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# An attentional drift diffusion model over binary-attribute choice

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ABSTRACT

In order to make good decisions, individuals need to identify and properly integrate information about various attributes associated with a choice. Since choices are often complex and made rapidly, they are typically affected by contextual variables that are thought to influence how much attention is paid to different attributes. I propose a modification of the attentional drift-diffusion model, the binary-attribute attentional drift diffusion model (baDDM), which describes the choice process over simple binary-attribute choices and how it is affected by fluctuations in visual attention. Using an eye-tracking experiment, I find the baDDM makes accurate quantitative predictions about several key variables including choices, reaction times, and how these variables are correlated with attention to two attributes in an accept-reject decision. Furthermore, I estimate an attribute-based fixation bias that suggests attention to an attribute increases its subjective weight by 5%, while the unattended attribute's weight is decreased by 10%.



## 1. Introduction

Except for very simple and familiar choices, most decisions require the identification and weighting of multiple attributes. Examples include choosing between two meals that differ in their taste, nutrition, and costs, or choosing between slot machines that differ in the likelihood and size of the potential rewards. Given their pervasiveness, understanding the algorithms that we use to make choices over alternatives with several attributes, and how they are affected by contextual variables, is a central question in psychology, economics, and neuroscience (Busemeyer & Johnson, 2004; Fehr & Rangel, 2011; Glimcher & Fehr, 2014; Mas-Colell, Whinston, & Green, 1995).

While much evidence suggests we differentially weight attributes in decision-making, the extent to which these weights are influenced by attention has not been resolved. For instance, suppose a restaurant menu contains a daily special of steak with a side of green beans, and that a consumer enjoys steak, but dislikes green beans. Is the probability that the consumer orders the steak influenced by contextual variables (e.g., how the menu is presented) that change the relative attention paid to the steak and the green beans at the time of choice? Are there models capable of providing a quantitative explanation of these effects? These questions are important because, as hinted in the example, many choices require weighting attributes properly, which might be impaired in the presence of the attentional effects hypothesized here.

This paper proposes and tests a modification of the attentional drift diffusion model (Krajbich, Armel, & Rangel, 2010; Krajbich, Lu, Camerer, & Rangel, 2012; Krajbich & Rangel, 2011) related to these effects, which I call the binary-attribute attentional drift diffusion model (baDDM). The model details the choice process by modeling how attention to two attributes, at the level of random eye fixations between those attributes, alters individual choices in an accept or reject decision.

The model builds on several main literatures. First, previous work has shown sequential sampling models of decision-making, such as the Drift-Diffusion model (Ratcliff, 1978; Ratcliff, Cherian, & Segraves, 2003; Ratcliff & Smith, 2004; Ratcliff, Smith, Brown, & McKoon, 2016), leaky-accumulator model (Usher & McClelland, 2001), Decision Field Theory (DFT) (Busemeyer & Diederich, 2002; Busemeyer & Townsend, 1992, 1993; Diederich, 1997; Roe, Busemeyer, & Townsend, 2001), and the attention drift diffusion model (aDDM) (Fehr & Rangel, 2011; Krajbich & Rangel, 2011; Krajbich et al., 2010, 2012) provide accurate quantitative accounts of how choice probabilities and response times vary with properties of the choice options. Within the literature, there are varying classes of sequential sampling models but many assume that choices are made using a relative value signal that is dynamically computed by integrating an instantaneous noisy measure of the desirability of options. Once the accumulated relative value signal becomes sufficiently strong in favor of one of two options, a choice is made. Furthermore, a growing body of evidence from

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neuroscience has found that the implementation of certain sequential integrator models is biologically plausible (Britten, Shadlen, Newsome, & Movshon, 1992; Gold & Shadlen, 2007; Hare, Schultz, Camerer, O'Doherty, & Rangel, 2011; Heekeren, Marrett, Bandettini, & Ungerleider, 2008; Rangel & Clithero, 2013).

Two broad classes of sequential sampling models are particularly related to this paper. The first concerns sequential sampling models that detail how multi-attribute decisions are made (Bhatia, 2013; Trueblood, Brown, & Heathcote, 2014; Tsetsos, Chater, & Usher, 2012; Usher & McClelland, 2004; Wollschläger & Diederich, 2012). A subset of these models treats choices as the accumulation of noisy evidence over time, although not all models of this class utilize momentary random fluctuations in preferences. Additionally, in some cases these multi-attribute models are able to incorporate attention effects. For instance, work in DFT has modeled attentional changes to attributes by appealing to a dynamic attention function that weights information over time, and Wollschläger and Diederich (2012) take a similar approach in their setting. Trueblood et al. (2014) use explicit attention weights that vary depending on how easily attribute values can be discriminated in their model of multi-attribute choice. In their model, attention weights are not meant to quantify the observed distribution of attention throughout a decision, but instead seek to capture the general trend that similar attributes receive more attention than vastly different ones. Additionally, Bhatia (2013) introduced a connectionist network that allowed more accessible attributes to be more likely to influence preferences. In the model, preferences are determined by weighting sums of attribute values where attributes with larger amounts also receive larger weights in decision-making. Although the models referenced above have differences in the how preferences and choices are formed, all are focused on detailing how the quantitative relationship between various attributes and their values impact decision-making.

