In-depth, Breath-first or Both? Toward the Development of a RUM-DFT Discrete Choice Model

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SHORT SUMMARY

Development in discrete choice modelling has been dominated by Random Utility Maximization approaches due to their ease of application and high economic interpretability. However, this model assumes that decision-makers perform an in-depth information search process (ISP) implicitly and instantaneously. It has not been investigated in detail whether the ISP of transport users is in depth or breadth-first in a public transport choice context, a gap that this research aims to fill. To this end, the ISP of public transport users has been characterized in three SP surveys with click-tracking, which were pivoted concerning commute and varied in the number of dimensions. The results allow us to conclude that the ISP is part of a heuristic, heterogeneous, complex, and mixed deliberation process, which depends on the dimensions of the choice tasks. However, breadth-first searches predominate, i.e., the evaluation of information is done by comparing alternatives under one attribute in each search.

Keywords: Information Search Process, Breadth-first, Public Transport SP, RUM -DFT

1. INTRODUCTION

Making a decision implies a deliberation process in which individuals, based on their preferences and valuations, choose an alternative among a given set (Engel et al., 1968). Several areas of knowledge have a great interest in comprehending the decision process, ranging from transportation and behavioural economy to psychology. To explain and predict how individuals make such decisions, choice models have been developed and widely used. Busemeyer and Townsend (1993) propose a classification of choice models into static and dynamic.

Static models define the choice probabilities in a way that is independent of the cognitive process and that does not vary in the choice process. Among the advantages, their simplicity of implementation and great explanatory power stand out, with the Random Utility Maximization (RUM) approach being the most widely used member of this group (McFadden, 1976). Static choice models consider that individuals are rational agents, possess complete information, and choose the alternative with the highest utility within the choice set by performing an in-depth information search of the attributes. In other words, RUM models assume an in-depth search first in which individuals consider all the attributes of an alternative to construct the utility of that alternative, which is then used to make a comparison and the choice.

RUM models are versatile, practical and provide transparent statistical a microeconomic framework for the analysis of discrete choices. However, they fail to consider the true cognitive process that individuals go through when deciding. RUM models assume that decision-makers somehow instantaneously evaluate all the attributes of all the alternatives involved in the choice situation, but evidence suggest that the process is dynamic. Individuals focus on some attributes of some alternatives in different stages, acquiring information sequentially to make a final decision. Among others, Noguchi, and Stewart (2014); Stewart et al., (2016a); Stewart et al., (2016b); Sui et al. (2020) have evidenced, through eye-tracking those preferences vary across attribute evaluation and that this behaviour occurs in simple, risky, strategic and with multi-attributes choices.

On the other hand, dynamic models consider that preferences change over the time of choice due to the cognitive process. This approach has been represented, among others, by Decision Field Theory (DFT) (Busemeyer and Townsend, 1993). The DFT considers that the cognitive process is iterative and that the sequence of information search is breadth-first. This means that individuals begin with some initially preconceived preferences toward the available alternatives. Then, they focus on and evaluate one specific attribute at a time among all alternatives (breath-first), and then iteratively update preferences by looking at other attributes until they finally choose an alternative when they reach their internal (preference) or external (time) limit. Recent studies show that the DFT model fits the data often better than conventional static models [Qin et al. (2013); Hancock et al. (2018)]. However, the DFT model presents important limitations, such as that it relays on ad-hoc matric implementation, lacks a robust statistical theoretical framework that allow transparent identification, and lacks compatibility with microeconomic theory.

The trade of between RUM and DFT motivates the development of a RUM based model that could account for the dynamics of the decision-making process that is captured by the DFT model. As a first stage toward this overall research goal, this article is devoted to the collection an analysis of data on the sequential process of attributes evaluation within a public transport stated preference experiment. The experiment has the purpose of confirming or rejecting the breath-first behavioural hypothesis that is behind the DFT model and to study the impact of various contextual settings that may influence such behaviour. Besides, the data collected and studied in this research will be used to generate a database on which, later, different practical RUM-DFT models can be assessed.

