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MIXTURE MODELS FOR CONSUMERS' PREFERENCES IN HEALTHCARE

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Mixture models for consumers' preferences in healthcare

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Abstract
This paper aims to explain preferences behaviour by a sample of Sardinia residents with respect to combined choice of attributes related to cardiology services. The rating of proposed cards, containing a combination of several attributes to qualify the services, are examined in terms of intrinsic components and main drivers to determine the ordinal choice: location, screening mode, cost, waiting time for the visit and subjects' covariates. The topic is relevant in telemedicine as experienced in Sardinia, a region with a mobility and a socio-economic disadvantage. The innovative approach allows for effective visual support to interpret and compare results and it is useful also to predict the respondents' profile with respect to their individual characteristics. Empirical evidence supports policy interventions and suggests the usefulness of the implemented statistical procedure.

Keywords: E-health Preferences; Discrete modelling; Decision drivers; CUB models.
Jel Classification: C13; C25; I12

1. Introduction

To overcome the increasing pressure on the health system, due to a gradual aging population and cuts in public spending, radical changes need to be pursued in terms of organization and management in the delivery of health services, the substance of the European welfare state. Effective self-management, as part of a paradigm shift in the long term health conditions, can help improve health outcomes and reduce costs (Panagioti, 2014; Coulter, 2015; Salisbury, 2016). In this respect, the European Union promotes policies aimed at offering citizens a wider range of e-healthcare services, or telemedicine (Eysenbach, 2001). E-health has the advantage to reduce public health spending while ensuring citizens' well-being, equity as well as guaranteeing the universality feature in healthcare. A systematic review (Flodgren, 2015) assessing the effectiveness, acceptability and costs of interactive e-health in differentiated clinical conditions, established an association between e-health and improved quality of life for heart failure patients (Macis, 2019). Evidence from a large randomized controlled trial indicated that, despite the absence of evidence of cost-effectiveness (Henderson, 2013) e-health is associated with lower mortality rates and emergency visits (Stevento, 2012). The introduction of an e-healthcare system potentially allows more people to access to a wider range of specialist healthcare services (e.g. rehabilitation, old aged care and palliative care) by minimizing the need for travel to service providers (WHO, 2011). So far, research has focused on older people's perceptions and acceptance of e-health (Chen, 2010; Cimperman, 2013); less is known about older people's preferences in relation to the salient features of e-health care (Kaambwa, 2017).

Given that cardiovascular pathologies are the main causes of death, 31% of all global deaths (WHO, 2018) and in Italy; the first three causes of death included vascular diseases (ISTAT, 2017), this paper explores potential users' preferences towards e-cardio services (i.e. remote monitoring systems and mobile health applications (Redfern, 2017).

The focus of this empirical study is the region of Sardinia (Italy) marked by insularity and costly mobility, two features which strongly support the value of e-health practices (Deidda et al., 2018). Notably, the various risk factors of death and illnesses in Sardinian population (35− 79 years) are overlapping with those of the national population (RAS, 2015).

A sample survey was carried out on patients' preference (utility) with respect to options (profiles) provided different circumstances and characteristics of the visit (attributes). The economic methods for eliciting consumer preferences require respondents to choose among alternative bundles of service characteristics. Usually, preferences are obtained by designing the questionnaire in order to either rank, rate or make a discrete choice between scenarios (Ryan, 1999; Bridges et al. 2011). Since the 1990s, conjoint–analyses have been widely employed in health studies to quantify preferences of patients, caregivers, physicians, and other stakeholders.

In this study, the objective of the statistical analysis is to understand the preferred combination for the visit according to qualitative (screening mode and location of the visit) and numeric factors (waiting time and cost of the visit). For each card, the probability profiles are estimated so as to assess a hierarchical graduation (rating) amongst several ordered options based on respondents evaluation. Such an experimental design could be framed within the standard approach of conjoint analysis (Green, 1974; Green and Rao, 1971; Green and Srinivasan, 1978; Green and Tull, 1978). This study, within a parametric rating framework, shows that valuable and comparable information can be exploited by means of models based on Combination of Discrete Uniform and shifted Binomial random variables (whose acronym is CUB). This class of models was proven to be effective in several contexts where perceptions and evaluations were analyzed (Capecchi, 2015; Capecchi and Piccolo, 2016; Capecchi et al., 2016, 2018), as well as for investigating e-health preferences (Capecchi et al., 2018). The framework of CUB models may offer important information to stakeholders on the basis of sampled results and without further requirements in terms of data and costs. Such an analysis is able to estimate probability profiles for each card so as to assess a hierarchical graduation among different options offered to respondents. Moreover, it allows to measure the importance of intrinsic and extrinsic components of the choice that respondents prefer, as well as the role, if significant, of personal subjects' characteristics in forming the expressed preferences.

Usually, the literature accounts for preference variation among individuals by interacting individual characteristics with the attributes included in the conjoint analysis and using them in the regression (Bridges et al., 2011). CUB models allow to account not only for the degree of consensus towards the scenario (i.e. feeling), but also for the heterogeneity among the expressed responses (i.e. uncertainty).

The paper is organized as follows: in Section 2 some methodological issues related to CUB models are presented, whereas in Section 3 survey design and data are discussed. Aggregate results are shown in Section 4. Section 5 focuses on the contribution given to the final model by a subset of covariates. Section 6 proposes a comprehensive model. The computation of explicative power is obtained and examined in Section 7. Policy implications and some concluding remarks are in the last section.

2. Methodology

A parametric approach is used to compare responses and to measure the impact of explanatory covariates. This strategy allows one to evaluate the utility of each component with respect to the respondents' preference. Although regression analysis is a consolidated procedure, a model-based methodology is motivated by the awareness that the probability distribution of the data generating process of the responses could be more fruitful in describing both consensus towards the submitted profiles and heterogeneity of such preferences.

