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How Information Availability Interacts with Visual Attention during Judgment and Decision Tasks

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ABSTRACT

Decisions in front of a supermarket shelf probably involve a mix of visually available information and associated memories—and interactions between those two. Several cognitive processes, such as decision making, search, and various judgments, are therefore likely to co-occur, and each process will influence visual attention. We conducted two eye-tracking experiments capturing parts of these features by having participants make either judgments or decisions concerning products that had been previously encoded. Half the time, participants made their choices with full information about the available products and half the time with crucial task-relevant information removed. By comparing participants' use of visual attention during decisions and search-based and memory-based judgments, we can better understand how visual attention is differently employed between tasks and how it depends on the visual environment. We found that participants' visual attention during decisions is sensitive to evaluations already made during encoding and strongly characterized by preferential looking to the options later to be chosen. When the task environment is rich enough, participants engage in advanced integrative visual behavior and improve their decision quality. In contrast, visual attention during judgments made on the same products reflects a search-like behavior when all information is available and a more focused type of visual behavior when information is removed. Our findings contribute not only to the literature on how visual attention is used during decision making but also to methodological questions concerning how to measure and identify task-specific features of visual attention in ecologically valid ways. Copyright © 2015 John Wiley & Sons, Ltd.

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KEY WORDS decision making; eye movements; preferential looking; transitions; visual attention; visual memory

INTRODUCTION

When we go to a complex environment like the supermarket to buy, for instance, jam, we engage in a multitude of interacting cognitive processes. First and foremost, a purchase is to be made. Purchasing decisions are often supported by visually available information displayed on the shelf or on the front and back of each package. Some product information, such as the brand, is available at a direct glance, while some, such as sugar content, requires search. Further, we will remember facts about the various jams and their locations from previous visits to the store. This information can also be used to guide the purchase. Decisions in front of a supermarket shelf appear to be influenced by visually available information, by associated memories, and by their interaction.

However, making decisions is not all we do in front of the supermarket shelf. We may also store information for future shopping trips, increase our understanding of the products on offer, or simply help a fellow consumer find the Fair Trade pasta. Such actions sometimes provide us with information relevant to an intended purchase and can be regarded as integral to the decision process. At other times, they will be unrelated to the decision at hand (cf. Gidlöf, Wallin, Dewhurst, & Holmqvist, 2013).

Regardless of the task, visual attention must be allocated to the environment in order to support decision and judgment processes. Hence, visual attention has become increasingly important for understanding the decision process (e.g., Glaholt & Reingold, 2009; Krajbich, Armel, & Rangel, 2010; Reisen, Hoffrage, & Mast, 2008; Russo & Leclerc, 1994; Shimojo, Simion, Shimojo, & Scheier, 2003; Schotter, Berry, McKenzie, & Rayner, 2010; Wedell & Senter, 1997). The supermarket example earlier reminds us of three important considerations for eye-tracking research into judgments and decision making. First, in natural settings, decision making is based not only on information available in the visual environment but also on previous memories of that environment. Second, cognitive processes such as decision making, search, and various judgments are likely to co-occur, especially in natural settings, and each process will have its own impact on visual attention. Third, because of the previous considerations, visual attention is not necessarily related to the decision at hand, and the items inspected will not be the only ones affecting the decision.

To understand how visual attention might aid and reflect decisions in natural environments, these three considerations must be tackled head on. The present study aims to investigate how visual attention supports decisions in pre-encoded settings. Specifically, it targets the following two questions: (1) How is visual attention affected by information availability? (2) How does the effect of information availability on visual attention change depending on the task?

To answer these questions, we conducted an eye-tracking study where participants were asked to make decisions or judgments about previously encoded products. They sometimes faced a task environment where all previously encoded information was presented again, and sometimes one where task-relevant attribute information was absent.

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Visual attention and decision making

Broadly speaking, visual attention can be understood to play at least one of two roles in decision making. First, visual attention can play the passive role of conveying new sensory input when decision-makers gather information about the options available. Second, visual attention can play an active role, directly influencing and supporting the decision process.

In decision research, the dominant view has long been that of visual attention as a passive information acquirer (for an overview, see Orquin & Mueller Loose, 2013). This view is present in pioneering process-tracing work, such as the information boards and MouseLab studies of Payne and colleagues (e.g., Payne, 1976; Payne, Bettman, & Johnson, 1988; Payne, Bettman, & Johnson, 1993). In these designs, attribute information is structured in matrices but hidden from the subjects until they place a mouse cursor over the relevant matrix cell. Because visual attention is closely associated with gaze, eye trackers were introduced as soon as they became affordable; however, the basic experimental design was unchanged. To take some recent examples, findings regarding differences in the allocation of visual attention have been used to test predictions of various models of risky choice (Fiedler & Glöckner, 2012; Glöckner & Herbold, 2011; Glöckner, Fiedler, Hochman, Ayal, & Hilbig, 2012; Su et al., 2013) and to evaluate decision strategies under certainty, especially in multi-attribute choice (Orquin & Mueller Loose, 2013).

Accumulating evidence suggests that visual attention also actively influences decisions. A prominent example is the gaze-cascade effect—the tendency to shift attention toward the option to be chosen immediately before making the choice (Fiedler & Glöckner, 2012; Glaholt & Reingold, 2009; Shimojo et al., 2003). Recent work has demonstrated that visual attention can affect the computation of the value ascribed to an object and hence also the likelihood that it will be chosen (Armel, Beaumel, & Rangel, 2008; Milosavljevic, Navalpakkam, Koch, & Rangel, 2012; Pärnamets et al., 2015). Similar conclusions can be drawn from computational models relating visual attention to consumer choice (Krajbich et al., 2010; Krajbich, Lu, Camerer, & Rangel, 2012). While more work is needed to fully understand the causal role of attention during choice, the mere possibility that attention may affect preferences—regardless of content—calls for caution when interpreting eye movements during decision making. Note, however, that the two roles of visual attention—passive information acquirer and active process carrier—are not necessarily orthogonal.

Memory and visually available information

When visual attention is seen as an active process carrier, previous memories associated with the decision task are of particular interest. The environment facing the jam buyer is more or less familiar to him or her, with respect both to what products are on offer and to where they are located on the shelf, and this is the case for most everyday decisions. When decision-makers are allowed to gradually learn to identify task-relevant information, they shift from saliency-driven (bottom-up) to utility-driven (top-down) allocation of visual attention (Orquin, Bagger, & Mueller Loose, 2013). Hence, studies of visual attention during decision making may yield different findings depending on whether the environment is familiar or not. Because process tracing has usually been performed on novel stimuli, we do not know enough about how memory processes affect visual attention in decision making (cf. Renkewitz & Jahn, 2012).