A second class of relevant work consists of multi-stage sequential sampling models, some of which also model multi-attribute decision-making (Diederich, 1995, 1997; Diederich, 2015; Diederich & Oswald, 2014; Diederich & Oswald, 2016; Holmes, Trueblood, & Heathcote, 2016; Ratcliff, 1980). Multi-stage models explicitly represent evidence for different processing stages of a decision rather than combining all information into one source of evidence, which had previously described the majority of sequential sampling models found in the literature. This multi-stage approach began by allowing for varying drift rates in a drift diffusion model (Ratcliff, 1980) and has progressed to modeling the switching of attention between options and attributes throughout the course of a decision. Related to this paper, previous work in the aDDM has allowed the drift rate to vary depending on which of several options is currently attended (Krajbich & Rangel, 2011; Krajbich et al., 2010, 2012), though this model has only been extended to choice over a small number of options. Nevertheless, explicitly relating fixations to information accumulation and drift rate changes allows a natural extension to better understanding how we make decisions with more than one attribute, which is related to the model presented here. Relatedly, Diederich and Oswald (2016) propose a sampling model for multi-attribute choice that allows a separate sampling process for each attribute and for attention to switch between different attributes throughout the decision. They use numerical calculations of their model to demonstrate that the order in which attributes are processed can influence choices, but do not analyze empirical data. Although their model would need to be further specified in order to easily adapt to various choice environments and their model did not utilize fixation data, their work takes an important step in detailing how attentional distributions to attributes at the time of choice can influence decisions.

Additionally, this paper adds to a large literature that uses process-tracing methods to understand the decision process (Camerer & Johnson, 2004; Glöckner & Herbold, 2011; Johnson, Schulte-Mecklenbeck, & Willemsen, 2008; Russo & Dosher, 1983; Russo & Rosen, 1975; Willemsen, Böckenholt, & Johnson, 2011; Horstmann, Ahlgrimm, & Glöckner, 2009; Orquin & Mueller Loose, 2013; Towal, Mormann, & Koch, 2013). While much of this work makes use of eye tracking, others test process-based models by tracking mouse movements on a computer screen. Largely, previous work using these methods has broadly confirmed many predictions consistent with decisions being made by different classes of sequential integrator models. Relatedly, a portion of this work has focused on how well alternative models, such as heuristic models of choice, can explain behavior (Payne, Bettman, & Johnson, 1992). While certain heuristics can lead to particular attentional patterns (Day, 2010; Day, Lin, Huang, & Chuang, 2009; Renkewitz & Jahn, 2012), there is currently little evidence to suggest that the particular heuristic used can determine attentional deployment or that the underlying heuristic can be inferred from the distribution of attention (Orquin & Mueller Loose, 2013; Knoepfle, Yao-yi Wang, & Camerer, 2009; Reutskaja, Nagel, Camerer, & Rangel, 2011).

The model proposed in this paper expands on the work above in a number of ways. First, it extends the previous theory and applications of the aDDM. Formerly, the aDDM has been used to estimate how attention biases the drift rate depending on which of several choice options is currently fixated. This operationalizes by applying a fixation bias parameter to the unattended option so that its value is discounted in the evidence accumulation process. The baDDM described here extends this model to cover a simple binary-attribute choice environment in which an individual accepts or rejects a consumption option. Critically, the model and experimental design allow for separate estimation for the degree to which the weight of the attended attribute is increased as well as the degree to which the weight of the unattended attribute is decreased. Estimating multiple fixation bias parameters that describe how attribute weights change over the course of a decision may yield new insights compared to modeling a single fixation bias. Furthermore, since the baDDM investigates an accept-reject choice with two attributes, the results can help us understand the additional tasks that models such as these are able to accurately capture, but also to what extent they can fail. By pushing these limits, we may ultimately be able to design rigorous models that more accurately capture human behavior across a variety of contexts.

Second, the work here extends previous multi-attribute and multi-stage sequential sampling models by collecting and incorporating physiological data on attention, as measured by fixations, throughout the duration of a choice with two attributes. I estimate the model using choices, response times, and fixation data and test how well the model can explain observed patterns that subjects display. Although several previous models of multi-attribute choice are able to incorporate attention effects to varying degrees (e.g., Bhatia, 2013; Trueblood et al., 2014; Wollschläger & Diederich, 2012) they do not explicitly allow fixation information at the time of choice and many do not test their predictions in out of sample data. Despite focusing on a simplified version of multi-attribute choice, which this paper refers to as binary-attribute choice, the setting here can help understand how fixation data can be fit to novel tasks and can ultimately better inform, design, and test models that are grounded in more traditional multi-attribute choice settings. Furthermore, similar to previous work in the aDDM and other multi-stage sequential sampling models, the baDDM also allows for varying drift rates and permits those drift rates to vary as a function of the currently attended information. Although the baDDM is highly related to Diederich