. □

Proof of Theorem 3. After removing the opt-out hospital $i = 0$ from the expression of the expected utilities

$$\Phi^k(u^k) = \mathbb{E}(\max\{u_1^k + \varepsilon_1^k, \ldots, u_n^k + \varepsilon_n^k\}),$$

the characterization of equilibria as the unique minimizer of the strictly convex smooth function $w \mapsto \Theta(w)$ remains valid with the same proof.

For the existence of equilibria, we observe that we still have $\Theta^\infty(d) = +\infty$ when $d_i < 0$ for some $i \in I$, and therefore we only need to check that

$$\sum_{i \in I} \bar{x}_i d_i > \sum_{k \in K} I^k \min\{d_1, \ldots, d_n\} \qquad (\forall d \geq 0, d \neq 0). \tag{12}$$

Let $m = \min\{d_1, \ldots, d_n\}$. The inequality (12) is again trivial when $m = 0$, whereas for $m > 0$ we have that the expression on the left is minimal when $d_i = m$ for all $i \in I$, in which case (12) reduces precisely to (7). □

Appendix B. Intervention study results

Base Base

Probabilities	DCE Only		DCE & Queuing		Sign Test	Nonzero
Pr(OO, M)	77.57	77.57	77.59	77.40	--	
Pr(1, M)	07.84	07.84	07.84	07.83	--	
Pr(2, M)	09.67	09.67	09.66	09.72	PP	
Pr(3, M)	04.92	04.92	04.91	05.05	PP	
Pr(OO, S)	00.06	00.06	00.06	00.06	--	
Pr(1, S)	19.17	19.17	19.18	19.06	--	
Pr(2, S)	27.09	27.09	27.09	27.01	--	
Pr(3, S)	53.68	53.68	53.67	53.87	PP	
W(1)	0.43	0.43	0.43	0.43	--	
W(2)	1.53	1.50	1.52	1.48	-	
W(3)	3.54	3.58	3.54	3.43	pp	

Base Reduced Opt Out Utility

Probabilities	DCE Only		DCE & Queuing		Sign Test	Nonzero
Pr(OO, M)	49.80	49.80	54.05	53.48	Pp	X
Pr(1, M)	17.55	17.55	18.59	18.44	Pp	X
Pr(2, M)	21.64	21.64	18.18	18.51	--	X
Pr(3, M)	11.01	11.01	09.17	09.57	--	
Pr(OO, S)	00.06	00.06	00.06	00.06	Pp	X
Pr(1, S)	19.17	19.17	20.79	20.53	Pp	X
Pr(2, S)	27.09	27.09	26.61	26.56	--	
Pr(3, S)	53.68	53.68	52.54	52.85	--	
W(1)	0.51	0.51 (739)	0.54	0.53	Pp	X
W(2)	4.08	4.19 (739)	2.62	2.50	--	X
W(3)	6.92	5.24 (739)	4.66	4.46	--	

Base Increased Waiting Time Sensitivity

Probabilities	DCE Only		DCE & Queuing		Sign Test	Nonzero
Pr(OO, M)	77.57	77.57	76.97	76.78	--	X
Pr(1, M)	07.84	07.84	07.73	07.73	--	X
Pr(2, M)	09.67	09.67	09.51	09.61	--	
Pr(3, M)	04.92	04.92	05.77	05.88	PP	X
Pr(OO, S)	00.06	00.06	00.07	00.07	PP	X
Pr(1, S)	19.17	19.17	22.52	22.27	PP	X
Pr(2, S)	27.09	27.09	27.53	27.50	PP	
Pr(3, S)	53.68	53.68	49.86	50.15	--	X
W(1)	0.43	0.43	0.46	0.45	pp	X
W(2)	1.52	1.48	1.55	1.50	pp	
W(3)	3.54	3.55	2.80	2.72	--	