Conjoint analysis helps underlining the relative importance of several attributes of a service, the trade-offs between attributes and individual consumer surplus. This approach was applied in marketing research, but there are also several studies in health economics (Ryan, 1999; Ryan and Farrar, 2000; Phillips et al., 2002; Pavlova et al., 2004; Lalla et al., 2014; Mazzocchi, 2008). The conjoint literature elicits preferences by asking individuals to rank, rate or choose (between two or more) scenarios (Ryan, 1996). In this paper, respondents are asked to assign a score (10-point Likert scale type) to each card. The decision making process within the scoring choice is based on the economic concept of utility and assumes that each person has a specific set of preferences for bundles of services, or products, and relative attributes. Individuals make decisions in order to maximize the level of satisfaction from consumption that is the utility level. From an operational perspective, data are examined using both graphical techniques and regression analysis (i.e. ordinary least square, ordered logit or probit). In this respect, conjoint analysis represents a decompositional method from an overall evaluation to elicit preferences for the single attribute, while overall utility is obtained by plugging given levels of attributes into the regression equation. A strength of the method is the joint analysis of the components of a product/service.

To capture the structural behaviour of the given preference and the possible role of subjective drivers (e.g gender, age, education), the framework of CUB models is implemented (see Appendix A for formal details). Following this paradigm, each response is modelled according to a probability mass function where the feeling/preference towards the card and the uncertainty/heterogeneity of the responses may be jointly taken into account. Important features of the approach (fully exploited in this paper) are the graphical representations of the estimated models and their interpretation as functions of significant covariates, as successfully experienced in different disciplines (e.g. Marketing, Sensory sciences, Psychology, Sociology) with reference to different topics (e.g. political trust, well-being assessment, job satisfaction, work-related stress) suitable to be analyzed as ordinal scores. With respect to more consolidated approaches for modelling ordinal data –as those described by Agresti (2010) and Tutz (2012) among others– the mixture models here preferred are comparatively more effective in terms of interpretation, parsimony and graphical tools, as discussed by Piccolo et al. (2018).

This class of models allows for the estimation of the degree of consensus towards the scenario described in the submitted card (denoted as *feeling*) and also of a measure of heterogeneity among the expressed responses (denoted as *uncertainty*); moreover, these two components may be related to (possible) significant drivers to detect. More explicitly, the explanatory covariates concern both attributes of the card and personal characteristics of the respondents. In discrete choice analysis, when the number of attributes increases, some inherent "noise" in the responses should be expected as a consequence of some difficulty arising from a correct evaluation of different profiles which may be not sharply defined. The latter circumstance is a further motivation for the inclusion of uncertainty as a fundamental component of the decisional process of eliciting preferences. Finally, when feeling and uncertainty include a common covariate, then a relationship between feeling and uncertainty is implicitly assumed by the model. With reference to the e-health context, this modelling procedure has been implemented to measure the subjective content of the discrete choices and the intrinsic uncertainty which surrounds the decision-making process (Capecchi et al., 2018).

In this framework, a further analysis may be pursued by distinguishing the models according to the presence of *intrinsic* and *extrinsic* components: in the first case, only uncertainty and feeling are included and, hence, no information but preferences are assumed in the fitting procedure. In the second case, both covariates related to the object (attributes of the card) and subject (personal characteristics of the respondents) are specified in the model. This procedure is sequentially implemented in order to measure the explicative strength of each group of covariates. Implications for the policy are immediate, since intrinsic components are difficult to modify whereas covariates related to the characteristics of the service are generally under the control of the proponents. Finally, subjective covariates specify clusters of possible users of the healthcare services to be convinced or oriented with adequate information campaigns.

3. Experimental design and data

The selected method consists in submitting a card with a prefixed combination of attributes to a sample of the population to infer on the drivers of their preferences. The experimental design consists of a set of admissible health services characterized by four attributes (full details in Table 1) that help to understand potential users' preferences towards e-cardio services, as follows: ***Screening mode*** (M) of the visit (5 levels), ***Location*** (L) where the visit should take place (5 levels), ***Time*** (T) for waiting list (4 levels), ***Costs*** (C) (4 levels).

Table 1. Experimental design: attributes and levels of cardio services

Attributes	Levels
Screening mode	M1=*NHS* (Status quo) National Health System, commonly used for cardio-logic checks/therapy
	M2=*Intramoenia*: Private consultation at a public hospital, as an alternative to the private and public system
	M3=*Private doctor*: used in Italy as an alternative consultation to the public system
	M4=*Family doctor* This consultation represents the e-cardio screening mode that can be developed within the NHS
	M5=*Pharmacy*: this level represents an e-cardio screening mode that has not yet developed at a large scale in Italy, and Sardinia
Location	L1=Place of *Residence*: service supplied only via e-cardio check
	L2=*Province* of residence (Status quo)
	L3=*Region* of residence
	L4=*Mainland* (Italy) service supplied only via e-cardio screening
	L5=*Abroad* : service supplied only via e-health
Time (Waiting list)	T = 0 days a real time check, via e-cardio screening
	T = 2 days
	T = 3 days
	T = 4 days (Status quo)
Cost of the visit	C = 40 Euro (Status quo)
	C = 62 Euro: average cost for an e-cardio check
	C = 90 Euro
	C = 120 Euro

The evaluation of the proposed cards is based on a rating method. A full combination of all the levels for each attribute would require 5 × 5 × 4 × 4 = 400 different options. To select a subset of all the possible scenarios, a Hyper Greco-Latin matrix solution is used as a consolidated fractional experimental design (Louviere et al., 2000). This method produces a limited and congruent combinations based on attributes and levels of the services. However, since some of the combinations proposed by the orthogonal design were not realistic, given the context of the research, a consistent and rational selection of possible combinations of attributes was pursued. Thus, a convenient subset of 24 congruent combinations based on these attributes and levels was defined. Table 2 provides an example of such a choice card, and the complete set is listed on the left side of Table 3.

Moreover, in order to avoid bias in respondent's answers (caused by giving him/her a long request of ratings), the initial 24 cards were divided into two convenient random sets (denoted as A1, . . , A12; B1,. . . , B12, respectively), with the only exception for the *status quo* card (i.e. NHS, province of residence, 4 days, 40 Euro; card A12 and B12, respectively). The *status quo* scenario represents the most common consultation mode with average costs and characteristics and it is employed as a control, and it has been duplicated so as to check for response consistency.

