A Choice Model for Estimating Realized Accessibility: Case Study for Obstetrics Care in Korea

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Abstract Improving accessibility to care in medically under-served areas(MUAs) is the goal of MUA support program in public health policy. In the planning phase of such programs, we often use geographical proximity of care facilities as a measure of accessibility, and the programs resource is used to maximize the geographical accessibility. While it is easy to assess the geographical accessibility, this is not always an accurate assessment of the actual, realized accessibility because true accessibility is realized by the actual service use by patients. The choice of a specific care provider by patients is made not just by a physical distance, but by many other factors including the size of a care provider, physician's demographic, etc. Predicting true accessibility thus requires a model that considers various factors in the patients decision making, and in this paper, we use a choice model known as the conditional logit model. We use the actual health insurance data from Korea to identify factors affecting patients choice of care providers and model the provider choice behavior of patients by using the MNL model. To validate the proposed model, we compare the actual patient volumes for care providers with the model prediction, and the results show a good agreement suggesting the MNL model is a promising approach to assess true accessibility to care.

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1 Introduction

A medically under-served area (MUA) is a region where access to health care services is limited. This is often caused by the lack of health care service capacity, hospitals in most contexts. Often, public health authority installs policy interventions, for example by establishing new care capacity, to improve accessibility to health care for people residing in MUAs [1].

Accessibility has two components: potential accessibility and realized accessibility [2]. Potential accessibility is measured by the existence of a hospital within reasonable proximity, e.g. 60-min for obstetrics care. The term *potential* indicates that the mere existence of a hospital does not necessarily mean it provides sufficient access to the patients due to various factors; they may travel long distance to get care from a hospital with higher quality of service or from a hospital with lower expenses. Realized accessibility, as its name suggests, measures accessibility in terms of actual, realized use of health care services.

While potential accessibility is prognostic and easy-to-measure in the planning stage, realized accessibility can only be guessed at the time of planning. In planning an intervention strategy, policy makers need to have a good understanding as to how health service consumers would respond to newly established capacity. Without it, they may invest in capacity that ends up being unused, yielding less-than-desired outcomes.

A key to the accurate prediction is the understanding of health service consumers' choice of care providers, and this type of problem has been analyzed by using what is known as a discrete choice model [3, 4]. Discrete choice models, originally developed in economics, describe choices between two or more discrete alternatives. For example, we can construct a model to describe patients' decision regarding a choice between available hospitals to visit to receive care. Specifically, the attributes of each of the patient and the attributes of the available hospitals are statistically related to the particular choice made by the patient.

In this paper, we develop a discrete choice model to capture patients' choice behavior for health care service providers. We use nation-wide data of MUAs for obstetrics care in Korea. Using the data, we construct a conditional logit model, which is one of the popular discrete choice models in economics and other relevant studies. In the context of the MUA support program, such a model would offer an opportunity to develop a location model that takes into account the future (expected) consumer responses to the care providers to establish. If we develop an accurate choice model with manageable degree of complexity, the expected responses can be endogenized into a location model.

Remainder of this paper is structured as follows. Section 2 provides a brief overview on discrete choice models. In Sect. 3 discusses the conditional logit model and its specification, along with the data used in our study. Section 4 summarizes the results and discusses the major findings from the model. Finally, Sect. 5 concludes with a few issues to address in future research.

2 Discrete Choice Model

Originated in psychology and economics, discrete choice models describe and explain choices between two or more discrete alternatives. Specifically, discrete choice models specify the probability that an individual decision maker chooses an option among a set of alternatives. For example, we can construct a discrete choice model to estimate the probability that a patient will choose to receive a tonsillectomy or not, or the probabilities for each of five available hospitals that the patient will choose to receive the surgery from. Such prediction is made by statistically relating the choice made by a decision maker to the attributes of the decision maker and the attributes of the alternatives.

