Choosing fast and slow: connecting response time to decision rules

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Abstract

A growing body of studies in the field of choice modelling suggests that utility maximising decision rules may be outperformed by other decision paradigms in some contexts. Recent findings also show that different respondents make use of different underlying paradigms in the same context. However, little is known about why different respondents employ different decision paradigms. In this paper, we test whether respondents employ different decision paradigms depending on their latent attitudes toward survey engagement that drive the response time of making choices. We use data from a controlled choice experiment on reforestation to estimate a latent class model where each class corresponds to a different decision rule. Two decisions rules are considered: Random Utility Maximisation (RUM) and Random Regret Minimisation (RRM). To control endogeneity, survey response time is not directly integrated as a covariate in the class allocation model, instead, we adopt a hybrid model structure where attitude toward survey engagement is treated as a latent component that drives survey response time. We find that only a small proportion of subjects employ RUM. Our results also suggest that a higher response time increases the chances to use RRM.

Keywords: random utility maximisation; random regret minimisation; hybrid choice model; latent class model; behavioural mixing

1. Introduction

Over the last decade, an increasing number of researchers have accepted that individuals may use different choice paradigms (i.e. decision rules) when making decisions in different contexts. Apart from the classical compensatory rule of Random Utility Maximisation (RUM), researchers also have applied rules such as Random Regret Minimisation (RRM) or elimination by aspects on choice models (e.g. Chorus, 2010; Jedidi and Kohli, 2005; Gilbride and Allenby, 2004; Kamel and Rajeev, 2008). In spite of this advancement, the common practice to model Stated Preference data in the non-market valuation literature is to assume that individuals use RUM (Thiene, Boeri, & Chorus, 2012). This is, however, a too strict assumption that sometimes is inconsistent with individuals' real decision processes. Even in the same context, decision processes may still vary across individuals. To lose this 'single-paradigm' assumption, Hess et al. (2012) as well as Hess and Strathopoulos (2013a) take individuals' heterogeneity in relations to decision rules into consideration. They make use of latent class models, demonstrating that incorporating different decision rules in choice models can improve the model fit significantly. Similarly, Chorus et al. (2013) proposed a mixed model, allowing some attributes to be processed by regret-minimization-based rules and others to be processed by utility-maximization-based rules. They find that incorporating different decision rules in a mixed model increases both model fit and out-of-sample predictive ability.

Allowing for different decision rules raises an inevitable question, that is, what drives respondents to 'choose' a given decision paradigm over another? Although it is still an open question, intuitively, the attitude of the respondent toward survey engagement may play an essential role (Hess and Strathopoulos, 2013b). For example, other things being equal, individuals who want to quickly complete a survey will adopt a decision process that requires low cognitive effort, so that they can make quick decisions, whereas those who want to make sophisticated and slow decisions will adopt a decision process that requires high cognitive effort. However, in most conditions, attitude of a respondent toward survey engagement is also unobservable. At the same time, asking individuals' attitudes directly may lead to significant biased answers. This is because, for example, in some contexts (e.g. experimental contexts) individuals may want to answer this question strategically to avoid being thought as a careless person. Given this situation, a good indicator that can reflect individuals' attitudes toward survey engagement is essential. In the present paper, we suggest that survey response time is a good indicator.

That response time is relevant to individuals' decision making processes is not only an intuitive argument. There is a substantial amount of evidence showing that individuals' response time can reflect or is related to many features of their decision makings. Individuals' longer response time are found to be associated with higher average payoffs (Arad and Rinimstein, 2012), higher level of rationality (Wengstrom, 2009; Lotito et al., 2013) and higher level of honesty (Jiang, 2013). Additionally, individuals response time tend to be long when they are in losing positions (Gneezy et al., 2010). In terms of decision rules, more explicitly, Matthey and Regner (2008) find that longer response time is related to cognitive dissonances. Rubinstein (2007) states that response time can be seen an interesting tool that is suitable for experimental results, as shorter response time is associated with more intuitive choices and less sophisticated reasoning (See also Klein and Yadav, 1989 and Rose and Black, 2006). These findings, although the causality is still unclear, both implicitly and explicitly indicate that the length of response time could be seen as a proper indicator that is associated with individuals' different decision processes.