A growing body of research suggests that the reconstruction of previous events fundamentally relies on mental simulations reinstating sensorimotor processes that were active during the original event (for recent reviews, see Danker & Anderson, 2010; Kent & Lamberts, 2008). For instance, participants who first encode an arrangement of objects and are later asked to recall aspects of that arrangement while looking at a blank screen will spontaneously execute eye movements "to nothing" on the blank screen, which largely correspond to the original object arrangement (e.g., Altman, 2004; Johansson & Johansson, 2014; Spivey & Geng, 2001). Research using such a blank-screen design has demonstrated that eye-movement patterns typical of various decision making strategies remain when decision-relevant information is removed from the display and the decision is made strictly from memory (Jahn & Braatz, 2014; Renkewitz & Jahn, 2012; Scholz, von Helversen, & Rieskamp, 2015). In addition, compatibility of gaze positions between encoding and retrieval can increase the likelihood of successful remembering (Johansson & Johansson, 2014) and may trigger other associated memories (Platzer, Bröder, & Heck, 2014).

In sum, converging evidence shows that there is an interaction between visual attention, the visual environment, and previous memories associated with that environment. Because most real-life decisions involve previously encoded information, visual attention is likely to be affected by how it is used to aid mnemonic retrieval.

Relating visual attention to different cognitive processes

The multiple roles of visual attention pose a particular challenge to anyone wishing to study decision-making processes through eye tracking. In particular, how can we know whether attentional processes assumed to be reflected in gaze patterns correspond to decision making rather than to other cognitive processes, such as visual search or memory retrieval?

In general, any study of decision making through visual attention must acknowledge that several cognitive processes may explain the same data. For example, in a study by Russo and Leclerc (1994), it was suggested that re-fixations signal comparison of different options. However, re-fixations do not necessarily have this function. An item could also be reinspected because it was forgotten or because it was not fully encoded the first time around (Gilchrist & Harvey, 2000)—and this is increasingly likely in more visually complex environments. In a field study

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comparing a search task and a decision task, the visual-attention patterns were found to be very similar for the two tasks when the entire time spent in front of the supermarket shelf was considered (Gidlöf et al., 2013).

When the decision tasks used approximate the real world more closely, the various roles of visual attention must be taken into account. One approach is to compare how visual attention is employed during different tasks with varying amounts of information available to the decision-maker. Such a contrastive method allows comparisons across tasks, potentially leading to the identification of stable patterns in the use of visual attention to support decisions and judgments. By identifying similarities in how visual attention supports these different processes, we can constrain interpretations of visual-attention and decision-making studies. This is especially important for the external validity of such studies.

EXPERIMENT 1

The present study aims to investigate how visual attention to products is employed differently during a decision task and a judgment task and how visual attention during those two tasks depends on the visual availability of task-relevant information. We conducted an eye-tracking experiment where participants were asked either to decide which out of three—previously encoded—products they would buy or to judge an attribute of those products, for example, identifying the jam with the lowest sugar content.

During their decisions and judgments, participants sometimes faced a task environment containing all the information required to solve the task and sometimes a task environment in which the relevant attribute information was absent. We could thus compare how visual attention is employed during decisions and judgments, made for the same products and attributes, with and without visual access to relevant information. The judgment task without access to that information is equivalent to a memory task requiring the retrieval of at least three attribute values. In contrast, the judgment task with all relevant information available is basically a visual-search task where the task environment is scanned for the correct response. Both memory retrieval and search are common uses for visual attention in many real-life decision situations, meaning that the present study allows those processes to be contrasted with the potentially more complex information integration involved in decision making.

To control for participants' prior exposure to products and the decision environment, and to ensure comparability across tasks, the study was conducted in a lab setting. To ensure that the combinations of attribute values were realistic, the products presented to participants existed but could hardly be recognized as belonging to a particular brand based on the attributes concerned.

METHOD

Participants

A total of 63 participants volunteered to take part in a "study on consumer decision making" in exchange for a cinema voucher. Five participants were removed owing to data loss in the eye-movement data collected, leaving 58 participants (18 male, 40 female) with an average age of 23.5 (standard deviation [SD] = 5.4).

Stimulus material and equipment

The participants' eye movements were recorded using SMI RED-m eye trackers (Teltow, Germany) recording binocularly at 120 Hz. Data were recorded with the I View X 2.2 software (SensoMotoric Instruments, Teltow, Germany) following five-point calibration plus validation. The average measured accuracy during calibration was below an error of 0.5° both vertically and horizontally (calibration points with an error over 1° were never accepted but prompted recalibration). The stimulus material was presented using PsychoPhysics toolbox 3 (Kleiner, Brainard, & Pelli, 2007) for MATLAB 8.0 (The MathWorks Inc., Natick, MA, USA, 2012) on a 19″ screen running at a resolution of 1680 × 1050 pixels. The participants responded using the keyboard.

Forty choice sets were constructed, each consisting of three products (belonging to one of nine product categories) sampled from existing ranges in local supermarkets. The product categories were chosen among foodstuffs and consumer goods, where a large variety of attributes with different values could be found (Appendix). Each individual product was characterized by three numerical attributes. One was always price, and the other two were ones considered typical of the product yet exhibiting sufficient variation. For example, fruit content (%) and sugar content (%) were the two additional attributes used for the product category of jam. To ensure that all potential judgment tasks were solvable, each numerical value of an attribute had to differ from the other two, so that it would always be possible to rank the products on each attribute. Additionally, half of the choice sets were constructed to have a negative inter-attribute correlation ($M = -0.387$, $SD = 0.067$) and the other half to have a positive inter-attribute correlation ($M = 0.629$, $SD = 0.179$).

Procedure and design

The participants were brought to the experiment room and informed that their eye movements would be monitored while they were choosing between three different options on the screen. Detailed written instructions were given on-screen, and two practice trials were run—one decision trial and one judgment trial. Then the participants could ask questions about the experimental procedure and task. Finally, the eye tracker was calibrated, and the experiment started.

This was a forced-choice experiment consisting of 40 trials, with the choice sets presented in random order. Each trial started with a preview screen where the product category and its three attributes were presented. This was always followed by two distinct phases: an encoding phase and a task phase. During the encoding phase, the participants were shown a display with three abstract representations of products belonging to the same category (e.g., jam) for 15 seconds. Each representation was a table consisting of three rows and two columns showing three attribute names (e.g., price,

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sugar content, and fruit content) and the corresponding values. The tables were not adjacent in the manner of an information board, but spatially separate (Figure 1).

After each encoding phase, participants were given either a decision task or a judgment task. In the decision tasks, they were asked "Which of the three products would you want to buy?" In the judgment tasks, they were asked a question about one of the attributes, for example, "Which of the three products has the lowest sugar content?" The judgment questions were constructed randomly during each judgment trial, meaning that they were equally likely to refer to each of the three attributes and to each of the three relative positions (lowest, middle, highest). The task phase was self-paced, and the participants gave their answers by pressing keys corresponding to the three options shown on the screen (the left, down, and right arrow keys).

During the task phase, participants completed, in random order, half of the trials facing a full display and half of the trials facing an empty display (20 decision tasks and 20 judgment tasks, equally distributed across full and empty display conditions). During a full-display trial, the same information was present as during the encoding phase. During an empty-display trial, the product and attribute names were still visible, but the values (necessary for solving the task) were blanked out. See Figure 1 for graphical representations of the experimental procedure and design.

Once participants had made their choice in a trial, they were asked to estimate their confidence in the decision on a scale from 1 to 8. Finally, when all 40 trials had been completed, the participants were asked to rate how important each attribute of each product category was to them, also on a scale from 1 to 8. After the experiment, the participants were debriefed, given the opportunity to ask follow-up questions, signed informed-consent forms, were given their cinema voucher and left.