Discrete choice models assume that a decision maker chooses an alternative that returns the greatest utility. Let U_{ni} denote utility that decision maker n obtains from alternative i. Then, the probability that decision maker n chooses alternative i is

$$P_{ni} = Prob(U_{ni} > U_{nj}, \forall j \neq i) \tag{1}$$

In discrete choice models, U_{ni} is assumed to consist of two parts: $U_{ni} = V_{ni} + \varepsilon_{ni}$ where V_{ni} is observable utility and ε_{ni} is unobservable utility. V_{ni} depends on the attributes that the modeller observes—the attributes of the decision maker n and the attributes of alternative i faced by n. ε_{ni} represents the random effects of all factors that are not observable to the modeller. It is assumed to follow some probabilistic distribution, giving the stochastic nature to discrete choice models. With V_{ni} and ε_{ni}, (1) can be rewritten as follows:

$$\begin{aligned} P_{ni} &= Prob(V_{ni} + \varepsilon_{ni} > V_{nj} + \varepsilon_{nj}, \forall j \neq i) \\ &= Prob(\varepsilon_{nj} - \varepsilon_{ni} < V_{ni} - V_{nj}, \forall j \neq i) \end{aligned} \tag{2}$$

Different choices for a stochastic distribution of ε_{ni} give rise to different choice models. For example, in the case of binary choices, assuming the extreme value distribution for ε_{ni} yields the *logit* model. If ε_{ni} is assumed to follow the standard normal distribution, then the resulting choice model is the *probit* model. A wide range of choice models have been developed, and the reader is referred to [5, 6] for a full account of the discrete choice models.

In our application, we use the conditional logit model to describe hospital choices by patients. The conditional logit model was introduced by McFadden [7], and has been extensively used to estimate choice behaviors in numerous applications. In the logit model, a decision maker faces more than two alternatives, hence multinomial choices, and its unobserved utility ε_{ni} is assumed to follow the extreme value distribution—the Gumbel distribution in particular. It is similar to the multinomial logit model, a more basic version of the multinomial choice models, but differs in its modeling scope. A key benefits of the conditional logit model is that *a choice among alternatives is treated as a function of the characteristics of the alternatives, rather than (or in addition to) the characteristics of the individual making the choice* [8]. In the conditional logit model, we have a closed-form expression for the choice probability that decision maker n chooses alternative i among the alternatives, J:

$$P_{ni} = \frac{\exp(V_{ni})}{\sum_{k \in J} \exp(V_{nk})} \tag{3}$$

Since Eq. (3) is a function of only the observable utilities, it can be easily calculated as long as we have identified V_{ni} in a functional form. Recall that the main motivation for us to develop a choice model is to use it in the context of location models. The fact that P_{ni} is easily computed under the conditional logit model enables us to conveniently incorporate the choice probability, hence the expected responses from the patients, into a location model.

3 Choice Model for Obstetrics Patients in Korea

This section presents the choice model that we construct to understand the hospital choice behavior of obstetrics patients in Korea. We first describe two modeling components in Sect. 3.1. Specifically, we define two major modeling components: a choice set J and decision maker n's utility V_{ni}. Then, we discuss the obstetrics care data we used to construct the model in Sect. 3.2.

3.1 Model Components

The choice set is a set of alternatives available to the decision maker. For our problem, the choice set consists of obstetric care providers in Korea. Korea runs its health care system under the national health insurance program, which is mandated for every resident to subscribe. Under the national health insurance program, individual health service consumers—pregnant women in our study—are given complete freedom to choose any obstetrics care provider.[1] In this sense, we may include all obstetric care providers in Korea in the choice set for each pregnant woman. However, using the entire set of obstetric care providers in Korea as the choice set for all decision maker

[1]In general, health service consumers in Korea has "almost" complete freedom in a sense that there exists a mechanism to induce appropriate use of health care resources. For example, the government implements price differentiation between care providers in different tiers to prevent over- and unwarranted use of high-tier care providers.

Table 1 Selected factors for the patients' hospital selection model

Group	Factors	Group	Factors
Accessibility easy access by transport (e.g., public or own, parking)	Travel time	Staff	Medical qualification; Specialization/interest; No. of staff per patient
Availability (e.g., open hr)	Language incentivizing by insurers	Organization of care	Convenience (e.g., open hours)
Type/Size of the institution	Provider ownership (e.g., public, for-profit, private non-profit) quality of facilities provider size (e.g., no. of beds)	Physician's demographic; Cost	Patient experience; Gender; Age; Out-of-pocket expenses

does not seem very sensible. First, we conjecture that many of the cases of deliveries at a hospital far away from their residence are possibly due to incomplete data, for example mismatch between actual residence at the time of delivery and the address on the national residence registry. Second, the actual data shows that majority of women have chosen a hospital not too far away from them. It turns out that 91.6% of the total delivery cases are handled by a hospital located within 120 minutes of travel distance from the mother's residence. Thus, we define the choice set for pregnant woman n as a set of hospital located within 120-min of n's residence.