Surprisingly, to date, very few scholars attach much importance to individuals' attitudes toward survey engagement, in terms of constructing choice models involving different decision paradigms. Our paper is an attempt to fill in this gap. In the present paper, we use data from a controlled choice experiment on reforestation to estimate a latent class model where each class corresponds to a different decision rule. Two decisions rules are considered: RUM and RRM. We extend the methodology introduced by Hess *et al.*, (2012) and link class allocation to respondents attitudesby formulating a class allocation model where survey response time has an indirect influence on the probability of choosing a given decision rule over another. Survey response time is not directly integrated as a covariate in the class allocation model because Hess and Strathopoulos (2013b) have suggested that such approach may provoke endogeneity issues. Indeed, survey response time is likely to be correlated with other unobserved factors. As a result, we adopt a hybrid model structure in which a latent variable is used inside the class allocation model to explain why respondents may use RUM instead of RRM as well as inside a separate measurement equation component to explain survey response time. This paper contributes both to the literature on non-market valuation by showing that a significant share of respondents use RRM rather than RUM, which makes the predominance of RUM-based approaches in non-market valuation questionable. Our paper also contributes to the literature on choice modelling as a whole by modelling the link between survey response time and decision paradigms.

The remainder of the paper is organised as follows: section 2 introduces experimental design; section 3 introduces the modelling methodology; section 4 reports the results and the last section gives the discussion and conclusion.

2. Experimental design

The data employed in our study were collected from a computer-based experiment conducted in spring 2015 at the University of Nantes, France. 400 undergraduate economic students participated in the experiment but only 205 provided suitable answers for the purpose of our analysis (the students have been facing different experimental treatments so only a subset of the complete survey sample is suitable for our analysis). The students were invited to answer a series of questions, including a choice experiment survey on reforestation in Senegal. The students had to answer to the questions on their own, using a computer program. They could not communicate with each other. Moreover, the students could not access the internet or run other programs while facing the survey in order to make sure that students could not be distracted and had to focus on the survey. Such experimental settings make the measure of the survey response time more reliable than the measures obtained by the mean of internet based surveys. The students could request the assistance of a survey manager if required and at least one survey manager was always present in the room (5 students were present at a time). The survey briefly describes the role of forests in ecological system, and then introduces a real environmental program, ‘reforest action’, which is managed by a non-governmental organization (NGO). The purpose of delivering this information is to let subjects be familiar with tree-planting programmes. The general recommendations from the literature on survey design were followed and the reforestation program was chosen because it is a real world program, which reduces the hypothetical bias and is incentive compatible (Carson and Groves, 2007).

After being shown an example choice set, all subjects had to complete a series of 16 choice sets (all the respondents faced the same 16 choice sets, which were generated using an orthogonal design) each containing two unlabelled tree-planting programmes and a no-programme option. Each programme features four attributes: *cost, online information* (*oi*), *country*, and *ecosystem services*. Cost represents the monetary cost for a donator planting a tree (€2,€5,€10, €15); online information (2 levels) represents whether or not the donator can be regularly updated with information (e.g. mails, photos) about the programme; country (2 levels) represents the location (i.e. Senegal or Peru) where the tree is planted, and ecosystem services (2 levels) represents the tree species and as a result the function of the tree in the ecosystem, either restoration or conservation of lands[1]. Figure 1 provides an example of a choice set.

[Figure 1 about here]

The survey response time of each subject doing each task was recorded. At the end of the experiment, one subject was randomly selected and the selected subject earned a €50 gift voucher. Table 1 introduces the variables and provides descriptive statistics.

[Table 1 about here]

[1] A series of papers using this dataset (references not included to preserve anonymity) have found that the *location* and *ecosystem service* attributes do not significantly influence respondents' preferences. We have conducted a series of tests and chose to not consider these attributes in the remainder of our analysis.

3. Modelling methodology

The general structure of the latent class model adopted in the present paper is based on Hess et al., (2012). Instead of simply allowing for differences in the utility parameters across classes, the model allows for differences across classes in the actual decision rules. The main difference between our model and theirs is that we incorporate a hybrid component which ultimately allows to model the effect of survey response time on the probability to use RUM or RRM.

