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Spatial competition has become the natural environment in which to study several problems in healthcare, ranging from hospital care to drug choices, both from a theoretical and an empirical point of view¹.

However, the market for healthcare is characterized by several important features. Consumers may have very weak incentives to seek out value for money (healthcare is mostly free at the point of use), while their willingness to pay for quality is much higher. However, their effort in seeking the best provider may be reduced by a lack of knowledge about the quality of healthcare. Patients are often infrequent users; key information is withheld by producers on both professional and commercial grounds (Siciliani et al., 2017); and their ability to process such information, as well as the cost of obtaining it, can be limited.

In this respect, several healthcare systems have made quality indicators widely available. For example, in the UK (CITAZIONE), while in Italy the National Healthcare Outcomes Program (Programma Nazionale Esiti, PNE) includes a total of 170 outcome or process indicators and provides specific rankings of all hospitals or local health units (European Observatory on Health Systems and Policies, 2017).

However, choice requires searching for information, and the latter has a cost. With the advent of the internet and the diffusion of data at hospital level, the cost of acquiring information—especially for patients who want to travel outside their catchment area—depends on how the latter is obtained. Reliability and speed of internet connections become important factors in influencing search choices by consumers, because much of the information on the internet is dispersed.

High-speed internet allows patients to access a variety of information sources and aggregate

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information. Therefore, the general availability of high-speed internet may affect patient decision-making more than any one individual source; in this respect, the diffusion of broadband is certainly an important element.

In this paper, we study the impact that broadband diffusion has on patients' choice to be treated outside their catchment area. To this end, we use data on hospital admissions in Sicily, the biggest Italian island, whose patients have to travel to the mainland if they want to shop around for quality. We contribute to two strands of literature. First, we contribute to the literature on the effect of increased information in healthcare markets, where information asymmetries are a concern. The second contribution is methodological: broadband data cannot be obtained at the patient level, as can the other variables used in these models. For this reason, we propose implementing a variation of the hybrid mixed logit model proposed by Czajkowski et al. (2017) to estimate beliefs within a discrete choice model.

To the best of our knowledge, although these models are often used in the context of the transportation literature, this is the first application concerning patients' choices.

The role of digital disadvantage in hospital choice: A hybrid mixed logit model

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Competing interests

None to declare

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Data availability

The data underlying this article cannot be shared publicly because they are owned by a third party and are subject to legal and administrative access restrictions. Access to the underlying hospital discharge microdata should be requested directly from the Italian Ministry of Health (Ministero della Salute). The study population comprises patients aged 18 years or older, resident in Sicily, admitted to any Italian hospital for cholecystectomy in 2010–2011, identified using ICD-9-CM procedure codes 51.22 (cholecystectomy) and 51.23 (laparoscopic cholecystectomy). All code used to clean the data, construct variables, and replicate the results can be made available by the authors upon reasonable request.

Ethics approval statement The study use retrospective anonymous administrative data for which an ethics approval is not necessary.

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1 Introduction

Spatial competition has become the natural environment where to study several problems in health-care, ranging from hospital care to drug choices, both from a theoretical and an empirical point of view¹. However, the market for health care is characterized by several important features: consumers may have very weak incentives to seek out value for money (health care is mostly free at the point of use), while their willingness to pay for quality is much higher. However, their effort in seeking the best provider may be reduced by lack of knowledge about the quality of health care (patients are often infrequent users, key information is withheld by producers on both professional and commercial grounds (Siciliani et al., 2017), by their ability to process such information, by the cost to obtain it. In this respect several health care systems have made quality indicators widely available. For example, in the UK (CITAZIONE), while in Italy the National Healthcare Outcomes Program (Programma Nazionale Esiti, PNE) includes a total of 170 outcome or process indicators and provides specific rankings of all hospitals or local health units European Observatory on Health Systems and Policies (2017).

However, choice requires searching for information and the latter has a cost. With the advent of the internet and the diffusion of data at hospital level the cost of acquiring information, especially for patients that want to travel outside their catchment area, depends on how the latter is obtained. Reliability and speed of the internet connections become important factors in influencing search choices by consumers because much of the information on the internet is dispersed. High-speed internet allows patients to access a variety of information sources and aggregate information. Therefore, the general availability of high-speed internet may affect patient decision-making more than any one individual source; in this respect the advent of the diffusion of the broadband is certainly an important element. In this paper we study the impact that broadband diffusion has on patients' choice to be treated outside their catchment area. To this end we use data on hospital admissions in Sicily, the biggest Italian island whose patients have to travel to the mainland if they want to shop around for quality.

