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The Attentional Drift-Diffusion Model for Simple Choice in the Quaternary Case, Measuring the Effect of Permutation of Item Location on Choice Behaviour*

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Abstract

In this paper, we study the Attentional Drift-Diffusion Model in two quaternary cases, both from the perspective of realized predictions and location permutation effects. From 16 chocolate packages specifically designed for this study, 4 were selected based on a ranking questionnaire, multidimensional scaling, and conjoint analysis, so that one package was slightly more attractive, while the other three were of similar attractiveness. These were shown in a 2x2 grid to two different groups of Arcada UAS students, varying the position of the packages for each group. Each student was asked to select the package found the most attractive, with no time pressure. The process was recorded with a desktop-mounted eye tracker. Thus, we were able to make predictions concerning the results assuming the Attentional Drift Diffusion model, combining the information from the package rankings, conjoint analysis, eye-tracking, and choice times. We found the model to be in high accordance with the predictions of the behaviour for the first group, less so for the other. This might suggest either the rejection of the model in the quaternary case, or a sizeable location permutation effect in the presence of, as in our case, several similarly valued alternatives. Results are non-conclusive due to sizeable data-loss during recording. This paper thus represents a work in progress.

Keywords: Eye Tracking, Choice, Decision Making, Microeconomics, Neuroeconomics, Attentional Drift-Diffusion Model.

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1 INTRODUCTION

Let us restate the question of how a low involvement purchasing decision by a consumer is made in, say, a supermarket. This is one of the core questions which consumer choice models try to answer. Traditionally this question has been tackled for example by using simple binary choice experiments were a participant chooses between two products from a larger set of alternatives. Further, the choice data has been used to estimate a logistic choice model which can be used to estimate the probability of certain choices. These choice probabilities can be calculated for specific background variables.

These logistic choice models have proved effective in many cases, and can be applied also to digital consumer choice behaviour (e.g. web-stores and online marketing) as using them for producing estimates is relatively easy with modern statistical computer software (with post estimation analysis, such as STATA and R).

The models have proved especially effective when the difference between choice alternatives of products is easy to perceive. The smaller the perceived difference between products, the worse the logit model becomes to measure choice probability. (Clithero and Rangel, 2013.) To address this gap, one option is to turn to neuroscience.

Despite the recent advances in neuroscience and dramatic price drops in technology for neurological research, we as of yet lack detailed insight into the nature of thought processes in the human brain. If we measure a subject's brain activity we can certainly detect neural processes, but this does not help us to conclusively elucidate, for example, *what* a person is thinking and what exactly is "going on" in the brain.[1] For economics, the recent advances constitute new angles from which to approach economic models and theories, and research combining these aspects has recently been grouped together under the heading of *neuroeconomics.* This field may be broadly described as a novel attempt to explain such aspects seminal to economics as decision making, choice, and risk aversion by combining theory and methods from economics, neuroscience, computer science, and psychology. The novelty can be characterised by noting (see for example Shiller, 2011, and Glimcher, 2010) that traditional economics bases its research on assumption-making models such as utility maximization and revealed preference, while in neuroeconomics research is based on the investigation, characterization, and understanding of actual (neuro-) physical processes and behaviour, and the thoughts and thought processes (both cognitive and non-cognitive) underlying these. Following Fehr and Rangel, neuroeconomics investigates

"[…] three basic questions: 1) what are the variables computed by the brain to make different kinds of decisions, and how do they relate to behavioural outcome? 2) How does the underlying neurobiology implement and constrain these computations? 3) What are the implications of this knowledge for understanding behaviour and well-being in various contexts: economic, policy, clinical, legal, business, and others?" (Fehr and Rangel, 2011, pp. 3-4).

[1] Research into the topic of imaging the thought processes in the brain made breakthroughs in 2011 at Princeton University and Harvard through the use of so-called functional MRI scans. As of yet, any accurate real-time imagining is not known by the present author to be possible.