2. LITERATURE REVIEW

The Information search process is defined as the stages where an individual performs cognitive tasks, such as searching their memory, acquiring new information and processing the data to carry out their choice (Payne, 1992; Riedl et al., 2008). Figure 1, Xie et al., (2019) presents this process that could be incorporated into discrete choice models.

On the one hand, there is the internal search related to retrieving information stored by individuals. Quite a few studies have been conducted to try to understand this process, but it is still unclear how to apply the findings of people's memory in choice models. And on the other hand, there is the external search, which corresponds to the stage of acquisition and processing of new information that individuals obtain from external sources (Hulland et al.,1994). According to Schulte-Mecklenbeck et al.,(2017) this sub-process is defined by the fixations on the attributes during the deliberation time that the decision-maker performs before making the choice. The transitions between these attentions allow the construction of the information search patterns that individuals perform in prior to the choice.

Therefore, efforts will be made to understand, analyse, and characterise the external information search process performed by public transport users. This is crucial for modelling discrete choices since ignoring the real dynamics behind this process will result in inconsistent model parameter estimators due to endogeneity (Guevara, 2015).

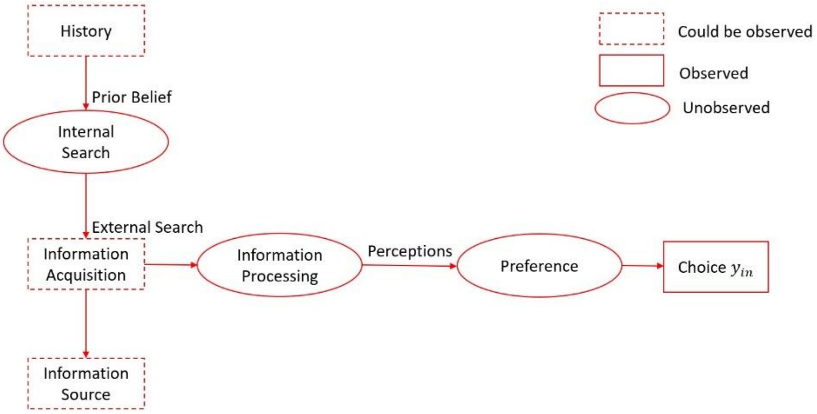

Figure 1: The information search process Xie et al., (2019).

Specifically, four different patterns of information search are considered in the analysis that depend on the transitions of the attributes addressed by the decision-makers in a sequential manner. Definitions like Bettman (1976), Payne (1976), Johnson et al., (2008), Noguchi et al., (2014), Jiang et al., (2016).

- Depth search occurs when the individual conceptualises all the attributes of an alternative before making comparisons with the rest of the options. Thus, attention is expected to fluctuate under different attributes but within the same alternative. The RUM models implicitly include this pattern in the calculation of the choice probabilities since it is assumed that individuals construct the utilities of the alternatives considering the value of all available attributes before choosing.

- Breadth-first search occurs when the individual focuses on a particular attribute and simultaneously updates the value of all available alternatives for comparison. Therefore, it is expected to focus more on one attribute, and transitions occur more frequently between the alternatives. This pattern has been incorporated into different discrete choice models. On the one hand, the RRM model implicitly includes it in the modelling since the probabilities of choice depend on the regret calculated through the bilateral comparisons of attributes (Chorus, 2010). On the other hand, the DFT model explicitly includes this pattern since updating preconceived preferences during the deliberation process is made concerning one attribute at a time (Hancock et al., 2018). It should be noted that this behaviour has been evidenced and supported by the findings of Noguchi et al., (2014), which indicate that comparisons of a pair of alternatives under the same attribute dimension occur more frequently. This is why psychological choice models should be modelled in such a way.

- Unusual searches occur when attention is more erratic than usual. On the one hand, the adjacent diagonal searches capture the transitions that occur towards contiguous attributes and alternatives. In contrast, non-adjacent diagonal transitions occur when attention goes between non-contiguous attributes and alternatives that imply greater cognitive cost.

The figure 2 shows the information search patterns adopted in the different discrete choice models (Inspired from Chorus (2012)). The solid arrows represent the conceptualisations, and the dotted arrows represent the information search process and comparisons of alternatives.