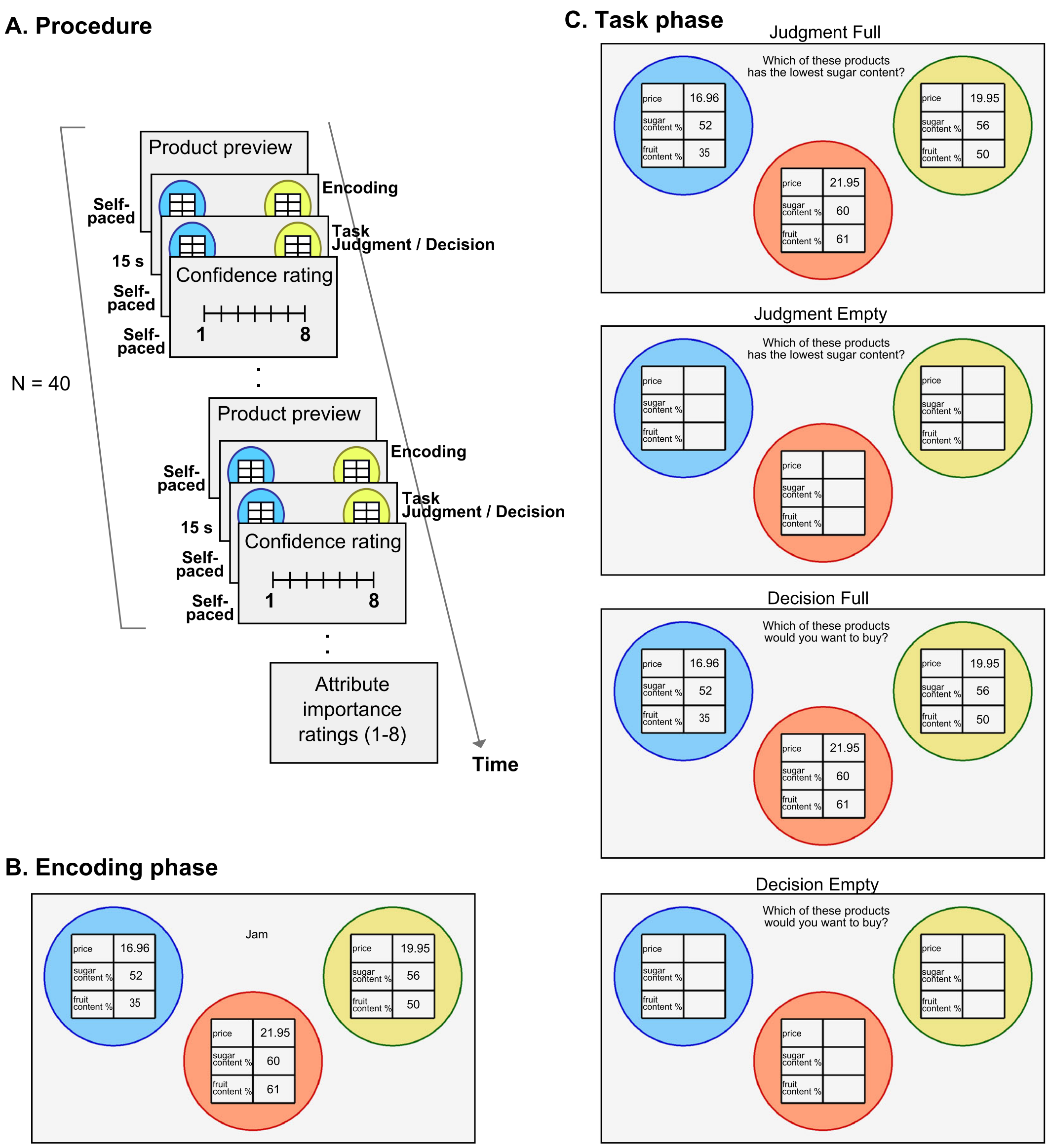

Figure 1. (A) Overall procedure of the experiment. (B) Example of a display during the encoding phase where the product category is jam and the attributes are price, fruit content (%), and sugar content (%). (C) Examples of all four possible conditions in the task phase

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Measures and analyses

To investigate visual attention to options, we primarily used two broad classes of measurements: gaze transitions between and within options and preferential looking.

Between-option transitions are commonly used to measure overall use of the task environment and scanning behavior (both related to search; cf. Rayner, 1998), whereas within-option transitions have been argued to reflect information integration and have been taken as indicative of compensatory decision strategies such as weighted additive rules (Fiedler & Glöckner, 2012; Payne, 1976; Renkewitz & Jahn, 2012). Transitions between options were defined as eye movements launched into one of the option areas from a position outside that option area; the three option areas were defined as the areas inside the differently colored circles surrounding the tables (Figure 1). Transitions within options were defined as eye movements launched from one of the three attribute areas within an option area into one of the other attribute areas in that option area; an attribute area was defined as the rectangular area comprising both an attribute name and the corresponding value (Figure 1). Because response times varied across trials in the task phase, gazetransition frequency (which is typically related to the effort needed to process information (Holmqvist et al., 2011, pp. 422–425)) was also analyzed, for both between-option and within-option transitions. Gaze-transition frequency was defined as the number of transitions per second.

The level of preferential looking was defined as the total duration of fixations (gaze dwell time) inside the option area of the option chosen as a percentage of the total duration of fixations inside all three option areas. Comparison of the values for the three option areas provides a rough indication of the extent to which the chosen option dominated the competition for visual attention. To obtain a more detailed picture, we also considered the time course of fixations on the chosen option. This equals a gaze-likelihood analysis, which indicates when participants identified their preferred option and thus serves as a window onto the evolution of visual attention within the cognitive process (Shimojo et al., 2003; Tanenhaus, Spivey-Knowlton, Eberhardt, & Sedivy, 1995). However, because of the variation in trial duration, it is difficult to make outright comparisons of trajectories in the different conditions. To circumvent this, we defined a window of analysis in terms of objective events in the experiment. Two such events can be readily defined for each trial: its onset and its termination (i.e., the time of the participant's response). Following existing practices (Shimojo et al., 2003), we chose a window of analysis corresponding to the 35th percentile of the total response time. This ensured that there were data to populate the entire analysis window in a large portion of cases (65%), but it should be noted that comparisons are more reliable closer to the point of alignment (outset/termination).

To assess the quality of decisions, we constructed a measure based on multi-attribute utility theory (Keeney & Raiffa, 1993), which recommends using the sum of the weighted attribute values. To calculate, this we first normalized, for each set of three options, the attribute values by the maximum value for that attribute. For attributes such as price, where lower values represent higher utility, the normalized values were multiplied by negative one. Each participant's importance ratings for the different attributes were multiplied by the normalized values and summed for each option. The option with the highest calculated value in that set of three was defined as the "optimal" choice for that participant.