Table 2. Example of a choice card

CARD B1	
Screening Mode	Intramoenia
Location	Mainland
Time (Waiting list)	0 days
Cost of the visit	40 Euro
Within a scale 1 *to* 10*, how do you evaluate such a scenario? (Please tick)* 1 2 3 4 5 6 7 8 9 10	

Table 3. Specification of the 24 cards used in the statistical models

Cards	*Description of attributes* (Screening mode, Location, Time, Cost)	*Specification of Dummies for the models* (M_1, M_2, M_3, M_4, L_1, L_2, L_3, L_4, T, C)
A1	(Pharmacy, Province, 0, 120)	(1, 0, 0, 0, 0, 0, 0, 1, 0, 120)
A2	(Private, Province, 0, 90)	(0, 1, 0, 0, 0, 0, 0, 1, 0, 90)
A3	(Private, Residence, 0, 40)	(0, 1, 0, 0, 0, 0, 0, 0, 0, 40)
A4	(Pharmacy, Mainland, 4, 90)	(1, 0, 0, 0, 0, 1, 0, 0, 4, 90)
A5	(NHS, abroad, 0, 90)	(0, 0, 1, 0, 1, 0, 0, 0, 0, 90)
A6	(Private, Mainland, 3, 62)	(0, 1, 0, 0, 0, 1, 0, 0, 3, 62)
A7	(NHS, Mainland, 2, 40)	(0, 0, 1, 0, 0, 1, 0, 0, 2, 40)
A8	(Private, Region, 4, 40)	(0, 1, 0, 0, 0, 0, 1, 0, 4, 40)
A9	(Intramoenia, Residence, 4, 120)	(0, 0, 0, 1, 0, 0, 0, 0, 4, 120)
A10	(Family-doctor, Mainland, 0, 120)	(0, 0, 0, 0, 0, 1, 0, 0, 0, 120)
A11	(Intramoenia, Region, 2, 90)	(0, 0, 0, 1, 0, 0, 1, 0, 2, 90)
A12	(NHS, Province, 4, 40)	(0, 0, 1, 0, 0, 0, 0, 1, 4, 40)
B1	(Intramoenia, Mainland, 0, 40)	(0, 0, 0, 1, 0, 1, 0, 0, 0, 40)
B2	(Family-doctor, Region, 0, 62)	(0, 0, 0, 0, 0, 0, 1, 0, 0, 62)
B3	(NHS, Residence, 0, 40)	(0, 0, 1, 0, 0, 0, 0, 0, 0, 40)
B4	(Pharmacy, Residence, 2, 62)	(1, 0, 0, 0, 0, 0, 0, 0, 2, 62)
B5	(NHS, Region, 3, 120)	(0, 0, 1, 0, 0, 0, 1, 0, 3, 120)
B6	(Private, abroad, 2, 120)	(0, 1, 0, 0, 1, 0, 0, 0, 2, 120)
B7	(Family-doctor, Residence, 3, 90)	(0, 0, 0, 0, 0, 0, 0, 0, 3, 90)
B8	(Intramoenia, abroad, 0, 62)	(0, 0, 0, 1, 1, 0, 0, 0, 0, 62)
B9	(Family-doctor, Province, 2, 40)	(0, 0, 0, 0, 0, 0, 0, 1, 2, 40)
B10	(Pharmacy, Region, 0, 40)	(1, 0, 0, 0, 0, 0, 1, 0, 0, 40)
B11	(Intramoenia, Province, 3, 40)	(0, 0, 0, 1, 0, 0, 0, 1, 3, 40)
B12	(NHS, Province, 4, 40)	(0, 0, 1, 0, 0, 0, 0, 1, 4, 40)

The full sample, split in two sub-samples (A and B, respectively), denoted to be substantially equivalent with respect to the variables of stratification. The only difference is that the combination of the levels of screening mode, location, cost and waiting time of the visit (the elements which characterize the card) are modified in A and B.

Hence, respondents were invited to express a score belonging to {1, 2, . . . , 10} on the basis of their individual preference in terms of judgment, opinion, evaluation. For each respondent, subject variables were coded to denote individual characteristics (i.e. gender, age, education, residence in the main province, presence of children, marital status) whose statistical significant effects are tested.

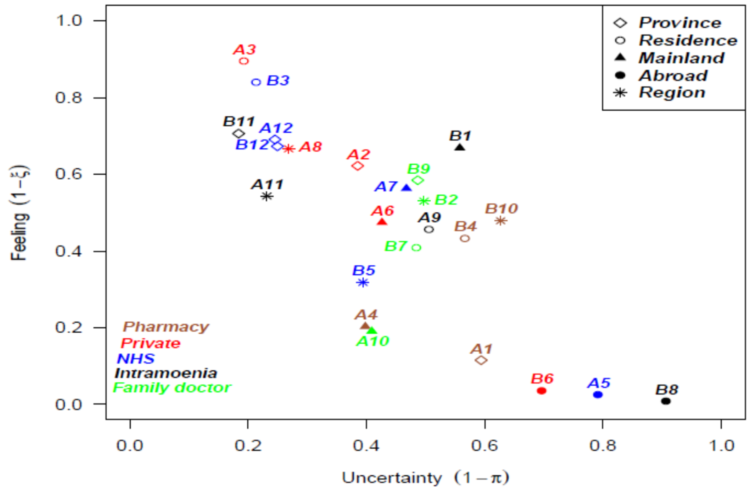
Face-to-face interviews run in 2015, targeted the Sardinian population older than 18 years old. The trained interviewers had to select individuals within selected age segments (i.e. 18-28; 29-39; 40-50; 51-65 and > 65 years old) and gender characteristics. These quotas were based on the distribution of Sardinian residents (ISTAT, 2013) in order to obtain a representative sample of potential users of e-cardio services.

A few observations with too many missing values were dropped. Finally, sub-samples A and B consist of 1080 and 1091 respondents, respectively. Thus, overall 2,171 valid questionnaires were collected, hence, higher than a target of a minimum of 1847 individuals, considering a 99% confidence level and a 3% interval error. Female in sub-samples A and B are 48.8% and 52.6%, respectively, and the age distribution is virtually the same in these two subgroups. Therefore, the two sub-samples may be considered as almost equivalent.

4. Aggregate results

As a first step, ratings to each card are separately considered and compared in terms of expressed consensus and inherent uncertainty by means of CUB models. The presence of attributes is considered as a distinctive trait of the submitted card and will be analyzed within the same framework. Figure 1 shows the representation of such estimated models for the expressed preferences of all the 24 combined attributes of *Screening mode*, *Location*, *Time* and *Cost* of the visit which characterize each card, as listed in Table 3.

