Running head: MOUSELAB – EYE-TRACKING

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Mouselab and Eye-Tracking as Tools to Measure Intuition

Elisabeth Norman

University of Bergen, Faculty of Psychology and Haukeland University Hospital

Michael Schulte-Mecklenbeck

University of Bergen, Faculty of Psychology

Abstract

Contemporary research on intuitive decision making emphasises the automaticity of intuitive compared to deliberate decision making processes. While automaticity cannot be observed directly, it is closely associated with unconscious or implicit mental processes that are studied within the implicit cognition domain. Research on intuitive decision making might therefore benefit from integrating operational criteria of consciousness from this research area.

We discuss the applicability of two process tracing tools, namely Mouselab and eye-tracking, for studying intuitive decision making and assessing automatic behaviour. While Mouselab, in its traditional form, remains a tool more suitable for assessing deliberate processes, eye-tracking holds the potential of allowing insights in the intuitive, automatic domain. We point to additional measures that could be integrated with these process tracing tools in order to identify whether or not participants are conscious of the basis of their decision.

Introduction

When investigating literature in intuitive decision making one will often find references or applications of a dual-systems approach (Stanovich & West, 2000). Within this framework intuition is viewed as the counterpart of rationality, and the two information-processing systems are thought to be largely independent. As pointed out by Glöckner and Witteman (this volume), a wide variety of cognitive mechanisms might be involved in intuitive decision making, ranging from simple learning mechanisms to the construction of complex mental representations. What they all seem to have in common is that their influence on decision making is largely *automatic*.

Automaticity in the context of decision making

A common view of automaticity is that it refers to mental processes that are effortless, unconscious and involuntary - they operate without cognitive effort, conscious control or monitoring (Bargh & Chartrand, 1999). In a classic study Bargh, Chen, and Burrows (1996) found that priming participants with words associated with either politeness or rudeness influenced their tendency to act politely or rudely in a staged social situation, even when participants showed no conscious awareness of this influence. How can we then measure the influence of automatic processes in decision making?

Automaticity is often associated with implicit or unconscious aspects of our mental processing. These labels are used interchangeably in the decision making literature and will be treated likewise here, although our readers should be aware that there are some debates about the degree of overlap between these concepts in the consciousness literature (see e.g., Tzelgov, 1997). Implied in the model of Glöckner and Witteman (this volume) is that automaticity involves the unintentional application of complex knowledge structures that are in themselves not consciously represented.

One approach to studying intuition in decision making is to focus on the automaticity of the information integration process itself (Glöckner & Betsch, 2008a, 2008b; Glöckner & Herbold, 2008). The central question is whether the decision maker integrates available information in a more controlled and serial manner, or in a more automatic and parallel manner. We later give examples of how this has been done.

Given the close association between automaticity and implicit or unconscious cognition, an alternative approach is to investigate whether decision makers showed conscious awareness of the basis of their decision. To decide whether a certain decision should be regarded as intuitive and characterised by automatic processing, one then needs to apply testable operational criteria of conscious awareness. Depending on the focus of the researcher, one might want to address whether the applied knowledge was unconscious, whether the intention to apply the knowledge was unconscious, or both. Because the measurement of consciousness is rarely addressed in the decision making literature, we will now exemplify how this can be done.

Measuring consciousness

Let us briefly turn to the implicit cognition domain. Implicit cognition refers to cognitive activity that influences a person's behaviour and judgement, while the person is not consciously aware of this activity and/or its influence on performance. Examples include implicit memory (Schachter, 1987), implicit learning (Reber, 1989; see also

Glöckner & Witteman, this volume) and implicit attitudes (Greenwald, McGhee, & Schwartz, 1998; see also Holland & De Vries, this volume).