Medium Skill Base

Probabilities	DCE Only			DCE & Queuing			Sign Test	Nonzero
Pr(OO, M)	74.04	74.04		74.11	73.90		--	
Pr(1, M)	12.04	12.04		11.98	11.97		--	
Pr(2, M)	09.22	09.23		09.24	09.31		PP	
Pr(3, M)	04.70	04.70		04.66	04.82		PP	
Pr(OO, S)	00.06	00.06		00.06	00.06		--	
Pr(1, S)	18.57	18.57		18.57	18.42		--	
Pr(2, S)	27.29	27.29		27.37	27.25		--	
Pr(3, S)	54.08	54.08		54.00	54.27		PP	
W(1)	0.46	0.46		0.46	0.45		--	
W(2)	1.51	1.48		1.51	1.47			
W(3)	3.60	3.59		3.57	3.43		pp	

Medium Skill Reduced Opt Out Utility

Probabilities	DCE Only			DCE & Queuing			Sign Test	Non Zero
Pr(OO, M)	44.99	44.99		48.38	47.90		Pp	X
Pr(1, M)	25.52	25.52		26.28	26.11		Pp	
Pr(2, M)	19.55	19.55		16.93	18.51		--	X
Pr(3, M)	09.95	09.95		08.40	08.77		--	
Pr(OO, S)	00.06	00.06		00.06	00.06		Pp	X
Pr(1, S)	18.57	18.57		19.83	19.60		Pp	X
Pr(2, S)	27.29	27.29		27.05	26.98		--	
Pr(3, S)	54.08	54.08		53.05	53.36		-	
W(1)	0.59	0.58 (785)		0.62	0.61		Pp	X
W(2)	3.23	3.21 (785)		2.45	2.34		--	X
W(3)	6.30	5.01 (785)		4.56	4.37		--	

Medium Skill Increased Waiting Time Sensitivity

Probabilities	DCE Only			DCE & Queuing			Sign Test	Nonzero
gPr(OO, M)	74.04	74.04		73.58	73.39		--	
Pr(1, M)	12.04	12.04		11.83	11.81		--	X
Pr(2, M)	09.22	09.23		09.10	09.18		-	
Pr(3, M)	04.70	04.70		05.49	05.61		PP	X
Pr(OO, S)	00.06	00.06		00.08	00.07		PP	X
Pr(1, S)	18.57	18.57		21.80	21.52		PP	X
Pr(2, S)	27.29	27.29		27.89	27.79		PP	
Pr(3, S)	54.08	54.08		50.23	50.62		--	X
W(1)	0.46	0.46		0.49	0.48		Pp	X
W(2)	1.51	1.47		1.55	1.50		Pp	
W(3)	3.60	3.55		2.82	2.73		--	X

Expert Skill Base

Probabilities	DCE Only			DCE & Queuing			Sign Test	Nonzero
Pr(OO, M)	75.87	75.87		75.45	75.26		--	
Pr(1, M)	10.94	10.94		10.80	10.79		--	
Pr(2, M)	08.38	08.38		08.14	08.22		--	
Pr(3, M)	04.81	04.81		05.60	05.73		PP	X
Pr(OO, S)	00.05	00.05		00.05	00.05		--	
Pr(1, S)	20.87	20.87		20.20	20.09		--	X
Pr(2, S)	30.68	30.68		29.49	29.44		--	X
Pr(3, S)	48.40	48.40		50.26	50.42		Pp	X
W(1)	0.47	0.47		0.46	0.46		--	X
W(2)	1.77	1.72		1.62	1.57		--	X
W(3)	2.41	2.36		2.85	2.76		Pp	X

Expert Skill Reduced Opt Out Utility

Probabilities	DCE Only			DCE & Queuing			Sign Test	Nonzero
Pr(OO, M)	47.42	47.42		50.18	49.81		Pp	X
Pr(1, M)	23.83	23.83		24.18	24.07		--	
Pr(2, M)	18.26	18.26		15.21	15.43		--	X
Pr(3, M)	10.49	10.49		10.42	10.69		PP	
Pr(OO, S)	00.05	00.06		00.06	00.06		Pp	
Pr(1, S)	20.87	20.87		21.50	21.33		Pp	
Pr(2, S)	30.68	30.68		29.04	29.03		--	X
Pr(3, S)	48.40	48.40		49.41	49.58		--	
W(1)	0.60	0.60 (925)		0.62	0.61		Pp	
W(2)	4.40	4.31 (925)		2.55	2.46		--	X
W(3)	3.49	3.49 (925)		3.80	3.67		--	

