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Decision moving window: using interactive eye tracking to examine decision processes

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Abstract It has become increasingly more important for researchers to better capture the complexities of making a decision. To better measure cognitive processes such as attention during decision making, we introduce a new methodology: the *decision moving window*, which capitalizes on both mouse-tracing and eye-tracking methods. We demonstrate the effectiveness of this methodology in a probabilistic inferential decision task where we reliably measure attentional processing during decision making while allowing the person to determine how information is acquired. We outline the advantages of this methodological paradigm and how it can advance both decision-making research and the development of new metrics to capture cognitive processes in complex tasks.

Keywords Decision making · Attention · Methods · Eye tracking

Although some decisions can be quite simple and made effortlessly (e.g., choosing between cereal or toast for breakfast), oftentimes, decision making is more complex and requires cognitive resources in order to make a choice or judgment (e.g., deciding whether or not to purchase a house, change jobs during a recession, etc.).The complexities of decision making, especially the processes involved in making decisions, are often overlooked, and much of the focus remains on decision outcomes: *what* is chosen, rather than *how*. In part, this emphasis is a product of the traditional approaches of judgment and decision-making (JDM) research that have emphasized deviations from normative models or errors (see Goldstein & Hogarth, 1997, for a historical overview), and to some degree, it is an artifact of the methodological constraints on capturing the decision process, such as relying on the presentation of simple stimuli and deducing process from observable decision outcomes. The increasing theoretical interest in capturing the cognitive processes associated with decision making, rather than relying exclusively on the decision outcome (e.g., Busemeyer & Johnson, 2004; Glöckner & Betsch, 2008; Norman & Schulte-Mecklenbeck, 2010; Payne, Bettman, & Johnson, 1988, 1993; Thomas, Dougherty, Sprenger, & Haribson, 2008; see Weber & Johnson, 2009, for a review), has increased the need to provide new methodologies that can better capture decision processes.

The goal of this article is to introduce a new methodology that is a hybrid of two successfully established methods that will enable researchers to have another tool to capture cognitive processing during decision making. In the next section, we briefly outline the mouse-tracing paradigm used in decision research. Next, we discuss the theoretical and methodological advantages of the moving-window paradigm used in reading and scene perception research. We then introduce the *decision moving window*, which capitalizes on the theoretical and methodological advantages of both paradigms, and then apply it to a decision-making task.

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Mouse-tracing paradigm

The earliest works examining process-tracing methods in decision making used "information boards" and think-aloud protocols (e.g., Payne, 1976). The pioneering work of Payne et al. (1988, 1993) is considered one of the first modern attempts to understand the processes associated with decision making. Subsequent work by these investigators and others has modernized the process-tracing paradigm, using the computer mouse as a means to track the access of information by individuals as they deliberate to make a decision. In the typical paradigm, an information table is displayed on a computer screen, with individual cells corresponding to specific attribute values for a given option; these remain concealed unless the cursor is positioned over the cell. Therefore, in order to "acquire" information, one must position the cursor on the cell to reveal the corresponding information. The cursor position and duration in the cell are recorded over time to provide a measure of how the information was accessed en route to making a decision.

This approach allowed researchers to infer what information was "attended to" during the acquisition and deliberation processes involved in decision making by examining summary information, such as the total number of acquisitions (cells accessed) and the average amount of time spent looking at each piece of information. Although recent attempts have tried to parse mouse-tracing data into more meaningful units of analysis (e.g., Ball, 1997; Willemsen, Johnson, & Böckenholt, 2006), it still remains at a summary level, without specifying attentional processing beyond immediate cursor placements. More seriously, it is difficult to assess "attention" by simply recording how long the cursor rests in a given cell. Although mouse movements are likely correlated with selective attention in a cell, this association is arguably not as strong as is typically assumed in process-tracing decision research (e.g., Lohse & Johnson, 1996; see also Johnson & Koop, 2010, for additional evidence and related criticisms). For instance, the cell information can readily be held and processed in working memory (Johnson & Koop, 2010), allowing mental attention to shift between cells without requiring a physical movement of the mouse back and forth. Thus, mouse movements provide only an indirect and imperfect measure of the attentional processing of information. In addition, research has questioned whether specific decision strategies and/or choice are dependent on the paradigm (cf. Billings & Marcus, 1983; Glöckner & Betsch, 2008) and whether the paradigm can adequately capture multiple aspects of decision making, such as automatic processes (for discussions of limitations, see Glöckner & Betsch, 2008; Norman & Schulte-Mecklenbeck, 2010). In general, the mouse-tracing approach has been valuable to researchers studying decision making. For the purpose of this article, we focus on one of its shortcomings—specifically, that the mouse-tracing paradigm provides an indirect measure of attentional processing, which may, therefore, only loosely approximate attentional mechanisms employed during decision making.