All analyses were conducted within subjects and, except for the time-course analysis of preferential looking (see the succeeding text), using paired-samples *t*-tests and repeated-measures analyses of variance with display (full versus empty) and task (decision versus judgment) as within-subject factors. Where appropriate, post hoc tests were conducted using paired-samples *t*-tests with an alpha level of .05 and adjusted for multiple comparisons using the Bonferroni–Holm method (Holm, 1979).

To analyze the trajectories yielded by the gaze-likelihood analysis, growth-curve analysis was used (Mirman, 2014). This is a multilevel regression approach designed to assess differences in trajectories over time. We used orthogonal time polynomials (linear, quadratic, cubic) fit to all subject and condition combinations (within-subject averaged). The use of orthogonal time polynomials makes the time terms independent of each other. Compared with using regular polynomial time terms in the regression, such as time-squared, this has the advantage of accounting for the correlation between time terms, leading to a more powerful analysis. It also facilitates the interpretation of time-term coefficients. Linear terms in the regression can be interpreted as giving the slope of the curve, while quadratic terms indicate the degree of curvature. Cubic and higher order terms give points of inflection. Further, orthogonal time terms also have the useful property of centering the intercept, making it equivalent to the average value in the window of analysis.

RESULTS AND DISCUSSION

General measures of performance

To assess the validity of our manipulations, we calculated the proportions of correct judgments and optimal decisions for the full and empty display conditions. We also compared response times and participants' overall confidence in their responses. See Table 1 and details in the succeeding text.

Correct judgments and optimal decisions

The participants made significantly more correct judgments when facing a full display than when facing an empty display, $t(57) = 12.26$, $p < .001$, $d = 2.1$ (Table 1). The average difference between conditions within each participant was 30.7% ($SD = 6.1$).

Likewise, participants made more optimal decisions when facing a full display than when facing an empty display, $t(57) = -3.52$, $p < .001$, $d = 0.5$ (Table 1). The average difference between conditions within each participant was 8.8% ($SD = 6.1$).

Taken together, these results show that removing information during the task phase (empty condition) significantly lowers performance. The decrease in performance appears

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Table 1. Mean values for the proportion of correct judgments, the proportion of optimal decisions, response time, and confidence ratings in experiments 1 and 2, with standard deviations within brackets

Experiment	Condition	Correct option (%)	Optimal option (%)	Response time (second)	Confidence
1	Full display Judgment	89.6 (4.0)	–	5.6 (3.7)	7.5 (1.2)
	Full display Decision	–	61.7 (6.4)	5.6 (6.9)	7.0 (1.2)
	Empty display Judgment	58.9 (6.5)	–	4.6 (2.6)	4.8 (2.3)
	Empty display Decision	–	52.9 (6.6)	2.4 (1.9)	6.1 (2.0)
2	Full display Judgment	91.3 (3.7)	–	5.8 (5.3)	7.4 (1.2)
	Full display Decision	–	65.9 (7.8)	6.0 (6.7)	6.9 (1.4)
	Empty display Judgment	58.2 (6.5)	–	4.9 (2.9)	4.8 (2.3)
	Empty display Decision	–	59.1 (8.1)	2.8 (2.4)	6.0 (2.3)

to be larger for judgments, indicating that they rely more on the visual environment than decisions do.

Response times

The response times were log-transformed prior to the statistical analysis. There were significant main effects of task, $F(1, 57) = 144.17$, $p < .001$, $\eta^2 = .29$, indicating longer overall response times for judgments, and of display, $F(1, 57) = 164.79$, $p < .001$, $\eta^2 = .25$, with longer overall response times for full displays. There was also a significant interaction between task and display, $F(1, 57) = 52.20$, $p < .001$, $\eta^2 = .07$ (Table 1).

Post hoc tests revealed significant differences between all trial types except decisions and judgments with a full display. Participants' responses take longer when they face an informative visual environment than when they face an uninformative one. This is particularly evident for the decision empty trials, where participants respond very quickly, again indicating less overall reliance on the visual environment.

Confidence ratings

The average confidence rating was 6.34 ($SD = 2.0$). A repeated-measures analysis of variance with display and task as factors showed significant main effects of display, $F(1, 57) = 346.93$, $p < .001$, $\eta^2 = .55$, and of task, $F(1, 57) = 24.03$, $p < .001$, $\eta^2 = .05$, with a significant interaction between the two factors, $F(1, 57) = 126.29$, $p < .001$, $\eta^2 = .24$ (Table 1).

Post hoc tests revealed significant pairwise differences between all combinations of display and task.

Transitions between options

The analysis of gaze transitions between options revealed a significant main effect of display, $F(1, 57) = 207.45$, $p < .001$, $\eta^2 = .78$, and a significant interaction between task and display, $F(1, 57) = 6.73$, $p < .05$, $\eta^2 = .11$. All comparisons between conditions were found to be significant during post hoc analysis, except between judgments and decisions in the full condition. Participants made frequent transitions during the full condition, for both judgments ($M = 5.34$, $SD = 1.5$) and decisions ($M = 5.68$, $SD = 2.6$), and fewer in the decision empty ($M = 2.91$, $SD = 1.2$) and judgment empty ($M = 2.43$, $SD = 1.1$) conditions (Figure 2).

The analysis of gaze-transition frequency between options revealed significant main effects of task, $F(1, 57) = 64.23$, $p < .001$, $\eta^2 = .53$, and display, $F(1, 57) = 21.27$, $p < .001$, $\eta^2 = .27$, and a significant interaction between task and display, $F(1, 57) = 66.59$, $p < .001$, $\eta^2 = .54$. Post hoc analyses revealed significant differences between all conditions except between decision full and decision empty. Decisions had the highest transition frequency (empty: $M = 1.13$, $SD = 0.4$; full: $M = 1.12$, $SD = 0.3$) with judgment full having a lower frequency ($M = 1.04$, $SD = 0.3$) and judgment empty the lowest ($M = 0.69$, $SD = 0.2$; Figure 2).

The larger number of transitions means that participants viewed the different products more times in the full condition than in the empty condition. This would seem to indicate that an information-poor visual environment directly influences how much participants spread their visual attention. However, if the uneven response times are taken into account using transition frequency, this conclusion must be qualified. In the judgment empty condition, participants made transitions between options at a much slower rate, which is the expected signature of gaze behavior associated with memory retrieval. By contrast, the decision empty condition has the highest overall transition frequency, suggesting rapid orientation toward a preferred option.