Expert Skill Increased Waiting Time Sensitivity

Probabilities	DCE Only			DCE & Queuing			Sign Test	Nonzero
Pr(OO, M)	75.87	75.87		75.04	74.89		--	X
Pr(1, M)	10.94	10.94		10.68	10.67		--	X
Pr(2, M)	08.38	08.38		08.11	08.18		--	
Pr(3, M)	04.81	04.81		06.17	06.26		PP	X
Pr(OO, S)	00.05	00.05		00.06	00.06		Pp	X
Pr(1, S)	20.87	20.87		23.33	23.10		Pp	X
Pr(2, S)	30.66	30.68		29.46	29.44		--	
Pr(3, S)	48.40	48.40		47.15	47.39		--	
W(1)	0.47	0.47		0.47	0.48		pp	X
W(2)	1.77	1.73		1.61	1.56		-	
W(3)	2.41	2.36		2.41	2.34		pp	

Upgrade Equipment Base

Probabilities	DCE Only		DCE & Queuing		Sign Test	Nonzero
Pr(OO, M)	71.29	71.29	70.46	70.29	--	X
Pr(1, M)	12.49	12.49	11.94	11.93	--	X
Pr(2, M)	11.70	11.70	11.10	11.10	--	
Pr(3, M)	04.52	04.52	06.50	06.57	PP	X
Pr(OO, S)	00.04	00.04	00.04	00.04	--	X
Pr(1, S)	32.20	32.20	30.03	29.94	--	X
Pr(2, S)	29.60	29.60	27.52	27.55	--	X
Pr(3, S)	38.16	38.16	42.41	42.47	PP	X
W(1)	0.62	0.61	0.58	0.57	--	X
W(2)	2.03	1.98	1.69	1.65	-	X
W(3)	1.49	1.46	1.91	1.86	pp	X

Advanced Equipment Reduced Opt Out Utility

Probabilities	DCE Only		DCE & Queuing		Sign Test	Nonzero
Pr(OO, M)		41.60	44.10	43.79	Pp	X
Pr(1, M)		25.41	24.67	24.61	--	X
Pr(2, M)		23.80	18.97	19.20	--	X
Pr(3, M)		09.20	12.27	12.40	PP	X
Pr(OO, S)		00.04	00.04	00.04	--	
Pr(1, S)		32.20	31.20	31.09	--	X
Pr(2, S)		29.60	26.36	26.41	--	X
Pr(3, S)		38.16	42.39	42.44	PP	X
	Infeasible					
W(1)		0.84 (530)	0.81	0.79	--	X
W(2)		5.63 (530)	2.75	2.66	-	X
W(3)		1.72 (530)	2.54	2.47	pp	X

Upgrade Equipment Increased Waiting Time Sensitivity

Probabilities	DCE Only		DCE & Queuing		Sign Test	Nonzero
Pr(OO, M)	71.29	71.29	70.24	70.09	--	X
Pr(1, M)	12.49	12.49	11.80	11.80	--	X
Pr(2, M)	11.70	11.70	11.26	11.36	--	
Pr(3, M)	04.52	04.52	06.70	06.75	PP	X
Pr(OO, S)	00.04	00.04	00.04	00.04	PP	X
Pr(1, S)	32.20	32.20	32.81	32.64	PP	
Pr(2, S)	29.60	29.60	26.63	26.72	--	X
Pr(3, S)	38.16	38.16	40.51	40.59	PP	X
W(1)	0.62	0.61	0.62	0.61	--	
W(2)	2.03	1.97	1.62	1.57	-	X
W(3)	1.49	1.46	1.77	1.73	pp	X