Moving-window paradigm

Researchers in cognitive psychology often utilize oculomotor measures (i.e., via eye-tracking methods) to examine attentional processing ranging from lower-level processes such as perception and pattern recognition (see Pashler, 1998, for an overview) to higher-level processes involved in reading and scene perception (see Rayner, 1998, for an overview). Eye-tracking measures provide a wealth of data and information regarding the attentional processing of specific information. Methodological advances have gone beyond recording eye movements as people read or acquire information presented on a screen to developing an interactive moving-window or moving-mask paradigm that enables the user to direct or to be directed to specific information (McConkie & Rayner, 1975; van Diepen, Wampers, & d'Ydewalle, 1998). Similar to the mouse-tracing paradigm, all information on a computer screen is occluded from the reader or viewer, except for a small window of text or a segment of a scene. In reading research, movement of the window is typically directed by the participant but can also be controlled by the experimenter (e.g., moving left-to-right or right to left only). The advantage of this paradigm is that the moving window occurs simultaneously with eye-tracking measurements, which allow for finer-grain measurements of attentional processing, as well as providing a mechanism to capture overt selective attention.

Interactive eye tracking during decision making

We introduce a new development for the use of an eye-tracking paradigm in decision research by borrowing from current methodologies employed in reading and scene perception research. The *decision moving window* is similar to the mouse-tracing paradigm, where only a small segment of all information is revealed to the person. However, capitalizing on eyetracking, the cell is revealed by an eye fixation, rather than by the cursor position. The primary advantage of using this combined paradigm to measure attentional processing in decision making is that one can more reliably measure which information is being acquired and the path to such acquisition while allowing the person to determine how the information is revealed. Specifically, it reduces the nonnegligible transaction cost associated with moving the mouse to acquire information. For example, Gray, Sims, Fu, and Schoelles (2006) have provided evidence that the parameters of the mouse-tracing paradigm, such as the physical distance the cursor must traverse or the latency of revealing the cell information, can greatly impact information acquisition.

In order to apply eye-tracking methodology to decision making, several assumptions must be specified. First, eye placement and fixation are assumed to correspond to immediate processing of the associated information. A similar “eye–mind” assumption in reading research presumes that the moment the eye moves to a particular target (e.g., a word), the mind begins to process the information associated with the target (Just & Carpenter, 1980). An analogous “correspondence assumption” relates cursor placement to attention in mouse tracing, but we would argue that the assumption is more appropriate for eye tracking. Although shifts in covert attention can occur without moving one’s eyes, overt attentional shifts and eye movements are coupled for complex information processing (Hoffman, 1998; Rayner, 1998). Thus, the assumption that eye movements provide a natural mechanism for understanding overt attention to presented information appears warranted and, arguably, stronger than using mouse movements to artificially capture attentional processing.

We are not the first to suggest the use of oculomotor measures as a tool for examining decision making. In fact, several researchers have used video cameras to record eye movements during the process of making a choice (Russo & Leclerc, 1994; Russo & Rosen, 1975) or have used eye-tracking methods to investigate consumer decision behavior, such as goal-directed viewing of advertisements (Rayner, Rotello, Stewart, Keir, & Duffy, 2001) or general memory for advertisements based on text and pictorial elements (Pieters, Warlop, & Wedel, 2002; Pieters & Wedel, 2004; Wedel & Pieters, 2000). However, the latter studies did not directly examine the decision process but, rather, relied on eye-tracking information to examine encoding and memorial processes or decision outcomes. Lohse and Johnson (1996) used eye-tracking measures as convergent validity for mouse-tracing methods. Although they found a strong correlation between mouse and eye measures during a decision task, they had distinctly different goals—namely, to validate the use of the mouse-tracing paradigm. Consequently, they compared information processing during the mouse-tracing paradigm with information processing during a full display (without hidden cells) while eye movements were measured (henceforth referred to as *open* eye tracking). Recent work has applied open eye-tracking technology to capture processes *naturally* invoked during decision making (Glöckner & Herbold, 2011; Horstmann, Ahlgrimm, & Glöckner, 2009; see also Norman & Schulte-Mecklenbeck, 2010, for a discussion of eye-tracking methods and advantages). Notably, eye-tracking measures have been used to dissociate between automatic and deliberate processing of information during a decision task (Glöckner & Herbold, 2011; Horstmann et al., 2009; see also Glöckner & Betsch, 2008). This work reveals that eye-tracking measures were better for capturing automatic processes that are often overlooked with mouse-tracing methods, and similar findings were observed when gambles were used as the decision task (Glöckner & Herbold, 2011). Thus, eye-tracking methodology has been successfully used to assess decision processes and choices across a variety of decision tasks. However, the comparisons to date have been between mouse-tracing methods (where information is occluded) and eye-tracking methods (where information is *not* occluded). That is, any such comparisons have confounded the user interface and the presence of information occlusion, making it difficult to determine which feature might be responsible for empirical differences. We believe that the decision moving window will allow for more direct comparisons across methodologies, since it capitalizes on strengths of both methods. In particular, the decision moving window adds to the decision researcher’s arsenal by providing an additional tool that simultaneously captures attention and information acquisition and provides a wealth of data that can be used to model attentional processing while allowing the user to interact with information on the screen. Before detailing our implementation and validation of the decision moving window, we briefly outline the key methodological advantages of the new paradigm.