Transitions within options

The analysis of gaze transitions within options revealed significant main effects of task, $F(1, 57) = 19.13$, $p < .001$,

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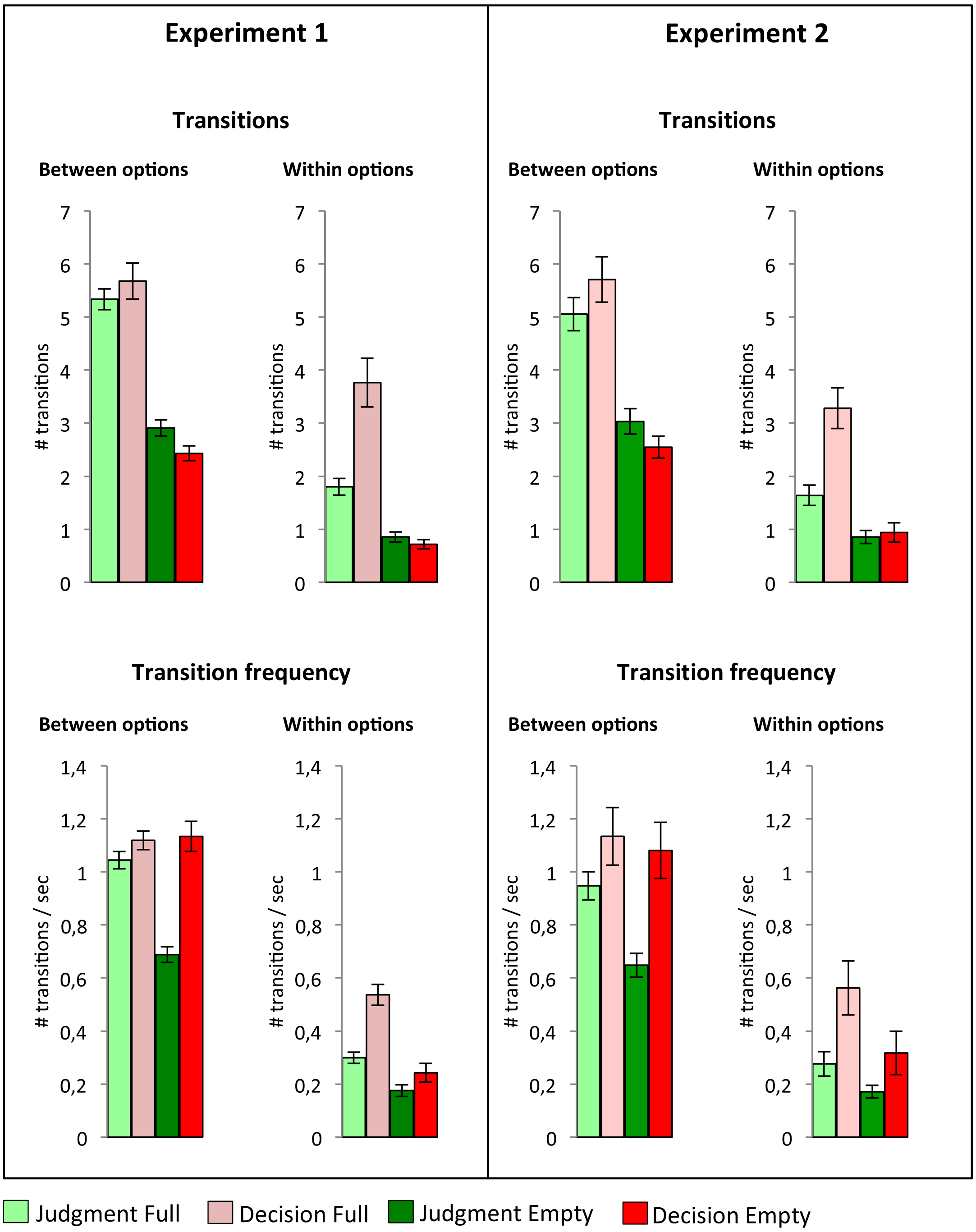

Figure 2. Mean numbers of transitions between and within options and mean frequencies of transitions between and within options, experiments 1 and 2. Error bars represent standard errors

$\eta^2 = .25$, and display, $F(1, 57) = 64.02$, $p < .001$, $\eta^2 = .53$, and a significant interaction between task and display, $F(1, 57) = 22.86$, $p < .001$, $\eta^2 = .29$. Post hoc analyses revealed significant differences between all conditions. Participants made the most transitions in the full condition, with more during decisions ($M = 3.76$, $SD = 3.5$) than during judgments ($M = 1.80$, $SD = 1.2$). Overall, there were few within-option transitions in the empty conditions, with more during judgments ($M = 0.86$, $SD = 0.7$) than during decisions ($M = 0.72$, $SD = 0.7$; Figure 2).

The analysis of gaze-transition frequency within options revealed significant main effects of task, $F(1, 57) = 44.16$, $p < .001$, $\eta^2 = .44$, and display, $F(1, 57) = 93.692$, $p < .001$, $\eta^2 = .62$, and a significant interaction between task and display, $F(1, 57) = 25.447$, $p < .001$, $\eta^2 = .31$. Post hoc analyses revealed significant differences between all conditions, with the highest transition frequency found for the decision full condition ($M = 0.53$, $SD = 0.31$) followed by judgment full ($M = 0.29$, $SD = 0.17$). The empty conditions had lower transition frequencies; decisions ($M = 0.24$, $SD = 0.27$) had higher ones than judgments ($M = 0.17$, $SD = 0.24$; Figure 2).

The decision full condition stands out in the analysis of within-option transitions, with both a higher absolute number of transitions and a higher frequency. This may indicate that

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participants use more complex decision strategies in this condition, weighing attributes against each other. By contrast, participants do not seem to engage in such behavior in the decision empty condition. For judgments, within-option transitions are rare, as would be expected given that they concern single-attribute questions.

Preferential looking to chosen option

The analysis of preferential looking to the chosen option revealed significant main effects of task, $F(1, 57) = 86.43$, $p < .001$, $\eta^2 = .24$, and of display, $F(1, 57) = 89.34$, $p < .001$, $\eta^2 = .26$, as well as an interaction between task and display, $F(1, 57) = 4.26$, $p < .001$, $\eta^2 = .01$. The decision empty condition exhibited the highest level of preferential looking to the chosen option ($M = 0.72$, $SD = 0.3$), while judgment full had the lowest ($M = 0.46$, $SD = 0.2$). Post hoc analyses revealed significant differences between all four conditions except between decision full ($M = 0.61$, $SD = 0.3$) and judgment empty ($M = 0.61$, $SD = 0.3$).

Time course of preferential looking

To investigate the time course of preferential looking, we fit two models, one for each window of analysis (2500 milliseconds). We first fit a model to the fixation curves aligned to trial onset. We used a third-order (cubic) orthogonal polynomial of time with fixed effects of display and task (combined into a four-level variable; within-participants) on all time terms. The model also included participant and condition-by-participant interaction random effects on all time terms. The model fit to the data is plotted in Figure 3.