Let's first assume that there are N decision makers, and each of them needs to complete T discrete choice tasks with J alternative choice options. In this context, to explain individuals' choices we need to make assumptions about the underlying choice process. For several decades, since the seminal paper by McFadden (1974), traditional practice across the non-market valuation literature has been to use Random Utility Maximization (RUM) model as the underlying decision process paradigm. However, recently, a number of non-RUM models have been developed, with the aim to provide alternative ways of looking at individuals' choices. One well-known example of a non-RUM model is the Random Regret Minimization (RRM) model (Chorus et al., 2008), applied initially in a travel behaviour context. In this paper, we consider two potential paradigms for individuals' choice processes: RUM and RRM. Before explaining the details of the approach developed for this paper, it is convenient to provide a summary of the intuition and formulation of both RUM and RRM respectively.

The RUM model assumes that when choosing among different options, the individual will choose the option that provides her/him with the highest level of utility. The most basic form a RUM model is specified as linear-in-parameters and with an additive error term, such that the utility of choosing alternative i can be expressed as follows:

$$U_i = V_i + \varepsilon_i = \sum_m \beta_m x_{im} + \varepsilon_i \qquad (1)$$

Where V_i represents the observable part of the utility function, and ε_i is the Extreme Value (EV) Type-I error term. The observable part is defined as a function (in this case, an additive sum) of the *m* attributes (*x)* of alternative i, where each attribute is multiplied by a parameter β_m that is to be estimated.

Under the RUM paradigm, the probability of the decision maker choosing alternative *i* is:

$$P_{i,RUM} = \prod_{t=1}^{T_n} P(U_{it} > U_{jt}, \forall j \in J) \quad (2)$$

$$P(U_{it} > U_{jt}, \forall j \in J) = \frac{e^{V_i}}{\sum_J e^{V_j}} \quad (3)$$

On the other hand, the RRM model assumes that, when facing a set of choice alternatives, the individual compares a considered alternative with the other options looking at their respective attributes, and chooses the option that provides her with less regret. In other words, the individual would avoid choosing an option that is outperformed by other/s option/s in one or more attributes, anticipating a feeling of regret (Chorus, 2012). The standard formulation of a regret function can be defined as follows:

$$RR_i = R_i + \varepsilon_i = \sum_{j \neq i} \sum_m \ln(1 + \exp[\beta_m * (x_{jm} - x_{im})]) + \varepsilon_i \quad (4)$$

Where RR_i represents the random regret associated to choosing option i, R_i is the observed part of the regret function and ε_i is a type-I EV error term. The attributes x_{jm} associated with the *J* choice options are the same as in the RUM model, but now the coefficients β_m relate to the differences in attributes between alternatives *i* and *j*. Under a random regret minimisation paradigm, the probability of the decision maker choosing alternative *i* is:

$$P_{i,RRM} = \prod_{t=1}^{T_n} P(R_{it} < R_{jt}, \forall j \in J) \quad (5)$$

$$P(R_{it} < R_{jt}, \forall j \in J) = \frac{e^{-R_i}}{\sum_J e^{-R_j}} \quad (6)$$

In this setting, we assume that each decision maker can only employ one of the two decision rules listed above. The choice of decision rule for a given subject is an unobservable latent component. The probability for the sequence of choices observed for subject *n* is now given by:

$$P_n = \pi_{n,RUM} P_{n,RUM} + \pi_{n,RRM} P_{n,RRM} \quad (7)$$

Where $\pi_{n,RUM}$ and $\pi_{n,RRM}$represent the probabilities for each class. We link these probabilities to underlying survey engagement attitudes using:

$$\pi_{n,RUM} = \frac{e^{\delta_{RUM} + \tau\alpha_n}}{e^{\delta_{RUM} + \tau\alpha_n + 1}} \quad (8)$$

$$\pi_{n,RRM} = \frac{1}{e^{\delta_{RUM} + \tau\alpha_n + 1}} \quad (9)$$

Under such settings, Hess *et al.*, (2013) show that δ_{RUM} captures the mean share of respondents using RUM in the sample (relative to RRM) while $\tau\alpha_n$ captures the shift in the probability for respondent *n* using RUM because of its underlying attitude toward the survey. Attitudes are given by α_n and the sign of the estimated parameter τ determines whether the probability for using RUM increases when α_n increases, which is translated by τ being positive, or decreases (which is translated by τ being negative). Following Hess *et al.*, (2013) and Hess and Strathopoulos (2013b), we propose to treat survey response time as an indicator of a latent attitude toward survey engagement. More precisely, we use a hybrid model structure where survey response time is treated as a dependent variable in a measurement equation component. As previously stated, survey response time is likely to be correlated with other, unobserved factors which may provoke bias related to endogeneity.