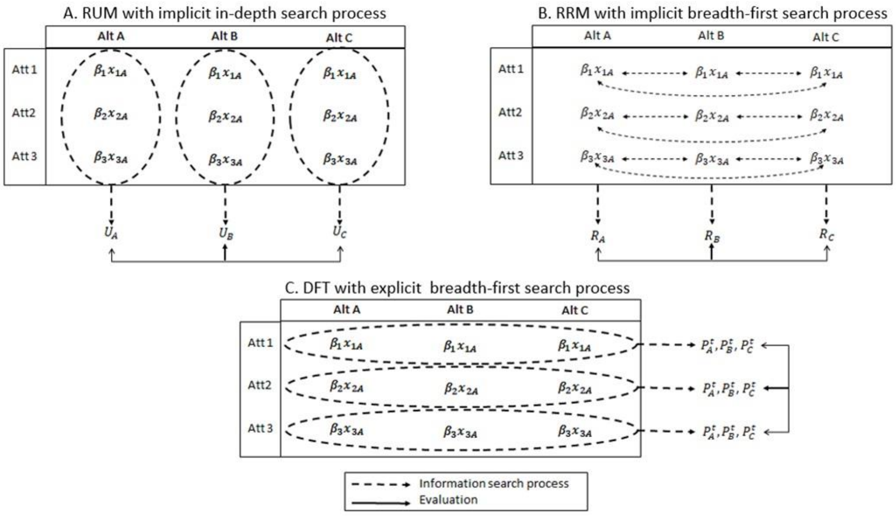

Figure 2: Choice process based on RUM (A), RRM (B) and DFT (C).

3. METHODOLOGY AND PROCEDURES

For studying the information search process, in this research a methodology was developed and applied to collect behavioural evidence of sequential attribute evaluation. Three click-tracking surveys are built that vary in the number of alternatives and attributes displayed as areas of interest (AOI), which are not visible and only one can be displayed at a time, following a Payne (1976)'s information board format.

Click tracking was used to evaluate the information search process as decision makers respond to pivoted Stated Preference (SP) surveys Public Transport trips occurring around the morning peak hour transit route choice study (click tracking), where the areas of interest shown (AOIs) representing the attributes of available alternatives are varied. In general, respondents were asked to report their socioeconomic characteristics, their typical commute, and then to choose one of the hypothetical public transport routes based on their walking time, waiting time, travel time, cost, number of transfers, and seat availability.

After the surveys are designed, they are implemented on a web page and evaluated by applying them in a focus group to verify that the sequence of attributes clicked, the time of each click, and the choices in each task are properly obtained. Likewise, to improve the instrument, comments and feedback are received. Figure 3.A shows the section of socioeconomic questions, figure 3.B shows the mobility questions (revealed preferences), and figure 3.C shows an example of a choice task; containing 3 alternatives and 6 attributes in a click-tracked information board format (declared preferences).

In particular, we measured (1) the amount of information search, which corresponds to the number of fixations on an attribute; (2) the pattern of information search, which reflects the search transitions in the attribute evaluations (in breadth-first search), which can be either by attribute (in-depth search), by alternative, or by attribute and alternative (diagonal searches); (3) the duration of fixation over the time course of a choice; and (4) the time spent on each choice task.