Figure 1. Estimated CUB models of the expressed ratings for each card



This parametric approach conveys valuable information and allows for a graphical support for further analyses. Figure 1 shows the estimated models as a function of the degree of consensus (ordinate) and uncertainty/heterogeneity (abscissa) of the expressed ratings.

For comparison, Table 4 reports the average preferences in decreasing order for each card and relates to a first non-parametric analysis of preference data.

Table 4. Average scores of the preference for the choice cards, in decreasing order

Card	*Average*	Card	*Average*	Card	*Average*	Card	*Average*
A3	8.501	B1	6.311	B10	5.194	B5	3.969
B3	8.044	A2	6.075	A6	5.061	A5	3.858
B11	7.055	B9	5.898	B4	4.767	B6	3.560
A12	6.942	A7	5.682	A9	4.727	A1	3.518
B12	6.780	A11	5.608	B8	4.642	A4	3.475
A8	6.679	B2	5.351	B7	4.569	A10	3.448

Some aspects of this representation merit further insight:

a. Both feeling and uncertainty span over the whole parameter space; then, the combinations of attributes included in the cards substantially represent all the possibilities and respondents adequately react to them as necessary. In addition, one observes that points are negatively correlated and this should imply a relationship between agreement and heterogeneity that may be explained by some drivers.

b. Cards A3 and B8 manifest substantially different patterns, as follows: A3 gets the maximum consensus with a minimum heterogeneity ("Private, Residence, 0 waiting

Time and lowest Cost"), whereas B8 is characterized by a very low agreement with the largest heterogeneity ("Intramoenia, Abroad, 0 waiting Time and intermediate Cost"). As Table 4 confirms, averages of preferences are not so informative: A3 shows the maximum of consensus but no information can be detected about response homogeneity. Moreover, card B8 is classified as intermediate according to average consensus, whereas it receives the lowest agreement and presents the highest heterogeneity.

c. All the cards including the "Abroad" option (full point in Figure 1) did not receive consent and these distributions are highly heterogeneous.

d. As expected, cards A12 and B12 are virtually coincident both for consensus and heterogeneity; this outcome proves the consistency of the responses in the two sub-samples.

e. A moderately high consensus is expressed when the attribute "Province" is in the scenario. "Family doctor" manifests an intermediate level of heterogeneity and different degrees of consensus depending on the other factors.

f. No definite patterns do exist with respect to the other factors; hence, responses are likely to be jointly motivated within a more complex framework, since no single covariate is able to dominate the consensus level towards any card.

Overall, it turns out that CUB models representation shown in Figure 1 is more accurately informative than the average preferences as listed in Table 4. Indeed, the order of cards resembles the order of feeling as emphasized in the graphical representation, although some key difference may be noticed when uncertainty assumes an important weight. As an example, cards B6, A5, B8 manifest almost intermediate averages, while they are sharply extreme in the CUB model representation.

5. Extrinsic components

In addition to the visual comparison of different groups of responses, the implemented models allow to link in a direct manner the parameters of feeling and uncertainty to subjects' covariates and also to the card options thanks to a logistic function (for more details, see Appendix A), as in linear regression model specification. In order to characterize the models to be fitted, we consider groups of explanatory covariates defined as *contextual* (i.e. screening mode, location, time and cost of the visit) and *individual* (i.e. respondents' subjective characteristics). The contribution given to the improvement of the model is evaluated accordingly. Such a procedure implies a preliminary selection of subjects' covariates present in the original information set, so to limit further analyses to models with statistical significant coefficients.

This stepwise procedure suggests the following covariates as important: *Lage* (i.e. respondent age, measured as deviation from the mean after logging), *Educ* (i.e. years spent in education), *Child* (this variable equals to one, if the respondent has children), *Sass* (equal to one if interviewee is resident in the province of Sassari,). Noticeably, *Gender* is not statistically significant when jointly considered with other covariates; as a consequence, potential gender heterogeneity in the response behaviour about e-health seems not remarkable.

To encode the categorical attributes, that is *Screening mode* and *Location*, dummies variables are defined (Table 5). Dummy variables M1, M2, M3, M4 and L1, L2, L3, L4 are necessary to consider the 5 categories of *Screening mode* and the 5 categories of *Location* of the visit. For convenience, starred variables M5 and L5 are listed; however, they do not enter into the model specification to avoid multicollinearity.

Thanks to this notation, for both sub-samples, each card can be uniquely characterized for the regression part of the model as in Table 3. In the model specifications, each row vector includes the first 8 values of dummies variables M1-M4 and L1-L4, respectively, whereas the last two values are the attributes for *Time* and *Cost* of the visit. As already stated, A12 and B12 coincide.

Table 5. Correspondence between dummies and categories

Screening Mode	M_1	M_2	M_3	M_4	$M_{5(*)}$	Location of visit	L_1	L_2	L_3	L_4	$L_{5(*)}$
Pharmacy	1	0	0	0	0	*Abroad*	1	0	0	0	0
Private	0	1	0	0	0	*Mainland*	0	1	0	0	0
Health National Service	0	0	1	0	0	*Region*	0	0	1	0	0
Intramoenia	0	0	0	1	0	*Province*	0	0	0	1	0
Family doctor	0	0	0	0	0	*Residence*	0	0	0	0	0

The most important assumption in this class of models (as a necessary condition to apply likelihood methods for parameters estimation and testing) is the conditional independence of the responses, given the specified factors and the significant covariates of the respondent. In other words, this implies that preferences expressed by a certain subject –conditionally to his/her individual characteristics and to attributes of a given card– are independent of the preference expressed for a difference card. Thus, it is postulated that the selected covariates to explain responses exhaust any further information about the probability distribution. Basically, this procedure is implemented by joining all the expressed preferences given to all the cards as a single vector, whereas the design matrix consists of rows for both the subject' covariates and cards' attributes.

Different models (and a comprehensive one) may be estimated. Some models include groups of covariates, but only the final model resulting from a stepwise selection will be presented. As a standard rule in the regression models, the interpretations are *ceteris paribus*, that is each covariate is considered *per se* and assuming constant the values of the other variables. In this context, feeling and uncertainty of the sample respondents are considered with respect to significant covariates, following the formal statements accounted in Appendix A, each model is presented by means of the logistic links between such components and the available covariates (standard errors are in parentheses to check for statistical significance by asymptotic Wald tests).