The latent attitude for respondent *n*, α_n, is defined by:

$$\alpha_n = \gamma_{age} I(age) + \gamma_{female} I(female) + \gamma_{income} I(income) + \eta_n \quad (10)$$

The variables are defined in Table 1 and η_n is a random disturbance which is assumed to follow a Normal distribution $g(\eta_n)$ across respondents, with a mean of zero and a standard deviation of one.

In the model, α_n is also used to explain the survey response time measures performed by the respondents. Survey response time is a continuous variable and could be treated as such. Yet, after numerous attempts to estimate our model, it has been found to be preferable to make survey response time a dummy which takes the value one if the respondent's survey response time is above average and zero else. The likelihood for this indicator is modelled as a binary logit:

$$L_{SRT} = I(dSRT = 0)\frac{1}{1+e^{\zeta\alpha_n}} + I(dSRT = 1)\frac{e^{\zeta\alpha_n}}{1+e^{\zeta\alpha_n}} \quad (11)$$

where ζ is the impact of α_n on the probability of being above the average survey response time. Finally, as demonstrated by Hess *et al*., (2013), estimating the model requires to maximise the joint likelihood of the observed sequence of choices and the observed measures of the survey response time (coded as a dummy). Both the measurement equation and the latent class model are conditional on a realization of α_n. Hence, the log-likelihood function of the model is obtained by integration over η_n. The log-likelihood function is the following:

$$LL = \left(\Omega_V, \Omega_\pi, \Omega_\alpha, \Omega_{QSRT}\right) = \sum_{n=1}^{N} \ln \int_{\eta_n} (P_n = \pi_{RUM} P_{RUM} + \pi_{RRM} P_{RRM}) L_{QSRT}\, g(\eta_n) d\eta_n \quad (12)$$

The model was estimated using R with the support of the maxLike package (Royle *et* al., 2012). Results are presented in the next section.

4. Results

Four models have been estimated: Model 1 assumes that all the respondents use RUM while Model 2 assumes that all the respondents use RRM. Model 3 is a simple RUM-RRM mixture while model 4 is a RUM-RRM mixture which also introduces *SRT* as a dependent variable by the mean of the hybrid component described in Section 3. Results are reported in Table 2. The average time per choice task is reported in Figure 2.

[Table 2 about here]

[Figure 2 about here]

First, we compare Model 1 and Model 2. In both models, *online information* and *price* are significant. *Price* is negative, as expected, while *online information* is positive, which means that respondents positively value the fact that they can check online how the tree they funded is growing. The RUM model fits the dataset better than the RRM model (a multinomial logit), which is in line from the results reported by Hess *et al*., (2012) using a different dataset.

Model 3 provides substantial gains in model fit in comparison to Model 1 and Model 2. δ_{rum}, the constant term in the class allocation model, is found to be significant an negative. Hence, we can observe that about 79.36% of the respondents fall in the RRM class, *versus* 20.64% in the RUM class. Such result confirm that RRM is better suited than RUM for a majority of the respondents who took part in the survey.

Finally, Model 4 reports a slightly worse fit in comparison to Model 3, which is a common result when adding a hybrid component (see Hess and Strathopoulos, 2013a). An important result is that τ is found to be significant and negative, which means that the chances to fall into the RRM class decrease when α increases. The presence of αn in the class allocation probabilities leads to very substantial variations in the probabilities for RUM and RRM as a function of the latent variable related to survey response time (see Table 3 for an in-depth description of the effects of $\tau\alpha$n on π_{RUM}. ζ being positive and significant means that increases in the latent variable α_{n} correspond to a higher probability of having a survey response time above the mean.

Since RRM involves more numerical calculations across alternative attributes than RUM, the former decision rule is associated with higher cognitive efforts. Accordingly, we hypothesize that individuals who want to make faster decisions and finish the experiment quick will adopt RUM rather than RRM.

[Table 3 about here]

Conclusion

In this paper, we take individuals' heterogeneity in terms of different decision rules into consideration. We propose a hybrid latent class model were attitude toward survey engagement is a latent variable which explains response time. We find that first, a big proportion of subjects tend to use RRM instead of RUM in our non-market valuation survey; second, subjects who made slower decisions (i.e. whose response time is above the mean) may tend to adopt the decision rule of RRM. Our research shed light on the model selection and model construction in non-market valuation surveys. According to our findings, RUM may not always be a well suited decision paradigm for treating non-market valuation survey data.