Benefits of the decision moving-window paradigm

Because complex decision making often requires attentional processing, there are several benefits to using interactive eyemovements, rather than mouse movements, to understand decision-making processes. First, one can more directly operationally define and measure attentional processing, similar to other areas of cognition (i.e., reading, scene perception, etc.). Another benefit is the abundance of new data available from eye tracking and the ability to obtain finer-grain measurements to quantify attention beyond summary measures. The most common oculomotor measures used are saccades (i.e., rapid simultaneous movement of both eyes) and fixations (stationary or relatively fixed eye position on a target). Much of the current cognitive research uses gaze duration (total time spent viewing the target word or elements of a scene); however, many additional measures can be recorded (e.g., average fixations, first fixations, number of regressions, and pupil dilation; for overviews, see Inhoff & Radach, 1998;

Rayner, 1998; see Horstmann et al., 2009, for decision tasks). Thus, eye-tracking methods offer promising potential to provide specification of the attentional stream during decision making that contemporary modeling endeavors require. Third, eye tracking provides a distinct advantage in terms of the "eye-mind" assumption relating overt (visual) and covert (cognitive) attention. Not only is the precedent better established in decades of eye-tracking research in reading and scene perception, but strong evidence suggests that attentional shifts and eye movements are coupled for complex information processing (Hoffman, 1998; Rayner, 1998). Fourth, the acquisition metrics can be empirically observed and provide statistical advantages, such as increased reliability and, presumably, a greater signal: noise ratio, as well as adherence to assumptions that may be dubious for mouse tracing, such as avoiding sparse matrices or extremely low frequencies when desiring chi-square analyses (cf. Stark & Ellis, 1981). Fifth, it provides a natural interface between the user and the information, which, in turn, reduces the transaction costs associated with acquiring information and allows one to record the acquisition of information that one wishes not to occlude, such as row and column headers (e.g., option and cue labels, in the present study). Lastly, it enables the researcher to increase internal validity by enabling greater experimental control over what the participant views. The advantage of our new paradigm can be seen by noting the theoretical and quantitative implications of (1) how eye tracking compares with mouse tracing and (2) how the moving-window occlusion compares with open eye tracking. These empirical comparisons are presented in the next sections.

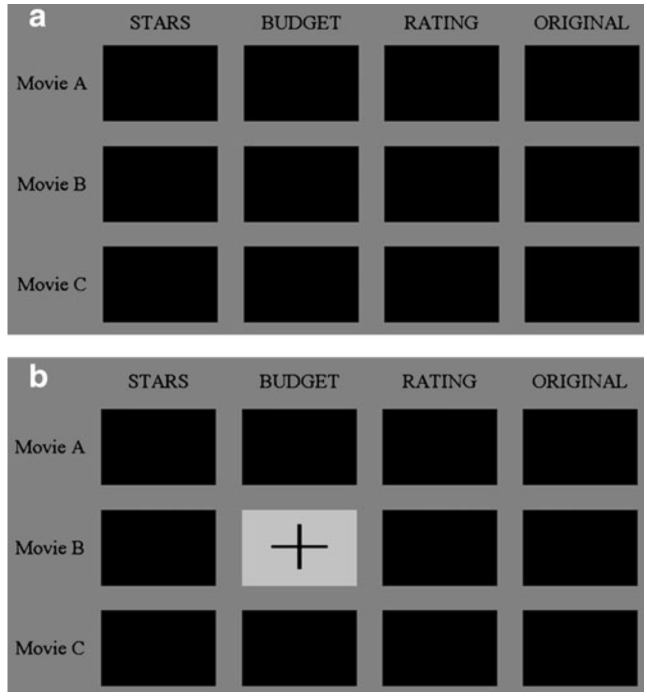

Fig. 1 Information table for movie task. **a** Choice options (i.e., movies) are shown in rows, with their corresponding attributes in columns. In the mouse-tracing and *decision moving-window* paradigms, information is hidden (black image) unless the mouse is positioned to a specific cell or the person fixates on a specific cell; then the information corresponding to the cell is revealed. **b** In this example, participants view the corresponding information (+) under "Budget" for movie B when the mouse or eye is positioned on cell B2. Cell labels (A1 thru C4) are not presented on the actual screen but are labeled for illustrative purposes