In research on implicit cognition several operational criteria for consciousness have been put forward. These mainly apply to whether knowledge is consciously represented or not. For the time being we will restrict ourselves to a classic principle: Knowledge or processing is regarded as unconscious when it is above an objective but below a subjective threshold (Cheesman & Merikle, 2003; Dienes & Berry, 1997). An objective threshold refers to whether the knowledge or process is expressed on overt behaviour, e.g., the ability to make discriminatory responses in line with this knowledge in a forced-choice situation. A subjective threshold refers to whether the person shows metacognitive awareness as reflected in a verbal report measure. For example, in a classic study of intuition by Bowers, Regehr, Balthazard, and Parker (1990), participants were shown two word triads on each trial, e.g., the words *playing*, *credit*, *report*, and *still*, *pages*, *music*. Only one triad in each pair was semantically coherent in the sense that all three words in the triad were semantically related to a fourth word that was not presented. (In our example, all three words on the first triad were semantically related to the word *card*). While participants showed no ability to verbally report the common associate, they showed an intuitive preference for the internally coherent triads on a forced-choice measure. Participants showed an intuitive preference for a certain decision alternative, even when the knowledge was not consciously represented – the preference was above an objective but below a subjective threshold. Recently, it has been found that trials where the coherence was perceived intuitively are associated with a different pattern of brain activity than correctly solved trials, as measured by fMRI (Ilg et al., 2007). It has also been found that undetected coherence gives rise to specific patterns of facial muscle reactions (Topolinski, Likowski, Weyers, & Strack, 2008), which could be seen as yet another objective measure.

This criterion can be applied to decision making situations, where dissociations between objective and subjective assessment of participants' preferences are indicative of intuitive decision making.

From outcomes to process measures

So far, research on intuitive decision making has largely focused on explicit choices rather than on the processes leading up to these choices. This focus on outcomes per se is not necessarily a problem as long as models make different predictions for decisions under different conditions (see Glöckner & Witteman, this volume; Bröder, this volume; Glöckner, this volume). However, the way in which outcome measures have been applied to intuitive decision making seems problematic especially concerning two points: Limited choice sets and deliberate choices. Participants are given a choice between a limited set of options, where choosing anything but the pre-defined 'rational' alternative is regarded as 'intuitive' (Hammond, Hamm, Grassia, & Pearson, 1997). They state their choice most often by saying or writing down which response alternative they prefer. This mainly reflects conscious preferences. However, if intuition is viewed as the outcome of largely automatic and unconscious processes, this type of measurement does not, on its own, allow for differentiation between intuition and deliberation.

Candidate methodological tools

It is clear that additional methodological tools are needed which are more likely to reflect the intuitive, automatic decision making process. Several candidates are presented in this book, including confidence and decision time (Glöckner, this volume), specific self-report (Witteman & van Geenen, this volume), physiological measures (Hochman et al., this volume) and implicit associations (Holland & de Vries, this volume).

In this chapter we explore whether Mouselab and eye-tracking, which are commonly used in the study of deliberate decision making, can also be used to explore intuitive decision making. Our main focus will be on whether these methods allow us to identify situations where a dissociation between objective and subjective measures indicates that the person is not consciously aware of the basis of his or her decision. We now discuss each of these tools in turn.

Mouselab

Mouselab is a computer program that records the acquisition of information that is presented in a matrix. The roots of Mouselab go back to studies with information boards (literal boards with envelopes attached to them, e.g., Payne, 1976). With the commercial introduction of computers, new ways to record information acquisition were created. Computer monitors replaced information boards as presentation devices, and keyboards were used to indicate which cell should be opened (Payne & Braunstein, 1978). In the next developmental step the computer mouse was introduced as a pointing device and Mouselab found its name.

Theoretical concepts close to Mouselab

Mouselab is closely related to the adaptive decision maker (ADM) framework (Payne, Bettman, & Johnson, 1988; 1993). In this framework the decision maker is understood as an information processor, with limited capabilities, who adapts to the environment at hand. This adaption is based on considering a trade-off between the accuracy of a certain strategy and the effort that this strategy requires. Putting a strategy on a continuum, optimal or normative versus random choice, determines its accuracy (see Payne et al., 1988 for several visualizations of such continua). To estimate the effort a strategy requires the authors went back to the ideas in production systems (Newell & Simon, 1972) and elementary information processes (EIP; Huber, 1980). First a strategy is broken down into simple operations or EIPs such as READ, COMPARE, ADD ..., then the number of EIPs necessary determines the effort for the given strategy. An interesting application of this approach is presented in Lohse and Johnson (1996), where the time needed to execute an EIP was used to build predictions for how long it would take the participant to finish different conditions of a task.

In the ADM framework, the decision maker can learn from prior experience, which eases strategy selection and availability. While the ADM framework does not directly refer to intuitive processes the authors acknowledge that the choice of a strategy is bound to a conscious process plus a ‘learned contingency between elements of the task and the relative effort and accuracy of a decision strategy’ (Payne et al., 1993, p. 14).

