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Information Acquisition During Online Decision Making: A Model-Based Exploration Using Eye-Tracking Data

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We propose a model of eye-tracking data to understand information acquisition patterns on attribute-by-product matrices, which are common in online choice environments such as comparison websites. The objective is to investigate how consumers gather product and attribute information from moment to moment. We propose a hierarchical hidden Markov model that consists of three connected layers: a lower layer that describes the eye movements, a middle layer that identifies information acquisition processes, and an upper layer that captures strategy switching. The proposed model accounts for the data better than several alternative models. The results show that consumers switch frequently between acquisition strategies, and they obtain information on only two or three attributes or products in a particular acquisition strategy before switching. Horizontal and contiguous eye movements play an important role in information acquisition. Furthermore, our results shed new light on the phenomenon of gaze cascades during choice. We discuss the implications for Web design, online retailing, and new directions for research on online choice.

Key words: process data; online choice; hierarchical hidden Markov model; eye tracking; information acquisition; gaze cascade; comparison websites
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1. Introduction

Consumers increasingly acquire information and make decisions about products online. The way in which they gather information affects their decisions. Web retailers and manufacturers recognize this and try to optimize online information displays to facilitate and direct choices. These online information displays often take the form of attribute-by-product matrices, which have become popular, especially on comparison sites (for instance, Bizrate.com, Dell.com, and Nextag.com all have more than 10 million monthly visitors) (eBizMBA 2012). These websites mainly use vertical and horizontal formats for presenting information: for example, as a default, Bizrate.com uses a horizontal format with products presented in the rows, and Dell.com uses a vertical format with products presented in the columns.

Studies with process tracing methods (Payne et al. 1993) have revealed two key processes that consumers use to acquire information on such displays: attribute based and product based (Ball 1997, Bettman et al. 1998, Payne et al. 1993). During attribute-based acquisition, information is obtained on a single attribute across multiple products before proceeding to the next attribute. During product-based acquisition, information is acquired on a single product across multiple attributes before proceeding to the next product. In theories of decision making, consumers are postulated to first adopt attribute-based acquisition to screen out certain products and then switch to product-based acquisition to evaluate the remaining products and make their final choice (Howard and Sheth 1969, Newell and Simon 1972). Thus, the idea is that the use of the two information acquisition processes over time is linked to different decision-making stages, and people switch once or twice between these processes. The presentation format has been shown to affect information acquisition: a horizontal format induces more product-based processing and a vertical format more attribute-based processing (Bettman and

Kakkar 1977). The managerial implications of this foundational research (Bettman et al. 1998, Payne and Venkatraman 2011, Weber and Johnson 2009) are becoming more significant because of the increased use of product-comparison matrices online.

Prior process tracing studies of consumer decision making have used methods such as information display boards, Mouselab and Flashlight[1] (see, for example, Costa-Gomes and Crawford 2006, Willemsen et al. 2011), in which information becomes available sequentially through manual inspection, such as mouse clicking or card turning. This renders the choice process in those studies more controlled and deliberate. However, comparison websites provide all attribute information of all choice options simultaneously. Information acquisition is then fast and governed by automatic processes. The simultaneous availability of information may also allow more flexible switching between information strategies than can be detected with more traditional process tracing methods. Eye-tracking methodology is particularly suited to provide insights under these conditions (Lohse and Johnson 1996, Russo 1978, Schulte-Mecklenbeck et al. 2011). Because of technological advances, eye tracking is now widely used in academia and practice (Wedel and Pieters 2008). Eye-movement data consist of eye fixations, which are brief moments that the eye is still and information is extracted from the stimulus (about two to four times per second); saccades are rapid jumps of the eye between fixations to redirect the line of sight to a new location.

Although introspection may suggest that information acquisition on comparison websites is a fairly well structured and orderly process, as will become clear below, the data collected in our experiment indicate a different conclusion. That is, whether information acquisition is attribute based or product based is often not immediately discernible from the large volumes of dense eye fixation data, and it is difficult to assess precisely how these two strategies are used over time and what information is acquired. The main aim of our research is therefore to develop a model-based approach that facilitates inferences about these rapid attribute- and product-based information acquisition processes during decision making as well as the switching between these processes, recognizing that they are fundamentally unobservable. Information acquisition processes are latent cognitive states that direct the eyes in a search for information on the display. Eye movements reflect these states probabilistically rather than deterministically (Lohse and Johnson 1996, Wedel and Pieters 2000).

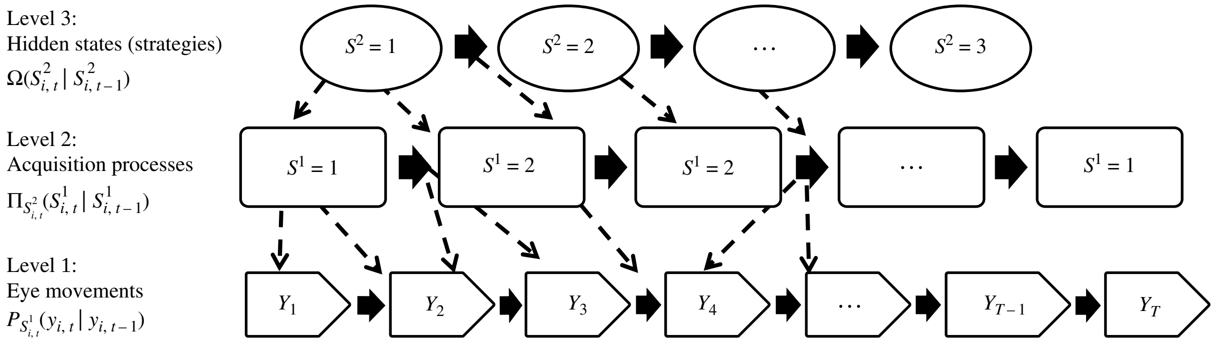
[1] MouselabWEB, http://www.mouselabweb.org/ (retrieved December 10, 2011); Application of FlashLight, http://vlab.ethz.ch/flashlight/ (retrieved December 10, 2011).

To infer and describe these latent cognitive states, we propose a model that extends hidden Markov models (HMM) that were previously applied to eye movement data (Liechty et al. 2003, van der Lans et al. 2008). The model is a hierarchical HMM (HHMM; Fine et al. 1998) that describes information acquisition through three hierarchical layers: (1) the lower layer describes the observed eye movements, (2) the middle layer describes unobserved (attribute- and product-based) information acquisition processes, and (3) the upper layer describes how consumers switch between them based on higher-order cognitive processes. The model is schematically depicted in Figure 1. It relaxes the assumptions of a standard HMM by allowing the transition probabilities between the states, representing information acquisition processes, to vary over time through upper-layer states, the number of which is a priori unknown. The model enables us to investigate how these information acquisition processes are used during decision making, how often people switch between them during a decision-making task, and what specific information they acquire while doing so. This provides new answers to longstanding questions about the information processing that takes place during constructive decision making.

1.1. Prior Literature

In spite of the growth of interest in using eye movements to better understand and predict choice behavior (see, for example, Pieters and Warlop 1999, Reutskaja et al. 2011, Russo and Leclerc 1994, Stüttgen et al. 2012), research on information acquisition on attribute-by-product displays such as used in comparison sites is as yet limited. Whereas research using traditional process tracing methods has shown that consumers sequentially use two stages (screening and evaluation) in decision making, in an analysis of eye and head movements of packages on a simulated shelf, Russo and Leclerc (1994) characterized the decision process as comprising three stages: screening, evaluation, and verification. Screening consisted of a serial inspection of mostly adjacent products, evaluation involved the comparison of a limited set of remaining products, and during verification the chosen product was compared with others. Research suggests that people switch between attribute- and product-based information acquisition processes when the demands of the task change (Ball 1997, Payne 1976, Pieters and Warlop 1999, Swait and Adamowicz 2001), for example, because of experienced accuracy and effort (Bettman et al. 1998) as a function of the information already acquired up to that point (Bettman and Park 1980, Russo and Rosen 1975). However, the extent of switching in natural tasks such as online choice has not yet been quantified.

Figure 1 Three-Layer Hidden Markov Model for Information Acquisition



Note. Pentagons represent the observations in the lower layer, with transition probabilities $P_{S^1_{i,t}}(y_{i,t} \mid y_{i,t-1})$; rectangles represent the hidden states in the middle layer (S^1), with transition probabilities $\Pi_{S^2_{i,t}}(S^1_{i,t} \mid S^1_{i,t-1})$; circles represent the hidden states in the upper layer (S^2), with transition probabilities $\Omega(S^2_{i,t} \mid S^2_{i,t-1})$.

Willemsen et al. (2011) show that counter to some sampling models of decision making in which potential information elements are assumed to be sampled independently (Roe et al. 2001), information is sampled depending on the current evaluation of the alternatives. Early encoding installs one of the choice options as the preferred one, and during the decision process attention shifts to this option, which then becomes central in the comparison process. This explains findings by Pieters and Warlop (1999) that the finally chosen product received significantly more fixations than did nonchosen products. This predecisional gaze bias on the chosen product has been called the gaze cascade (Shimojo et al. 2003). It has recently received much interest because it enables the prediction of choice from eye movements (Krajbich et al. 2010). It is consistent with diffusion models of decision making, in which evidence in favor of a product accumulates at a rate that depends on the fixations (Krajbich and Rangel 2011). Relative to this prior research, the contribution of our study is that it proposes a model of eye movements that helps to identify information acquisition processes that consumers use during decision making and their determinants and consequences. The model distinguishes information processing by attribute and by product (Bettman et al. 1998); it allows the information sampled during a particular eye fixation to depend on the information sampled before (Willemsen et al. 2011), and it allows two or more higher-order cognitive states to drive switching between these processes (Howard and Sheth 1969). The model enables testing the empirical contribution of these higher-level states in accounting for the observed eye-movement data. We conjecture that these higher-level states may reflect decision goals (Bettman et al. 1998) that govern the overall information acquisition process (Krantz and Kunreuther 2007), and in the final section call for more research to examine these further. The model describes the time-dependent switching between information acquisition processes as a function of these states and the switching between these states as well.