Decision moving window: basic methodology

The general method is one where the decision maker acquires information via eye movements en route to making a decision. The basic design consists of matrix display of information (see Fig. 1a) where only one cell in the foveal region is revealed at a time. When the decision maker fixates on a given cell, the information hidden under the masked cell is revealed (see Fig. 1b). Once the decision maker moves his or her eyes away from the cell, the mask returns, and the information is hidden again. Each cell in the matrix becomes an area of interest (AOI), and all eye-tracking data pertaining to each AOI are recorded. Additionally, other information on the screen can be deemed an AOI. In this example, the alternative labels (movies A, B, and C) and attribute labels (stars, budget, rating, and original) are also considered AOIs, and eye-tracking information is gathered when the decision maker fixates on these cells. In contrast, the only way to record attention to alternative and attribute labels in a mouse-tracing paradigm is to occlude them, which unnecessarily burdens working memory and substantially increases the artificiality of the task. Eyetracking allows for greater flexibility, in that AOIs can be fixed or interactive depending on what information needs to be accessed or remain constant on the screen.

We used the Tobii 1750 eyetracker (17-in. monitor with 1,024 × 768 pixels; sampling rate, 50 Hz; spatial resolution, 0.5°; calibration accuracy, 0.5°) with E-Prime extensions for Tobii (Psychology Software Tools) for the decision moving window.[1] All AOIs (information cells, as well as alternative and attribute labels) were identical in size. Eye movements were recorded using the binocular tracking. Eye-tracking output includes gaze position relative to stimuli, position in camera field, distance from camera, pupil size, and validity codes recorded per eye every 20 ms. In turn, these measurements allow for a rich data set

[1] We modified the code in the TETVaryingPoistionAOITracking sample to reveal cell information within the matrix.

whereby one can build different eye movement metrics to examine the decision process. The purpose of this article is to introduce the decision moving window methodology, rather than exhaustively define these derivative metrics; thus, we present summary statistics in line with current process-tracing research. We computed a fixation by summing eye placement on a specific AOI (from the onset of eye movement to AOI until the eye movement was displaced from the given AOI), using the raw eye-tracking data generated in the experiment. In the next section, we describe how we tested and implemented this methodology using a probabilistic inferential decision task similar to the tasks used to examine both eye tracking and information processing during decision making (e.g., Glöckner & Betsch, 2008; Horstmann et al., 2009).

Decision task The task required participants to make a probabilistic inferential decision about which *option* (movie) was the highest on some *criterion* value (box office revenue) based on a set of *attributes* that had differential predictive value (*validity*). Participants searched within a 3 (options) × 4 (attributes) matrix table for information, as displayed in Fig. 1. The information table was arranged such that row headings list options (e.g., "Movie A"), column headings show the attributes associated with these options (e.g., "Budget"), and the individual cells corresponded to specific attribute values for a given option (e.g., binary values of +/–). The goal of the decision maker was to evaluate the attribute information and select the option that had the highest criterion value (earned the highest revenue). As can be noted from Fig. 1, the labels for each option and attribute remained visible on the screen; however, cell information was hidden until the participant's eye movements were directed to the cell.

Although the task was based on data on actual movie earnings, participants received generic labels (i.e., movie A, B, or C) to eliminate previous knowledge from biasing the decision process and choice. Thus, participants were instructed to consider only the attributes provided to them during the task as they made their decisions. Each movie had four attributes—star power, big production budget, PG-13 rating, and original screenplay—each of which corresponded to a specific predictive validity: .90, .80, .70, and .60, respectively.[2] The predictive validity was defined for participants as "how often the attribute *alone* correctly predicts the movie with the highest earnings, assuming that it discriminates among movies." They were given the example that "if an attribute has a predictive validity of .90, that means that in a set of three movies, if two movies do not have the attribute, and the other movie does, then there is a 90% chance that the movie that *does* have the attribute is actually the one that earned more money." Cues were presented in a fixed order, left-to-right, by decreasing predictive validity. Although the actual predictive validities were not displayed on the screen, these values were prominently displayed next to the computer if the participant needed a reminder during the task. Instructions to participants informed them that each movie could have the presence (denoted as "+") or absence (denoted as "–") of an attribute.