Our results lead to two serious conclusions. First, RUM may not always be the ideal choice paradigm for analysing non-market valuation data. However, other choice paradigms may not allow to derive welfare estimates, which questions which practice is the best. Second, our results indicate that RUM is a choice paradigm which is chosen by respondents who tend to think faster or provide quicker, more immediate answer. Hence, quicker response times may not always reflect a lack of involvement in the survey, but could also mean that a respondent is using different choice paradigms.

In the present study we only consider two decision rules - RUM and RRM - and take survey response time as a key indicator. Future versions of this paper will incorporate more decision rules such as elimination by aspects and give a deeper analysis of the links between survey response time and decision rules.

Acknowledgements

the authors acknowledge the financial support by the European Research Council through the consolidator grant 615596-DECISIONS.

References

Araña, J.E., León, C.J. & Hanemann, M.W., 2008. Emotions and decision rules in discrete choice experiments for valuing health care programmes for the elderly. Journal of Health Economics, 27(3), pp.753–769.

Carson, R. T. and Groves, T., 2007. Incentive and informational properties of preference questions. Environment and Resource Economics, 37, pp. 181-210.

Chorus, C. G., 2010. A new model of random regret minimization. Ejtir, 10(2), pp.181–196.

Chorus C.G. 2012. Random Regret-based discrete choice modelling: A tutorial. Springer, Heidelberg, Germany

Chorus, C.G., Arentze, T. and Timmermans, H. 2008.A Random Regret-Minimization model of travel choice. Transportation Research Part B, 42, pp.1-18.

Chorus, C.G., Rose, J.M.. & Hensher, D.A., 2013. Regret Minimization or Utility Maximization: It Depends on the Attribute. Environment and Planning B: Planning and Design, 40, pp.154–169.

Gilbride, T.J. & Allenby, G.M., 2004. A Choice Model with Conjunctive, Disjunctive, and Compensatory Screening Rules. Marketing Science, 23(3), pp.391–406.

Gneezy, U., Rustichini, A. & Vostroknutov, A., 2010. Experience and insight in the Race game. Journal of Economic Behavior and Organization, 75(2), pp.144–155.

Hess, S. & Stathopoulos, A., 2013a. A mixed random utility - Random regret model linking the choice of decision rule to latent character traits. Journal of Choice Modelling, 9(1), pp.27–38.

Hess, S. & Stathopoulos, A., 2013b. Linking response quality to survey engagement: A combined random scale and latent variable approach. Journal of Choice Modelling, pp. 1-12.

Hess, S., Stathopoulos, A. & Daly, A., 2012. Allowing for heterogeneous decision rules in discrete choice models: an approach and four case studies. Transportation, 39(3), pp.565–591.

Jedidi, K. & Kohli, R., 2008. Inferring latent class lexicographic rules from choice data. Journal of Mathematical Psychology, 52(4), pp.241–249.

Jedidi, K. & Kohli, R., 2005. Probabilistic Subset-Conjunctive Models for Heterogeneous Consumers. Journal of Marketing Research, 42(4), pp.483–494.

Jiang, T., 2013. Cheating in mind games: The subtlety of rules matters. Journal of Economic Behavior & Organization, 93, pp.328–336.

Klein, N. M., Yadav, M. S., 1989. Context effects on effort and accuracy in choice: An enquiry into adaptive decision making. Journal of Consumer Research: An Interdisciplinary Quarterly 15(4), pp.411-21.

Lotito, G., Migheli, M. & Ortona, G., 2013. Is cooperation instinctive? Evidence from the response times in a public goods game. Journal of Bioeconomics, 15(October), pp.123–133.

Manski, C.F., 1977. The structure of random utility models. Theory and Decision 8, pp.229–254.

Matthey, A. & Regner, T., 2008. Is observed other-regarding behavior always genuine? Jena.

McFadden, D., 1974. Conditional logit analysis of qualitative choice-behaviour. In: Zarembka, P. (Ed.), Frontiers in Econometrics. Academic Press, New York.

Piovesan, M. & Wengström, E., 2009. Fast or fair? A study of response times. Economics Letters, 105(2), pp.193–196.