1.2. The Study: Information Acquisition on a Comparison Website

The Dell website (http://www.Dell.com/) was selected as context for our study. It provides the option of comparing various personal computers that are relevant for our participants. We manipulated the display format by transposing rows and columns in a between-participants design. The comparison matrix contains 12 attributes: "picture," "price," "processor," "operating system," "memory," "keyboard/mouse," "monitor," "hard drive," "optical drive," "wireless," "office software," and "warranty"; and four desktop models: "Inspiron 864," "Inspiron 619," "Inspiron 758," and "Inspiron 689." In the vertical condition the products are presented in the columns; in the horizontal condition the comparison matrix is transposed so that the products are in the rows. A total of 108 undergraduate students (55 male), all in the market for buying a desktop computer, were randomly assigned to either the vertical or the horizontal condition. They read the instructions that asked them to make a choice for a desktop computer for use at home. After having made their final choice, participants indicated how easy it was to collect information during the task, how easy it was to decide among the various computers, and how confident they were about the final choice, all on 5-point response scales ("1" = not at all, "5" = very much).

Tobii 1750 infrared eye-tracking equipment was used to record eye movements (http://www.Tobii.com/). It leaves participants free to move their heads; cameras in the rim of a LCD-computer monitor (1,280 × 768 pixel resolutions) track the position of the eye and head. Measurements were taken with a frequency of 50 Hz and a precision better than 0.5 degree

Table 1 Data Description

Percentage of	Vertical format			Horizontal format		
Fixations on product 1		25.65			25.69	
Fixations on product 2		26.33			25.80	
Fixations on product 3		20.46			20.68	
Fixations on product 4		19.65			17.78	
Consecutive fixations on contiguous cells		65.45			63.78	
Decision time	First 1/3	Mid 1/3	Last 1/3	First 1/3	Mid 1/3	Last 1/3
Type 1 (attribute-based) eye movements	42.61	52.87	42.64	40.66	38.77	45.21
Type 2 (product-based) eye movements	32.89	29.71	40.77	41.65	44.93	38.99
Type 3 (other) eye movements	25.08	21.10	20.28	18.48	21.41	20.91
Number of consecutive fixations	$M=2$	$M=3$	$M=4$	$M=2$	$M=3$	$M=4$
M consecutive saccades on the same product	33.46	16.01	1.51	39.21	20.44	11.48
M consecutive saccades on the same attribute	43.99	25.84	15.74	39.84	22.09	12.25
The last M saccades on the chosen option	40.82	30.61	24.49	40.68	32.20	20.33

Note. Refixations on the same cell are excluded from the data.

of visual angle. Instructions and stimuli were presented on the monitor, and participants continued to a next page by pressing the space bar. Saccades between cells of the comparison website (a total of 18,172 observations) are the unit of analysis; refixations were excluded.

Table 1 provides a description of the data. The relative percentage of fixations that each product receives is similar across the two formats, with product 2 receiving the most and product 4 the least fixations. Around 65% of the fixations are on contiguous cells. Following Ball (1997), we distinguish three elementary types of saccades. During a type 1 saccade, the eye jumps between two products for the same attribute. During a type 2 saccade, the eye jumps between two attributes for the same product. During a type 3 saccade, the eye jumps from a particular attribute for one product to a different attribute for another product. Type 1 (attribute-based) eye movements are most prevalent (53%) in the middle part of the decision for the vertical format and most prevalent at the end (45%) for the horizontal format. Type 2 (product-based) saccades are most prevalent at the end of the decision (41%) for the vertical format and most prevalent in the middle of the decision (45%) for the horizontal format. This indicates that the switching between attribute- and product-based eye movements is nonstationary across the decision time. Type 3 (other) saccades are somewhat stable around 20%. For the vertical (horizontal) format, in 33% (39%) of the cases, two consecutive saccades include the same product; only in 2% (11%) of the cases do four consecutive saccades include the same product. Thus, although reflected in a few saccades between information elements only, product-based processing is more prevalent in the horizontal format and attribute-based processing more prevalent in the vertical format. Finally, the data provide evidence of a gaze cascade: in around 41% of the cases, the last two fixations on the display include the chosen alternative.

2. Hierarchical Hidden Markov Model

We develop a hierarchical hidden Markov model (HHMM) that has three hidden layers. The lower layer captures observable eye movements; the middle layer captures the attribute-based and product-based acquisition processes that drive the eye movements; the upper layer captures switching between the two acquisition processes. We let $i=1,\ldots,I$ denote participants and $t=1,\ldots,T$ denote fixations. We let $y_{i,t}=(a_{i,t},p_{i,t})$ denote the particular cell in the display defined by attribute ($a\in\{1,\ldots,A\}$) and product ($p\in\{1,\ldots,P\}$), at eye-fixation t for participant i. In addition, $y_{i,t-1}=(a_{i,t-1},p_{i,t-1})$ denotes the cell at the previous eye-fixation $t-1$. The model is represented by three sets of transition probability matrices:

1. the matrix of transition probabilities between the states of the upper layer, $\Omega(S^2_{i,t}\mid S^2_{i,t-1})$;
2. the matrices of transition probabilities between states of the middle layer, $\Pi_{S^2_{i,t}}(S^1_{i,t}\mid S^1_{i,t-1})$, given the states $S^2=1,\ldots,M$ of the upper layer;
3. the matrices of transition probabilities between cells on the display $P_{S^1_{i,t}}(y_{i,t}\mid y_{i,t-1})$, given the states $S^1=1,\ldots,N$ of the middle layer (Figure 1).

Switching between the unobserved upper-layer hidden states follow a Markov process described by the $(M\times M)$ transition probability matrix $\Omega(S^2_{i,t}\mid S^2_{i,t-1})$. The number of states in the upper layer, M, is a priori unknown and will be empirically determined. These states govern the selection of the middle-layer states and the switching between them.

Below, we discuss the possible interpretation of these states in terms of decision goals.

Switching between the middle-layer hidden states, $S^1_{i,t}$, follows a Markov process with a $(N \times N)$ transition probability matrix $\Pi_{S^2_{i,t}}(S^1_{i,t} \mid S^1_{i,t-1})$, given a specific upper-layer state $S^2_{i,t}$, (Figure 1). Because there are M upper-layer states, there are M such matrices. Theory specifies the number of middle-layer states to equal $N = 2$ because these states present the latent attribute-based and product-based information acquisition processes (Payne et al. 1993).

At the lower layer, observed saccades of the eye between the cells of the display matrix are represented by the matrices of transition probabilities $P_{S^1_{i,t}}(y_{i,t} \mid y_{i,t-1})$. The model distinguishes three elementary types of saccades as described earlier. An attribute-based information acquisition process consists of a sequence of mostly attribute-based (type 1) saccades. A product-based information acquisition process is characterized by a sequence of mostly product-based (type 2) saccades. Other (type 3) saccades may result from exploratory eye movements, corrective eye movements, or switches between attribute-based and product-based saccades. Thus, given state 1 of the middle layer (the attribute-based acquisition state), the model parameters of the lower-layer transition matrix are constrained such that they allow for eye movements that are mostly consistent with attribute-based acquisition. In this state, for $a_{i,t} = a_{i,t-1}$, the eyes jump from product $p_{i,t-1}$ to product $p_{i,t}$ with probability

$$P_{S^1_{i,t}=1}(y_{i,t} \mid y_{i,t-1}) = v \cdot P_{S^1_{i,t}=1}(p_{i,t} \mid p_{i,t-1}), \quad \text{if } a_{i,t} = a_{i,t-1}. \tag{1}$$

Then all other saccades (types 2 and 3) have a small probability $1 - v$. Conversely, given state 2 of the middle layer (the product-based acquisition state) for $p_{i,t} = p_{i,t-1}$, the eyes jump from attribute $a_{i,t-1}$ to $a_{i,t}$ with probability

$$P_{S^1_{i,t}=1}(y_{i,t} \mid y_{i,t-1}) = w \cdot P_{S^1_{i,t}=2}(a_{i,t} \mid a_{i,t-1}), \quad \text{if } p_{i,t} = p_{i,t-1}. \tag{2}$$

Then all other saccades (types 1 and 3) have small probability $1 - w$ (neither v nor w are constrained in the estimation). The formulation in (1) and (2) is conservative in its identification of switching between the underlying acquisition processes, because it allows the corresponding states in the middle layer to produce eye movements that deviate probabilistically from strict attribute-based and product-based eye movements. This is consistent with findings on the stochastic nature of higher-order processes driving eye movements (Feng 2009, Wedel and Pieters 2000).