Implementation of interactive eye-tracking program The starting state consisted of the table matrix where cell attribute information was masked by a black box (an image) while option labels and attribute labels remained visible (see Fig. 1). Next, we created two images to represent our attribute binary cues [presence ("+") and absence ("–") of information]. The infile E-Prime code corresponds to each given cell and trial, with a 1 displaying the "+" image; else, the "–" image is displayed. For example,

```
If c.GetAttrib(``A1") <> ``" Then
        A1 = ``plus.bmp"
Else
        A1 = ``minus.bmp"
End If
```

In E-Prime, each attribute cell (A1 thru C4) is indicated as 1 to denote the presence of the attribute or left blank to denote the absence of the attribute, allowing for the appropriate image to be displayed on the screen.[3] In summary, the program finds the current eye position, and if the eye is fixed on a specific cell, it uses the attribute information in E-Prime to reveal the image that corresponds to the specific cell. When the user moves his or her gaze away from the cell, the mask (black image) replaces the previous image. Hence, cell attribute information is available only when the user fixates on the cell, and only one attribute is revealed at any given time.

Comparison of methods: decision moving window, open eye tracking, and mouse tracing

In this section, we present data from 71 participants who completed the decision task using the mouse-tracing (n =

[2] These attributes are indeed predictive of movie earnings, and the real-world ordinal relationship among them was preserved; however, the actual validities were changed to more easily construct theoretically diagnostic stimuli in this task.

[3] Sample programs are available upon request.

30), the open eye-tracking (n = 19), or the decision moving-window (n = 22) paradigm. The decision moving window was conducted at a large public university in the southeastern U.S., and the other conditions were conducted at a large public university in the midwestern U.S. In the decision moving window, participants had 20 s to acquire information and then choose which movie had the highest box office earnings.

Method

Stimuli The stimuli for the experiments were created by first designing five choice matrices (see the Appendix). All choice matrices were designed for other research purposes—namely, to be diagnostic between two very popular and often-tested strategies in the decision-making literature; however, the details of these theoretical comparisons are not central to the goals of the present article. Each matrix represented a decision trial, and each block of trials contained all five basic matrices. However, the five matrices were transformed using complete row permutation, resulting in six blocks, with each block consisting of a unique permutation of the five basic matrices, resulting in a total of 30 decision trials. Participants completed one block of the five distinct matrices before advancing to the next block. The order and location of the row and column headings remained the same for all matrices.

Procedure Participants were welcomed to the lab and viewed a self-paced Power Point presentation that provided them with details about the nature of the decision task, including detailed descriptions of the various cues and concepts, such as cue validity (explicitly provided to participants). They were provided with an animated demonstration about the information acquisition apparatus specific to their condition (eye-tracking, moving-window, or mouse-tracing paradigm), followed by practice trials using their assigned apparatus before commencing the study trials. Participants viewed the matrix and then made a decision regarding which movie grossed the most box office earnings. No feedback was given during the task to induce participants to change from their naturally preferred strategy. Between matrices in the eye-tracking studies, a decision screen (where the participant selected movie A, B, or C) was inserted, as well as a rest screen where the participant pressed the space bar to view the next matrix, to reduce the potential for carryover effects between trials.

Results

With the introduction of a new method like the decision moving window, it is important to provide some basic descriptive statistics, as well as a comparison with the currently dominant similar methodology. We have summarized these basic statistics across all 30 trials in Table 1, comparing our new moving-window technique with the popular mouse-tracing and open eye-tracking paradigms.

Across all of the major variables shown in Table 1—number of cell acquisitions, proportion of entire table acquired, number of reacquisitions, time per acquisition (average fixation duration), and search direction—there were significant main effects of method (see Table 1 for F-ratios, all p-values less than .01). More interesting are the pairwise comparisons between our new decision moving-window paradigm and either the mouse-tracing paradigm (with which it shares information occlusion) or the open eye-tracking paradigm (with which it shares the use of the eyes as an input device). Both eye-tracking methods led to a greater number of cell acquisitions, with the new decision moving window showing significantly more acquisitions than did mouse tracing, $t(50) = 9.60$, $p < .01$, $d = 2.70$, but not significantly different from open eyetracking, $t(39) = 1.36$, $p = .18$, $d = 0.42$. Both eye-tracking methods also produced significantly greater reacquisition rates of information already attended, from approximately one third to nearly three quarters. Specifically, as with the acquisition data, the decision moving window showed a statistically significant difference from the mouse-tracing paradigm, $t(50) = 15.43$, $p < .01$, $d = 4.33$, but not from the

Table 1 Comparison of methods: open eye-tracking, moving-window, and mouse-tracing paradigms