The aim of neuroeconomics is thus to provide a novel way of understanding the relations and interdependencies described by traditional economics, one foundational component being the measurement of neural processes in real time involved in, say, decision processes using, among others, such tools as functional magnetic resonance imaging (fMRI) and eye tracking. As pointed out by several authors such as (Loewenstein, Rick, and Cohen, 2008), (Fehr and Rangel, 2011), (Braeutigam, 2005) and in various overviews, neuroeconomics bridges the gap between economics, neuroscience, and psychology and can trace its roots to the "embrace" of behavioural economics and neuroscience which took place in the late 1990s (Loewenstein, Rick, and Cohen, 2008). Furthermore, as Shiller (2011) points out, one of the pioneers of the field of neuroeconomics, Paul W. Glimcher began his academic career with a Ph.D. in neuroscience and not, as perhaps someone could expect, in economics. The field is relatively new within economics, and a community-wide consensus regarding any potential 'game-changing' power is yet to be acknowledged.

It is important to keep in mind however, that neuroeconomics does not forward a *rival* theory to traditional and successful microeconomics models which have shown wide applicability – as Glimcher notes (2001), microeconomics and game theory have had a "tremendous impact in psychology and ecological biology" (p. 657).[2] Rather, neuroeconomics proposes a challenge to both the perspectives and intuitions of standard theories and strives to provide a foundation for results of other research, employing modern technological equipment that has previously not been readily available, thereby also expanding current research areas.

As neuroeconomics has developed, and corroborative research data accumulated, a number of mathematical and computational models have been advanced aiming at being compatible with, and deepen the understanding of, traditional economic theories. A central underlying idea then becomes that our decision making may be expressed through these models, and they render future decisions of subjects "like" us predictable.

With the risk of stating a truism, decision making and choice in any situation is influenced by input gathered from all our senses, and in different cases, the input from some particular sense is dominating, for example hearing when judging music, taste and smell when eating food, and an obvious well known fact is that products with packages perceived as being visually aversive by consumers will also often be found less desirable overall. Only a very small part of these deliberations however, are made consciously.

Returning to the topic of choice prediction models, recent advances have been made with the aid of eye trackers. With these, choice patterns and response times can be correlated with visual fixations and search patterns. Using eye trackers provides previously unattainable data, as a test participant is not required to provide any information concerning what was fixated on in the experiment (this task would be impossible in any case) as the eye movement and search pattern is recorded automatically and in real time. The data gained in such a way is thus much more immediate and uninterpreted as opposed to, say, data gathered using a post-choice questionnaire. Hence, the equipment is able to record the focal points of a person's gaze also in such cases when a person is not

[2] The former has been able to describe animals' decision making when foraging for food and the latter competition for resources among a group of subjects, such as animals competing for access to mates.

consciously thinking about what he or she is looking at. By combining eye tracking measurements with choice data and response times using a so-called *Attentional Drift-Diffusion Model*, we can discover a connection between, choice, value, potential bias, and fixation time, in a simple choice situation.

However, as of yet, no studies (to the knowledge of the author) have been carried out concerning the role of the specific visual location of the choice items (e.g. on a computer screen) when the choice take place - a line of research is suggested by Krajbich, Armel and Rangel (2010). In this paper the effect of location permutation on choice and fixation is studied specifically, in the quaternary case using the Attentional Drift-Diffusion Model.