We can now write the saccade probabilities between cells of the comparison matrix, conditional on the states of the two hidden layers that participant i is in at fixation t, $S^1_{i,t}$ and $S^2_{i,t}$, as

$$\begin{aligned} P(y_{i,t} \mid y_{i,t-1}; S^1_{i,t}, S^2_{i,t}) &= \sum_{S^2_{i,t-1}=1}^{M} \Omega(S^2_{i,t} \mid S^2_{i,t-1}) \sum_{S^1_{i,t-1}=1}^{N} \Pi_{S^2_{i,t}}(S^1_{i,t} \mid S^1_{i,t-1}) \\ &\quad \cdot P_{S^1_{i,t}}(y_{i,t} \mid y_{i,t-1}), \end{aligned} \tag{3}$$

with $P_{S^1_{i,t}}(y_{i,t} \mid y_{i,t-1})$ provided in Equations (1) and (2). If Θ collects all parameters, and $P_{S^1_{i,1}}(y_{i,1})$ is the initial fixation probability, the likelihood function of participant i is

$$\begin{aligned} L(y_i \mid \Theta) &= P_{S^1_{i,1}}(y_{i,1}) \prod_{t=2}^{T} \sum_{S^2_{i,t}=1}^{M} \cdots \sum_{S^2_{i,T}=1}^{M} \Bigg(\sum_{S^1_{1i,t}=1}^{N} \cdots \sum_{S^1_{i,T}=1}^{N} \prod_{t=2}^{T} \Omega(S^2_{i,t} \mid S^2_{i,t-1}) \\ &\quad \cdot \sum_{S^1_{i,t-1}=1}^{N} \Pi_{S^2_{i,t}}(S^1_{i,t} \mid S^1_{i,t-1}) P_{S^1_{i,t}}(y_{i,t} \mid y_{i,t-1}) \Bigg). \end{aligned} \tag{4}$$

We specify uninformative conjugate priors on all model parameters and use the Markov chain Monte Carlo to estimate the model (using *R*). Single-move sampling schemes are used to sample middle-layer hidden states S^1, upper-layer hidden states S^2, and the parameters of the transition matrices (Robert et al. 1993). The initial fixation probabilities are estimated as the stationary probabilities of the lower-layer Markov chain (Scott 2002). Tests on simulated data reveal accurate recovery of the parameters. We use 25,000 draws and discard the first 5,000 draws to burn-in. The chains appear stationary after 5,000 draws. We take 1 in 10 target draws and report the mean and standard deviation of the resulting 2,000 draws to summarize the posterior distributions of the parameters. We test for the number of upper-layer states of our model, and we compare the model with several alternative models described later, using the log-marginal density (LMD). We compute the LMD using Chib's (1995) method, which provides unbiased and stable estimates:

$$\text{LMD}(Y) = \ln f(Y \mid \Theta^*) + \ln \pi(\Theta^*) - \ln \pi(\Theta^* \mid Y). \tag{5}$$

Calculation of $\ln \pi(\Theta^*)$, the log-prior density, and $\ln \pi(\Theta^* \mid Y)$, the log-posterior density, both computed at the mean of the posterior density Θ^*, is straightforward. We compute the high-dimensional sum in the likelihood in (5) using Scott's (2002) likelihood recursion.

Although we estimate the full switching matrices between products, $P_{S^1_{i,t}=1}(p_{i,t} \mid p_{i,t-1})$ and attributes

$P_{S^1_{i,t}=2}(a_{i,t} \mid a_{i,t-1})$ at the lower level of the model, we report saccade probabilities between contiguous (and noncontiguous) products $P_{S^1_{i,t}=1}(p_{i,t} \in N(p_{i,t-1}))$ and attributes $P_{S^1_{i,t}=2}(a_{i,t} \in N(a_{i,t-1}))$, where, for example, $N(a_{i,t-1})$ is the set of attributes adjacent to $a_{i,t-1}$. These are not only more parsimonious but also more theoretically relevant probabilities. People acquire detailed information mostly locally from a small area around the current fixation point of the eye (van der Lans et al. 2008). This leads to eye movements that predominantly fall on adjacent locations in a display (Liechty et al. 2003, Russo and Leclerc 1994) and to such adjacent information being better integrated in and retrieved from memory (Johnson and Mayer 2012).

A key result of the estimation is the marginal posterior probability that participant i is in information acquisition state $S^1_{i,t}$ at fixation t: $P(S^1_{i,t} \mid y_{i,t}, \Theta)$ as well as the marginal posterior probabilities of being in the upper-level states $S^2_{i,t}$: $P(S^2_{i,t} \mid y_{i,t}, \Theta)$. Those allow us to describe the information acquisition processes that participants use from moment to moment.

3. Results

3.1. Model Comparisons

We compare the proposed model with several alternatives (see Table 2). Alternative model 1 is an HMM without the upper layer, but it is otherwise the same as our proposed model. If this two-layer model would be best, the probabilities of switching between attribute-based and product-based information acquisition would be constant over time. It would imply that switching between attribute-based and product-based processes would be the same early on and later during decision making. It would go against current theories and findings about stages in decision making. Alternative model 2 is a two-layer HMM without the constraints of attribute-based and product-based acquisition processes in the lower layer. This model allows any type of saccade in each of the two states. If this model would be best, it would imply that eye movements do not reflect the two information acquisition processes at all or that such processes do not reliably emerge. Alternative model 3 is a model in which the upper layer is a mixture rather than a Markov chain; that is, the model is a mixture of HMMs. In this model, there are no dynamics in the upper layer. Finally, we test for two, three, and four upper-layer hidden states both for the hierarchical mixture of HMMs (model 3) and for our model. We perform all these tests separately for the vertical and horizontal formats.

Table 2 Log-Marginal Density of Alternative Models

Model		Experimental condition: Vertical	Horizontal
Alternative model 1	Constrained HMM	−13,697.0	−13,169.0
Alternative model 2	Unconstrained HMM	−13,132.8	−12,205.7
Alternative model 3	Mixture HMM, $S=2$	−11,190.5	−11,458.4
	Mixture HMM, $S=3$	−10,093.3	−10,354.7
	Mixture HMM, $S=4$	−10,085.2	−10,371.9
Proposed model	HHMM, $S=2$	−10,392.0	−10,877.8
	HHMM, $S=3$	−9,066.1	−9,503.6
	HHMM, $S=4$	−9,058.1	−9,484.5

Our model with two, three, or four upper-layer hidden states outperforms models 1 and 2, as revealed by the higher LMDs in Table 2. For each particular number of states, the proposed model also has a higher likelihood than the corresponding model 3, the mixture of HMMs. This holds for both conditions (vertical and horizontal). These results provide support for a hierarchical multistage decision process: a three-layer model explains the decision process better than the two-layer models do. It also provides support for the dynamics in the third layer of the model: the proposed HHMM explains the data better than does a mixture of HMMs. For the proposed model, the value of the LMD levels off after three upper-level states (Table 2), and the parameter estimates of two hidden states in the four-state model are very similar. We thus report the results of the model with three upper-layer hidden states.

3.2. Estimation Results

The parameter estimates characterizing the lower layer are shown in Table 3 for the vertical and horizontal formats. For the vertical format (products in columns) and while in the attribute-based state, participants are 14.0 (0.929/0.066) times more likely to move their eyes within the same attribute than making other eye movements. For the horizontal format, this ratio is lower: 8.1 (0.892/0.110). For the vertical format and while in the product-based state, participants are 1.7 (0.641/0.360) times more likely to make an eye movement within the same product than making other types of eye movements. For the horizontal format, this ratio is higher: 2.8 (0.736/0.264). Two conclusions are apparent. First, participants are much more consistent in moving their eyes along the same attribute, regardless of whether the products are presented in rows or columns. Second, for both acquisition processes consistency is substantially higher if the corresponding information mode is presented row-wise. This corroborates previous findings on the dominance of horizontal eye movements (Gilchrist and Harvey 2006, van der Lans et al. 2008, Tatler and Vincent 2008). In various visual tasks a horizontal, left-to-right dominance in consumers' eye movements has been observed, such as when searching store shelves (van der Lans et al. 2008). There are

Table 3 **Parameter Estimates for Eye Movements (Lower Layer) and Information Acquisition Strategies (Middle Layer) (with Standard Deviations in Parentheses)**

Acquisition strategy (middle layer)	Eye-movement features	Information presentation format: Vertical	Horizontal
Attribute based	Consistent	0.929 (0.001)	0.892 (0.001)
	Inconsistent	0.071 (0.022)	0.108 (0.011)
	Contiguous (products)	0.444 (0.007)	0.283 (0.006)
	Noncontiguous (products)	0.171 (0.009)	0.157 (0.007)
Product based	Consistent	0.641 (0.005)	0.736 (0.002)
	Inconsistent	0.359 (0.016)	0.264 (0.008)
	Contiguous (attributes)	0.362 (0.000)	0.338 (0.002)
	Noncontiguous (attributes)	0.036 (0.001)	0.041 (0.000)

Notes. "Consistent" is the probability of staying with the same attribute or product (v or w); "Inconsistent" is the probability of moving to another attribute or product ($1-v$ or $1-w$). "Contiguous" is the average of the transition probabilities between block-diagonal submatrices (all elements on the 2×2 diagonal blocks); "Noncontiguous" is the average of the transition probabilities between the cells in the off-diagonal blocks (all elements except those in the diagonal blocks).

several reasons for this. The dominance of horizontal eye movements may be due to the generally horizontal layout of visual displays (Tatler and Vincent 2008). Left-to-right eye-movemement tendencies are also caused by a more rapid decline in the resolution of the retina in the vertical than in the horizontal direction, which causes more information to be available to direct the eyes horizontally (Gilchrist and Harvey 2006). Horizontal movements occur especially during reading of roman type (Feng 2009, Rayner 1998). Information that is largely textual, as is typical for comparison websites, facilitates left-right reading-like patterns even more. A specific information acquisition process is thus facilitated when the display is organized so it is consistent with the preferential left-to-right direction of eye movements (Spalek and Hammad 2005).