Upskill and Upgrade Base

Probabilities	DCE Only		DCE & Queuing		Sign Test	Nonzero
Pr(OO, M)	68.56	68.56	67.91	67.76	--	X
Pr(1, M)	17.13	17.13	16.11	16.11	--	X
Pr(2, M)	09.97	09.97	09.27	09.38	--	X
Pr(3, M)	04.35	04.35	06.71	06.76	PP	X
Pr(OO, S)	00.03	00.04	00.04	00.04	--	X
Pr(1, S)	34.03	34.03	31.58	31.51	--	X
Pr(2, S)	32.54	32.54	30.05	30.11	--	X
Pr(3, S)	33.39	33.39	38.33	38.34	PP	X
W(1)	0.72	0.71	0.66	0.65	--	X
W(2)	2.26	2.20	1.79	1.73	-	X
W(3)	1.26	1.24	1.61	1.58	pp	X

Upskill and Upgrade Reduced Opt Out Utility

Probabilities	DCE Only		DCE & Queuing		Sign Test	Nonzero
Pr(OO, M)	38.47	38.47	40.78	40.42	Pp	X
Pr(1, M)	33.52	33.52	30.88	30.86	--	X
Pr(2, M)	19.50	19.50	15.76	16.03	--	X
Pr(3, M)	08.51	08.51	12.58	12.68	PP	X
Pr(OO, S)	00.04	00.04	00.04	00.04	--	
Pr(1, S)	34.03	34.03	32.18	32.07	--	X
Pr(2, S)	32.54	32.54	29.09	29.20	--	X
Pr(3, S)	33.39	33.39	38.69	38.69	PP	X
W(1)	1.26	1.23 (660)	1.04	1.00	--	X
W(2)	8.70	5.11 (660)	2.69	2.58	-	X
W(3)	1.43	1.40 (660)	2.09	2.02	pp	X

Upskill and Upgrade Increased Waiting Time Sensitivity

Pr(OO, M)	68.56	68.56	67.68	67.63	--	X
Pr(1, M)	17.13	17.13	15.93	15.95	--	X
Pr(2, M)	09.97	09.97	09.50	09.58	--	
Pr(3, M)	04.35	04.35	06.80	06.84	PP	X
Pr(OO, S)	00.04	00.04	00.04	00.04	Pp	X
Pr(1, S)	34.03	34.03	33.94	33.81	--	
Pr(2, S)	32.54	32.54	28.82	28.92	--	X
Pr(3, S)	33.39	33.39	37.19	37.23	PP	X
W(1)	0.72	0.71	0.70	0.68	--	X
W(2)	2.26	2.21	1.67	1.63	-	X
W(3)	1.26	1.24	1.55	1.51	pp	X

References

Antonakis, John, Bendahan, Samuel, Jacquart, Philippe, Lalive, Rafael, 2010. On making causal claims: A review and recommendations. Leadersh. Q. 21 (6), 1086–1120.

Arsenault, Catherine, Kim, Min Kyung, Aryal, Amit, Faye, Adama, Joseph, Jean Paul, Kassa, Munir, Degfie, Tizta Tilahun, Yahya, Talhiya, Kruk, Margaret E, 2020. Hospital-provision of essential primary care in 56 countries: determinants and quality. Bull. World Health Organ. 98 (11), 735.

Berhane, Adugnaw, Enquselassie, Fikre, 2015. Patients' preferences for attributes related to health care services at hospitals in Amhara region, northern ethiopia: a discrete choice experiment. Patient Prefer. Adherence 9, 1293.

Brown, Paul, Panattoni, Laura, Cameron, Linda, Knox, Stephanie, Ashton, Toni, Tenbensel, Tim, Windsor, John, 2015. Hospital sector choice and support for public hospital care in new Zealand: Results from a labeled discrete choice survey. J. Health Econ. 43, 118–127.

Chao, Jianqian, Lu, Boyang, Zhang, Hua, Zhu, Liguo, Jin, Hui, Liu, Pei, 2017. Healthcare system responsiveness in Jiangsu Province, China. BMC Health Serv. Res. 17, 1–7.