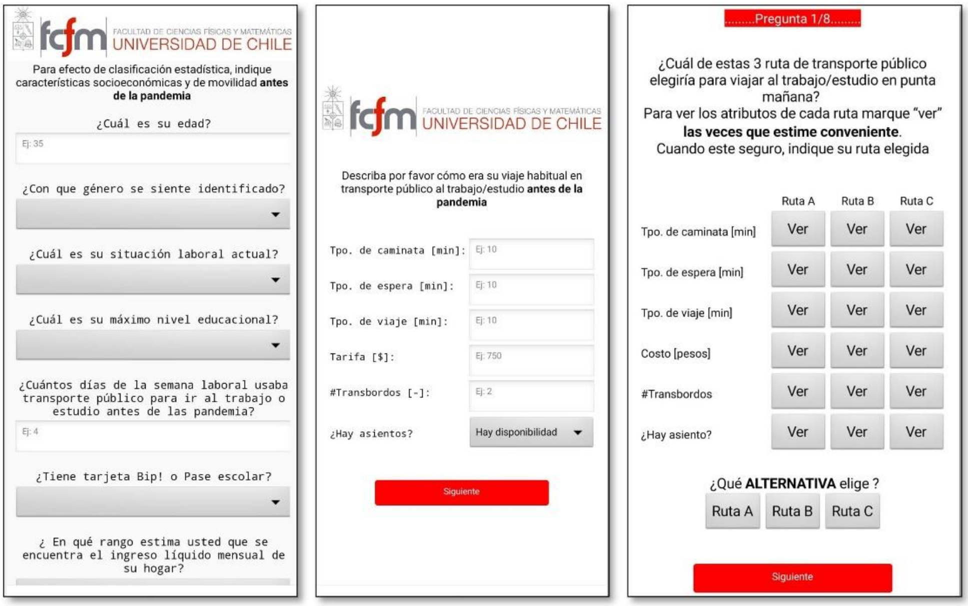

Figure 3: A) Socio-economic questions. B) Revealed preference questions: Mobility. C) Revealed questions: Information board with Click-Tracking

4. 4. RESULTS AND DISCUSSION

Amount of information search

The information searches carried out by the respondents before the choice, and the mean values, together with their standard deviation, are summarised in the table 1. On average, more information searches were carried out than the total number of areas of interest shown in each instrument, realising that public transport users do not capture the value of the attributes in the first instance and need to reconceptualise these values to include them in their utilities or preferences. Moreover, this construct grows significantly as the number of attributes or alternatives increases. On the other hand, when considering the AIS normalised by the AOI in the different surveys and performing a test of means, it can be noted that a more significant increase in the number of searches is generated when attributes are added (t=6.36) compared to when the alternatives are increased (t=2.71). Therefore, the amount of information search increases at decreasing rates with the AOIs shown in the surveys, but to a greater extent when attributes are added.

Table 1: Amount of information search in surveys

Survey	J	K	AOI	AIS	AIS/AOI
CT36	3	6	18	19.5 (11.8)	1.1 (0.7)
CT26	2	6	12	14.6 (10.1)	1.2 (0.8)
CT23	2	3	6	9.2 (5.4)	1.6 (0.9)
no differentiated AOI				14.4 (10.2)	1.3 (0.8)

The boxplot with the fixations made by the respondents normalised by the amount of AOI corresponding to each survey reinforces the previous finding since the confidence intervals are different from each other. Furthermore, it is shown that less information is sought by AOI when cognitive load increases. Also, the greatest difference is between the CT23-CT26 surveys, more than the CT26-CT36 surveys, showing that the number of searches intensifies to a greater degree with the attributes increase.

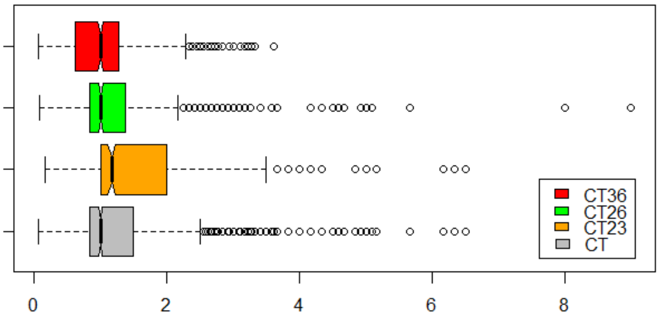

Figure 4: Amount of information search standardised by AOI.

To close this construct analysis, it can be commented that these results are consistent with those found by Meiβner et al, (2020), who conclude that the dimensions of the election situation affect the information search process. The findings show that increasing the number of attributes and alternatives leads to an increase in the information search and induces certain filtering of attributes. The novelty of this research lies in the fact that these results are replicated in the public transport route choice SP context, and a greater impact is evidenced in the deliberation process when adding attributes to the number of alternatives.