Table 3 also shows the probabilities that participants make contiguous (adjacent cells) and noncontiguous eye movements. For the vertical format, eye movements between contiguous attributes are 10.1 (0.362/0.036) times more likely than between noncontiguous ones. This ratio is 8.2 (0.338/0.041) for the horizontal format. For contiguous/noncontiguous products, these ratios are substantially lower. Participants are 2.6 (0.444/0.171) times more likely to collect information on contiguous products for the vertical and 1.8 (0.283/0.157) times for the horizontal format. Thus, participants are much more prone to compare information from adjacent attributes than from adjacent products, regardless of the orientation of the display. However, they are even more likely to do so when attributes are presented in the rows (vertical format). The vertical format induces more contiguous information acquisition than the horizontal format. The dominance of information acquisition on adjacent cells of the matrix is in line with prior accounts of the dominance of local eye-movement patterns (Liechty et al. 2003, Russo and Leclerc 1994) and may lead to more extensive integration of information that is present in close proximity (Johnson and Mayer 2012).

The estimates of the switching probabilities characterizing the middle and upper layers are provided in Table 4. We begin by providing a number of summary statistics for the attribute-based and product-based states of the middle layer. The initial probabilities of these two states are 0.444 and 0.556, respectively, for the vertical format and 0.383 and 0.617 for the horizontal format. Thus, respondents are somewhat more likely to start in the product-based state, especially for the horizontal format. While respondents are in the attribute-based state, the average number of products inspected for each attribute is a little more than two (2.28 in the vertical and 2.07 in the horizontal condition). In that same state, one to two attributes are inspected consecutively (1.55 in the vertical and 1.38 in the horizontal condition).[2] When respondents are in the product-based state, the average number of attributes inspected for one product is a little more than three (3.11 in the vertical and 3.20 in the horizontal condition), although on average only about a single product is inspected (1.04 in both conditions). On average, participants spend about 45.61% of the time in the attribute-based state ($M = 30.88$ seconds, $SD = 24.38$), 54.38% ($M = 36.81$ seconds, $SD = 22.25$) in the product-based state, and switch on average 47.91 times ($SD = 20.6$) between these states. This high frequency of switching is remarkable, and we will return to it later.

Table 4 shows that upper-layer state $S^2 = 1$ induces state dependence with a large probability of sticking to the current acquisition state and with switching into but not out of the product-based state. This holds for both display formats. State $S^2 = 2$ induces switching to and staying in the attribute-based acquisition state.

[2] The average number of products inspected is about 1.7 at the beginning and end of the decision process.

Table 4 **Transition Probabilities Between Middle- and Upper-Layer States for the Two Information Presentation Formats (with Standard Deviations in Parentheses)**

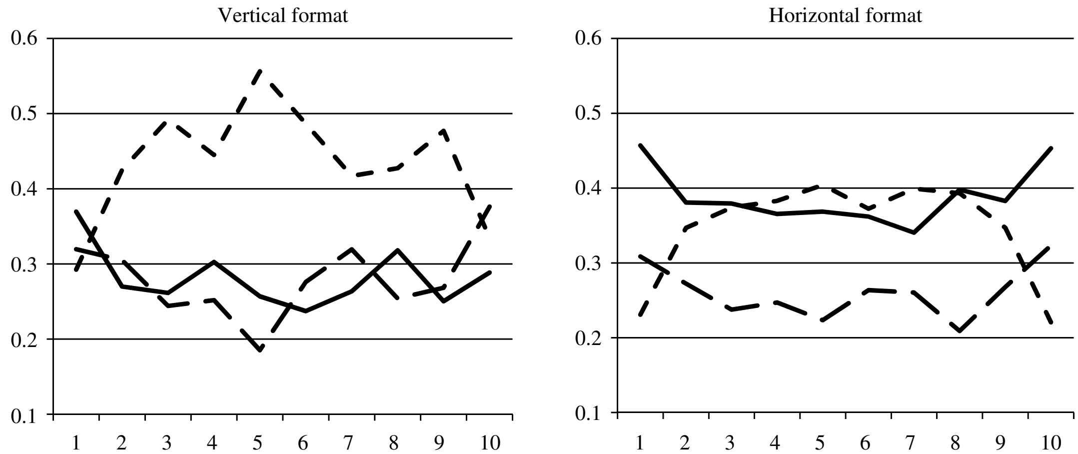
	Vertical format				Horizontal format		
		$S^1 = \text{AB}$	$S^1 = \text{PB}$			$S^1 = \text{AB}$	$S^1 = \text{PB}$
	Middle-layer transition matrices						
	$S^2 = 1$				$S^2 = 1$		
	$S^1 = \text{AB}$	0.769 (0.021)	0.231 (0.021)		$S^1 = \text{AB}$	0.746 (0.047)	0.254 (0.047)
	$S^1 = \text{PB}$	0.096 (0.038)	0.904 (0.038)		$S^1 = \text{PB}$	0.047 (0.011)	0.953 (0.011)
	$S^2 = 2$				$S^2 = 2$		
	$S^1 = \text{AB}$	0.586 (0.029)	0.414 (0.029)		$S^1 = \text{AB}$	0.719 (0.036)	0.281 (0.036)
	$S^1 = \text{PB}$	0.456 (0.071)	0.544 (0.071)		$S^1 = \text{PB}$	0.552 (0.087)	0.448 (0.087)
	$S^2 = 3$				$S^2 = 3$		
	$S^1 = \text{AB}$	0.520 (0.056)	0.480 (0.056)		$S^1 = \text{AB}$	0.323 (0.019)	0.677 (0.019)
	$S^1 = \text{PB}$	0.451 (0.013)	0.549 (0.013)		$S^1 = \text{PB}$	0.334 (0.038)	0.666 (0.038)
	$S^2 = 1$	$S^2 = 2$	$S^2 = 3$		$S^2 = 1$	$S^2 = 2$	$S^2 = 3$
	Upper-layer transition matrices						
$S^2 = 1$	0.461 (0.099)	0.244 (0.012)	0.295 (0.090)	$S^2 = 1$	0.549 (0.047)	0.161 (0.088)	0.290 (0.070)
$S^2 = 2$	0.225 (0.067)	0.400 (0.045)	0.375 (0.034)	$S^2 = 2$	0.204 (0.099)	0.493 (0.054)	0.303 (0.101)
$S^2 = 3$	0.209 (0.111)	0.446 (0.091)	0.345 (0.089)	$S^2 = 3$	0.187 (0.087)	0.496 (0.026)	0.317 (0.095)

Notes. For each format, there are one upper-layer transition matrix and three middle-layer transition matrices—one for each upper-layer state ($S^2 = 1, 2,$ and 3). AB: attribute-based acquisition; PB: product-based acquisition. The rows of the matrices present the states at time $t-1$; the columns those at time t.

State $S^2 = 3$ indicates a similar pull of the product-based acquisition state because it induces switching to and staying in that state. Note that this holds in particular for the horizontal format; in the vertical format the switching probabilities for the latter two states are more evenly distributed. Although in both conditions the stationary probabilities of the switching matrices indicate that for upper-layer states 2 and 3, participants spend about half of the time in the attribute-based state and half of the time in the product-based state; in upper-layer state 1 they spend more time in the product-based state (63.6% for the vertical and 57.8% for the horizontal condition). Table 4 shows that among the three upper-layer states, state 1 has the highest stickiness (0.461 for the vertical and 0.549 for the horizontal format), followed by state 2 (0.400 for the vertical and 0.493 for the horizontal format), and then state 3 (0.345 for the vertical and 0.317 for the horizontal format). Participants spend about one-third of the time in each of these states, and all participants use all three states.