2 METHODS

2.1 The Attentional Drift-Diffusion Model

The *Attentional Drift-Diffusion Model* (aDDM) proposes to describe how simple value-based choices are made, integrating response time and visual fixations in the decision process, computing a decision value (i.e., which choice a subject makes) as a function of the *time spent fixating on each of the alternatives.* Such a model was introduced by Krajbich, Armel, and Rangel (2010) where it was also tested for binary choice using eye tracking, while related work, without eye tracking, was carried out previously by Armel, Beaumel, and Rangel (2008). The existence of these decision variables ("computed by the brain") was shown for trained rhesus monkeys in (Platt and Glimcher, 1999) and for humans (even when no choice takes place) in Levy, Lazzaro, Rutledge and Glimcher (2011). The model specifically aims to capture the process of a consumer fixating several times on the available alternatives (when, say, choosing between three different chocolate boxes) before making a choice, by defining the function separately for each choice-object involved. Further, it discounts the value of the non-fixated items relative to the fixated ones during the decision process, something which has not been incorporated in previous models. Finally, perceived values of the alternatives as well as potential biases for fixated (or non-fixated, depending on the experiment setup) options were included in the calculation. The model was shown in Krajbich, Armel and Rangel, (2010) to fit data notably well, compared to some alternatives, in the binary choice case, and later, was further explored and shown to extend robustly from the binary to the tertiary case in Krajbich and Rangel (2011).

The aDDM proposes that the brain, faced with a simple choice such as having to choose between an orange and an apple for dessert, computes a relative decision value (RDV) that evolves over time. This function is defined separately for each alternative in the choice situation. So, for example, when a subject is faced with a choice between two products (positioned, say, side by side) the decision value function is defined separately for whether the subject is fixating on the left-hand product or the right-hand product. The model accounts for biases in the integration process, while additionally discounting the value of the non-fixated item. When the RDV process reaches a certain 'choice barrier', the computation stops and a choice is made. Some evidence for the existence of decision values was given by Plassman, O'Doherty, and Rangel (2007). Value-assignment was researched also by Padoa-Schioppa and Assad (2006) in connection with willingness-to-pay, where it was suggested that, for simple economic choice, values are assigned to goods rather than actions, which is supportive of the aDDM.

In order to give the reader a clear picture of the model, a short example situation is illustrated below, describing the model in the binary case. Assume a test where two alternative products are place side by side (for example an apple and a pear) and a person is asked to choose (without a time constraint) the one that he or she favours for dessert. The participant looks in turn at both alternatives while contemplating the choice, and ultimately chooses the apple. The aDDM model predicts that the relative decision value has been computed according to the following formula. When looking at the alternatives the relative decision value begins at $V_0 = 0$ and changes according to

$V_t = V_{t-1} + d(r_{left} - \vartheta r_{right}) + \varepsilon_t$ when fixating on the left object, and

$V_t = V_{t-1} + d(r_{right} - \vartheta r_{left}) + \varepsilon_t$ when fixating on the right object, where

V_t is the decision value at time t,

d is a constant that controls the speed of integration in units of ms^{-1}

r_{left} and r_{right} denote the values of the two options

ϑ is a parameter $0 \leq \vartheta \leq 1$ that reflects the bias towards the fixated option, and

ε_t is Gaussian noise with variance σ^2.

The model is so defined, that the choice barrier occurs at $V_t = 1$ or $V_t = -1$, for left and right choices respectively. The discounting is constituted by the subtracted term in the respective equations. The following illustration exemplifies the case of the two choices having equal relative value:

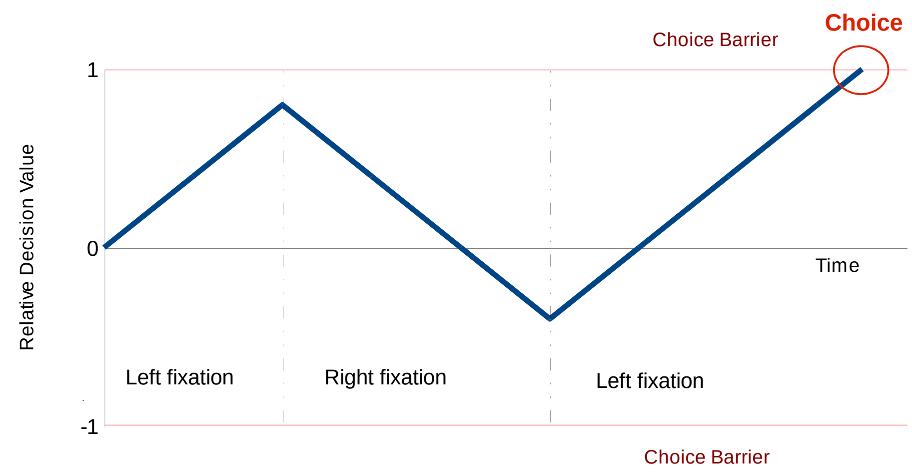

Figure 1. Example model of how the RDV evolves over time, until it "hits" the choice barrier and a choice, in this case in favour of the left object, is made. The slope of the RDV function depends on the bias towards the fixated object and the perceived relative difference in value. In this case the perceived relative values are equal.

In case the perceived relative values of two alternatives are non-equal, the RDV will evolve towards the higher valued option with a “sharper” slope, as illustrated in the figure below:

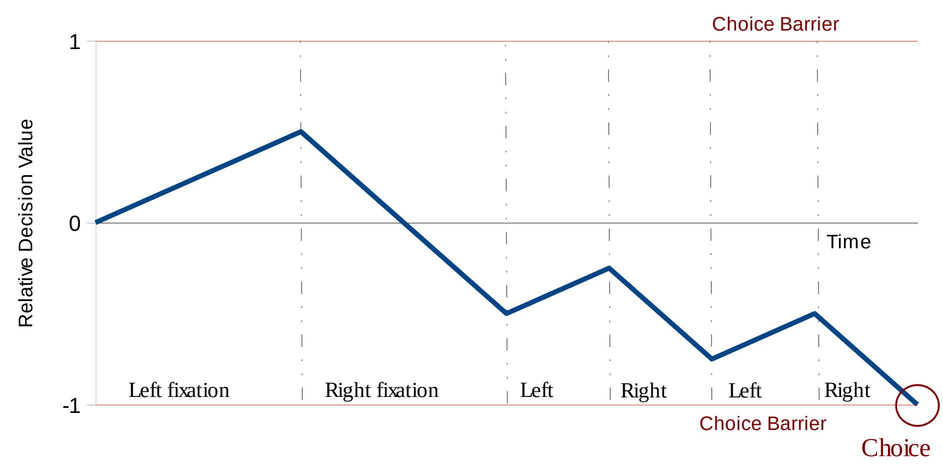

Figure 2. Model of how the RDV evolves over time, where the subject’s preference for the right side object results in a sharper slope towards the right choice barrier.

For simulated runs of the model, varying the values of the different parameters, we refer to Krajbich, Armel, and Rangel (2010). The model is mathematically extended to the tertiary case in (Krajbich and Rangel, 2011). Below, we will examine the model in the quaternary case, from the point of view of predictions and outcomes, leaving the mathematical modelling aside for now.

2.2 Set-up for Measuring Location Effects

The test involved subjects, consisting of university students, being shown simultaneously (on a computer screen) four images of imaginary (*i.e.*, specifically designed for this test) chocolate packages arranged in a 2 x 2 grid (see figure 3), and asked to pick the package that they found the most appealing by indicating their choice with a mouse click. In figure 3a, we label the package items from left to right, top to bottom as 1, 2, 3, and 4 respectively; hence the order of the package items in figure 3b is 4, 3, 2, and 1.