Filtration

Figure 5 shows the percentage of areas of interest that were not fixed during the deliberation process in each of the surveys presented. In this image, it can be seen, in general, that increasing the number of alternatives or attributes leads to a significant increase in filtered information. This was already evident with the other results for amount information search, which show observations that did not fix on certain attributes or alternatives at any point in time. It can also be seen that the percentage of neglected areas of interest increases as the decision-maker progresses through the choice tasks.

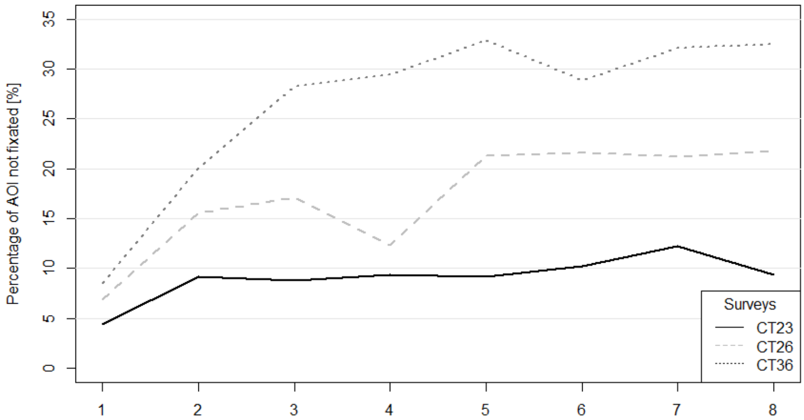

Figure 5: Percentage of areas of interest not fixed in surveys.

Search pattern order

Figures 6, 7, and 8 plot the curves that represent the times in which respondents performed the different information search patterns, at each step of the deliberation process. From this analysis, it is possible to deduce the order in which these types of searches are carried out.

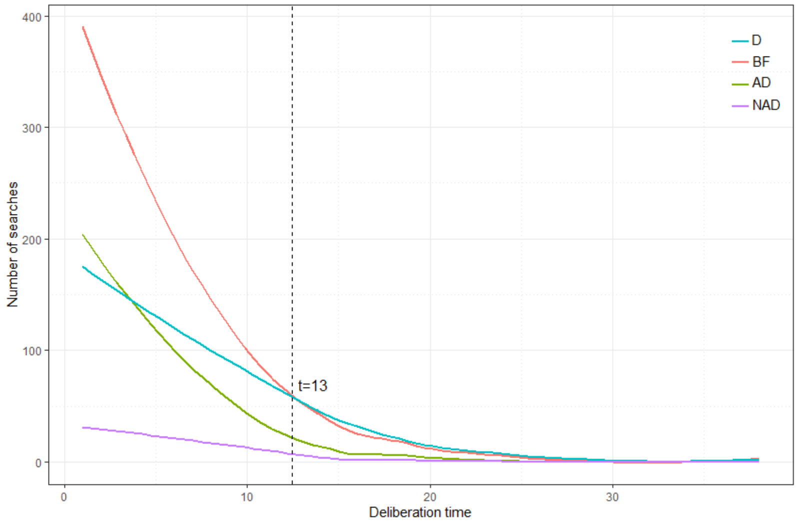

Figure 6: Information search pattern order in CT23.

Firstly, from the CT23 survey (figure 6), there is a greater number of respondents who preferably perform breadth-first searches; in the first instance, and this is maintained during most of the deliberation time (up to t=13 there are 83.5\% of respondents who have already decided on an alternative). Then until t=4, it is followed by adjacent diagonal searches and depth transitions for the rest of the time (until t=13). The non-adjacent patterns are smaller and correspond to the minimum value in 92% of the deliberation time concerning the other transitions.

It should be noted that more depth comparisons are made as the deliberation time progresses, which can be evidenced for two reasons. First, the slope of the curve is less than the decay rate of the breadth-first transition. And secondly, the number of depth searches is greater than the rest of the patterns from the first third of the process onwards.