Rose, J. M., Black, I. G., 2006. Means matter, but variance matter too: Decomposing response latency influences on variance heterogeneity in stated preference experiments. Marketing Letters 17(4), pp.295-310.

Royle, J. A., Chandler, R. B., Yackulic, C. and Nichols, J. D., 2012. Likelihood analysis of species occurrence probability from presence-only data for modelling species distributions. Methods in Ecology and Evolution 3, pp.545–554.

Rubinstein, A., 2007. Instinctive and Cognitive Reasoning: A Study of Response Times. Economic Journal, 117(523), pp.1243–1259.

Table 1. Descriptive statistics

Variable	Description	Mean	Std. Dev.	Min	Max
age		20.039	2.024	18	32
income	Monthly income	284.366	159.865	0	650
SRT	Time for completing the choice tasks	144.112	52.362	37	332
dSRT	Dummy. = 1 if the respondent took more than the average time in the sample to complete the choice tasks and 0 else	0.444	0.497	0	1
female	Dummy. = 1 if the respondent is female and 0 else	0.439	0.496	0	1

Table 2
Estimation results

	MNL			RRM			MNL + RRM			Hybrid MNL + RRM		
Log-Likelihood	-2597.29			-2606.17			-2262.88			-2399.21		
	Coeff.	S. Dev.	T ratio	Coeff.	S. Dev.	T ratio	Coeff.	S. Dev.	T ratio	Coeff.	S. Dev.	T ratio
RUM_asc	-2.1593	0.1901	-11.36	-	-	-	-0.2319	0.3537	-0.66	-0.2373	0.351	-0.68
RUM_oi	1.2196	0.0985	12.38	-	-	-	1.1723	0.2339	5.01	1.1775	0.2221	5.3
RUM_price	-0.1595	0.0115	-13.91	-	-	-	-0.176	0.0404	-4.36	-0.1755	0.0397	-4.41
RRM_asc	-	-	-	1.8957	0.1767	10.73	3.9532	0.4332	9.13	3.9841	0.4243	9.39
RRM_oi	-	-	-	0.8524	0.0964	8.84	0.9348	0.1201	7.78	0.9339	0.1202	7.77
RRM_price	-	-	-	-0.0977	0.0065	-15.14	-0.0987	0.0077	-12.88	-0.0987	0.0077	-12.88
δrum	-	-	-	-	-	-	-1.3469	0.2272	-5.93	-1.4126	0.2183	-6.47
τ	-	-	-	-	-	-	-	-	-	-0.0319	0.0186	-1.72
ζ	-	-	-	-	-	-	-	-	-	0.0301	0.0174	1.73
γincome/100*	-	-	-	-	-	-	-	-	-	4.8115	1.6177	2.97
γfemale	-	-	-	-	-	-	-	-	-	-2.2342	3.0801	-0.73
γage*	-	-	-	-	-	-	-	-	-	4.108	1.9406	2.12
πRUM	100%			-			20.64%			19.58%		
πRRM	-			100%			79.36%			80.42%		

* The variable has been normalised to the mean

Table 3

Marginal effects - Class membership probability

Age	19	21	23	25	27	29	31	32
πRUM	22.43%	18.20%	14.62%	11.64%	9.20%	7.23%	5.66%	5.00%
Income	0	100	200	300	400	500	600	650
πRUM	21.65%	19.48%	20.01%	19.50%	19.01%	18.52%	18.05%	17.81%