Next, to define decision maker n's utility, V_{ni}, we need to identify the variables that characterize the attributes of alternative i faced by decision maker n. Simply put, we need to identify factors affecting the decision maker's choice of a hospital. In this paper, we follow the framework proposed by Victor et al. [9]. It identifies various factors that are found to affect patients' hospital selection. These factors are classified into seven groups. See Table 1.

We examine each of the factors shown in Table 1 for their relevance to our problem and availability of necessary data. Factors in the organization of care, cost groups, and physician's demographic are excluded due to data unavailability. Language and insurance factors in the availability group are excluded as they are irrelevant to Korean heath care environment. We adopt travel time factor in the Accessibility group, while the easy-access-by-transport factors are excluded due to the data issue. For the institution factors, we use two alternative factors that are available for our study: level of a hospital and the degree of urbanization of the town a hospital is located. For the Staff category, we adopt the number of obstetrics specialists as a representative alternative for the factors identified above. We assume, albeit without empirical evidence, these three factors are reasonable surrogates to capture the attributes that the institution and staff factors intend to represent in [9].

Let us use t_{ni}, Lv_i, Urb_i, and Num_i denote the travel time, hospital level, urbanization of the hospital location, and the number of obstetrics specialists, respectively. Their operational definition used in our model is as follows.

- Level of hospital, Lv_i

The level of a hospital is an important factor when patients choose the hospital to receive care. Like the health care systems in many other countries, medical institutions in Korea are hierarchically structured—primary, secondary, and tertiary.[2] For the purpose of our discussion here, we can further simplify it into a two-tier system as there is not much difference between the primary and secondary hospitals when it comes to obstetric care provision. Then, Lv_i enters the model as a dummy variable:

$LvH_i = 1$ if i is a tertiary hospital, and 0 otherwise;
$LvL_i = 1$ if i is an either primary or secondary hospital, and 0 otherwise.

- Urbanization of the hospital location, Urb_i

It is expected that whether a hospital is located in a metropolitan area or a rural county influences patient's perception, hence their choice, of the hospital. In Korea, for many types of health care services, it is believed that patients strongly prefer hospitals located in metropolitan areas. Due to its categorical nature, this variable enters the model as a dummy variable as well:

$UrbMetro_i = 1$ if i is in a metropolitan region, and 0 otherwise;
$UrbCity_i = 1$ if i is in a city region, and 0 otherwise;
$UrbRural_i = 1$ if i is in a rural region, and 0 otherwise.

- Number of obstetrics specialists, Num_i

The number of obstetrics specialists is another variable relevant to the size and quality of a hospital. It is also correlated to the number of female obstetrics physicians, which is another presumably important factor when pregnant women choose a hospital for their delivery. According to our survey through obstetrics care providers' web page, the correlation coefficient between the number of physicians and the number of female physicians is 0.82.

- Travel time, t_{ni}

Presumably, travel time is important consideration when choosing a hospital as it is a primary determinant of physical accessibility. Note that, unlike the other variables, t_{ni} depends on a patient-hospital pair, indicated by its double-index ni. We use the hospital addresses and residential addresses to compute travel times for all $\{ni\}$ pairs, assuming automotive transportation.

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[2]The hierarchical structure in Korea's healthcare system is a little more complicated than that, but for the purpose of our discussion it suffices to use a three-tier (primary, secondary, and tertiary) classification.

With these four variables, our specification for V_{ni} is as follows:

$$V_{ni} = \beta_{Lv} * Lv_i + \beta_{Urb} * Urb_i + \beta_{Num} * Num_i + \beta_t * t_{ni} \tag{4}$$

Coefficients in Eq. (4) are estimated by the maximum likelihood estimation method, and we use the MDC Procedure in SAS.

3.2 Data

We use the data for actual uses of obstetrics care providers by pregnant women for their deliveries in Korea in year 2015. Given the model specification (4), we need data, for each delivery case, on the mother's residential address and identification of the hospital she gave birth in. Then, for these hospitals, we need information on their designation level, address, and the number of obstetrics specialists. These sets of data have been obtained from three sources: National Health Insurance Service (NHIS), Health Insurance Review & Assessment Service (HIRA), and National Transportation DB center. Using these data sources, we define the choice set (Fig. 1).

Birth data from NHIS consists of mothers' residential addresses and the id code of the hospitals they used. After excluding invalid entries, 291,126 delivery cases have been obtained from the database. It should be noted that due to the NHIS privacy requirement, we were not given an individual mother's residential address; individual birth records have been compiled at an aggregate geographical unit before being made available for our analysis.