We contribute to two strands of literature: first, we contribute to the literature on the effect of increased information in health care markets where information asymmetries are a concern. The second contribution is methodological: broadband data cannot be obtained at patient level, as much as the other variable that are used in these models. For this reason, we propose to implement a variation of the hybrid mixed logit model proposed by Czajkowski et al. (2017) to estimate beliefs into a discrete choice model. To the best of our knowledge these models, which are often used in the context of the transportation literature, this is the first application as concerns patients choices.

2 Literature Review

The traditional approach to estimate patients choices stems from the random utility theory (McFadden, 1974). Specifically, each patient i faces a choice among $j = 1, 2, \dots, J$ mutually exclusive hospitals from which the individual would acquire an utility U_{ij} . Hospital j is chosen by patient i only if utility is maximized ($U_{ij} > U_{ik}, \forall k \neq i \in J$). Their utility are additive in two components: u_{ij} , and ϵ_{ij} , i.e. $U_{ij} = u_{ij} + \epsilon_{ij}$. u_{ij} depends on patient's and hospital's observable characteristics while ϵ_{ij} is a random component that encompasses all the non-measurable patient's and hospital's attributes. If the random components of utility ϵ_{ij} are extreme value distributed and i.i.d., then

¹See Brekke et al., 2020; Siciliani, 2018; Levaggi and Levaggi, 2024

the probability of choosing hospital j for patient i is described by the conditional logit expression (Equation 1).

$$P_{ij} = Pr(Y_i = j) = \frac{\exp(u_{ij})}{\sum_{k \in J} \exp(u_{ik})} \quad (1)$$

To estimate such models, most literature restricts the choice sets (i.e., the set of possible hospitals chosen by patients) to the closest hospitals to patient i 's city of residence (Siciliani, 2018; Varkevisser et al., 2012). In other words, this literature implicitly assume that information on hospital quality is costless while traveling time (and related costs) determines the set of option to choose the best one in terms of balance between quality and travel time. This may not be the case: information has a cost to be acquired as the literature on information search has long pointed out (references); on the other hand, distance may not be a relevant variable for long distance journeys outside the region of residence of the patients (Balia et al., 2017, 2020). As shown above, data on hospital quality and satisfaction is more and more made available, but needs to be acquired and processed by patients. In this respect internet allows to reduce search costs and may change patients decision. However data on speed and quality of the internet connection are not available at patients level. Most literature in this case use data on the availability of infrastructure at local level rather than data on its use at patients level Amaral-Garcia et al. (2024); Billari et al. (2019); Van Parys and Brown (2024); Liu et al. (2024). In this article we propose to use data on broadband as a latent variable that, as in the hybrid mixed logit models (Hess and Daly (2024)) which does not require to be collected at individual level. Hybrid Mixed Logit (HMXL) approaches, allows to model an unobserved belief as a latent variable in a Random Utility Maximization (RUM) framework and from their estimation it is possible to derive several measures of willingness to pay for several utility attributes.

3 Methods

Hybrid choice models combine a random-utility discrete choice model with a latent-variable system, typically specified through (i) structural equations for the latent construct(s) and (ii) measurement equations linking latent constructs to observed indicators (Czajkowski et al., 2017). In our context, the hybrid framework allows us to incorporate an individual's unobserved *digital divide*—i.e., digital disadvantage in accessing and using online resources—into the hospital-choice model, while acknowledging that the empirical proxy for local digital infrastructure is measured with error.

3.1 Discrete choice component

Consider patient $n = 1, \dots, N$ choosing among J in-region hospitals plus an outside option (out-of-region care), indexed by $j \in \mathcal{J} = \{0, 1, \dots, J\}$. Utility is

$$U_{nj} = V_{nj} + \varepsilon_{nj}, \quad (2)$$

where V_{nj} is the systematic component and ε_{nj} captures unobserved factors affecting choice.