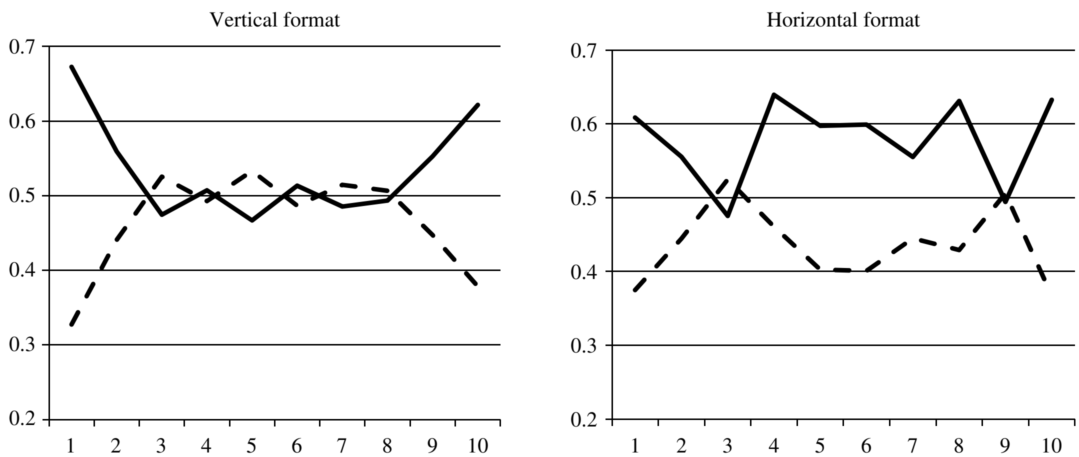
Figure 2(a) presents the posterior probabilities of the three upper-layer states across normalized time for all participants; Figure 2(b) graphs the probabilities of the two middle-layer information acquisition states. Counter to theories of two-stage decision-making processes that postulate a first screening stage of attribute-based acquisition followed by second evaluation stage of product-based acquisition, Figure 2(a) shows that in both display formats, the pull of attribute-based acquisition ($S^2 = 2$) dominates in the middle part of the decision process, whereas the state-dependence ($S^2 = 1$) and pull of product-based acquisition ($S^2 = 3$) dominate both in the early and in the late parts. The fact that upper-layer state $S^2 = 1$ is more prevalent in the beginning and at the end indicates that participants tend to stick more with the current state. Saccade lengths (calculated as the Euclidean distance between the corresponding cells of the comparison matrix) are much larger for upper-layer state 1 ($S^2 = 1$: 35.4) than those for states 2 ($S^2 = 2$: 12.2) and 3 ($S^2 = 3$: 7.8). This suggests that, independent of the display format, participants tend to adopt and stick with more global information acquisition in the beginning and end of the decision process. The use of product-based acquisition in the beginning of the decision process may indicate exploration. In our experiment, the products differed in 12 features, described in textual or numerical detail. This does not enable consumers to grasp (the gist of) the product as a whole in a single fixation (counter to the stimuli and exposure situation in the experiment of Russo and Leclerc 1994). Then participants tend to start with product-based information acquisition. As compared to participants who started with attribute-based acquisition, those who started with product-based acquisition had significantly higher perceived easiness of information collection (3.70 versus 3.49), easiness of making a decision (2.95 versus 2.71), and confidence in their final choice (3.71 versus 3.39). The usage of product-based acquisition at the end of the decision process is consistent with a predecisional gaze bias that reflects a cascading preference formation and decision justification (Pieters and Warlop 1999, Russo and Leclerc 1994, Shimojo et al. 2003).

Figure 2(a) **Aggregate Time Course of the Upper-Layer States: $S^2 = 1$ (Long Dash), $S^2 = 2$ (Short Dash), and $S^2 = 3$ (Solid Line) for the Two Information Presentation Formats**



Note. x-axis: normalized decision time; y-axis: probabilities of three upper-layer states.

Figure 2(b) **Aggregate Time Course of Attribute-Based ($S^1 = 1$, Dashed) and Product-Based ($S^1 = 2$, Solid Line) Information Acquisition States for Two Information Presentation Formats**



Note. x-axis: normalized decision time; y-axis: probabilities of two middle-layer states.

Although one may envision the upper layer of the model simply as a way to represent nonstationary switching between the attribute- and product-based states, based on the above description it may be possible to interpret these states as reflecting higher cognitive processes (Russo and Leclerc 1994, Salvucci and Anderson 1998), such as decision goals, which determine the selection of the specific information acquisition process (Krantz and Kunreuther 2007). Bettman et al. (1998) distinguish four decision goals, of which accuracy maximization and effort minimization may be most relevant to the product-based and attribute-based information acquisition processes that our study focuses on. When an accuracy-maximization goal is activated, product-based information acquisition may be most effective, yet it is also most effortful. When an effort-minimization goal is activated, attribute-based information acquisition may be most effective, yet it is less accurate. Tentatively, it is reasonable to expect that the upper-layer states reflect the effects of participants' moment-to-moment trade-offs between these goals. Yet more precise inferences on the upper-layer states of the model await further research.

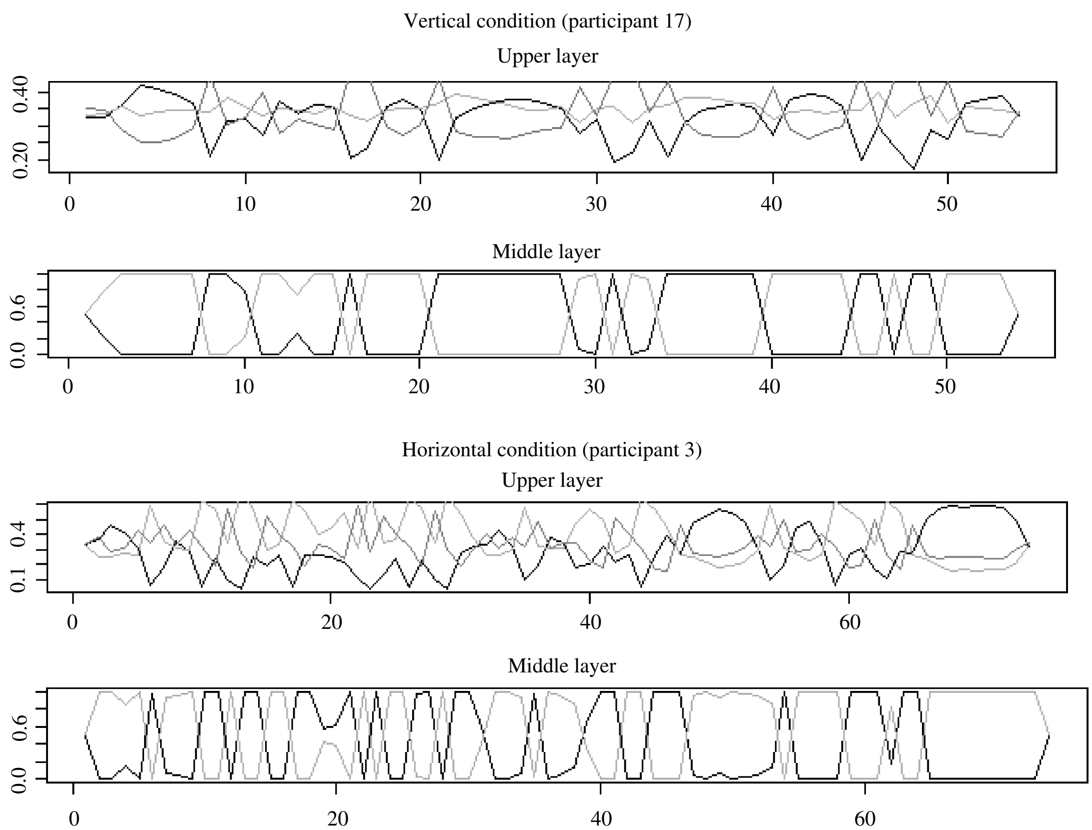
As for the impact of format, Figure 2(a) shows that for the horizontal format the prevalence of the upper-layer state 3, which reflects a pull of product-based information acquisition, is much higher than for the vertical format. For the latter format, upper-layer state 2 dominates, reflecting a pull of attribute-based acquisition. Thus, the horizontal format induces more product-based acquisition, which confirms previous findings with other process tracing techniques (Bettman and Kakkar 1977). But here we establish that this occurs irrespective of the tendency to make horizontal eye movements. Furthermore, Figure 2(b) shows that the dominance of product-based acquisition in the horizontal format manifests itself only in the middle of the decision process. For the vertical format, product-based and attribute-based acquisitions are equally prevalent in the mid-range of the decision. The dominance of product-based acquisition at the beginning and end is unaffected by the display format.

A multinomial logit model with the total (posterior mean) durations of different acquisition states as predictors (pseudo-$R^2 = 0.821$) shows that more attribute-based acquisition significantly increases the probability of choosing product 1 over 4 ($b = 6.32$, $p = 0.003$), while it reduces that of the other products ($b = -7.01$ for product 2, $p = 0.001$; -6.33 for product 3, $p = 0.063$). Product 1 (Inspiron 864) is superior on most non-price attributes. Thus, participants in the vertical condition are more likely to choose the dominating product than are those in horizontal condition (choice probabilities: vertical: 0.26 versus horizontal: 0.20). They also are less likely to choose the second product (choice probabilities: vertical: 0.08 versus horizontal: 0.13), which is inferior on most non-price attributes.

3.3. Switching Between Information Acquisition States

We find a high incidence of switching between the information acquisition states, which is remarkable and has not been documented before. To illustrate, Figure 3 plots the probabilities information acquisition states over time for one representative participant in the vertical and for one in the horizontal condition. The figure shows that switching between the two middle-layer information acquisition states is very frequent, even more so for the horizontal format. On average, participants switch once every 1.64 seconds and once every 1.20 seconds, respectively, for the vertical and horizontal conditions. In fact, if one were to count the (observed) single-step transitions in the eye movements directly, one would obtain even higher switching frequencies, namely, once every 0.79 seconds (vertical) and 0.73 seconds (horizontal). The model-based switching frequencies are lower because eye movements are treated as probabilistic indicators of the information acquisition states. Such high switching rates cannot be identified with traditional process tracing methods such as information display boards or Mouselab because these require additional

Figure 3 Examples of the Time Course of the Three Upper-Layer States ($S^2 = 1$, Long Dash; $S^2 = 2$, Short Dash; $S^2 = 3$, Solid Line), and of the Two Middle-Layer States ($S^1 = 1$, Attribute-Based Acquisition, Short Dash; $S^1 = 2$, Product-Based Acquisition, Solid Line), for One Participant in Each Condition (Presentation Format)



Note. x-axis: fixation number; y-axis: probabilities of each state in the middle and upper layers.

hand movements for enactment, capture more deliberate processes, and remove peripheral information (Lohse and Johnson 1996, Schulte-Mecklenbeck et al. 2011). Participants switch between the upper-layer states once every 1.19 seconds for the vertical condition and once every 1.14 seconds for the horizontal condition. As discussed above, these states may reflect decision goals that govern longer sequences of specific information acquisition processes, and although their usage is affected by presentation format (Figure 2(a)), the format has less impact on switching between these states.