	Open Eye	Moving Window	Mouse Tracing	F Ratio
Time per acquisition (ms)	188	289	643	88.68
Number of cell acquisitions (fixations)	42	49	20	21.61
Proportion of cell information acquired	.77	.97	.93	171.90
Cell reacquisition rate	0.72	0.74	0.33	6.32
Search index	0.17	0.42	0.48	65.06

Time per acquisition gives the average fixation duration, in milliseconds, but does not include the time cells remained occluded in the moving-window or mouse-tracing paradigms. Data include only fixations to attribute information in matrix cells, not to row and column headers. F-ratios are calculated across the three conditions in the associated row with $df = (2, 68)$; all p-values <.01.

open eye-tracking paradigm, $t(39) = 0.99$, $p = .33$, $d = 0.31$. Interestingly, in terms of the proportion of the 12 information cells accessed at least once on each trial, the moving-window paradigm was more similar to (not statistically different from) the mouse-tracing paradigm, $t(50) = 1.24$, $p = .22$, $d = 0.35$, than to the open eye-tracking paradigm, from which it did differ, $t(39) = 6.09$, $p < .01$, $d = 1.91$. All three methods seemed to produce different average fixation durations (the average time per acquisition), with the moving window producing significantly shorter average fixation times as compared with mouse tracing, $t(50) = 8.66$, $p < .01$, $d = 2.43$, but significantly longer average fixation times as compared with open eyetracking, $t(39) = 3.85$, $p < .01$, $d = 1.21$. Our results are in line with Horstmann et al.'s (2009) probabilistic inferential task in terms of number of fixations, average fixation duration (open eyetracking), and increase in reacquisition rates providing convergence for eye-tracking methods.

The search direction or pattern of information acquisition was measured by using the search pattern index of Payne et al. (1988), indicating whether adjacent acquisitions (transitions) occur primarily across rows (values from 0 to +1) or across columns (values from –1 to 0). The former is associated with gathering information about multiple attributes for one option, then moving on to the next option, whereas the latter suggests that one primarily looks across multiple options, comparing one attribute at a time. Greater absolute magnitudes imply greater systematicity (assuming these two search styles) in search behavior. Our data suggest that information acquisition in all three methods occurred largely across rows, with all mean values greater than one. However, again we found that those searching with a decision moving window did so in a manner that was not significantly different from those searching within the mouse-tracing paradigm, $t(50) = 0.69$, $p = .50$, $d = 0.19$, although it was significantly different (with relatively greater systematicity) than the patterns produced in the open eye-tracking paradigm, $t(39) = 4.55$, $p < .01$, $d = 1.42$. The latter result is consistent with Horstmann et al. (2009); however, it differs from the result reported by Lohse and Johnson (1996) for a more complex preferential choice task, where they found approximately equal number of transitions across rows and across columns in open eye tracking.

It is interesting to note some of the similarities and differences across methods that can be attributed, at least in part, to the freedom the decision moving window offers, relative to mouse tracing, versus the occlusion that it offers relative to open eye tracking. Although significant, the increase of only 100 ms, on average, in time per acquisition between open eye tracking and the moving window is encouraging for our new paradigm, since it suggests that the paradigm does not suffer from artificially inflated fixation times stemming from stabilizing on a cell after the information is revealed. Similarities between the decision moving window and open eye tracking in terms of total number of acquisitions and reacquisitions support the assertion that information occlusion per se does not decrease the desire for the participant to acquire information. Rather, decreases in information acquisition may be better attributed more specifically to the navigation required by using the mouse as an input device.

An especially interesting comparison across methods involves the percentage of the total information (12 table cells, in our case) that was acquired. Specifically, this was an instance where the moving-window paradigm produced results more in line with mouse tracing than with open eye tracking. One possible explanation is that the open eye-tracking paradigm allows the person to view information in the periphery, therefore reducing the number of cells fixed upon. Another possibility is that, perhaps, the information occlusion introduced some sort of implicit obligation on the part of participants to reveal (almost) all of the table cells to see what was behind them, where open eye tracking allowed for scanning the table that did not promote such behavior—especially for such simple cue information as "+" and "–" in our task. The similarity of the two occlusion methods (moving window and mouse tracing) in terms of the search pattern index also suggests an increased systematicity that might have led to acquiring a higher proportion of the total information available. Interestingly, data reported by Lohse and Johnson (1996) suggests as well that open eye tracking produces a significantly smaller proportion of total information acquired, relative to mouse tracing. This is the one result from their study that does not seem to fit with their hypothesis that eye tracking results in more search across all metrics. They raise the possibility that ("open") eye tracking allowed for information to be collected using the periphery that would not be registered as an acquisition, since acquisitions were operationalized using a foveal fixation. This argument is controlled for in our study by implementing the decision moving window, under which case we see the result becomes more in line with their original hypothesis (and our own intuitions).