5.1 Individual covariates

According to the procedure above explained, the best estimated model including individual covariates is:

$$
\begin{cases}
logit\,(1-\hat{\pi}_i) = \underset{(0.145)}{1.921} - \underset{(0.207)}{0.940}\, Lage_i^2 - \underset{(0.008)}{0.055}\, Educ_i - \underset{(0.093)}{0.479}\, Sass_i + \underset{(0.077)}{0.379}\, Child_i\,; \\
logit\left(1-\hat{\xi}_i\right) = \underset{(0.055)}{0.166} + \underset{(0.003)}{0.009}\, Educ_i - \underset{(0.042)}{0.083}\, Sass_i\,.
\end{cases}
$$

This model improves the log-likelihood $\ell(0) = -58703.22$ of the benchmark CUB model without covariates up to $l(\tilde{\theta}) = -58608.42$. Thus, a high significant Likelihood Ratio Test (LRT= 189.6, with g = 6 degrees of freedom) is obtained. Some aspects need to be highlighted, as follows:

- Uncertainty and feeling parameters indicate both *Educ* and *Sass* as common components; then, the estimated model implies a relationship between uncertainty and feeling components.
- *Educ* exerts an impact in different directions on the two components: an increase in *Educ* reduces uncertainty and increases agreement, and viceversa. This behaviour is expected, since more educated people would agree about the implementation of innovative procedure in healthcare, and this belief is generally more homogeneous than in the average of population.
- The presence of children increases heterogeneity among respondents, and this may be caused by different issues related to their age and number, here not considered.
- *Sass* has a negative effect on both components: people living in the province of Sassari express lower uncertainty in the responses as well their consensus towards the options. Thus, they are convincingly more critical with respect to others respondents, as a possible consequence of a different socio-economic status.
- The transformed *Lage*, for age, presents a statistically significant coefficient in the squared term. This implies that uncertainty induces a different effect in the central classes of ages with respect to the extreme ones (young and elderly).

5.2 Contextual covariates

The aforementioned groups of covariates include both categorical (*Screening mode* and *Location*) and numeric variables (waiting *Time* and *Cost*) of the visit; thus, it may be of interest to examine them separately.

5.2.1 Screening mode and Location of the visit

Exploiting the dummies previously defined, the estimates of a CUB model with such covariates are as follows:

$$
\begin{cases}
logit\left(1-\hat{\pi}^{(k)}\right) = -\underset{(0.125)}{1.391} + \underset{(0.132)}{1.506}\, L_1^{(k)} + \underset{(0.143)}{0.238}\, L_2^{(k)} + \underset{(0.146)}{0.693}\, L_3^{(k)} + \underset{(0.145)}{1.824}\, L_4^{(k)} \\
\qquad + \underset{(0.100)}{1.974}\, M_1^{(k)} + \underset{(0.094)}{1.545}\, M_2^{(k)} + \underset{(0.175)}{2.727}\, M_3^{(k)} - \underset{(0.093)}{0.050}\, M_4^{(k)}\,; \\
logit\left(1-\hat{\xi}^{(k)}\right) = -\underset{(0.034)}{0.293} - \underset{(0.059)}{0.018}\, L_1^{(k)} + \underset{(0.053)}{2.070}\, L_2^{(k)} + \underset{(0.053)}{2.239}\, L_3^{(k)} + \underset{(0.053)}{0.237}\, L_4^{(k)} \\
\qquad - \underset{(0.201)}{5.219}\, M_1^{(k)} - \underset{(0.052)}{1.704}\, M_2^{(k)} + \underset{(0.066)}{0.376}\, M_3^{(k)} - \underset{(0.039)}{1.234}\, M_4^{(k)}\,.
\end{cases}
$$

Here, $k = 1, 2, \ldots, 24$ denotes the k^{th} card. Except for L2 and M4 (uncertainty) and L1 (feeling), all dummy covariates are important and significant; as a whole, the model achieves a sensible increase in log-likelihood up to $l(\tilde{\theta}) = -56{,}754.69$. Moving from a CUB model without covariates, notwithstanding the large increase in the number of parameters (from 2 to 18), the BIC index of the last model decreases from 117,426.8 to 113,692.3.
The model suggests a sensible increase of uncertainty when L1 ("Abroad") and L2 ("Mainland") attributes are present whereas the minimum is for "Residence" and "Family doctor" options; instead, the consensus is higher for L2 ("Mainland") and L3 ("Region") and very low for "Residence" and L1 ("Abroad"). The only screening mode which positively affects the consensus is M3 ("NHS").

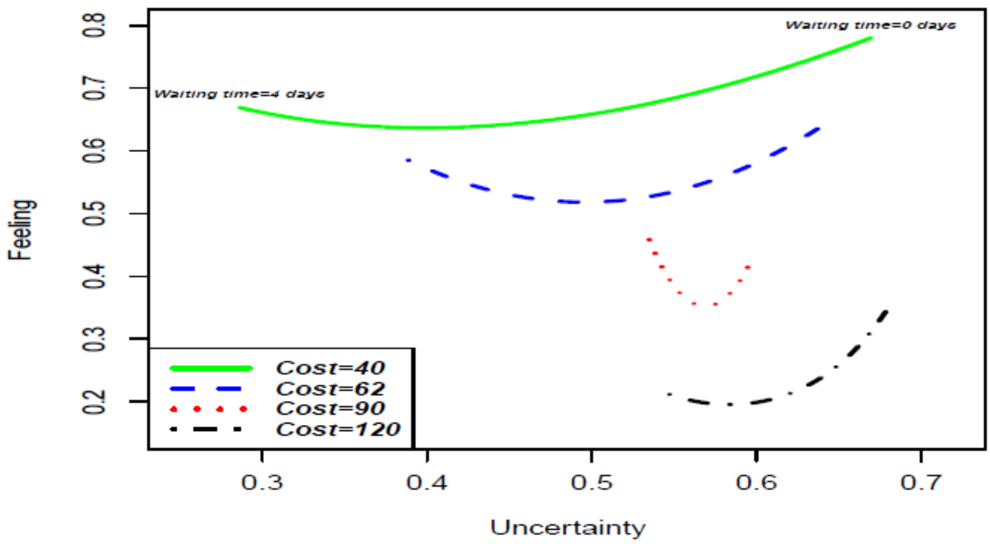
5.2.2 *Waiting Time and Cost of the visit*