To investigate determinants of the switching between states, we estimated logit regressions of participant-specific switching on the percentages of products (P) and attributes (A), respectively, inspected up to that time point. In the middle layer, switching from product-based to attribute-based acquisition is predicted by the percentage of attributes already inspected (vertical condition: $b = 0.29$, $p = 0.08$; horizontal condition: $b = 0.38$, $p = 0.07$). Switching from attribute-based to product-based acquisition, on the other hand, is predicted by the percentage of products already inspected (vertical condition: $b = 0.48$, $p = 0.03$; horizontal condition: $b = 0.96$, $p < 0.001$). This shows that the probability of switching to another acquisition process increases as more information has been acquired in that process. It provides additional evidence that the upper-layer states may capture the effects of decision goals.

Frequent switching significantly increases decision time (regression coefficient $b = 1.53$ for middle-layer switching, $p = 0.06$; $b = 2.30$ for upper-layer switching, $p < 0.001$). The stronger effect for switching between upper-layer states on decision time supports their interpretation as outcome and monitoring goals. Decision time is significantly prolonged when a participant dynamically adjusts these goals. Furthermore, switching significantly reduces the experienced ease of processing (average of post-choice evaluation items, $M = 2.78$, $b = -0.33$ for middle-layer switching, $p = 0.002$). As a consequence of the more frequent switching that the horizontal condition induces, participants perceive the decision process to be less easy in that condition than in the vertical condition ($M = 3.02$ and $M = 2.64$, respectively; $p = 0.059$).

3.4. Selective Attention to Products and Attributes

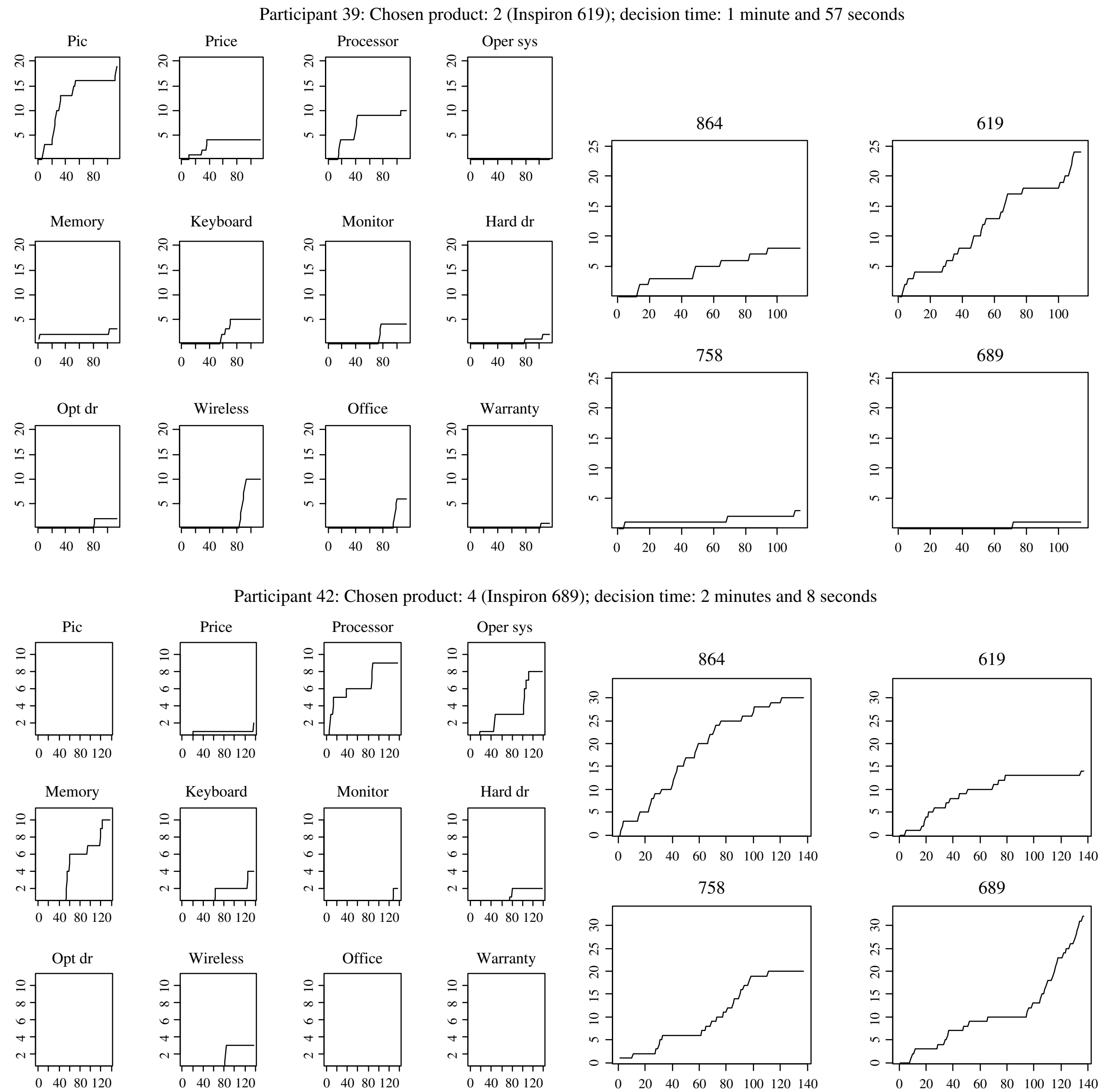
In both formats, participants do not examine all products until about halfway through the decision process. The increase in the number of attributes inspected with increasing decision time is close to linear, with around half of the attributes (51% in the vertical and 46% in the horizontal condition) inspected halfway through. However, interestingly, about one-fifth of the attributes (25% in the horizontal condition and 17% in the vertical condition) are never inspected. Both the number of attributes and the number of products inspected are lower in the horizontal than in the vertical condition. This selectivity in information acquisition may be due to information overload that limits the uptake of available information or due to the acquired information being experienced as sufficient to make a choice.

Next we show what specific product and attribute information consumers acquire over time, respectively, in the attribute-based and product-based acquisition states. For that purpose two representative participants for the vertical and for the horizontal conditions are selected by K-means clustering of participants based on their fixations on products and attributes and selecting the most central participant for each cluster. The cumulative numbers of fixations on products in the attribute-based state and on attributes in the product-based state are shown in Figures 4 (vertical condition) and 5 (horizontal condition), respectively. Although there is considerable heterogeneity between participants, four key insights can be obtained.

First, in many cases, some products seem to be taken out of consideration and receive no additional gaze after a certain point in time: the cumulative product fixations in the attribute-based state level off. This is even more so for the horizontal than for the vertical format. It is in line with theories of hybrid decision making (Bettman 1979). However, contrary to single-stage consideration set models (Howard and Sheth 1969), initially removed options were sometimes reconsidered later on in the decision process. Take product 3 (Inspiron 758) in the left bottom of Figure 4 as an example (participant 42, vertical condition). This product receives constant attention in the earlier stage of decision making (up to about 25 fixations), after which cumulative fixations level off while two or three products are compared. However, at a later stage of decision making (after a wait of about 60 fixations), this product (Inspiron 738) is being considered again, as reflected by increasing fixations from that point onward. It might be that product 3 is being "put on hold" while other alternatives are compared, or it is possible that this product is taken out of consideration at first and then is being reconsidered later. It seems that the consideration set changes over the entire time course of decision making. Indeed, the scope of the set shrinks and expands (between one and four, $SD = 1.10$). Thus, in contrast to theories postulating that after a certain time point options can only drop from consideration, our results reveal that options can flexibly leave and enter the set at different points in time.

Second, in the product-based acquisition state, attributes enter the decision process sequentially.