We specify

$$V_{nj} = \alpha_j + \beta_d \text{dist}_{nj} + \beta_w \text{wait}_j + \underbrace{\beta_d^{LV} \text{dist}_{nj} LDD_n + \beta_w^{LDD} \text{wait}_j LDD_n}_{\text{digital-divide sensitivity channel}}, \quad (3)$$

where α_j are alternative-specific constants, dist_{nj} is travel distance (or generalized travel cost), and wait_j is waiting time (or another congestion/availability measure). The interaction terms in (3) constitute the *digital-divide sensitivity channel*: they allow the latent digital divide LDD_n to moderate how patients trade off distance and waiting time across hospitals. Intuitively, higher digital disadvantage may limit information acquisition and processing, thereby altering the salience of observable attributes in provider choice.

The outside option $j = 0$ represents treatment outside the region. As standard, utility is normalized by setting $V_{n0} = 0$, so that all parameters are interpreted relative to out-of-region care. Conditional on LDD_n and parameters, and under the usual i.i.d. Extreme Value assumption for ε_{nj} , the choice probability is the multinomial logit form:

$$P(y_n = j \mid LDD_n, \Theta) = \frac{\exp(V_{nj})}{\sum_{k \in \mathcal{J}} \exp(V_{nk})}. \quad (4)$$

3.2 Latent digital divide: structural equation

We allow for an unobserved latent construct LDD_n capturing individual n 's *digital divide* (digital disadvantage), which may reflect both constraints and costs of accessing and using online information relevant to hospital choice. We allow LV_n to vary with basic socio-demographics and morbidity burden, and specify:

$$LDD_n = \gamma_0 + \gamma_1 \text{Age}_n + \gamma_2 \text{Female}_n + \gamma_3 \text{DiagTot}_n + \xi_n, \quad (5)$$

where Age_n is measured in years (or age groups), Female_n is an indicator equal to one for women, and DiagTot_n denotes the total number of diagnoses observed for individual n . Let $\mathbf{z}_n = (1, \text{Age}_n, \text{Female}_n, \text{DiagTot}_n)'$ collect these covariates. The disturbance term ξ_n captures residual heterogeneity in the latent digital divide not explained by observed characteristics. Because LDD_n is latent, its scale is not identified. We normalize it by fixing $\text{Var}(\xi_n) = 1$ (or, equivalently, by fixing one loading in the measurement system), which pins down the units of the latent construct.

3.3 Measurement equation: linking the broadband-based indicator to the latent digital divide

We observe an ordinal municipality-level indicator based on broadband coverage. Let $I_n \in \{0, 1, 2, 3, 4, 5\}$ denote the indicator assigned to patient n based on the municipality of residence, coded so that larger values correspond to worse digital access (i.e., lower broadband availability). We treat I_n as an imperfect proxy for the latent digital divide LV_n and specify an ordered probit measurement equation. Specifically, we assume a latent index

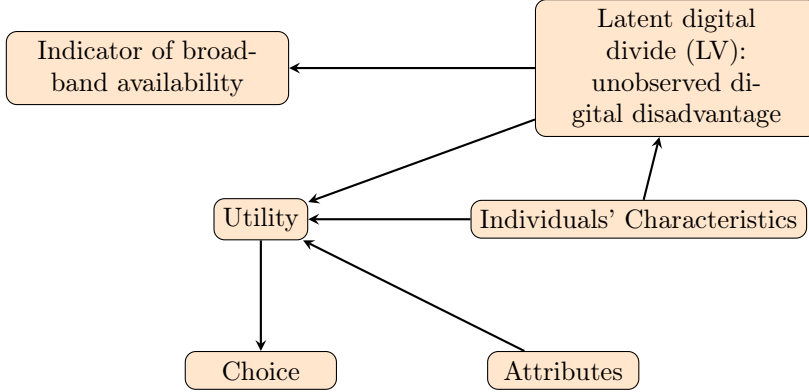
$$I_n^* = \delta LV_n + \nu_n, \quad (6)$$

with $\nu_n \sim \mathcal{N}(0, 1)$. The observed ordinal outcome I_n is generated by thresholds $\{\kappa_\ell\}_{\ell=0}^5$:

$$I_n = \ell \quad \text{if} \quad \kappa_{\ell-1} < I_n^* \leq \kappa_\ell, \quad \ell = 0, 1, \dots, 5, \quad (7)$$

where $\kappa_{-1} = -\infty$ and $\kappa_5 = +\infty$. Thus, a positive loading δ implies that higher values of LV_n are associated with worse digital access (higher I_n).

Figure 1: Components of the hybrid choice model with latent digital divide.