Amongst the other attributes, waiting *Time*, *Cost* of the visit and their interaction *Time*×*Cost* are prominent factors for explaining the observed preferences towards the card choice. More specifically, the estimated model is as follows:

$$
\begin{cases}
logit\left(1-\hat{\pi}^{(k)}\right) = \underset{(0.113)}{0.965} - \underset{(0.077)}{0.684}\, Time^{(k)} + \underset{(0.016)}{0.002}\, Time^{2\,(k)} \\
\qquad - \underset{(0.001)}{0.006}\, Cost^{(k)} + \underset{(0.001)}{0.007}\, Cost^{(k)} \times Time^{(k)}\,; \\
logit\left(1-\hat{\xi}^{(k)}\right) = \underset{(0.065)}{2.554} - \underset{(0.038)}{0.670}\, Time^{(k)} + \underset{(0.007)}{0.093}\, Time^{2\,(k)} \\
\qquad - \underset{(0.001)}{0.032}\, Cost^{(k)} + \underset{(0.0003)}{0.0040}\, Cost^{(k)} \times Time^{(k)}\,.
\end{cases}
$$

For both uncertainty and preference/feeling components, waiting *Time* and *Cost* are both significant as well as their interaction. Moreover, a quadratic term is required for waiting *Time*. As a consequence, both interaction and parabolic effects are not so immediate to be interpreted from the previous expressions, and a graphical inspection is needed. If *Time* is assumed as a continuous covariate varying in [0, 4], given the four levels of *Cost*, the joint effect of these covariates on the preferences and heterogeneity of preferences is summarized in Figure 2.

Figure 2. Effects of waiting Time and Cost on the preferences



It seems evident that reducing waiting time lowers heterogeneity of the responses for any value of cost; however, *Cost* is the covariate to assess the respondents' consensus in terms of expressed preferences. The significant interaction induces a restricted range of values when the cost of the visit approximates 100 Euro. Finally, people express more homogeneous preferences when the choice set includes longer waiting time.

6. A comprehensive model

Given the significance of each group of variables for explaining the responses, it is useful to assembly the available covariates related to subjects and/or cards in order to achieve a comprehensive model conditional to the sample information set. Such a research requires a stepwise strategy aimed at including in the final models all and only the significant covariates for both uncertainty and feeling. With respect to previous models, it should be noticed that the joint presence of covariates of different nature may alter significance, weight and also sign of previously estimated parameters.

At the end of the procedure of selection, the following comprehensive CUB model is estimated:

$$
\begin{cases}
logit\left(1-\hat{\pi}_i^{(k)}\right) = \underset{(0.157)}{0.529} - \underset{(0.103)}{0.137}\, L_1^{(k)} - \underset{(0.096)}{1.129}\, L_2^{(k)} - \underset{(0.100)}{0.975}\, L_3^{(k)} - \underset{(0.097)}{0.702}\, L_4^{(k)} \\
\quad + \underset{(0.120)}{2.541}\, M_1^{(k)} + \underset{(0.082)}{0.787}\, M_2^{(k)} + \underset{(0.092)}{0.060}\, M_3^{(k)} + \underset{(0.127)}{0.558}\, M_4^{(k)} \\
\quad - \underset{(0.058)}{0.300}\, Time^{(k)} - \underset{(0.002)}{0.006}\, Cost^{(k)} + \underset{(0.001)}{0.004}\, (Time \times Cost)^{(k)} \\
\quad - \underset{(0.062)}{0.335}\, Sass_i + \underset{(0.054)}{0.159}\, Child_i - \underset{(0.164)}{0.377}\, Lage_i^2\,; \\
logit\left(1-\hat{\xi}_i^{(k)}\right) = \underset{(0.070)}{2.149} - \underset{(0.047)}{0.440}\, L_1^{(k)} + \underset{(0.033)}{0.831}\, L_2^{(k)} + \underset{(0.037)}{0.591}\, L_3^{(k)} + \underset{(0.032)}{0.791}\, L_4^{(k)} \\
\quad - \underset{(0.240)}{4.301}\, M_1^{(k)} - \underset{(0.034)}{1.045}\, M_2^{(k)} - \underset{(0.037)}{0.408}\, M_3^{(k)} - \underset{(0.055)}{0.170}\, M_4^{(k)} \\
\quad - \underset{(0.028)}{0.311}\, Time^{(k)} - \underset{(0.001)}{0.026}\, Cost^{(k)} + \underset{(0.0004)}{0.0025}\, (Time \times Cost)^{(k)} \\
\quad + \underset{(0.002)}{0.012}\, Educ_i - \underset{(0.024)}{0.137}\, Sass_i\,.
\end{cases}
$$

For a correct interpretation, the quantities $(1-\hat{\pi}_i^{(k)})$ and $(1-\hat{\xi}_i^{(k)})$ estimate uncertainty and feeling, respectively, of the i^{th} subject, for $i = 1, 2, \ldots, n$, when he/she is faced with the k^{th} card, for $k = 1, 2, \ldots, 24$ (whose composition is listed in Table 3).

Given the complexity of the model, any consideration should be examined *ceteris paribus* and, under this constraint, some comments are needed:

- Waiting time exerts a decreasing impact on both uncertainty and preference and this result, which is expected for uncertainty, seems to be dubious with respect to preferences. In fact, the model shows that respondents are more confident when some waiting *Time* is necessary for scheduling the visit.
- A higher *Cost* of the visit induces both lower uncertainty and preferences as expected,

given that interviewees are heavily conditioned by healthcare expenses.
- A positive effect of the interaction between waiting *Time* and *Cost* of the visit on both consensus and uncertainty is suggested by the model. This result may be interpreted as a sort of compensation with respect to the negative signs of such variables.
- Education is confirmed to have an important weight to assess preferences. Similarly, residence in Sassari induces a negative effect on the evaluations (by also reducing heterogeneity), and it seems to confirm the results of previous model.
- The presence of children in the interviewees' household exerts an increasing effect on heterogeneity.
- Noticeably, this model does not include *Gender*, whereas *Age* is important only for uncertainty. This is a consequence of a common preference behaviour of women and men. The absence of *Age* among the explanatory variables for the feeling component may be due to the education level which is of course related to respondent's age. Indeed, the role of *Age* to modify uncertainty at a large extent (see Figure 2) is confirmed also when so many covariates are considered in the model.