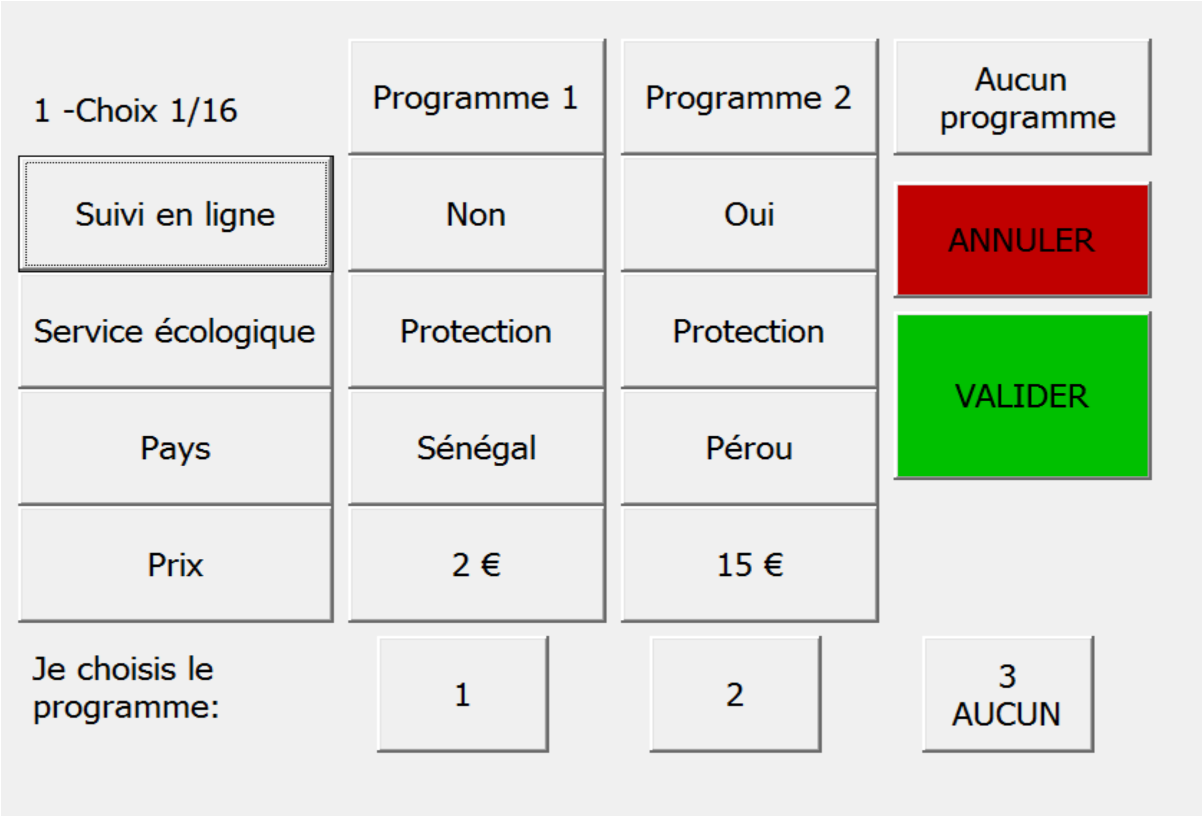
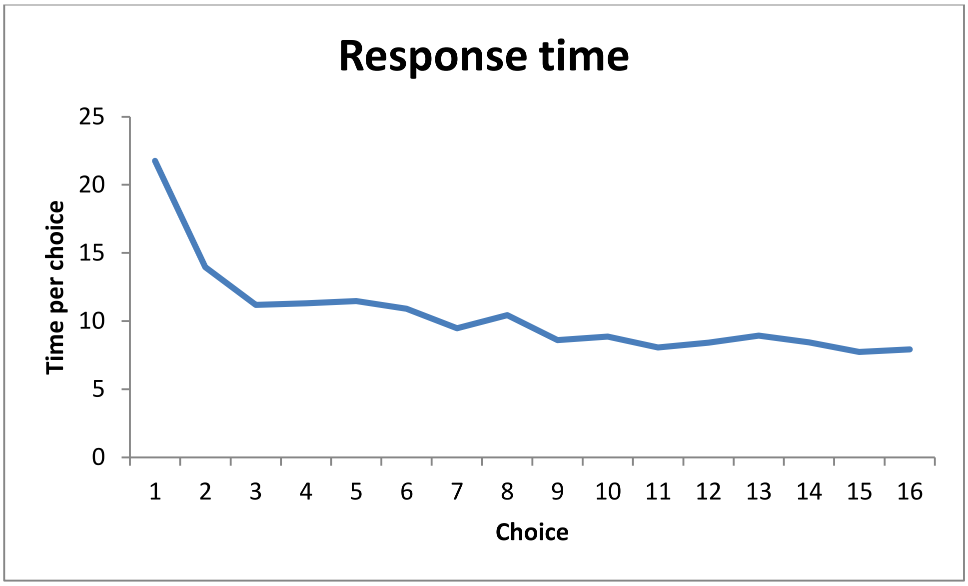


Figure 1. Computer program interface (in its original language).



2. Average response time per choice task