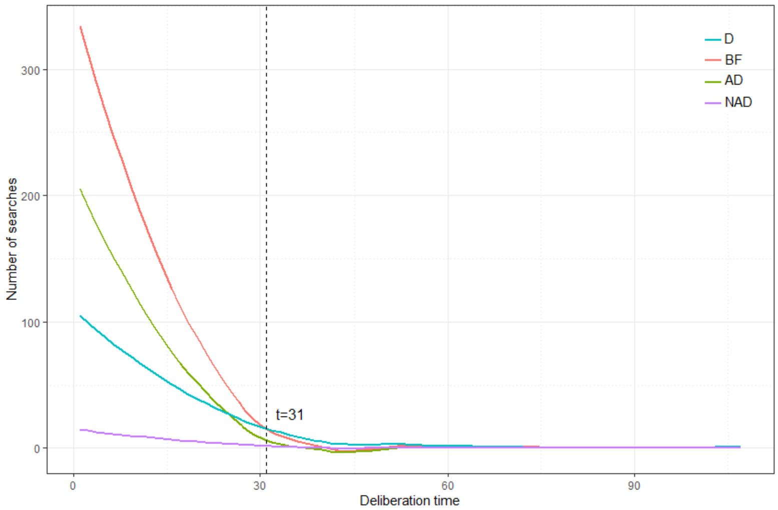

Figure 7: Information search pattern order in CT26.

On the other hand, in the CT26 and CT36 survey, there is a clear predominance of breadth-first search occurrences performed in the first stage of the deliberation time. It stands out, as in the previous case, as time progresses, more depth searches are generated concerning the rest of the patterns, and there is a turning point after the first third of the deliberative process.

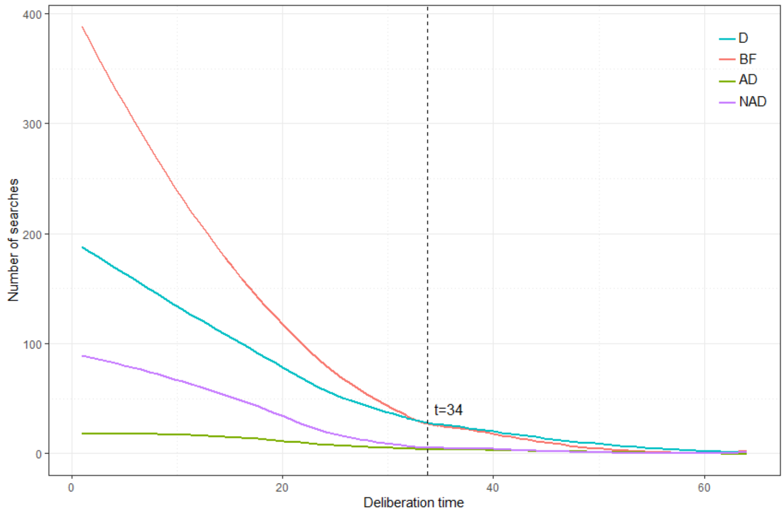

Figure 8: Information search pattern order in CT36.

Transition Matrix

Transition matrices show the relative frequencies between consecutive fixations. These results are summarised in figures 9, 10 and 11, which reveal the probabilities that respondents attend a particular area of interest in timestep t conditional on a previous AOI. From the figures, two important findings can be obtained. First, it is possible to know the aggregate information search patterns that predominate among the participants to reach their final decision. Secondly, it can empirically know the probability of observing an attribute in the next step in the information search process. This allows to include how the evidenced information is acquired and its attention weights in the model to be proposed, which incorporates the sequential evaluation of attributes. Therefore, this modelling allows for the first time to adequately integrate the updating of utilities or preferences for the subsequent comparison of alternatives and choices.