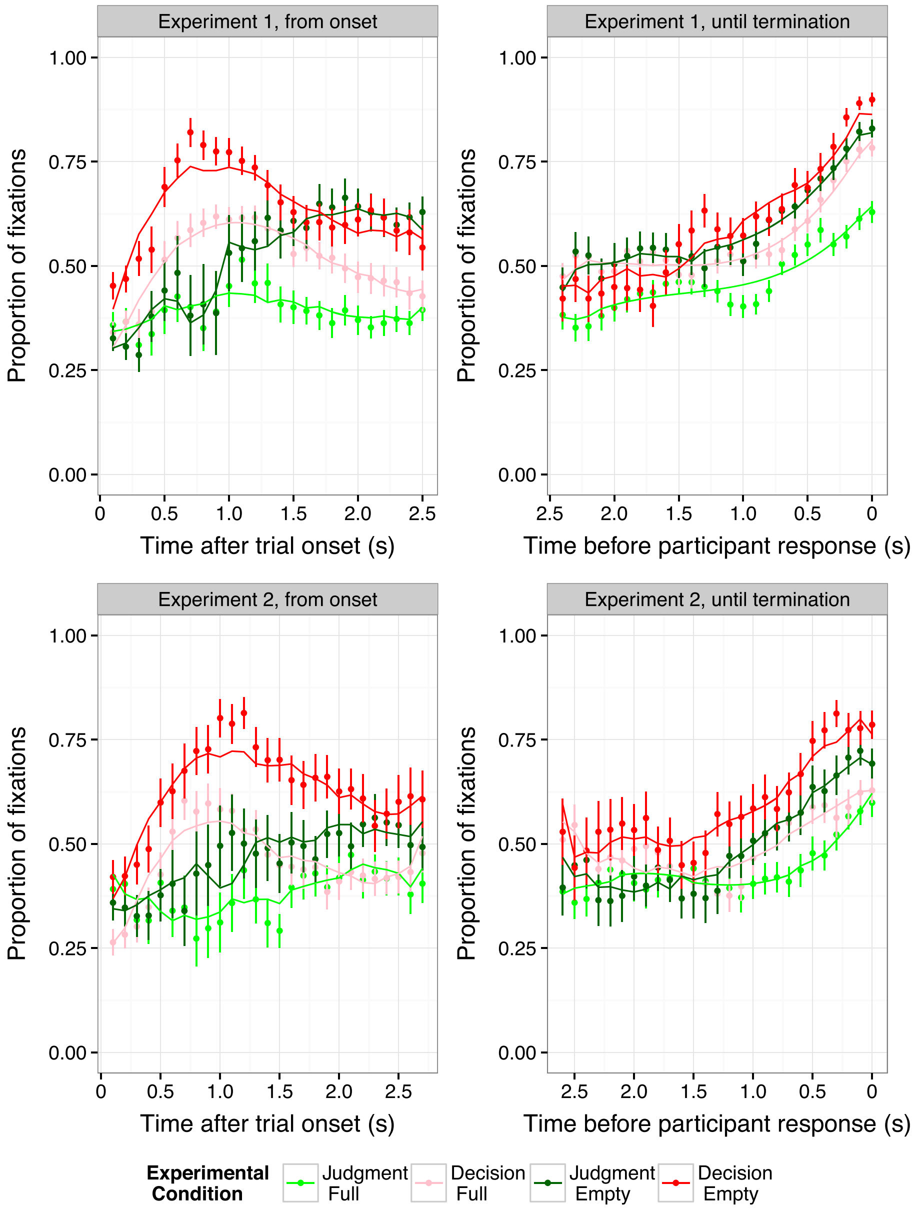

Figure 3. Time course of fixations to chosen option, by condition, plotted from onset of trial (left panels) and until participant response (right panels), experiments 1 and 2. Points represent empirical data in 100 milliseconds time bins. Error bars represent standard errors. Lines represent values from the growth-curve analysis

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The parameter estimates were relative to the judgment full condition, $b = 0.39$, standard error (SE) $= 0.022$, $p < .001$. Significant effects were found on the intercept terms for decision full, $b = 0.12$, $SE = 0.028$, $p < .001$, judgment empty, $b = 0.16$, $SE = 0.029$, $p < .001$, and decision empty, $b = 0.26$, $SE = 0.029$, $p < .001$. The intercept terms capture the difference in the overall proportion of fixations to the option later chosen in those three conditions compared with judgment full; the largest proportion was found for decision empty. There were significant effects on the linear term in the judgment empty condition, $b = 0.52$, $SE = 0.104$, $p < .001$. This term captures the gradually increasing likelihood of preferential looking over the duration of the analysis window. For decision full, $b = -0.28$, $SE = 0.098$, $p < .01$, and decision empty, $b = -0.24$, $SE = 0.100$, $p < 0.05$, both quadratic terms revealed similar, significant, estimates owing to their parabolic trajectories. There was also a significant effect on the cubic term in the decision empty condition, $b = 0.21$, $SE = 0.086$, $p < .05$, capturing the inflection in the parabolic trajectory from the sustained preferential looking in this condition throughout the time window. All other estimates were nonsignificant.

We also examined the time course during the last 2500 milliseconds of each trial, aligning the analysis window to the termination—participant response—rather than the onset of the trial. Once again, we fit a third-order orthogonal polynomial with the same fixed and random factors as in the model described in the preceding text. The data with the model fit are plotted in Figure 3. The parameter estimates were relative to the judgment full condition, $b = 0.47$, $SE = 0.017$, $p < .001$. The intercept terms were significant for decision full, $b = 0.10$, $SE = 0.022$, $p < .001$, judgment empty, $b = 0.13$, $SE = 0.023$, $p < .001$, and decision empty, $b = 0.13$, $SE = 0.023$, $p < .001$. Both empty conditions had similar overall levels of preferential looking during this window of analysis, higher than decision full. There was a significant effect on the linear term in the decision empty condition, $b = 0.36$, $SE = 0.104$, $p < .001$, while the quadratic term was significant for decision full, $b = 0.17$, $SE = 0.081$, $p < .05$. All other effects were nonsignificant. In general, the results from this second model are dominated by strong tendencies in participants to orient toward their chosen option prior to their response.

Taken together, these results confirm the findings from the analysis of preferential looking and further elucidate how visual attention is differently deployed over time. Both decision empty and decision full are characterized by strong initial preferential looking. For decision empty, this is sustained throughout the window of analysis, while in decision full trials, participants engage much earlier with the rest of the visual environment. However, caution is warranted when interpreting the results for the decision empty condition. Because many of the trials in this condition were considerably shorter than those in the other conditions, there is inevitably some overlap between the two windows. Part of the effect seen in the analysis window aligned to trial onset is likely due to participants not only orienting to a preferred option but also preparing to act on this preference.

Discussion

Experiment 1 indicates that changes in the availability of task-relevant information in the visual environment affect participants' behavior and visual attention differently in judgment tasks and decision tasks. In the full conditions, participants had similar response times and generally behaved as would be expected from someone making judgments and decisions with visually available task-relevant information; the judgment full condition amounts to a visual search for the correct answer, and the decision full condition is similar to results from classical process-tracing tasks.

When searching for the correct option in the judgment full condition, participants exhibited high transition frequencies between options, low transition frequencies within options, and a low degree of preferential looking until right before their moment of choice. In the decision full condition, by contrast, participants maintained a high transition frequency both between and within options. This is consistent with attribute-information integration (Payne, 1976; Renkewitz & Jahn, 2012) and replicates the findings of within-gamble transitions in eye-tracking studies of decisions under risk (e.g., Fiedler & Glöckner, 2012). Participants also exhibited a high degree of preferential looking, not only late in the trial but also unexpectedly, very early after trial onset. This novel finding is likely a result of our use of an encoding phase and suggests that partial evaluations of the options have already been made during encoding.

The empty condition induced marked behavioral differences, both between decisions and judgments in that condition and compared with the full condition.