6.1 Profiling respondents

Previous model may be exploited to study how the preferences for the services change according to the respondent's profile. Hence, it is necessary to consider an "average respondent" who, for the given sample, may be considered as a man/woman, aged 50 years old, resident in Sassari, married with children and with a high-school education. This profile has been obtained by an approximate combination of mean/modal values of all the individual covariates. To emphasize the utility of *Screening mode* and *Location* of the service to be offered, the average cost (i.e. Euro 62) and the average waiting time in Sardinia for a standard cardiology visit (i.e. 4 days) are included.
As a consequence, by letting $Sass_i = 1$, $Child_i = 1$, $Educ_i = 13$, $Age_i = 50$, $Cost^{(k)} = 62$ and $Time^{(k)} = 4$, the previous model simplifies to:

$$\begin{cases} logit\left(1-\hat{\pi}^{(k)}\right) &= -1.634 - 0.137\,L_1^{(k)} - 1.129\,L_2^{(k)} - 0.975\,L_3^{(k)} - 0.702\,L_4^{(k)} \\ & \quad + 2.541\,M_1^{(k)} + 0.787\,M_2^{(k)} + 0.060\,M_3^{(k)} + 0.558\,M_4^{(k)}\,; \\ logit\left(1-\hat{\xi}^{(k)}\right) &= -0.043 - 0.440\,L_1^{(k)} + 0.831\,L_2^{(k)} + 0.591\,L_3^{(k)} + 0.791\,L_4^{(k)} \\ & \quad - 4.301\,M_1^{(k)} - 1.045\,M_2^{(k)} - 0.408\,M_3^{(k)} - 0.170\,M_4^{(k)}\,. \end{cases}$$

After a simple algebra, the estimated marginal effect (in terms of uncertainty and feeling, respectively) of each attribute are analyzed (Table 6), as follows:
- Uncertainty/heterogeneity in responses are mainly due to the screening mode of visit; respondents are more homogeneous with respect to the location of the visit.
- The attributes "Mainland", "Region" and "Province" have similar effects in terms of preferences, whereas "Abroad" is at a minimum and "Residence" is intermediate.
- "Family doctor" is the attribute that mostly improves the preference for the choice

card followed by “Intramoenia”. The lowest preferences are those induced by “Pharmacy”, a confirmation that cards containing such attributes are always located at low levels of agreement (Figure 1).

- “Residence”, as a location, and “Family doctor”, as a screening mode (that is, the status quo reference), have the same value since they are computed when all the dummies coincide with zero. Hence, the values are determined only by the constants of the uncertainty and feeling links.

Table 6. Marginal effects of each attribute

Location of visit	Uncertainty	Feeling
Abroad	0.145	0.381
Mainland	0.059	0.687
Region	0.069	0.634
Province	0.088	0.679
Residence	0.163	0.489
Screening mode	Uncertainty	Feeling
Pharmacy	0.712	0.013
Private	0.300	0.252
Health National Service	0.172	0.389
Intramoenia	0.254	0.447
Family doctor	0.163	0.489

7. Explicative power of covariates

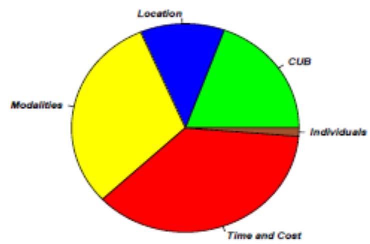
To detect the main drivers of the expressed preference towards e-health options, a parametric approach was selected to summarize the main content of the formulation of respondents’ judgment. Hence, it is important to exploit as much as possible the strength of such models by means of explicative power, a further concept which involves both estimated models and sample data. This concept will be briefly summarized with reference to an application to e-health data set (more details are provided in Appendix B).

When statistical models are of increasing complexity and each estimated model may be considered as nested in the previous one, an important aspect to be considered is the additional explicative power that each group of covariates (or of a single covariate) provides to the final results. “Explicative” should be defined more precisely, and fitting measures are possible starting points. In this regard, the log-likelihood function is a direct measure of fitting and explicative power of a model; more refined measures, as BIC for instance, consider also model parsimony, but for the moment it may be sufficient to introduce log-likelihood functions (as in Appendix B).

Since for ordinal responses with m categories the worst possible model is a discrete uniform distribution with constant probability, we denote as M0 this extreme structure. Then, M1 is an intrinsic model since there are no explanatory covariates in the specification; subsequent models include an increasing number of covariates as groups of drivers for a better interpretation. At the other extreme, one should introduce saturated models: since they have to be computed on the basis of the discrete values of the sample, the comprehensive estimated model presented in Section 5 (denoted as M5) will be considered as a convenient proxy. The explicative power expressed by log-likelihood functions (estimated at maximum) is reported in the Table 7. Of course, different sequences of nested models are also legitimate and the solution here proposed refers to selected groups of covariates which are of interest for the project.

Table 7. Explicative power of selected group of covariates

Models	Explanatory groups of covariates	Estimated log-likelihood	Additional explicative power
M_0	Uniform distribution	−59 593.20	0.00%
M_1	Intrinsic (Feeling + Uncertainty)	−58 703.22	19.45%
M_2	Location	−58 154.99	11.98%
M_3	Location + Screening Location	−56 754.69	30.60%
M_4	+ Screening		
	+ Time + Cost + Time×Cost	−55 075.51	36.69%
M_5	Individual+ Location+ Screening		
	+ Time + Cost + Time×Cost	−55 016.72	1.28%



As confirmed by the outcome, about 1/5 of distribution of responses is explained by intrinsic components of consensus and heterogeneity. *Time* and *Cost* are the most important drivers of the expressed preferences as well as *Screening mode*. Instead, *Location* improves models just a bit more than 1/10; finally, individual characteristics are almost uninfluential on the final decision (their contribution is hardly more than 1%).

8. Conclusions

The results and the information obtained by the present parametric framework may help developing policies in health services and planning future interventions in e-health consultation modes directed to cardiac pathologies. Stakeholders should consider as most relevant *Cost* and waiting *Time* as components of the e-health services supplied, since these elements are decisive in assessing preferences. Yet also, location is found to be a key factor.