Citation record of Mouselab studies

To evaluate the impact Mouselab has had in decision making research an ISI Web of Science search with the keyword combination: ‘decision making’ and ‘mouselab’ was conducted (see Table 1). The citation count is reported and a subjective categorization into different research areas performed. Citation numbers were cutoff at a minimum of 15 citations because of a long tail of studies with only few citations.

Insert TABLE 1 about here

In the literature, a broad area of applications for Mouselab can be found ranging from research on gambles (Payne et al., 1988, Costa-Gomes, Crawford, & Broseta, 2001) and heuristics (Bröder, 2003) to method comparisons (Lohse & Johnson, 1996). Half of the published studies are situated in the area of consumer decision making (Dhar, Nowlis, & Sherman, 1999, 2000, Lurie, 2004, Levin, Huneke, & Jasper, 2000). More important for our topic, all of the studies are concerned with the question of deliberate decision making. Only a small number of papers can be found that use Mouselab in the area of intuition, namely a series of studies by Glöckner and Betsch (2008a, 2008b), which we will discuss in more detail below.

Setting up a Mouselab study

There are different flavours of Mouselab available which can be used online or offline in a laboratory (e.g., MouselabWeb, Willemsen and Johnson, 2008, or Web Mouselab, Payne, 2005). In what follows we will use MouselabWeb as an example because it is freely available and frequently updated. The basic design of a MouselabWeb page is a matrix like setup (e.g., Figure 1, but see Glöckner and Betsch, 2008a, Experiment 3, for a different setup) of an arbitrary number of information cells. Each information unit is presented in a box which is covered by an overlay. Simply moving the mouse pointer over one of the boxes shows the participant the content. Upon leaving the box area the information is covered again. The closing of a box, after leaving the box area, can be suppressed in a design where re-acquisitions are of less interest.

Insert FIGURE 1 about here

For setting up a MouselabWeb experiment a program within the MouselabWeb package called ‘Designer’ is very useful. The Designer helps creating the basic matrix layout with the information boxes. There are sophisticated counterbalancing options available to avoid unwanted effects of, e.g., reading order. In a process tracing study the reading order (left - right in Western cultures) can have an effect on the acquisition order of information. The heart of the Designer (see Figure 2) is the MouselabWeb Table which helps to create the actual information matrix. Each cell is automatically named after pressing 'new Col' or 'new Row', but it is highly recommended to change cell naming to something sensible in reference to the desired content because the cell labels are reflected in the data-sets. For each cell the status can be set to *active*, to have actual search capabilities, or *passive*, e.g., for adding column or row names. Two additional fields ask for the text on the box (boxtxt) and the actual information (text).

Insert FIGURE 2 about here

If the research question asks for time restrictions the latest version of MouselabWeb (1.0 beta, as of December 2008) provides the option of adding a timer bar that either counts down from or up to a pre-defined value in seconds. This feature can be useful to run studies with time constraints, e.g., Glöckner and Betsch (2008b). Again several options to fine tune this feature are available (see Willemsen and Johnson, 2008 or Schulte-Mecklenbeck, Kühberger, and Ranyard, in preparation, for detailed instructions).

Analysis of data collected in MouselabWeb

MouselabWeb collects a large amount of information per participant. This, often overlooked, fact sometimes makes it tricky to separate actual data from noise. Therefore it is important to have a set of specific hypotheses to investigate. Simply data mining the results will often lead to tears and frustration. MouselabWeb is event driven, i.e., each event (click, cell opening) generates a data row with a time-stamp. It is therefore hard to

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specify the amount of data generated for a certain experiment length.[1] However, it is clear that several kilobytes of data per person are to be expected when running a MouselabWeb study. Access to the results of a study can be gained with the 'Datalyzer' application which offers a convenient way to pre-process and download data sets. Pre-processing removes, for example clicks below a certain threshold or splits data sets into halfs, thirds or smaller parts. These pre-processed data files can be downloaded to a local hard-drive and analyzed in a statistics package. Access to raw data files is also available in Datalyzer.

The data collected in a Mouselab study can roughly be organized into two types: 1) basic measures such as choices, time and clicks and 2) transitions betweens cells as a measure of information search.

Basic Measures. The handling of the basic measures involves calculating, for example, the proportion of choices for each task type or condition in an experiment; time spent on a cell or summed up time for all cells (task length) as well as number of clicks for each cell or for a task. Note that the time and click measures are often correlated and result in highly similar patterns. The following statistics are sufficient with the `basic measures' in most cases: proportions and ratio analysis, means, ANOVAs, MANOVAs, time series and Random Effect Models. For each of these it is common practice to log-transform click and time measures in order to get more normal distributed variables.