			Attribute observed in step t+1						
			Alt. A			Alt. B			
Attribute observed in step t			WT	TT	C	WT	TT	C	
Alt. A	WT	Waiting Time	0	6	1	13	1	0	21%
	TT	Travel Time	3	0	4	1	12	1	20%
	C	Cost	1	1	0	2	0	8	13%
Alt. B	WT	Waiting Time	4	9	0	0	5	0	19%
	TT	Travel Time	2	3	6	2	0	4	18%
	C	Cost	2	1	3	1	1	0	9%

Figure 9: Transition matrix of CT23

	Attribute observed in step t+1												
	Alternative A						Alternative B						
Attribute observed in step t	WKT	WT	TT	C	T	SA	WKT	WT	TT	C	T	SA	
Alternative A WKT Walking Time	0	2	0	0	0	0	8	0	0	0	0	0	11%
Alternative A WT Waiting Time	1	0	2	0	0	0	0	7	0	0	0	0	11%
Alternative A TT Travel Time	0	1	0	1	0	0	0	0	8	0	0	0	11%
Alternative A C Cost	0	0	0	0	1	0	0	0	0	6	0	0	8%
Alternative A T Transfer	0	0	0	0	0	1	0	0	0	0	5	0	7%
Alternative A SA Seat Avaibility	0	0	0	0	0	0	0	0	0	0	0	4	5%
Alternative B WKT Walking Time	2	6	0	0	0	0	0	2	0	0	0	0	10%
Alternative B WT Waiting Time	1	2	5	0	0	0	1	0	1	0	0	0	10%
Alternative B TT Travel Time	0	0	3	4	0	0	0	1	0	1	0	0	10%
Alternative B C Cost	0	0	1	1	4	0	0	0	0	0	1	0	8%
Alternative B T Transfer	0	0	0	0	1	4	0	0	0	0	0	1	6%
Alternative B SA Seat Avaibility	0	0	0	0	0	1	0	0	0	0	0	0	2%

Figure 10: Transition matrix of CT26.

	Attribute observed in step t+1																		
	Alternative A						Alternative B						Alternative C						
Attribute observed in step t	WKT	WT	TT	C	T	SA	WKT	WT	TT	C	T	SA	WKT	WT	TT	C	T	SA	
Alternative A WKT Walking Time	0	2	0	0	0	0	4	0	0	0	0	0	0	0	0	0	0	0	7%
Alternative A WT Waiting Time	1	0	2	0	0	0	0	3	0	0	0	0	0	0	0	0	0	0	7%
Alternative A TT Travel Time	0	1	0	2	0	0	0	0	4	0	0	0	0	0	1	0	0	0	7%
Alternative A C Cost	0	0	0	0	1	0	0	0	0	3	0	0	0	0	0	1	0	0	6%
Alternative A T Transfer	0	0	0	0	0	1	0	0	0	0	2	0	0	0	0	0	0	0	5%
Alternative A SA Seat Avaibility	0	0	0	0	0	0	0	0	0	0	0	2	0	0	0	0	0	0	3%
Alternative B WKT Walking Time	1	0	0	0	0	0	0	2	0	0	0	0	4	0	0	0	0	0	7%
Alternative B WT Waiting Time	0	1	0	0	0	0	1	0	2	0	0	0	0	3	0	0	0	0	7%
Alternative B TT Travel Time	0	0	1	0	0	0	0	1	0	1	0	0	0	0	3	0	0	0	7%
Alternative B C Cost	0	0	0	1	0	0	0	0	0	0	1	0	0	0	0	3	0	0	6%
Alternative B T Transfer	0	0	0	0	1	0	0	0	0	0	0	1	0	0	0	0	2	0	5%
Alternative B SA Seat Avaibility	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	3%
Alternative C WKT Walking Time	1	2	0	0	0	0	1	0	0	0	0	0	0	2	0	0	0	0	7%
Alternative C WT Waiting Time	0	1	2	0	0	0	0	1	0	0	0	0	1	0	2	0	0	0	6%
Alternative C TT Travel Time	0	0	1	2	0	0	0	0	1	0	0	0	0	1	0	1	0	0	6%
Alternative C C Cost	0	0	0	1	2	0	0	0	0	1	0	0	0	0	0	0	1	0	5%
Alternative C T Transfer	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	1	4%
Alternative C SA Seat Avaibility	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2%

Figure 11: Transition matrix of CT36.