Lohse and Johnson (1996) did not, however, record data on acquisitions to row (movie option) and column (attribute) labels and admit, therefore, that they "cannot determine the effect this additional information would have on the amount of information searched" (p. 37). We explicitly recorded the acquisition of this information in both eye-tracking conditions and found that across all participants, blocks, and trials in the decision moving window, there were 2.97 fixations across the four attribute labels (average time per acquisition: 181 ms) and 1.53 fixations across the three movie option labels (average time per acquisition: 231 ms). Note that these labels were not occluded in the decision moving-window paradigm (cf. Fig. 1). In the open eye-tracking condition, there were greater numbers of fixations to the attribute (8.23 fixations, with an average time of 281 ms) and alternative (3.40 fixations, average time of 296 ms) labels. Note that integrating these results with those for the information cells presented in Table 1 only increases the similarity between the open eye-tracking and moving-window conditions.

Finally, it is very interesting to look at the patterns that emerge when the data in Table 1 are examined across blocks (reported in Table 2). In particular, there is a striking effect of experimental block on all of the relevant search metrics for the mouse-tracing paradigm and virtually no systematic effect for the two eye-tracking paradigms. The data in Table 2 suggest that, with standard mouse tracing, participants acquire less information (both first acquisitions and reacquisitions) and attend to acquired information for much shorter durations as an experiment progresses. Across all six blocks, decreases in metrics were almost completely monotonic; a repeated measures MANOVA showed a significant effect of block, $F(5, 145) = 5.73$, $p < 0.01$; subsequent ANOVAs revealed significant effects of block on the number of acquisitions, $F(5, 145) = 22.86$, $p < 0.01$, partial $\eta^2 = .44$; proportion of table acquired, $F(5, 145) = 8.76$, $p < 0.01$, partial $\eta^2 = .23$; reacquisition rate, $F(5, 145) = 19.27$, $p < 0.01$, partial $\eta^2 = .40$; and average time per acquisition, $F(5, 145) = 24.41$, $p < 0.01$, partial $\eta^2 = .46$. Although there was not a significant effect revealed for the search index variable, there was a significant, albeit small, effect on the search index when the first block was excluded from analysis, $F(4, 116) = 2.79$, $p = .03$, partial $\eta^2 = .09$. An optimistic interpretation might be that the decreased search revealed by these metrics represents a practice effect with only minor implications; a more dire assessment is that this reveals the onset of fatigue associated with the mouse-tracing paradigm. This analysis again supports the notion that transaction costs in the mouse-tracing paradigm are nonnegligible and can have serious consequences on behavior, as inferred from the common metrics. Fortunately, the decision moving window (and eye tracking in general, as evidenced in the present study and Horstmann et al., 2009) does not seem to suffer from these effects.

Discussion of advantages and disadvantages

Both eye-tracking methodologies seem to have an advantage over mouse tracing in that they produce a greater number of fixations, of shorter duration, and are not susceptible to significant variability over the course of an experiment. Given the advantages of eyetracking over mouse tracing, there are also direct benefits to using the decision moving-window paradigm, rather than an open eye-tracking paradigm. First, practically, it allows for more direct comparison with existing mouse-tracing research. Prior comparisons of the two methods in decision making confounded the two hardware approaches with the use of information occlusion (Lohse & Johnson, 1996). Second, the latency before the occlusion is removed can be manipulated not only to ensure that fixations are meaningful (and not simply sweeping of the eyes over information en route to other fixation locations), but also to examine

Table 2 Differences in information search variability across time (experimental blocks)

Information Variables	Method	Experimental Block					
		1	2	3	4	5	6
Time per acquisition (ms)	Open Eyes	188	182	193	195	186	184
	Moving Window	285	285	304	293	291	285
	Mouse Tracing	923	676	649	588	520	505
Number of cell acquisitions (fixations)	Open Eyes	40	38	42	41	49	44
	Moving Window	49	50	47	48	49	49
	Mouse Tracing	25	22	20	20	18	15
Proportion of cell information acquired	Open Eyes	.74	.77	.78	.79	.79	.77
	Moving Window	.97	.97	.97	.97	.97	.97
	Mouse Tracing	.98	.98	.95	.92	.91	.86
Cell reacquisition rate	Open Eyes	0.72	0.70	0.71	0.71	0.74	0.73
	Moving Window	0.73	0.74	0.74	0.73	0.74	0.74
	Mouse Tracing	0.43	0.38	0.33	0.33	0.29	0.22
Search index	Open Eyes	0.15	0.18	0.20	0.17	0.15	0.19
	Moving Window	0.40	0.42	0.41	0.45	0.38	0.45
	Mouse Tracing	0.45	0.58	0.52	0.49	0.49	0.37