In the judgment empty condition, participants exhibited low transition frequencies both between and within options. Together with the gradual increase in preferential looking over time, this is consistent with participants performing a slow search over the options, with visual attention playing an active role in recall (Johansson & Johansson, 2014). The overall shorter response times compared with the full conditions (both decision and judgment) may be due to the complexities of recalling and keeping attribute values in mind; resampling memory might introduce noise and uncertainty (Robinson, Johnson, & Herndon, 1997).

In the decision empty condition, participants responded decidedly faster than in any other condition and appeared to orient quickly toward their preferred option and respond. This is evidenced not only by the high overall degrees of preferential looking but also by its highly curved and inflected time course. However, we note that many of the trials in this condition were quite short; hence, in many cases, the analysis will reflect the full length of the trial. This highlights why we also need transition frequencies to interpret these trials correctly. That analysis showed high between-option and low within-option transition frequencies. This indicates that the information integration found in decision full is lacking from decision empty. It is possible that during decision tasks in pre-encoded environments, participants rely heavily on evaluations made during the encoding phase, using visual attention to aid recall of particular attribute values (or evaluations), as happens during judgment empty trials. When task-relevant information is present, as in

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decision full, participants reexamine options and attribute levels in order to calibrate their initial preference.

EXPERIMENT 2

The results from experiment 1 suggest that the allocation of visual attention is highly sensitive to the availability of task-relevant information in the visual environment and previous memories associated with that environment. However, one possible explanation of our findings could be that the differences observed in the results are attributable to the differences in the amount of visual input available between display conditions rather than in the amount of relevant information available. In reading research, it has been shown that the blanking out of text segments can have a large impact on when and where eye movements are launched (e.g., Yang & McConkie, 2001) and different degrees of visual crowding are known to heavily influence fixations and saccades during visual search tasks (e.g., Vlaskamp & Hooge, 2006).

To deal with this potential confound, we conducted a new experiment where, instead of blanking out the attribute values, we replaced them with equivalent but non-informative visual input. For example, an attribute value of "100" would now be replaced with "###". This manipulation thus keeps the amount of visual input constant across conditions.

METHOD

Apart from the new manipulation of information availability, experiment 2 was identical to experiment 1.

Participants

A total of 38 participants volunteered to take part in experiment 2 in exchange for a cinema ticket voucher. One participant was removed owing to data loss in the collected eye-movement data, leaving 37 participants (17 male, 20 female) with an average age of 26.9 ($SD = 9.1$).

RESULTS AND DISCUSSION

General measures of performance

To assess the validity of our manipulations, we analyzed the same general measures of performance as in experiment 1. See Table 1 and details in the succeeding text.

Correct judgments and optimal decisions

Participants made significantly more correct judgments when facing a full display than when facing an empty display, $t(36) = 10.17$, $p < .001$, $d = 2.05$ (Table 1). The average difference between conditions within each participant was 33.1% ($SD = 7.7$).

Participants made more optimal decisions when facing a full display than when facing an empty display, $t(36) = 1.85$, $p = .07$, $d = 0.37$ (Table 1). The average difference between conditions within each participant was 6.8% ($SD = 4.1$).

Response times and confidence ratings

The patterns of results were similar to those found for experiment 1; see Supporting Information for details.

Transitions between options

The analysis of gaze-transition frequency between options revealed significant main effects of task, $F(1, 36) = 18.78$, $p < .001$, $\eta^2 = .34$, and display, $F(1, 36) = 42.00$, $p < .001$, $\eta^2 = .54$, and a significant interaction between task and display, $F(1, 36) = 18.75$, $p < .001$, $\eta^2 = .34$. Post hoc analyses revealed significant differences between all conditions except between decision full ($M = 1.13$, $SD = 0.7$) and decision empty ($M = 1.08$, $SD = 0.6$) and between judgment full ($M = 0.95$, $SD = 0.3$) and decision empty. Judgment empty ($M = 0.65$, $SD = 0.3$) had the lowest transition frequencies (Figure 2); see Supporting Information for an analysis of the mean number of transitions.

Transitions within options

The analysis of gaze-transition frequency within options revealed significant main effects of task, $F(1, 36) = 14.00$, $p < .01$, $\eta^2 = .28$, and display, $F(1, 36) = 18.08$, $p < .001$, $\eta^2 = .33$, and a significant interaction between task and display, $F(1, 36) = 9.95$, $p < .01$, $\eta^2 = .22$. Post hoc analyses revealed significant differences between all conditions except between judgment full and decision empty. Decision full ($M = 0.56$, $SD = 0.6$) had the highest transition frequency, followed by decision empty ($M = 0.32$, $SD = 0.5$). Judgment full ($M = 0.28$, $SD = 0.3$) and judgment empty ($M = 0.17$, $SD = 0.2$) had lower transition frequencies (Figure 2); see Supporting Information for an analysis of the mean number of transitions.

Preferential looking to chosen option

The analysis of preferential looking to the chosen option revealed significant main effects of task, $F(1, 36) = 22.31$, $p < .001$, $\eta^2 = .11$, and of display, $F(1, 36) = 38.54$, $p < .001$, $\eta^2 = .17$, but no significant interaction between task and display, $F(1, 36) = 1.00$, $p = .32$, $\eta^2 = .004$. Decision empty had the highest proportion of preferential looking to the chosen option ($M = 0.67$, $SD = 0.3$), while judgment full had the lowest ($M = 0.45$, $SD = 0.3$). Post hoc analyses revealed significant differences between all four conditions except between decision full ($M = 0.53$, SD = 0.3) and judgment empty ($M = 0.54$, $SD = 0.3$).

Time course of preferential looking

To investigate the time course of preferential looking, we fit two models, the same as in experiment 1. The window of analysis was 2750 milliseconds because of longer overall response times in experiment 2. The model fit to the data is

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plotted in Figure 3. The overall patterns of results were similar to those found in experiment 1. See Supporting Information for details.

Discussion

All in all, experiment 2 replicates all the main findings of experiment 1, which indicates that the manner in which task-relevant information is removed from the environment does not considerably affect how visual attention is differently deployed. This provides evidence that visual attention plays a role over and above mere information acquisition in the tasks measured in experiments 1 and 2.

ENCODING PHASE—EXPLORATORY ANALYSIS

To better understand the results of experiments 1 and 2, we performed an exploratory analysis of some aspects of participants' visual behavior during the encoding phase. For this analysis, in light of the results of experiment 2, we combined the two data sets. We investigated whether there was any evidence of biased attention toward the option later to be chosen.

Preferential looking to option to be chosen

We analyzed participants' attention during the encoding phase to the option they would later choose using task and display as within-subject factors. The results indicated a significant main effect of task, $F(1, 93) = 70.26$, $p < .001$, $\eta^2 = .14$, while neither display, $F(1, 93) = 0.87$, $p = .35$, $\eta^2 = .002$, nor the interaction between task and display, $F(1, 93) = 0.04$, $p = .83$, $\eta^2 < .001$, reached significance. The proportion of attention directed to the option later to be chosen was highly similar in decision full ($M = 0.376$, $SD = 0.05$) and decision empty ($M = 0.372$, $SD = 0.06$) and larger than in both judgment full ($M = 0.335$, $SD = 0.05$) and judgment empty ($M = 0.330$, $SD = 0.05$). Post hoc analyses showed that all comparisons between decision and judgment conditions were significant, while no within-task comparisons reached statistical significance. We also analyzed visual attention over time (Supporting Information).