3.4 Full-information likelihood and estimation

The hybrid model combines (i) the discrete choice likelihood from (4) with (ii) the measurement likelihood implied by (6)–(7), and (iii) the latent-variable density implied by (5). Let Θ collect all parameters. The individual likelihood contribution is

$$L_n(\Theta) = \int P(y_n | LV_n, \Theta) f(I_n | LV_n, \Theta) f(LV_n | \mathbf{z}_n, \Theta) dLV_n. \quad (8)$$

Because the latent variable is not observed, it must be integrated out. Following (Czajkowski et al., 2017), we estimate the model by maximum simulated likelihood, approximating the integral in (8) using simulation draws. Taken together, equations (2)–(8) define a hybrid choice (HMXL/ICLV) model in which the latent digital divide affects hospital choice through interactions with key attributes and is measured through the ordinal broadband-based indicator.

4 Health care system in Italy

In Italy primary source of funding for health care services is represented by taxation so that health care is free at the point of use. While each region must guarantee a minimum level of care (LEA, Livelli Essenziali di Assistenza) devolution of powers gave rise to 21 health care systems responsible for health care provision, funding, organization, and delivering health care services to guarantee the LEA de Belvis AG et al. (2022); Martini et al. (2022). For hospital care, providers have to compete on quality under a prospective payment oriented system based on Diagnosis Related Groups (DRGs), but the heterogeneity in health care organizations has create a large jurisdictional differences in hospital capacity, technology endowment, income, and financing ability. The difference are quite widespread as concerns the organisation of primary and hospital care, inputs and outcome indicators and waiting times (Osservasalute (2016); Francese and Romanelli (2014)). As in many European healthcare systems, in Italy patients can choose to an extent their preferred provider and may also choose to be treated outside the boundaries of their own Region. Compared with other countries, they travel long distances (an average of 725km), a phenomenon that has not counterpart anywhere in Europe (Osservasalute (2016); Francese and Romanelli (2014)). This is the result of

a push and pull effect. From one side, waiting times make people pay for elective surgery outside their Region (about 22% in the north and 33% in the South according to RBM-Censis (2019)). A pull effect is also present; in order to contain costs and offset incentives to increase admissions, all Italian regions have some spending threshold for the hospital is reached, but this does not apply to extra-regional patients, who are not under the budget cap and are reimbursed by the region of origin using national tariff rates as reference (Ferre et al. (2014); de Belvis AG et al. (2022)). Since 2010 quality of health care is evaluated through the PNE (Piano Nazionale Esiti, see Lega and Prenestini (2024) which is one of the most complete national healthcare evaluation models, with more than 60 outcome indicators. Overall, the system includes a total of 170 outcome or process indicators and provides specific rankings of all hospitals or local health units. Although the main aim, however, is not the ranking itself, it is to identify the providers with the lowest performance and encourage them to conduct quality-of-care audits, The PNE may be used by patients to evaluate the relative performance of hospitals.

5 Data

We use data on hospital discharge episode on patients from Sicily admitted in any Italian hospital for a cholecystectomy in the period 2010-2011.

During this period, Sicily implemented two major restructuring waves aimed at containing expenditure. These interventions reduced the number of acute-care beds, merged or closed hospitals, and reorganized service lines, producing substantial changes in local capacity and patient flows. Patients are free to choose their treating hospital, regardless of municipality of residence, and may select either public or accredited private providers. In addition Sicily reverses a large number of patients treated outside the regional health service (high volume South to North);

We study adult patients (18+) undergoing cholecystectomy, the standard surgical treatment for symptomatic gallstone disease. Cholecystectomy is a simple procedure, but quality is relevant (e.g. laparotomy and laparoscopy; one of the record in the Italian National Healthcare Outcomes Program). For each admission we observe the chosen hospital, patient demographics, and municipality of residence.

Broadband data on the *supply* of internet quality were obtained from the “Osservatorio Banda Larga-Between”, which reports municipal-level ADSL coverage in Italy. The dataset provides, for each municipality and year (2010–2011), the percentage of households with access to ADSL-based services classified into a six-category scale corresponding to the following brackets: 0%, 1–50%, 51–75%, 76–85%, 86–95%, and above 95%. Following previous literature in broadband penetration (e.g. Donati et al., 2025), we recode this measure into an indicator I_n (assigned based on the municipality of residence) such that larger values correspond to worse digital access: $I_n = 0$ indicates coverage above 95%, whereas the lowest-coverage category (0%) corresponds to the highest value of I_n .