Hospital information is obtained from HIRA. There are 576 medical institutions that has at least one case of delivery during year 2015. Some of these institutions have less than 50 cases of deliveries in one year. Also there are some institutions for which HIRA data shows no obstetricians. Our discussion with the government officials and public health experts suggests that these institutions do not provide delivery services under nominal circumstances or as part of their regular services, and thus we exclude these institutions from our analysis. This leaves us 480 hospitals across the country. The HIRA database contains information on each hospital for their designation, address, number of beds and labor beds, number of obstetrics specialists and physicians, number of nurses and other equipment.

The travel time between each geographical unit and hospitals is obtained by using the network analysis tool offered in ArcGIS 10.0. For each unit, we use a population-weighted centroid as its center point from which we measure the travel distance to each of the hospitals. Traffic analysis network data from the National Transportation DB Center is used to provide information on the road network and average vehicle speed, etc.

Motivated by the MUA support program for obstetrics care in Korea, our objective of constructing the choice model is to understand the choice behavior of prospective mothers in MUAs. We conjectured that the choice behavior of prospective mothers will be largely influenced by where they live. In particular, people who live in and

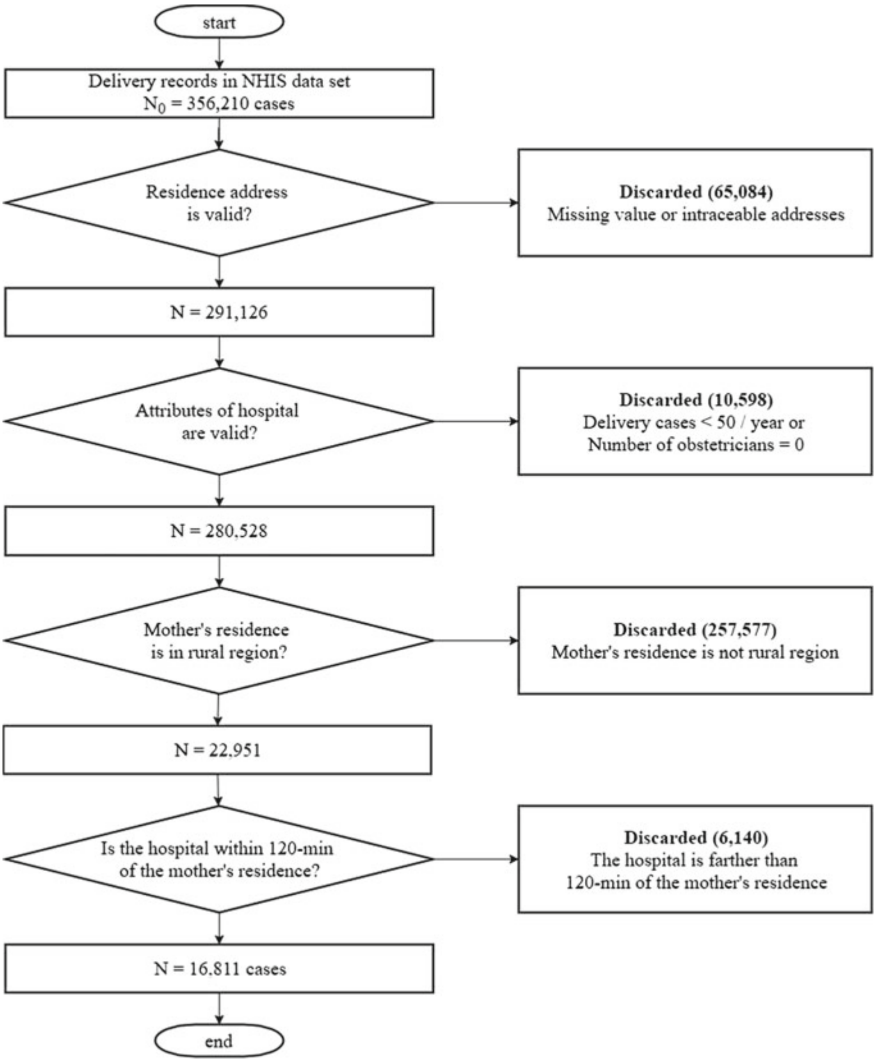

Fig. 1 Flow chart to define the final data set

around MUAs are likely to choose a hospital on the different rationale than those who have access to abundant alternatives. Thus from the entire records of delivery cases in Korea, we include delivery cases from the rural regions. Note that 33 out of 34 MUAs are rural region and that 33 out of 82 rural regions in Korea are MUAs. The final data used in our analysis is, for each of 82 rural regions, a list of hospitals and the number of cases each hospital served. The descriptive statistics of hospitals are shown in Table 2.