In line with previous studies (Deidda et al., 2018; Capecchi et al., 2018), the average user has shown an increase preference/utility for a cardiac visit nearby their place of residence, while abroad is the least preferred. This outcome is further confirmed by the finding that the average user would prefer a visit at the "family doctor", which would further encourage the implementation of e-health services in their own municipality.

In light of the evidence of drivers which consistently orient preferences, homogeneous preferences among individuals are found also for lower waiting time, although such a relationship is not linear and respondents seem to be more confident when some waiting time is required to book a cardiac visit. Possibly, this outcome is consistent with the belief that good physicians are usually very busy and may have a full agenda requiring the necessary time to schedule a visit. A higher cost of the visit induces both lower uncertainty and preferences, implying that interviewees have a low propensity to pay.

Education has also an important role in assessing preferences. People who are more educated would opt for innovation in medicine and this belief is generally more homogeneous than the average of population. The presence of Children in the interviewees' household exerts an increasing effect on heterogeneity, probably due to different issues associated to their age and number, here not taken into account. Interestingly, female and male do have rather similar preferences.

Overall, there is further empirical evidence that people are homogeneously willing to accept e-health that helps to reduce costs and waiting lists, while guaranteeing patients monitoring. This novel check up and monitoring practice, especially in remote areas, would simplify healthcare services, making them more accessible both physically and financially.

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Appendix A. An overview of CUB models

The preferences (r_1, r_2, . . ., r_n) expressed by n subjects towards a card including discrete choices are realizations of a random sample (R_1, R_2, . . . , R_n). Generally, in a sample survey, also a set of v covariates summarizing all the available information about respondents are collected and are stored in the matrix
T = $||t_{ij}$, i = 1, 2, . . . , n; j = 1, 2, . . . , v$||$.

Formally, a CUB model is specified by two sets of equations:

1. A stochastic component:

$$Pr\left(R_i = r|\,\boldsymbol{\theta};\, \boldsymbol{x}_i,\, \boldsymbol{w}_i\right) = \pi_i\,\left[\binom{m-1}{r-1}(1-\xi_i)^{r-1}\xi_i^{m-r}\right] + (1-\pi_i)\left[\frac{1}{m}\right] \qquad (1)$$

for r = 1, 2, . . . , m, and i = 1, 2, . . . , n.

2. Two systematic components:

$$\begin{cases} logit(1-\pi_i) = \log\left(\dfrac{1-\pi_i}{\pi_i}\right) & = -\boldsymbol{x}_i\boldsymbol{\beta} = -\beta_0 - \beta_1\, x_{i1} - \cdots - \beta_p\, x_{ip}\,; \\ logit(1-\xi_i) = \log\left(\dfrac{1-\xi_i}{\xi_i}\right) & = -\boldsymbol{w}_i\boldsymbol{\gamma} = -\gamma_0 - \gamma_1\, w_{i1} - \cdots - \gamma_q\, w_{iq}\,. \end{cases} \qquad (2)$$

where θ = (β', γ')' is the parameter vector to be estimated, and xi and wi are the row vectors of T corresponding to covariates values for the i-th subject, suitable to explain πi and ξi, respectively. For convenience, $x_{i0} = w_{i0} = 1$, i = 1, 2, . . . , n.
Given the finiteness of the covariates, the parameter space **Ω**(β, γ) is an open set and a CUB model is well defined since $\pi_i \in (0, 1]$ and $\xi_i \in [0, 1]$, i = 1, 2, . . . , n.
Since $1-\pi_i$ and $1-\xi_i$ are related to uncertainty and feeling of the i-th subject, the representation of how these quantities are modified by significant covariates in the logistic links is very useful for interpretation. Thus, estimated models are compared and discussed by only examining the sign and the values of the parameters in the logistic links (2) which exhaust all the statistical aspects of a CUB model with covariates.
Further characteristics and generalizations of CUB models, first proposed by Piccolo (2003); D'Elia and Piccolo (2005), are presented and fully discussed by Piccolo (2018); Piccolo et al. (2018). An effective R package is available for maximum likelihood inference on parameters, diagnostics on the estimated model and plotting tools (Iannario et al., 2018).

Appendix B. Explicative power of estimated models

Given a sequence of nested models $M_0 \subset M_1 \subset \cdot\cdot\cdot \subset M_M$, M_0 is the null model (when no structure on data is imposed, e.g. discrete Uniform distribution) and M_M is the more comprehensive model given the available information set: in some circumstances this is the saturated model, in other cases it is the best model given data in a given class. Let us define ℓ_{M_j} the log-likelihood function for the model M_j computed at the maximum $\theta = \hat{\theta}$.
Then, the maximum explicative power $M_M - M_0$ may be decomposed according to the following formula:

$$\left(\frac{\ell_{\mathcal{M}_1} - \ell_{\mathcal{M}_0}}{\ell_{\mathcal{M}_M} - \ell_{\mathcal{M}_0}}\right) + \left(\frac{\ell_{\mathcal{M}_2} - \ell_{\mathcal{M}_1}}{\ell_{\mathcal{M}_M} - \ell_{\mathcal{M}_0}}\right) + \cdots + \left(\frac{\ell_{\mathcal{M}_M} - \ell_{\mathcal{M}_{M-1}}}{\ell_{\mathcal{M}_M} - \ell_{\mathcal{M}_0}}\right) = 1\,.$$

Then, it is possible to assess the contribution supplied by any model component Cj by introducing the measure of the explicative powers of the model which adds Cj in the nested sequences:

$$\mathcal{E}_{C_1} = \frac{\ell_{\mathcal{M}_1} - \ell_{\mathcal{M}_0}}{\ell_{\mathcal{M}_M} - \ell_{\mathcal{M}_0}}\,; \qquad \mathcal{E}_{C_2} = \frac{\ell_{\mathcal{M}_2} - \ell_{\mathcal{M}_1}}{\ell_{\mathcal{M}_M} - \ell_{\mathcal{M}_0}}\,; \qquad \ldots\,; \qquad \mathcal{E}_{C_M} = \frac{\ell_{\mathcal{M}_M} - \ell_{\mathcal{M}_{M-1}}}{\ell_{\mathcal{M}_M} - \ell_{\mathcal{M}_0}}\,.$$

According to features of the nested sequence, the explicative power of specific components may be introduced; as an instance, the explicative power of the intrinsic component of CUB model has been discussed in this paper (Piccolo, 2018).

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