Duration

The boxplots in figure 12 show the average information search time for each of the 8 choice tasks of the CT23, CT26 and CT36 surveys, respectively. Also, the average of these values is highlighted in red. These values are obtained as the amount of time the clicked areas of interest remain visible. From these values, there is a steady decline in average click durations as respondents progress through the survey. This suggests two possible reasons. The respondents acquire knowledge to use the instrument and click faster, or participants begin to memorise the location of the relevant areas of interest to make their choice and perform certain information search heuristics acquired during the previous answered tasks.

Therefore, the duration is not constant during the deliberation process and contradicts the results shown by Stewart et al., (2016). This is because the experiments carried out in this work are more complex. As has been evidenced from the different constructs, different information search patterns are involved, showing instability in information processing. This implies differences in the duration of information acquisition and processing (Rayner et al., 2012). However, short durations and variability throughout the deliberation are more consistent with automatic processes such as accumulating models (Glockner et al., 2011).

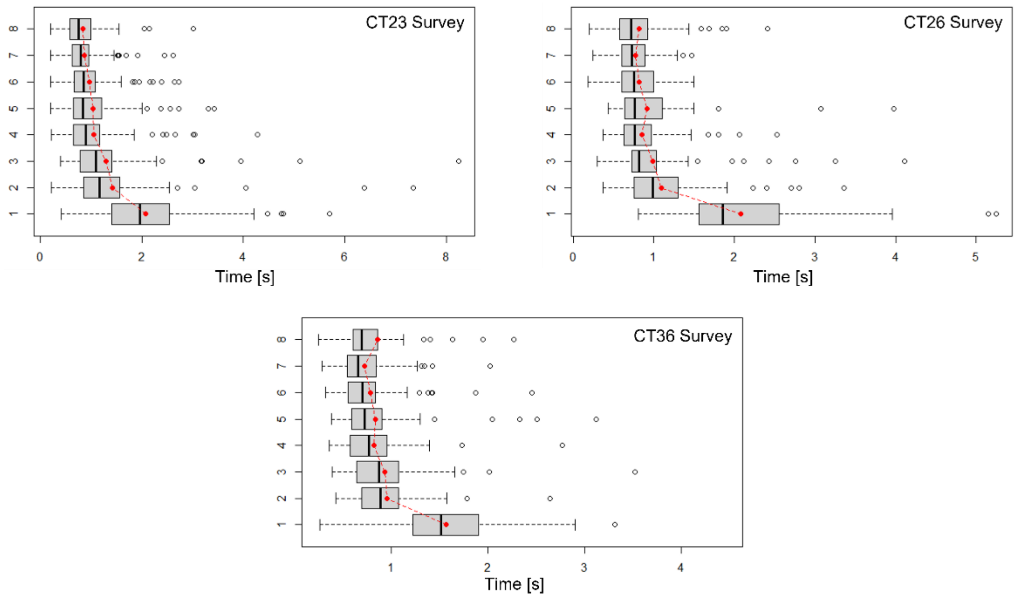

Figure 12: duration per task and survey.

5. CONCLUSIONS AND FUTURE RESEARCH

Based on this analysis, we found 3 main findings. The first, that transit users have a change in the pattern of information search that depends on the number of alternatives and attributes (AOI) shown in the choice situation. On the one hand, as AOIs increase, people search more frequently for information in breadth-first. In addition, we find that users, on average, perform breadth-first and then in-depth search to validate their chosen alternative. A second finding, we found that the sequential evaluation of attributes, number of steps, increases with increasing AOI and a higher number of diagonal searches is observed. Third, doing an analysis of the transition matrices of the AOIs, we find that the most likely transition corresponds to a search for information in breadth-first in all experiments, and that the effect becomes more acute with the number of AOIs.

The evidence found suggests that there is a predominance of information search in breadth-first, so that the RUM model would not be able to adequately describe the choice process and that the DFT approach would be more appropriate, but not necessarily fully comprehensive, for these purposes. Evidence shows that the search for information in breadth-first is not total and this behavior becomes more acute with increasing AOI. Given these results, it seems that a latent class model, incorporating both types of searches (in-depth and breath-first), may be the more suitable to address the problem. The development an assessment of this and other models with the collected data remains as future work.

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