Table 2 Descriptive statistics of alternatives

Categorical factor		N		Ratio (%)
Hospital level		468		100.0
LvL		370		79.1
LvH		98		20.9
Hospital location		468		100.0
UrbMetro		311		66.5
UrbCity		147		31.4
UrbRural		10		2.1
Numerical factor	Mean	Std.	Min	Max
Number of obstetricians				
Num	5.42	4.61	1	38

4 Result

Observable utility V_{ni} of hospital i faced by pregnant women in region n is

$$V_{ni} = -1.0722 * LvH_i - 0.1738 * UrbCity_i - 0.8619 * UrbRural_i + 0.1511 * Num_i - 0.0637 * t_{ni} \tag{5}$$

The detailed results for the conditional logit model is shown in Table 3. All coefficients are statistically significant with their p-value very small. The last column of

Table 3 Results of the patients' hospital choice model

Factor	DoF	Estimate	Relative risk	Standard error	t-value	p-value	VIF
Hospital level *LvL* (reference) *LvH*	1	−1.0722	0.34	0.0287	−37.32	≤ 0.0001	1.06
Hospital location *UrbMetro* (reference) *UrbCity*	1	−0.1738	0.84	0.0305	−5.7	≤ 0.0001	1.11
UrbRural	1	−0.8619	0.42	0.0499	−17.28	≤ 0.0001	1.06
Number of obstetricians *Num*	1	0.1511	1.16	0.0023	65.22	≤ 0.0001	1.17
Travel time (min.) *t*	1	−0.0637	0.94	0.0001	−116.92	≤ 0.0001	1.02

McFadden's pseudo R-squared = 0.2748

Table 3 shows the VIF values for the factor variables, which suggests they are not correlated with each other.[3] Note that the model's McFadden's pseudo R squared is 0.2748, and thus the goodness of fit of the model is deemed appropriate [10]. In addition to the goodness of fit, we examine the validity of the model for its prediction. We validated our model by 5-fold cross-validation [12]. Since the purpose of the model is to predict the number of visits for each hospitals, we examine R^2 between the actual and the predicted number of visits in the test data set. R^2 value for the entire dataset is 0.7326. R^2 is decreased to an average of 0.7195 (0.7389, 0.7062, 0.7006, 0.7319, 0.7199) in the 5-fold cross-validation, which is still acceptable.

The coefficient of each variable is interpreted via its relative risk as follows:

$$\frac{P_{ni|LvH_i=1}}{P_{nj|LvH_j=0}} = \frac{\frac{e^{V_{ni}}}{\sum_k e^{V_{nk}}}}{\frac{e^{V_{nj}}}{\sum_k e^{V_{nk}}}} = \frac{e^{\beta_{Lv}\star(LvH_i=1)}}{e^{\beta_{Lv}\star(LvH_j=0)}} = e^{\beta_{Lv}} = e^{-1.0722} = 0.34 \tag{6}$$

- Probability of choosing a high-level (tertiary) hospital is, with everything else being equal, 0.34 times the probability of choosing a low-level hospital (primary and secondary);
- Probability of choosing a hospital in a city region is 0.84 times the probability of choosing a hospital in a metropolitan region;
- Probability of choosing a hospital in a rural region is 0.42 times than the probability of choosing a hospital in a metropolitan region;
- Probability of choosing a hospital in a city region is 2.0 times the probability of choosing a hospital in a rural region;
- Probability of choosing a hospital that has one more obstetricians over the probability of choosing the hospital with one less obstetrician is 1.16;
- Probability of choosing a hospital that takes one additional minute of travel is 0.94 times the probability of choosing the hospital that takes one less minute to reach.

In the above results, there are a few notable findings from the results. First, pregnant women living in rural regions in Korea would choose a hospital of the lower level (primary and secondary) over a tertiary hospital. This is probably due to the fact that, under current obstetrics practices in Korea, those lower level hospitals provide care with reasonable quality. Also, getting care at a tertiary hospital generally accompanies significant overhead and additional cost to patients, which can only be justified for high risk delivery cases. Second, the results show that hospitals located in a large, urban environment are favored over the ones in a more local and rural setting. This will be a concern in the MUA support program for its possible implication; newly established obstetrics hospitals in MUAs may not effectively attract and serve the target population. Third, the number of obstetricians influences the choice of obstetric hospital. This can also be a concern since it will be practically

[3]The multicollinearity between variables is judged by Variance Inflation Factor(VIF); if any of the VIF values exceeds 5 (or 10), it implies that the associated regression coefficients are poorly estimated because of multicollinearity. VIF of all variables in Table 3 is less than 1.2, so there is no multicollinearity problem in our model.