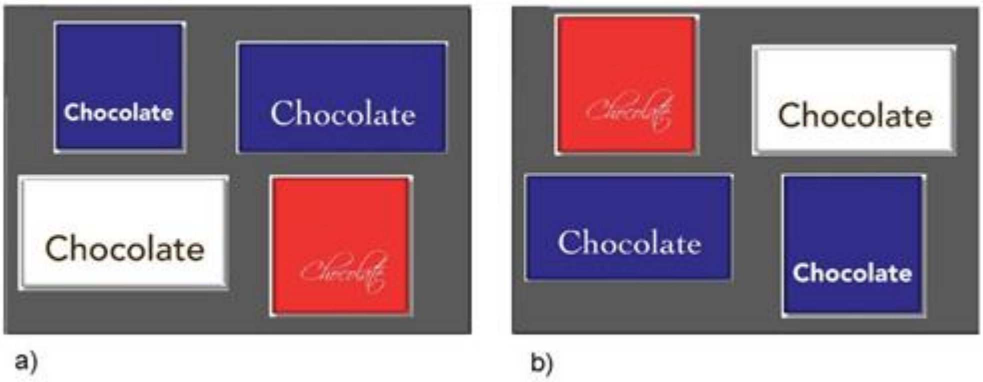

Figure 3. Choice set a) was presented to the first group of subjects, choice set b) to the second group.

The test was carried out in several stages. First, 16 package images were designed in Photoshop varying colour (blue, red, brown, white), package form (rectangular, square, oblong), font of logo text (Scriptina Pro, Cochin Regular, and two different sizes of Avenir Black.) and the presence of an image of chocolate (yes/no). The exact combination of properties, in order to narrow down the number of packages to 16, was defined through a conjoint analysis using SPSS. 27 Arcada UAS students were then asked to rate the visual attractiveness of each package on a scale from 0-100, 0 indicating total lack of attractiveness and 100 indicating a very high attractiveness. Packages were allowed to be given equal scores and use of the whole scale was not required. Then, through multi-dimensional scaling and relative positioning, 4 images were selected out of the 16.

Three of these were picked on the basis of being ranked similarly non-attractive, and the fourth on the basis of being slightly more attractive than the other three. These images were collected in one image in a 2 x 2 grid. The image was then shown to two groups (N=38 and N=22) of Arcada students (who had not been involved in the previously mentioned ranking process), with a permutation of the location of the packages for the second group (see figure 3). Then, each student was asked to choose the most attractive package (without time constraint) and indicating their choice with a mouse click. The students were eye-tracked during the choice process using a desktop mounted Tobii

T120 eye tracker. Before being shown the four alternative choice items, students were asked to focus on a X at the bottom centre of the screen for 2 seconds, in order to ensure that each trial begin with subjects fixating on the same position. Some data unfortunately had to be omitted from the analysis because of unsuccessful eye-tracking recordings.

2.3 Predictions

In accordance with the aDDM model and the MDS, we predicted that the highest ranked item, item nr. 4 should be the package most frequently chosen in both trials and with the lowest fixation time. Further, in case the subject *did not* choose package nr 4, the decision time for the other packages should be quite similar, because, based on the multidimensional scaling and relative positioning, the difference in perceived attractiveness between these alternatives was judged to be low, thus leading to similarly sloping decision value functions. Choice behaviour between the three similarly ranked items in terms of *de facto selections* may or may not alter between the trials, as we cannot assume them to be selected with similar frequency just because they were ranked as similarly attractive. As the packages were given very similar scores in terms of visual attractiveness, then according to aDDM, *choice times* should be similar.

3 RESULTS

In terms of absolute fixation duration, we found that 58 of 59 participants fixated most on the chosen item (one participant's fixation data had to be discarded). The results of the 'time trials' are indicated in Table 1.

Table 1a) Details of choices [sec.] for the first group of subjects.