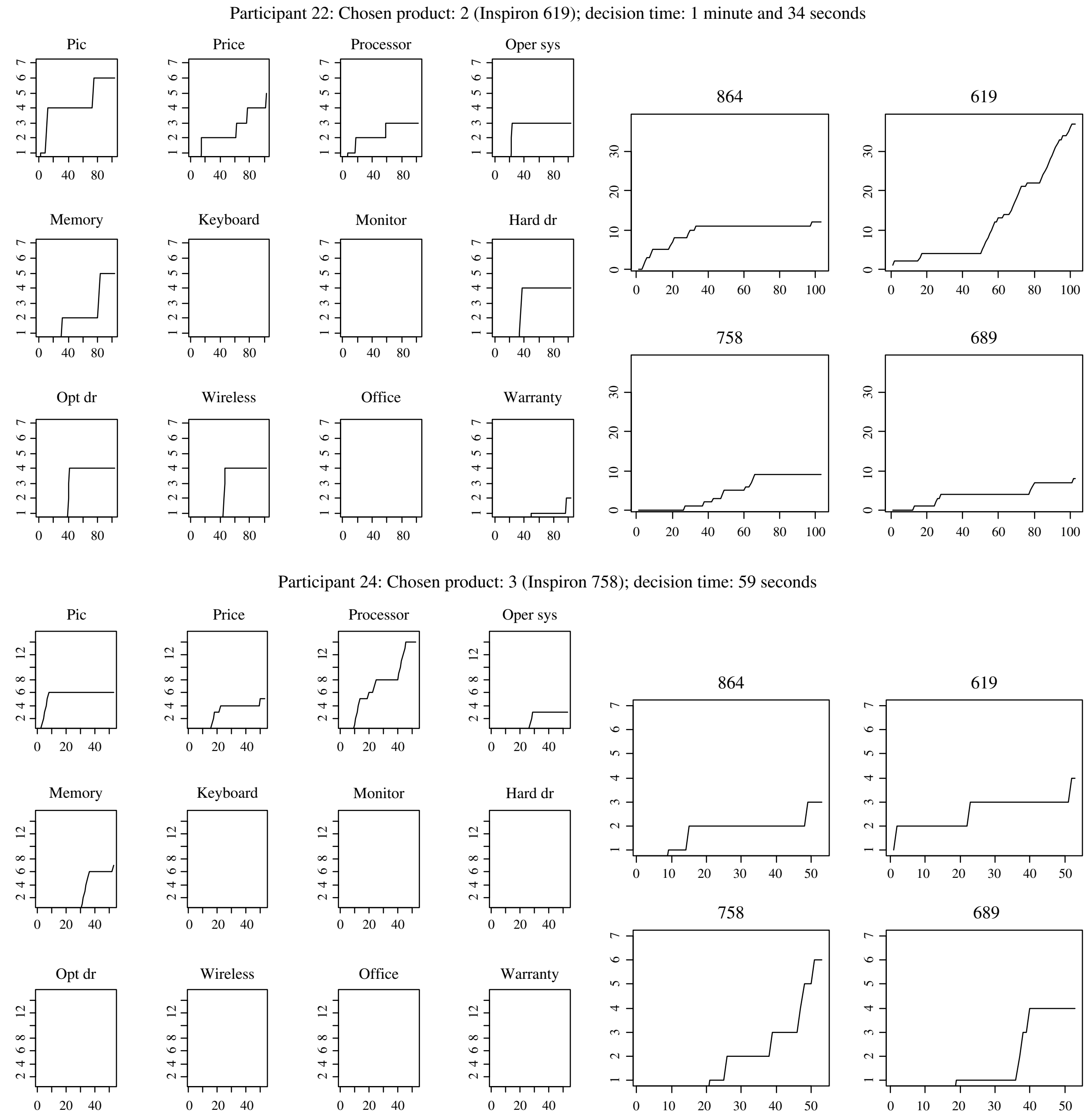
Figure 4 **Cumulative Numbers of Fixations on Attributes and on the Products for Two Participants in the Vertical Condition**



Notes. The small plots on the left show the cumulative number of saccades on the same attribute (y-axis) while in the product-based state. This shows how over time (x-axis, in fixation number) fixations on each attribute accumulate and when the first and last times are that the attribute is looked at. The large plots on the right show how saccades on each of the products accumulate over time and when the product is first and last considered. Increased fixations toward the end provide evidence of a gaze cascade on the chosen alternative.

Many are considered only once. An example is in the top left part of Figure 5 (participant 22, horizontal condition). After looking at the product picture, attributes enter the decision process in the sequence "processor," "price," "operating system," "memory," "hard drive," "optical drive," "wireless," and "warranty." Only "price" seems to be considered continuously during the entire decision process. This participant chose product 2 (Inspiron 619), which has the lowest price among all alternatives. The temporal sequence of the selection of attributes may reflect their relative importance to the decision goal at hand (Bettman et al. 1998, Wedell and Senter 1997). It seems that for each of the representative participants, a fair number of attributes is not considered at all, which is the case for the attributes "keyboard," "monitor," "hard drive," "optical drive," "wireless," "office software," and "warranty," in the example of

Figure 5 **Cumulative Numbers of Fixations on Attributes and on Products for Two Participants in the Horizontal Condition**



Notes. The small plots on the left show the cumulative number of saccades on the same attribute (y-axis) while in the product-based state. This shows how over time (x-axis, in fixation number) fixations on each attribute accumulate and when the first and last times are that the attribute is looked at. The large plots on the right show how saccades on each of the products accumulate over time and when the product is first and last considered. Increased fixations toward the end provide evidence of a gaze cascade on the chosen alternative.

participant 24 in the horizontal condition (Figure 5). Indeed, this seems to be the case even more in the horizontal than in the vertical condition.

Third, regularly, attributes and products that have been rejected earlier are briefly revisited in the final stage of the decision process. Take, for example, participant 24 (horizontal condition), depicted in Figure 5. The attributes "price," "processor," and "memory" receive a sudden burst of attention at the end of the decision process, as do the options 1 (Inspiron 864), 2 (Inspiron 619), and 3 (Inspiron 758). This may reflect the final verification of the option (Inspiron 864 and Inspiron 619) to which the participant has committed (Inspiron 758; Russo and Leclerc 1994, Russo and Rosen 1975). Some attributes appear to be exclusively used in this final stage of the decision, for example participant 22 in Figure 5 (horizontal condition) only uses "price," "memory," and "warranty" in the final stage of the decision.

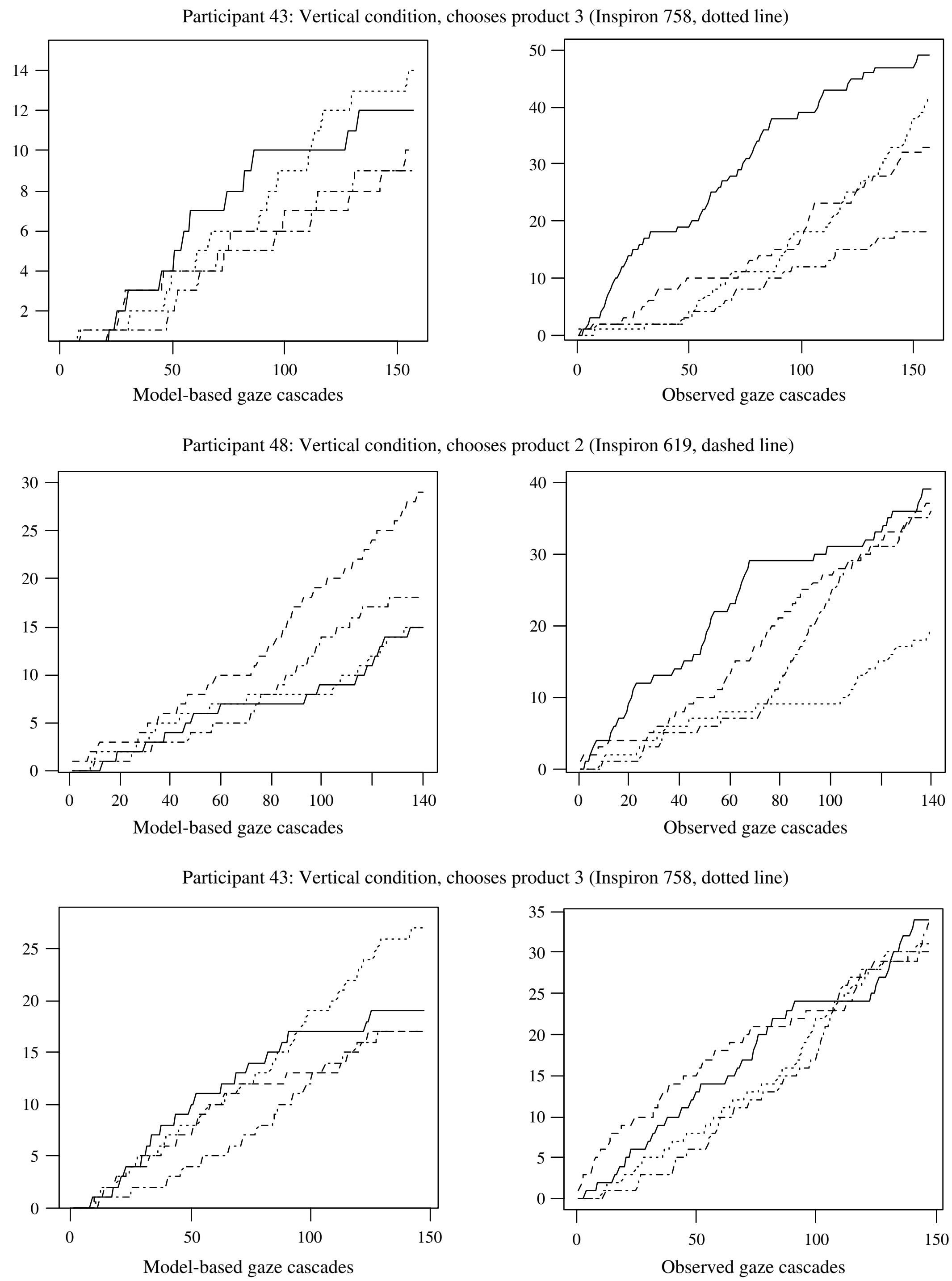
Finally, in the majority of the cases there is a clear predecisional acceleration of gaze on the chosen alternative toward the end of the decision, in the attribute-based state. A good example is in Figure 4, participant 39, where in each case the chosen alternative 2 reveals a gaze cascade, but in fact, all participants shown in Figures 4 and 5 exhibit a gaze cascade on the chosen alternative. Our results generalize the previously found gaze cascade (Glaholt and Reingold 2009, Pieters and Warlop 1999, Shimojo et al. 2003) to situations with more than two alternatives and to attribute-by-product presentations. Importantly, in the raw data the gaze cascade is often not visible from the cumulative saccades on the chosen product (i.e., there is no predecisional acceleration on the chosen alternative; see Table 1). Yet in many of these cases, the model-based estimates of cumulative saccades on the chosen product in the attribute-based state do reveal such a cascade. Figure 6 illustrates this for selected participants. The left panel shows the model-based estimates; the right panel shows those obtained from the raw data. The estimates derived from our model show that for the vertical (horizontal) format, 56.33% (55.25%) of the participants has the last two saccades on the chosen alternative. Those percentages are 34.85% (35.39%) and 25.10% (22.63%) for the last three and four fixations. Note that these are conservative estimates because refixations are removed before analysis. In particular for the last two eye movements, the model-based estimates are considerably higher than those for the raw data reported in Table 1 (40.82% and 40.68% for the vertical and horizontal formats). Thus, our model shows that the gaze cascade occurs in the last moments of the decision when participants compare the product that ends up being chosen to other products on one or more attributes. These results attest to the ability of our model to generate new insights into the gaze cascade on product-attribute matrices.