Differences in preferential looking by optimality of decisions

Finally, we investigated whether the amount of biased attention varied depending on whether the later choice was "optimal" to the participant or not. Four participants were removed from the analysis for having made no nonoptimal decisions. Using display and optimality as within-subject factors, we found a significant main effect of optimality, $F(1, 89) = 31.91$, $p < .001$, $\eta^2 = .09$, but there was no significant main effect of display, $F(1, 89) = 0.053$, $p = .82$, $\eta^2 < .001$, and no display–optimality interaction, $F(1, 89) = 0.12$, $p = .73$, $\eta^2 < .001$. The proportion of attention directed to the option to be chosen was large and similar during optimal choices in decision empty ($M = 0.393$, $SD = 0.08$) and decision full ($M = 0.389$, $SD = 0.07$). The proportion of attention was the same for nonoptimal decision empty ($M = 0.344$, $SD = 0.07$) and decision full ($M = 0.344$, $SD = 0.08$). Post hoc analyses showed significant differences in all pairwise comparisons between optimal and nonoptimal decisions, while no within-display differences were significant.

Discussion

The exploratory analysis of the encoding data from experiments 1 and 2 indicated that participants' visual attention is biased toward the option they will later choose. This finding might explain how participants can orient early toward their preferred option in the decision condition. This is consistent with models of decision making, suggesting that visual attention affects value computations underlying choice (cf. Krajbich et al., 2010). We also found that participants' bias during the encoding stage was stronger in those trials where they later made optimal decisions. By contrast, in trials where the decisions were nonoptimal, the proportion of attention toward the option later chosen was near chance. We found no differences in the size of bias between display conditions. Taken together, this suggests that, while participants are likely to be calculating which option is their best during the encoding phase, their ability to fully act on this is determined by their interaction with the task environment during the choice phase.

GENERAL DISCUSSION

In two experiments, we investigated how decision and judgment processes interact with the task environment through visual attention by manipulating the type of task (decision versus judgment) and the visual availability of task-relevant information (full versus empty).

The deployment of visual attention in judgment and decision tasks appears to be differentially sensitive to the amount of visually available task-relevant information. Interaction with task-relevant, visually available information increases performance but leads to longer response times. In a visually impoverished environment, participants react differently depending on the task type. During judgments, they attempt to compensate for the lack of task-relevant information and engage in a slow, attention-guided recall process. In decisions, they instead seem to rely on pre-encoded valuations that are quickly recalled and relatively efficiently stored. Participants appear to use their visual attention as an active process carrier above and beyond information acquisition.

Implications and future research

We consider the contrast between the decision full and decision empty conditions to be our most important finding. That participants' visual attention depends on early evaluations made in the encoding phase presents a challenge for the use of eye tracking to study preferential decisions based on memory. On the other hand, the generalizability of a study of visual attention without an encoding phase might be limited,

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given that most everyday decisions occur in familiar (and to some extent pre-encoded) environments.

An alternative interpretation of the results for the decision empty condition might be that some participants switch to a less cognitively demanding, non-compensatory decision strategy. However, this interpretation could apply only to participants in the right-hand side of the response-time distribution curve, because the small absolute number of between-option transitions and the short overall response times indicate that many participants only have time to attend to one option. An individual-differences approach might be used in future studies to expand our understanding of how decision-makers adapt to changes in the visual environment.

Computational modeling in future studies may help us disentangle the influence exerted on the final decision by visual attention to options in each phase. This may improve our understanding of how encoding and task phases support decisions. Likewise, additional task constraints may open up further routes to investigate the degree to which participants rely on pre-encoded valuations. For instance, it is possible to vary the relative proportion of judgment and decision tasks.

The contrast between judgments and decisions in the empty condition is intriguing. The judgment empty condition appeared to induce participants to use visual attention to support recall of attribute values. This was not the case in the decision empty condition, but even so, participants may have used visual attention to support spatial indexing, thereby facilitating recall of prior valuations. Because visual attention also supports and affects valuation directly (e.g., Krajbich et al., 2010, 2012), future work should investigate what role it plays here. This could be performed, for example, by introducing a central-fixation condition (Johansson & Johansson, 2014) or by changing the positions of the options between the encoding and task phases.

One limitation of the present study may be that the results reflect, to some extent, the all-or-nothing aspect of our manipulation. Hence, our results could be argued to be artifacts of removing all task-relevant information or none of it. In a real-world setting, it might be the case that some task-relevant information is easily visually available while other such information is only potentially available, for example because it is printed on the back of the package. In naturalistic settings, eye movements will always depend on several bottom-up and top-down factors (cf. Kowler, 2011). To fully disentangle the relationship between visual attention and information availability in decision tasks, additional experiments are needed where different degrees of actual task-relevant information can be manipulated and controlled for. One possibility is to remove only some of the attribute information. Another is to use a degraded font, making the information present but more difficult to access visually. Such further investigations were outside the scope of the present study; hence, the results reported should be cautiously interpreted.

Note, however, that this limitation applies only to the contrast between the full and empty conditions. The starkly different behavior of participants in the judgment empty and decision empty conditions highlights the importance of taking information availability and encoding seriously. This is particularly important for researchers interested in decisions from memory.

We conclude that, while the links between visual attention and decision making are both pervasive and robust, the exact role played by visual attention depends on the setup of the task environment and participants' previous interactions with it. Taking both of these factors into account is key to conducting research that is more likely to generalize to how decision-makers behave in the real world. It would be of great interest to learn more about how evaluations during encoding are formed and how they interact with later decisions. The combination of traditional process-tracing methods with computational modeling and environmental manipulations opens up new and exciting avenues for the study of both preference formation and decision making. These links certainly deserve to be explored further.

APPENDIX

Full list of choice sets. The columns represent product category, the three different attributes, the number of choice sets with positive (easy) or negative (difficult) inter-attribute correlations, and the number of unique options, that is, products, used to construct the choice sets for each product category.

Product category	Attribute 1	Attribute 2	Attribute 3	No. of choice sets ± inter-attribute corr.	No. of unique options
Hair dryer	Price (SEK)	Noise level (dB)	Heat (°C)	Difficult: 2 Easy: 4	9
MP3 player	Price	Weight (grams)	Battery time (hours)	Difficult: 2 Easy: 2	8
Mobile phone	Price	Storage capacity (GB)	Camera (Mpix)	Difficult: 2	6
Vacuum cleaner	Price	Power (W)	Noise level (dB)	Difficult: 4 Easy: 2	10
Muesli with dried fruit	Price per kilogram	Fruit content (%)	Sugar content (%)	Difficult: 2 Easy: 3	9
Electric toothbrush	Price	Price of replacement brush head	Frequency (strokes/minute)	Difficult: 2 Easy: 2	7
Coffee machine	Price	Brewing temperature (°C)	Brewing time (minutes)	Difficult: 2 Easy: 3	8
Jam	Price	Sugar content (%)	Fruit content (%)	Difficult: 2 Easy: 4	7
Yogurt	Price per liter	Sugar content (%)	Fruit content (%)	Difficult: 2	5

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