Item nr.	Times chosen	Mean time until chosen	St.Dev.	Max. time	Min. time
1	4	6,88	2,88	9,88	2,98
2	4	6,67	4,22	12,60	3,01
3	10	6,90	4,34	15,46	2,43
4	20	3,98	2,13	10,45	1,54

Table 1b) Details of choices [sec.] for the second group (*i.e.*, after location permutation of alternatives)

Item nr.	Times chosen	Mean time until chosen	St.Dev.	Max. time	Min. time
1	0	-	-	-	-
2	5	7,53	5,19	13,64	2,80
3	7	6,00	2,08	9,28	3,06
4	10	5,17	2,92	12,84	2,26

We see in table 1a) that, for the first group, our predictions were realized remarkably well, as, first, item 4 was chosen the most often (with a relative frequency of 10/19) with the fastest mean choice time (and a relatively low standard deviation). Post permutation we see its advantage marginally reduced in table 2b, to a relative frequency of 10/22. This small difference is well within a reasonable error margin. However, mean decision times between item 2 and 3 had a greater difference than in the first trial. The standard deviation and mean choice time, and maximum choice time, was higher for item 2 in the second trial while for item 3 they were reduced, in the case of standard deviation particularly – from 4,34s to 2,08s.

In the first trial, the choice times for items 1-3 are clearly similar, in contrast to that of item 4. Although item nr. 4 in the post-permutation trial still has the shortest choice time, this contrast is no longer visible.

4 DISCUSSION

We need to repeat the circumstances that, due to the group of participants being smaller than expected, and the number of eye tracking trials that needed to be discarded due to poor tracking data, the sample group is not large enough to draw conclusive results. Indeed, trials should be carried out using this model also for tertiary and secondary case to establish validity. Hence, at this point results of this study must be regarded as provisional. However, the method used in the trials, incorporating MDS and positioning, aDDM, and eye tracking certainly displayed promise. We saw in the first trial, a provisional result that agreed remarkably well with predications based on the aDDM model, and the valuations of the packages we determined using the MDS and positioning. The validation of this preliminary result should be a priority, as it would establish a *de facto* empirically sound research framework for investigating across-the-scale relative attractiveness of product packages.

However, as we see a somewhat different pattern in the second trial, and all participants but one, for both trials, fixated longest on their chosen item, we cannot rule out that location affects choice in situations where a small number of options of presumably equal value are presented (*i.e.*, subjects that *did not* choose item nr.4). If the results were taken at face value, a graphical representation of an averaged choice between product 2 and 3 for the first and second trial, would then differ in the way that the slope for their respective RDV value functions would be steeper for item 2 and less so for item 3 in first trial compared to the second trial.

Item 1 was not chosen a single time when positioned in the bottom right corner of the screen, it thus fared worse than when positioned top-left, and “lost out” to the other two similarly ranked competitors. We also note that time-to-choice was larger for item nr.2 when positioned in the bottom left corner (second trial) than in the top right corner (first trial). Thus, both items 1 and 2 fared worse when moved from the top row to the bottom row, measured with different indicators. Interpreting this increased time-to-choice for item nr.2 within the aDDM framework, it would indicate a small loss in attractiveness (less steeply evolving RDV) due to this inferior position. The “biggest loser” was thus a poorly ranked product moved from the upper row to the lower – a fact that agrees well with current research and practice concerning physical placement of products on shelves in supermarkets.

Speculating that we take these results and the aDDM seriously, it would seem that location indeed affects the decision process by making it longer - the slope of the RDV function for item nr. 4 would thus be less steep in the second trial as selection time increased almost 30% - from 3,98s to 5,17s - although it was still ultimately selected with a high frequency.

More data is needed for both the pre- and post-permutation cases, and the upper number of products for which the aDDM can predict choice behaviour with a reasonable precision should additionally be ascertained - a matter raised also by Krajbich and Rangel (2011). 4 packages permit 4! = 24 different grid set-ups which combined with repeated trials with a greater number of participants across second set-up would reveal whether the aDDM model is able to sufficiently handle 4 alternatives. Based on our results, in particular trial 1, it is not impossible that the model does indeed extend to 4 options, yet trial nr. 2 shows that position may be a factor for items similarly ranked. To sum up, the variations in trial nr 2, might be the result of one or more of the following: 1) The aDDM does not extend to the quaternary case, 2) the location permutation has a significant impact on the model, or 3) insufficient amount of data. All these are suggested as lines of further research.

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