4. Discussion

High-frequency eye-movement data hold much promise in providing new answers to longstanding questions about constructive information acquisition, decision making, and choice processes that consumers engage in. Decision theorists have extolled the unique insights that eye tracking can provide on these issues (Lohse and Johnson 1996, Schulte-Mecklenbeck et al. 2011), but data collection used to be cumbersome and expensive. In recent years, affordable and easy to use eye-tracking equipment has become widely available. With these developments, the challenge has shifted from collecting eye-tracking data to describing the large volumes of data that eye-tracking studies produce in a meaningful manner. For this purpose, the proposed hierarchical hidden Markov model can help. The model can disentangle eye movements (lower layer) from information acquisition processes (middle layer), and from the higher-order mechanisms (upper layer), such as goals, that give rise to them. The proposed approach uses data about eye saccades between cells of the information display as input and does not include, as a source of information refixations on the same cell (reflecting reading of the cell's content, among others) or the duration of fixations (reflecting inspection of text and pictorial information, among others), which we think is an important task for future research (Feng 2009).

The present study applied the HHMM to eye-tracking data to describe moment-to-moment information acquisition on product-by-attribute matrices. This revealed that participants switched very frequently between product-based and attribute-based acquisition states: 48 times during the 67 seconds that a decision took, on average. This high degree of switching during real-life decision making has not been documented previously. Before switching, participants limited their attention to about three attributes for a single product or to two products for a single attribute. This might be due to limits on the amount of information that can be processed in working memory at a particular point in time (Cowan 2001) or the restricted rate at which this information can be consolidated in long-term memory (Marois and Ivanoff 2005). The amount of information already collected on attributes induces switching away from the product-based mode, and the amount of information on products induces switching away from the attribute-based mode. Instead of sequentially adopting attribute-based acquisition to eliminate alternatives followed by product-based acquisition, participants appear to sample "parcels" of mostly contiguous attribute and product information. The upper-layer states of our model capture how consumers flexibly switch between these mostly local product- and attribute-based information acquisition strategies. Tentatively, it is reasonable to expect that these upper-layer states reflect the effects of consumers' moment-to-moment trade-offs between various decision goals, such as accuracy, effort, and verification (Bettman et al. 1998). However, more precise inferences on the cognitive states that are reflected in the upper-layer states await further research. Such research might, for instance, explicitly manipulate the importance of accuracy versus effort goals and examine their influence on the middle- and upper-layer states of the proposed model.

Figure 6 **Model-Based (Cumulative Number of Fixations on Products While Being in the Attribute-Based State) and Observed Gaze Cascade (Raw Data, Cumulative Number of Fixations on Products) for Three Selected Respondents**



Notes. Product 1: solid line; product 2: dashed line: product 3: dotted line; product 4: dot-dash line. *x*-axis: fixation number; *y*-axis: cumulative number of fixations.

The high frequency of switching revealed in this study casts doubt on whether "attribute-based" and "product-based" information acquisition are necessarily conscious and deliberate strategies. Rather, low-level eye-movement tendencies that could not be incorporated in previous accounts of decision making appear to play an important role. Over-learned and largely unconscious routines may govern in situations of information overload and time pressure (Lee and Lee 2004, Pieters and Warlop 1999). Such situations are common when choosing in Web-based environments.

The present study documents a strong left-to-right tendency in the eye movements that remains even if the orientation of the display is changed. This may make it appear as if there is a dominant "product-based" or "attribute-based" strategy of processing, depending on whether the orientation of the matrix display has products or attributes in the rows. However, left-to-right eye movements result from a visual field that is wider in the horizontal direction because the resolution of the retina declines more rapidly in the vertical than in the horizontal direction (Gilchrist and Harvey 2006). Moreover, especially in online product-attribute displays, information consists mostly of text. Thus, to read and absorb that textual information within each cell of the comparison matrix, horizontal eye movements are needed (Rayner 1998). Although we have removed refixations within the same cell to minimize the impact of reading, tendencies to read still may facilitate left-right reading-like patterns even between cells of the comparison matrix and induce left-right patterns of saccades.

In line with previous accounts (Liechty et al. 2003), we found information acquisition to be predominantly local, confined to adjacent cells on the display. This may be caused by the limited visual detail that people can acquire beyond the immediate eye fixation point, particularly in the case of textual and numerical information (Rayner 1998) that dominates comparison websites. This tendency is stronger for the attributes than for products and stronger when attributes are presented row-wise. In our study the presentation format appears to impact the way that information is acquired because when the format changes, several of the low-level eye-movement tendencies (left-right, local) do not. If eye-movement patterns stay the same when the information display changes, then this causes different information to be extracted and different decisions to be made. This may make information acquisition and decision making seem adaptive when in fact they are not. Because the evidence from our study is indicative but not conclusive, we believe that this is an important issue to address in further studies.

The use of our model to analyze eye-tracking data yielded insights that contribute to a growing stream of research on the gaze cascade (Glaholt and Reingold 2009, Pieters and Warlop 1999, Shimojo et al. 2003). The end of the decision process reveals a predecisional gaze bias that reflects a cascaded process of preference formation and is predictive of the final choice. Whereas previous research on the gaze cascade has mostly been done for binary choice tasks and with products that are presented in a holistic manner, our research has confirmed the gaze cascade on multialternative choice tasks and product-attribute displays. Our analysis revealed that the model-based estimates of the gaze cascade are stronger and show that it occurs mostly while participants process information by attribute. That is, the gaze cascade reflects that participants make saccades on multiple products for the same attribute. Thus, the gaze cascade primarily occurs in the stage of the decision process that has been called verification by Russo and Leclerc (1994). Indeed, Willemsen et al. (2011) show that as soon as one of the choice alternatives becomes the preferred one during the decision process, attention shifts to it, and it becomes the central basis for comparison. Such a comparison in the final stages of the decision, we conjecture, results in saccades back and forth to the preferred option. That comparison necessarily operates "by attribute" and will result in a cascade on the chosen alternative, which largely coincides with a verification stage.

Instead of purposely using attribute-based and product-based processes across longer sequences of eye fixations, participants tend to use local information acquisition and tend to make preferentially horizontal movements. Such tendencies provide opportunities for managers to strategically place product-attribute information to facilitate comparisons and to adopt specific presentation formats to encourage desired information acquisition processes. Comparison website providers can thus adopt display formats in a proactive fashion to stimulate consumers' use of specific information acquisition process favorable to their goals. For example, price-comparison websites currently often adopt a horizontal format. This favors product-based information acquisition and results in fewer local eye movements and fewer products and attributes being inspected. It increases switching between acquisition processes, which makes choice more difficult, and reduces the probability of choosing a dominating product. This may be in conflict with desirable price (attribute)-based information processing for these websites. Eye-tracking research has thus rightfully begun to play a key role in pretesting and improving alternative presentation formats in practice.

Comparison websites, the context chosen for the present research, are a relatively new shopping environment, yet rapidly increasing in popularity. We demonstrated the effects of the orientation of the website as a starting point for research in this area. With the advance of network engineering, comparison websites are now able to provide more and more extensive and dynamic product-attribute comparisons. Website designers therefore have increasing abilities to improve comparison website usability and may use the results of this and future studies to help induce information acquisition modes that are congruent with their goals. Our study has revealed spatial contiguity of information to be a particularly important factor. We hope it stimulates further research, which could include the influence of website design factors such as sorting (arranging the product order such that it reflects relative importance), grouping (placing similar or related elements close together), trimming (eliminating unnecessary information), and highlighting (visually accentuating important information through colors and shading).

The information-rich environments offered by the Internet pose serious challenges to consumers (Davenport and Beck 2001). Simon (1978) already argued that consumers' attention is a scarce resource in information acquisition and decision making: "a wealth of information creates a poverty of attention" (Simon 1971, p. 40). This is even more so the case now, and some argue that attention has become "the most valuable business currency" (Davenport and Beck 2001, p. 3). Payne and Venkatraman (2011, p. 224) point out that "understanding what drives selective attention in decision-making is one of the most critical tasks for a researcher," and Johnson et al. (2008) advocate more research that applies process data and models to document how decisions are actually made. The present study has done that in the context of decisions made on comparison websites. We believe that the results are of interest to various disciplines, and we hope that they inspire further eye-tracking studies to examine and formalize how consumers acquire and process information and make decisions in information-rich Web-based environments.

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