theoretically meaningful questions, such as the impact of information acquisition costs. Lastly, it allows the researchers to manipulate information search processes by guiding the direction of search and/or the rate in which the information is revealed; this, in turn, might allow for finer-grain model and theoretical testing. One disadvantage of the moving-window paradigm is its potential to decrease the external validity of the search process and potential impact on decision strategies such as those noted with mousetracing by Glöckner and Betsch (2008). Although beyond the scope of the present work, additional research designed specifically to draw accurate inferences regarding strategy use could empirically assess the severity of this potential drawback. Future work could also look at extending our paradigm, and methodological comparisons, to other task domains, such as preferential choice (Glöckner & Herbold, 2011; Lohse & Johnson, 1996). An additional concern is that periphery information is restricted in the moving window, thereby restricting some of the natural attention processes captured when all information is available to the decision maker. Despite the loss of potential periphery vision, the time to acquire information will potentially allow for the integration of several pieces of information at a quicker rate than could be integrated with mouse-tracing processes. Thus, it seems that the use of a decision moving window with eye tracking provides a sort of “best practices” solution that enjoys the benefits of two paradigms, while minimizing the practical and inferential drawbacks.

Conclusion

In sum, mouse movements have provided an initial step toward capturing and understanding the deliberation process and acquisition of information in decision making. However, because cursor movements are used as a proxy for attentional processing, a better direct measure of attention (via eye movements) provides an improvement in both the method and measurement of attentional processing within a decision-making framework. In addition, eye movements provide an extremely rich data source, in that several different measures can be collected. Considered independently, each type of data provides information into the cognitive processes of attention and deliberation; however, combining multiple sources of data is a useful tool for providing convergence in understanding the dynamic processes associated with the acquisition and use of information in decision making. The decision moving window capitalizes on both mouse-tracing and eye-tracking methods to provide another tool in the researcher’s toolbox for better capturing attentional processing during decision making.

Our results are consistent with the notion that information occlusion and the cost associated with mouse movement have separable effects on the basic statistics used to characterize information acquisition in decision making (Table 1). Comparing open eyetracking with our moving window suggests that information occlusion increases the systematicity of information search, including the tendency to examine all information at least once, without affecting the total amount of information acquired. Comparing our moving window with mouse tracing suggests that requiring physical movement of the mouse decreases the reacquisition of information and, thus, the total number of acquisitions, as well as the average time spent acquiring each piece of information, while producing similarly systematic search and acquisition of nearly all pieces of information at least once. Using both information occlusion and the physical requirements of the mouse, as is the modal tendency in current process-tracing research, can be expected to combine these effects (compare open eye-tracking with mouse tracing in table and cf. Lohse & Johnson, 1996). Regardless of the task and paradigm, these effects should be kept in mind when interpreting *any* decision research using process-tracing techniques.

Although beyond the aims of the present article, the wealth of data provided by utilizing the decision moving window allows researchers to advance their understanding of the cognitive processes invoked during decision making. Recently, Weber and Johnson (2009) outlined the need to translate attention into decision weights as one of the key future issues for decision research. The attentional-processing data provided by the decision moving window, coupled with the decision maker being an active participant in the decision process, allow one to better establish how covert attention can be mapped and modeled into the decision process. Especially promising is the potential to develop specific models that could relate cognitive states to visual attention, thus specifying not only how visual attention provides input to cognitive processing, but also how the latter guides the former (mainstream approaches from reading are summarized excellently in a 2006 special issue of *Cognitive Systems Research*, Vol. 7).

As we advance our theoretical models to capture *how* a choice is made, rather than simply *what* is chosen, newer methodologies are required to better capture and develop theories of information acquisition and deliberation during decision making. Notably, both mouse-tracing and moving-window paradigms have improved our understanding of processing information in complex tasks. Thus, our complementary integration of these successful paradigms not only will contribute to the theoretical content in decision research, but also will advance the methodology and measurements in behavioral science more generally.

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Appendix

Matrix 1

	Stars	Budget	Rating	Original
Movie A	+			
Movie B			+	+
Movie C		+		+

Matrix 2

	Stars	Budget	Rating	Original
Movie A	+	+		
Movie B	+		+	+
Movie C		+	+	+

Matrix 3

	Stars	Budget	Rating	Original
Movie A	+			+
Movie B		+	+	+
Movie C	+			

Matrix 4

	Stars	Budget	Rating	Original
Movie A	+			+
Movie B		+	+	
Movie C			+	+

Matrix 5

	Stars	Budget	Rating	Original
Movie A	+			
Movie B		+		
Movie C			+	+

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