6 Results

Table 1 reports the estimates of the HMXL reference model with a latent digital divide (LDD). Panel A presents the measurement equation (ordered probit), where the latent factor is positively associated with the observed broadband-penetration indicator, providing empirical support for the proposed measurement strategy. The threshold parameters are precisely estimated, indicating a well-defined mapping between the latent construct and the ordered categories of the indicator.

Panel B reports the structural equation for LDD. The included individual-level covariates (age, gender and morbidity proxy) are not statistically significant, suggesting that—within this specification—the latent digital divide is not strongly explained by these observed characteristics. This pattern is consistent with LDD capturing additional unobserved heterogeneity beyond the available socio-demographic information.

Panel C reports the discrete choice component. The mean coefficients for distance and waiting time are negative and statistically significant, implying that, on average, individuals prefer alternatives that are closer and associated with shorter waiting times. The estimated standard deviation of the distance coefficient is large and highly significant, pointing to substantial heterogeneity in spatial mobility costs. In contrast, the standard deviation of the waiting-time coefficient is not statistically different from zero, indicating comparatively limited residual heterogeneity in the valuation of waiting time once the latent structure is accounted for.

The key results concern the interactions between LDD and the two generalized costs. The interaction with distance is negative and significant, indicating that higher values of the latent digital divide amplify the disutility of distance, i.e. individuals with higher LDD are more distance-averse. Conversely, the interaction with waiting time is positive and significant, implying that higher LDD attenuates the disutility of waiting time. Taken together, these findings show that the latent digital divide shifts the trade-off between spatial access and timeliness of care: it strengthens the role of geographic proximity while reducing the marginal penalty associated with waiting time.

Finally, Panel D reports model fit. Relative to the constant-only benchmark, the log-likelihood improves markedly, resulting in a McFadden’s pseudo- R^2 close to 0.19. This indicates that incorporating both random taste heterogeneity and the latent digital divide yields a sizeable gain in explanatory power.

Simulated willingness to wait across the latent digital divide. In order to facilitate the interpretation of the effects of the latent digital divide (LDD) on willingness to wait (WTW) for distance, we simulate WTW for respondents whose implied levels of LDD vary. Because WTW is computed as a ratio of (potentially correlated) marginal utilities, and because LDD enters the discrete choice component through interactions with both $\ln(\text{distance})$ and $\ln(\text{waiting time})$, the net effect of LDD on WTW is not straightforward from the signs of the interaction coefficients alone. Specifically, we compute

$$\text{WTW}_{\text{dist}}(LDD) = -\frac{\beta_{\ln d} + \gamma_{\ln d} LDD}{\beta_{\ln wt} + \gamma_{\ln wt} LDD},$$

and evaluate this expression at representative points of the implied LDD distribution in the sample, from the bottom 10% to the top 10% (including the 25th percentile and the mean). The resulting point estimates and confidence bands are reported in Figure 2.²

Results reveal a clear monotonic gradient: the simulated WTW declines steadily as LDD increases, with the point estimate moving from positive values at the bottom tail of the latent distribution to negative values at the top tail, crossing zero around the centre of the distribution.

This pattern is consistent with the HMXL estimates reported in Table 1. In the discrete choice model, the interaction between LDD and distance is negative, implying that the marginal utility of

²Following Czajkowski et al. (2017) we obtain confidence bands using a two-step Krinsky and Robb simulation procedure: we first draw parameter vectors from the asymptotic distribution defined by the estimated coefficients and their variance-covariance matrix, and next draw correlated random parameters from their respective model-implied distributions. Each step uses 10,000 iterations, allowing us to simulate moments and quantiles of the WTW distribution and derive standard errors.