Transitions Between Cells. There are four possible types of transitions in an information search task using a matrix layout: A Type II transition (see Figure 3) corresponds to an alternative-wise search pattern, where the transition moves within the same alternative but changes the attribute. A Type III transition is attribute based, where

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the transition stays within the same attribute but changes the alternative. These are the transitions most often analyzed in decision making studies. However, Type I transitions (no transition, the same information item is inspected again) and Type IV transitions (a diagonal transition, which switches alternative as well as attribute) hold valuable information, too.

Insert FIGURE 3 about here

Transitions are tricky in the sense that the above mentioned `simple' approaches are not sufficient for this type of analysis. Therefore several indices have been suggested to condense data based on transitions into measures that can be handled more easily.

The Search Index (SI), based on work of Payne (1976), is also often referred to as the Payne Index in the literature. Assuming that the total number of within-alternative transitions is $N_{alternative}$ (Type II) and the total number of across-attribute moves is $N_{attribute}$ (Type III), the Search Index is the ratio:

$$SI = \frac{N_{alternative} - N_{attribute}}{N_{alternative} + N_{attribute}} \qquad (1)$$

This index ranges from -1.00 to 1.00 indicating a completely attribute based vs. a completely alternative based information search respectively. If there are equal numbers of both types of transitions, the index equals 0. A positive index value is often assumed to indicate the usage of compensatory strategies (e.g., equal weight strategies), whereas a negative index value is interpreted as indicator for more non-compensatory strategies (e.g., lexicographic strategies).

Böckenholt and Hynan (1994) showed in a simulation study that the SI is unreliable when the number of alternatives and attributes is not identical. When the number of attributes is larger than the number of alternatives a positive SI index is more likely and when the number of attributes is smaller than the number of alternatives a negative SI index is more likely. In order to overcome the problems identified with SI, the authors introduced a strategy measure (SM) that compared the observed frequency of transitions against those expected by chance (see Formula 2 in the original notation).

$$SM = \frac{\sqrt{N((\frac{AD}{N})(r_a - r_d) - (D - A)}}{\sqrt{A^2(D-1) + D^2(A-1)}} \qquad (2)$$

Here N denotes the total number of cell openings; A and D define the information matrix with A defined as the number of alternatives and D as the number of dimensions; r_a is the frequency of alternative-wise transitions (Type II), r_d is the frequency of dimension-wise transitions (Type III).

Several other approaches to represent transitions and search behaviour were introduced by different authors: Van Raaij (1977) approached the problem with an index that compared the first and second half of the search process to the total number of cell opening. Koele and Westenberg (1995) suggested to combine the variability of searches with the depth of searches in a compensation index denoted C and showed the psychometric properties of this index to be superior to SI.

The above described simple measures represent overt, voluntary responses (i.e., moving the mouse cursor and clicking). It becomes clear that most of them are useful as dependent variables in questions regarding deliberate search behaviour and indeed they have mostly been used in that domain. We now turn to whether information search patterns measured in Mouselab can also be used to identify more intuitive processes. One way to identify intuitive processes would be to show that large amounts of information are integrated in a largely automatic manner. Another would be to show that a preference for a certain option is revealed on objective but not subjective indices. Objective measures would here include fixation times, opening length, information search patterns and response times. The subjective measure would be explicit choice.

Mouselab: A tool for studying intuitive decision making?

So far only a handful of studies have applied Mouselab for investigating intuitive decision making (Glöckner & Betsch, 2008a; 2008b). The basic setup of these studies involved presenting participants with a series of decisions between two or three alternatives, e.g., to decide which city has more inhabitants. Participants were for instance presented with a number of cues for each decision alternative, together with information about the relative validity of each cue.

Two variants of Mouselab were used in these studies. One was the traditional setup where information is hidden behind boxes and information search behaviour can be measured through standard Mouselab data (see e.g., Glöckner & Betsch, 2008b, Experiment 2). Another variant was to present information in an open matrix, and to infer decision strategy from the explicit choice (see e.g., Glöckner & Betsch, 2008b, Experiment 1).