Cominetti, Roberto, Melo, Emerson, Sorin, Sylvain, 2010. A payoff-based learning procedure and its application to traffic games. Games Econom. Behav. 70 (1), 71–83.
Cominetti, Roberto, Van de Klundert, Joris, Python Code for Equilibrium Computation, https://github.com/JorisAtWork/HospitalChoiceandWaitingTimeEquilbria/blob/main/Copy_of_HospitalChoice.ipynb.
de Bekker-Grob, Esther W, Donkers, Bas, Bliemer, Michiel CJ, Veldwijk, Jorien, Swait, Joffre D, 2020. Can healthcare choice be predicted using stated preference data? Soc. Sci. Med. 246, 112736.
Domencich, Thomas A., McFadden, Daniel, 1975. Urban Travel Demand-A Behavioral Analysis. North-Holland Publishing Company Limited, Oxford, England.
Erev, Ido, Roth, Alvin E., 1998. Predicting how people play games: Reinforcement learning in experimental games with unique, mixed strategy equilibria. Am. Econ. Rev. 848–881.
Fischer, Sophia, Pelka, Stefanie, Riedl, René, 2015. Understanding patients' decision-making strategies in hospital choice: Literature review and a call for experimental research. Cogent Psychol. 2 (1), 1116758.
Ghebreyesus, Tedros Adhanom, Fore, Henrietta, Birtanov, Yelzhan, Jakab, Zsuzsanna, 2018. Primary health care for the 21st century, universal health coverage, and the sustainable development goals. Lancet 392 (10156), 1371–1372.
Guevara, C. Angelo, 2015. Critical assessment of five methods to correct for endogeneity in discrete-choice models. Transp. Res. A 82, 240–254.
Hart, Sergiu, 2005. Adaptive heuristics. Econometrica 73 (5), 1401–1430.
Jones, Simon, Moulton, Chris, Swift, Simon, Molyneux, Paul, Black, Steve, Mason, Neil, Oakley, Richard, Mann, Clifford, 2022. Association between delays to patient admission from the emergency department and all-cause 30-day mortality. Emerg. Med. J. 39 (3), 168–173.
Kucukyazici, Beste, Zhang, Yue, Ardestani-Jaafari, Amir, Song, Lijie, 2020. Incorporating patient preferences in the design and operation of cancer screening facility networks. European J. Oper. Res. 287 (2), 616–632.
Laiyun, Sheng, et al., 2013. An Analysis Report of National Health Services Survey in China. Center for Health Statistics and Information.
Lee, Hau Leung, Cohen, Morris A., 1985. Equilibrium analysis of disaggregate facility choice systems subject to congestion-elastic demand. Oper. Res. 33 (2), 293–311.
Li, Xi, Krumholz, Harlan M, Yip, Winnie, Cheng, Kar Keung, De Maeseneer, Jan, Meng, Qingyue, Mossialos, Elias, Li, Chuang, Lu, Jiapeng, Su, Meng, et al., 2020. Quality of primary health care in China: challenges and recommendations. Lancet 395 (10239), 1802–1812.
Li, Xi, Lu, Jiapeng, Hu, Shuang, Cheng, KK, De Maeseneer, Jan, Meng, Qingyue, Mossialos, Elias, Xu, Dong Roman, Yip, Winnie, Zhang, Hongzhao, et al., 2017. The primary health-care system in China. Lancet 390 (10112), 2584–2594.
Liu, Yun, Kong, Qingxia, Wang, Shan, Zhong, Liwei, van de Klundert, Joris, 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.
Liu, Yun, Kong, Qingxia, Yuan, Shasha, van de Klundert, Joris, 2018. Factors influencing choice of health system access level in China: a systematic review. PLoS One 13 (8), e0201887.
Liu, Yun, Zhong, Liwei, Yuan, Shasha, van de Klundert, Joris, 2018. Why patients prefer high-level healthcare facilities: a qualitative study using focus groups in rural and urban China. BMJ Glob. Health 3 (5), e000854.
Lu, Yina, Musalem, Andrés, Olivares, Marcelo, Schilkrut, Ariel, 2013. Measuring the effect of queues on customer purchases. Manage. Sci. 59 (8), 1743–1763.