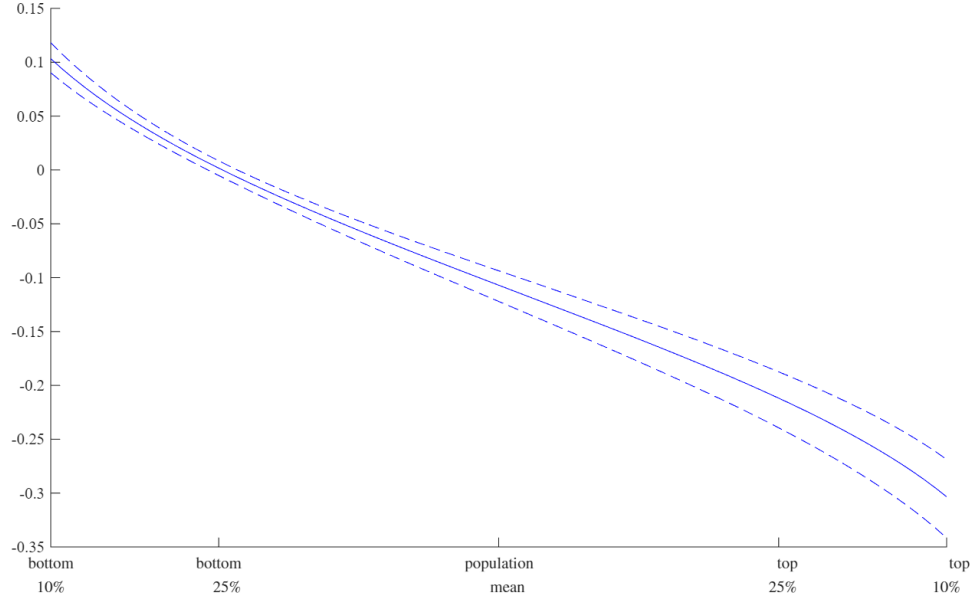


Figure 2: Simulated willingness to wait (WTW) for distance across varying strength of the latent digital divide (LDD). Solid line: point estimates; dashed lines: 95% confidence bands. Percentile groups refer to the implied LDD distribution in the sample.

distance becomes progressively more negative as LDD increases. At the same time, the interaction between LDD and waiting time is positive, attenuating the disutility of waiting time at higher levels of LDD. Because WTW is constructed as a ratio of marginal utilities, the combined effect of these two mechanisms generates a non-trivial, potentially non-linear response across the latent distribution and can lead to sign changes, as observed in the figure.

Positive values of WTW indicate that respondents are, at the margin, willing to accept higher waiting time when distance increases, whereas negative values indicate that respondents would require shorter waiting times to compensate for additional travel. Hence, the figure suggests that respondents in the lower tail of the LDD distribution exhibit relatively weak distance aversion (or even a tendency to accept longer travel without requiring a reduction in waiting time), whereas respondents in the upper tail become increasingly distance-averse: for them, additional distance must be offset by a sufficiently large reduction in waiting time.

Overall, the simulation highlights that the latent digital divide does not simply shift “general cost sensitivity”, but reshapes the trade-off between spatial access and timeliness. In practical terms, higher LDD places greater emphasis on proximity relative to waiting time, which is consistent with the idea that digital disadvantage may limit the ability to exploit or act upon waiting-time information and therefore increases reliance on geographic closeness as a decision criterion. The confidence bands, while widening somewhat towards the extremes of the latent distribution, indicate that the gradient is statistically meaningful across most of the range considered.

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Table 1: HMXL reference model with latent digital divide

Panel A: Measurement equation (ordered probit) dependent variable: broadband penetration indicator		
	Coefficient	Std. err.
Latent digital divide (LDD)	0.0369*	0.0202
Threshold parameters:		
α_1 (Cutoff 1)	1.6365***	0.0202
α_2 (Cutoff 2)	1.9835***	0.3744
α_3 (Cutoff 3)	2.1840***	0.3913
α_4 (Cutoff 4)	2.4059***	0.4067
α_5 (Cutoff 5)	2.5256***	0.4151

Panel B: Structural equation for latent digital divide (LDD)		
Age	−0.4177	0.4752
Gender	0.6653	0.6680
Diagtot	3.0247	2.5999

Panel C: Discrete choice model (mixed logit, preference-space)			
	Means – main effects	Means – interactions with LDD	Standard deviations
	Coefficient (s.e.)	Coefficient (s.e.)	Coefficient (s.e.)
ln(distance)	−0.0744*** (0.0021)	−0.0110*** (0.0019)	0.1120*** (0.0034)
ln(waiting time)	−0.3620*** (0.0613)	0.1480*** (0.0245)	0.0290 (0.0570)

Panel D: Model diagnostics	
Log-likelihood (constant only)	−27,882.68
Log-likelihood	−22,564.93
McFadden’s pseudo R^2	0.1907
AIC/n	4.1688
BIC/n	4.2238
n (observations)	10,865
k (parameters)	82

Note: *, **, *** denote significance at the 10%, 5% and 1% levels, respectively. The discrete choice component includes a full set of alternative-specific constants (not reported). Estimation by simulated maximum likelihood with 1000 Halton draws.