These studies show that people are able to integrate information in a weighted compensatory manner very quickly. The observed decision times were interpreted as being far below the time necessary to integrate information deliberately. Inspired by Hammond et al. (1987) this was taken to indicate the usage of computationally powerful automatic-intuitive processes. However, a comparison between an Open-Mouselab setup in which all information was instantly presented on the screen and a classic Mouselab setup in which information had to be deliberately looked up using the mouse-pointer indicated that the classic Mouselab might hinder information search and that it might induce the application of deliberate strategies. Glöckner and Betsch (2008b) therefore recommend that Mouselab might not be the optimal tool to study intuition.

Based on the few studies available, a tentative conclusion is that Mouselab, at least in its traditional closed cell format, is relatively limited as a tool for studying intuitive processes or even promotes more deliberate processes (Glöckner & Betsch, 2008b, Epxeriment 2). While the open matrix display seems to encourage more intuitive processing (Glöckner & Betsch, 2008b, Experiment 1) it comes with the downside of not recording mouse movements. It hence takes us back to insight on the pure choices level, which is fine for some research questions but makes us incapable of investigating information search behaviour. Mouselab therefore seems to have limited usefulness for researchers interested in testing specific hypotheses about the automaticity of information search and knowledge integration derived from different theoretical models of decision making (see Glöckner & Betsch, 2008b). It is also of limited value for researchers who want to look for dissociations between objective and subjective measures of consciousness, e.g., observing whether information search behaviour starts favouring one decision alternative before an explicit choice is made.

Eye-Tracking

An eye-tracker measures eye positions and eye movements. Interest in vision in general and eye-movements in particular has a long history dating back to Kepler and his work on the optics of the eyes in the 17th century. In the 19th century Javal (1878) realized that reading involved short stops and not a smooth transition from one word to the next, an observation that led to one of the central measures in eye-tracking research: fixations (stabilized position of the retina). With the turn of the century and the introduction of more sophisticated eye-tracking devices this research grew rapidly. Yarbus (1967) made an important contribution that emphasized the serial processing of pictures which was well in contrast to the dominating view of Gestalt psychology's parallel, one-step process. The author demonstrated that the task given to a participant greatly influenced the scanpath of the eyes (the pattern generated by a series of fixations) while the actual stimulus stayed the same. While these first attempts seem somewhat crude from today's perspective they laid the groundwork for modern eye-tracking research and technology.

Theoretical concepts close to eye-tracking

Several theoretical concepts are relevant for understanding eye-tracking data. We will briefly review two that closely connect to decision making research and intuition. From a process perspective the levels-of-processing framework (Craik & Lockhart, 1972) had a huge influence on cognitive psychology in general and eye-tracking specifically. A two-level model is assumed for visual stimuli in which objects are first localized in the environment (pre-attentive or ambient), then a selection of information is further analyzed on the second level (attentive or focal). Several additional levels of processing have been suggested, with the semantic and metacognitive levels being the more prominent ones (Velichkovsky, Rother, Kopf, Donhofer, & Joos, 2002).

The strong ‘eye-mind hypothesis’ (Just & Carpenter, 1980) postulates a direct mapping of fixation length to the actual length of a cognitive process, since a good deal of the visual information during fixation seems to be accessed and processed instantaneously. There has been a broad discussion of this hypothesis and less strong versions were formulated. Today it is more generally agreed that in addition to an overt orientation system that guides the eyes, a secondary covert system provides attentional guidance. The combination of fixation patterns and fixation time can be used to determine whether a strategy was influenced more by automatic or controlled processes (Glöckner & Herbold, 2008).

Citation record of eye-tracking studies

To evaluate the impact of eye-tracking in decision making research an ISI Web of Science search with the keyword combination: ‘decision making’ and ‘eye-tracking’ was performed (the same procedure was used as above in the Mouselab section, see Table 2).

Consumer Research again shows up often in terms of published papers. In the method comparison class we find Lohse and Johnson (1996) again, which is to our knowledge the only work that compares Mouselab with eye-tracking as tools for measuring deliberate decision making. One strong contestant in a literature search is Russo and Dosher (1983) in a study using simple gamble stimuli. Since 1983 this paper has been cited 200 times and surely it has had a large impact on different research areas. Only one study uses eye-tracking in the area of intuition in decision making, namely Glöckner and Herbold (2008), and this study will be described in more detail later.