Marianov, Vladimir, Ríos, Miguel, Icaza, Manuel José, 2008. Facility location for market capture when users rank facilities by shorter travel and waiting times. European J. Oper. Res. 191 (1), 32–44.
Martinez, Diego A, Zhang, Haoxiang, Bastias, Magdalena, Feijoo, Felipe, Hinson, Jeremiah, Martinez, Rodrigo, Dunstan, Jocelyn, Levin, Scott, Prieto, Diana, 2019. Prolonged wait time is associated with increased mortality for Chilean waiting list patients with non-prioritized conditions. BMC Public Health 19 (1), 1–11.
McIntyre, Daniel, Chow, Clara K., 2020. Waiting time as an indicator for health services under strain: a narrative review. INQUIRY: J. Health Care Organ. Provis. Financ. 57, 0046958020910305.
Meng, Qingyue, Mills, Anne, Wang, Longde, Han, Qide, 2019. What can we learn from China's health system reform? bmj 365.
National Health Commission of the People's Republic of China, 2020. Notice of the national health commission on comprehensively promoting the construction of community health centers. http://www.nhc.gov.cn/jws/s3581/202007/2aab83700656411e9ab35ae9049dc732.shtml.
Natural Bureau of Statistics of China, 2019. China Statistical Yearbook 2019. China Statistics Press.
Rockafellar, R. Tyrrell, 1997. Convex Analysis. Vol. 11, Princeton University Press.
Rouyard, Thomas, Attema, Arthur, Baskerville, Richard, Leal, José, Gray, Alastair, 2018. Risk attitudes of people with 'manageable'chronic disease: an analysis under prospect theory. Soc. Sci. Med. 214, 144–153.
Shanghai, MSB, 2018. Shanghai Statistical Yearbook. China Statistics Press.
Sheffi, Yosef, Daganzo, Carlos F., 1978. Another "paradox" of traffic flow. Transp. Res. 12 (1), 43–46.
Smith, Honora, Currie, Christine, Chaiwuttisak, Pornpimol, Kyprianou, Andreas, 2018. Patient choice modelling: how do patients choose their hospitals? Health Care Manag. Sci. 21 (2), 259–268.
Stolk-Vos, Aline C, Attema, Arthur E, Manzulli, Michele, van de Klundert, Joris J, 2022. Do patients and other stakeholders value health service quality equally? A prospect theory based choice experiment in cataract care. Soc. Sci. Med. 294, 114730.
Ta, Yuqi, Zhu, Yishan, Fu, Hongqiao, 2020. Trends in access to health services, financial protection and satisfaction between 2010 and 2016: Has China achieved the goals of its health system reform? Soc. Sci. Med. 245, 112715.
Train, Kenneth E., 2009. Discrete Choice Methods with Simulation. Cambridge University Press.
Varkevisser, Marco, van der Geest, Stéphanie A, Schut, Frederik T, 2010. Assessing hospital competition when prices don't matter to patients: the use of time-elasticities. Int. J. Health Care Finance Econ. 10, 43–60.
Victoor, Aafke, Delnoij, Diana MJ, Friele, Roland D, Rademakers, Jany JDJM, 2012. Determinants of patient choice of healthcare providers: a scoping review. BMC Health Serv. Res. 12 (1), 1–16.
Williams, Huw CWL, 1977. On the formation of travel demand models and economic evaluation measures of user benefit. Environ. Plan. A 9 (3), 285–344.
Young, H. Peyton, 2004. Strategic Learning and Its Limits. OUP Oxford.
Zhang, Yue, Atkins, Derek, 2019. Medical facility network design: User-choice and system-optimal models. European J. Oper. Res. 273 (1), 305–319.
Zhu, Jingrong, Li, Jinlin, Zhang, Zengbo, Li, Hao, Cai, Lingfei, 2019. Exploring determinants of health provider choice and heterogeneity in preference among outpatients in Beijing: a labelled discrete choice experiment. BMJ Open 9 (4), e023363.
Zou, D.D., Zhang, Z.F., et al., 2017. Analysis on outpatient stay in tertiary public hospitals in shanghai and relative patient satisfaction degree. Chin. Health Resour. 20 (6), 464–468.