Table 4 Confusion matrix for the prediction from the choice model

		Model prediction	
		MUA	non-MUA
Actual	MUA	28	28
	non-MUA	2	194

very difficult to operate a hospital in MUAs—rural environment in general—with many obstetrics specialists.

With the coefficients estimated from the data as shown in Eq. (5), now we can evaluate Eq. (3) to determine the choice probability and assess the fidelity of the derived choice model. We compare the model's prediction on the choice of hospitals with the actual choices in the data. Specifically, from the actual data we examine the number of delivery cases in each region that were served by a hospital farther than 60-min travel distance. From the model, we obtain P_{ni} as given in Eq. (3) and multiply the number of women between age 15–49 in regional unit n to compute the counts of corresponding cases. Note that 60-min is the travel time standard used by the Korean government to measure accessibility to obstetrics care. When the fraction of delivery cases served beyond the 60-min travel distance is higher than 70%, then the region is considered as an MUA from the realized accessibility criteria [11].[4] Thus, we obtain the model's prediction on the MUA status for each region and compare the prediction with the actual MUA status for the region. This is a relevant test for us as the choice model will be used in answering the question of whether a new obstetrics capacity will relieve the MUA status of the region it is intended to serve.

Table 4 shows that the overall accuracy of the prediction is 88%. Its sensitivity is rather low at 50%, while specificity is very high at 99%; thus the MUA prediction based on our model is highly specific but not sensitive. Our model rarely mistake a region as an MUA when it actually is not (few false positives). On the other hand, there is a good chance of overlooking many regions that are actually MUAs (many false negatives). In the context of MUA support program, this can be overly conservative, and its sensitivity should be enhanced.

While the results shown in Table 4 certainly suggest the need to improve the underlying choice model, we would like to emphasize it is still much better than the current practice. In the current practice of the MUA support program, location decisions for new hospitals are made based on the potential accessibility. That is, whether a region will be relieved from its MUA status is predicted purely by geographic proximity criteria. To examine the accuracy of the prediction based on such simple model—i.e., using the geographic proximity as a rule for allocating patients to hospitals, we conduct the same test and evaluate the prediction outcome. The results

[4]The other criteria is the potential accessibility, which concerns geographical accessibility due to the existence of care provider within the time standard. If more than 30% of a region's patients do not have a hospital within 60-min, then the region is MUA from the potential accessibility criteria [11].

Table 5 Confusion matrix for the prediction using the proximity-rule

		Model prediction	
		MUA	non-MUA
Actual	MUA	18	38
	non-MUA	0	196

are shown in Table 5. It turns out that the overall accuracy drops to 85%, primarily due to its poor sensitivity at 32%.

5 Conclusion

In this paper, we construct a choice model to describe and predict the hospital choice decision for obstetrics care in Korea. Specifically, we use the actual records of delivery cases during year 2015, and the data is fitted by a conditional logit model. The resulting model confirms a prior notion that the distance to the hospital is an important consideration, that the size of the hospital matters as well (measured by the number of obstetrics specialists), and that the hospitals in a more urban region are preferred. On the other hand, being a tertiary hospital does not translate into an attractive attribute as the data shows lower-level hospitals are in fact preferred.

These findings cast some implications for designing and implementing the MUA support program in Korea. In the MUA support program, new obstetrics hospitals are established within or near MUA regions with an expectation that this hospitals will absorb the demand from the region, hence relieving its MUA status. But then in most cases MUAs are rural regions, and practically it is difficult to expect more than one obstetrics specialist in those hospitals. These newly established hospitals may not be able to attract as many pregnant women for their deliveries as expected in the planning phase. Our model allows to predict the obstetrics care consumers' response to new hospitals in a way that the prediction can be incorporated into a location decision model.

There are a few aspects in which the choice model developed in this study can be improved. First, even though we adopt a conditional logit model, we use primarily the hospital attributes. We need to refine and expand the current model by including more attributes for the decision makers. Second, other than the distance variable, the attributes in V_{ni} are assumed to be independent of individual decision makers. Certainly there are possibility that other multinomial choice models provide a better description for the choice behavior, and further exploration into alternative models is warranted.

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