Insert TABLE 2 about here

Setting up an eye-tracking study

The market for eye-tracking systems is large. Walthew (2008) lists 23 websites for commercial and open source (free) eye-tracking systems which provide hardware as well as software solutions, often in a convenient package. As a different approach, without an actual eye-tracker, 'Flashlight' (Schulte-Mecklenbeck, Murphy, & Hutzler, in preparation) could be used. All of these require instructions specific to each system so it is not sufficient or feasible (as in the Mouselab example above) to provide a general guide. Therefore we will try to highlight important issues independent of one specific technology and refer the reader to the eye-tracking manual of the system at hand as well as to Russo's Chapter on eye-tracking in decision making research in Schulte-Mecklenbeck, Kühberger, and Ranyard (in preparation).

Multiple methods are available to record eye movements. The most commonly used method today (Video-Based Combined Pupil/Corneal Reflection) involves projecting an infrared light on the eye and measuring the corneal reflection ('Purkinje reflections') of this light relative to the pupil center location with a camera.

Insert FIGURE 4 about here

There are two types of video-based systems which differ in the location of the camera. In remote mounted systems the camera is often installed underneath or above the presentation monitor (see Figure 4, top part), or built within a box including a chin rest (most often in high resolution eye-trackers). A computer monitor is used to present

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stimuli in the visual field of the participant. Head movement is not desired and either compensated through head tracking (i.e., the camera following small head movements) of the camera or a chin rest. More mobility for the participant is provided with a head-mounted system which has a fixed connection between the participant's head and the camera, most often through a helmet (see Figure 4, bottom part) or through glasses. With such a system the participant can move freely and investigate the environment, e.g., in a supermarket or museum.

A calibration process precedes eye-tracking studies using the corneal reflection method. Most often this includes displaying several fixation crosses in the extreme positions of the viewing area (outer left, outer right, top, bottom). The eye tracker then calculates the Point of Regard (POR) in these positions to be able to estimate all the PORs in-between for the actual measurements. While the calibration process is very smooth in many systems today, especially Tobii systems (http://www.tobii.com) excel here, there are still participants for which the calibration is very hard or impossible, e.g., due to very dark eyes and resulting problems for the system to identify the pupil.

Analysis of data collected with an eye-tracker

Depending on the sampling rate of the eye-tracking system, raw data files can grow to several Megabytes for a short recording session for one person. A 60Hz eye tracker records the position of the eyes 60 times per second which results in 36000 measurements for a 10 minute experiment. It is important to keep this in mind when preparing an experiment! Eye-tracking systems are delivered with software that helps to get a grip on this data volume by running basic analyses for the user.

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Two measures are central to the analysis of eye movements: fixations and saccades (A third important measure is *smooth pursuit* which refers to the tracking of moving objects. We will not describe this measure in more detail, because it is less relevant to decision making and intuition as it is researched at the moment). Saccades refer to rapid eye movements used in repositioning the fovea to a new location in the visual environment (usually lasting 10-100 ms). A saccade can be voluntarily invoked or reflexive in order to correct the position of the eyes. Fixations refer to the phase in an eye movement sequence where the retina is stabilized over a stationary object (usually lasting 250-300 ms). The interesting paradox with fixations is that while it seems that the eyes rest on one position there is actual movement which can be categorized in three classes: tremor, drifts and micro-saccades (Tremor is a very small, high frequency (90Hz) movement, drift refers to low frequency movements parallel to tremor and between micro-saccades which are fast movements around 25ms. See Martinez-Conde, Macknik, and Hubel, 2004 for more details). Without this movement a sharp picture of the environment would not be possible.

In Mouselab there is a clear connection between an information cell in the matrix and the actual relevant information for the participant. Only the opening of a cell is recorded as actual data - moving the mouse around the information matrix is not reflected in the final data set. For eye-tracking studies the whole stimulus (most often a picture) is used to record the positions of the eyes, i.e., fixations on the whole stimulus area are reflected in the final data set. To make an analysis more focused on the parts of a stimulus that are relevant for the research question, areas of interest (AOI) can be defined. If a fixation falls inside an AOI it is recognized as data, if it falls outside an AOI it is left out of the analysis. The above mentioned indices can easily be used with AOIs, too. More commonly used in eye-tracking research are the percentage of fixations within an AOI and re-acquisitions of an AOI.

Eye-tracking: A tool for studying intuitive decision making?

In decision making research, there is so far only one study that specifically addresses whether eye-movements can reflect intuitive decision making. Glöckner and Herbold (2008) presented their participants with a series of two-alternative gambles where information about the two gambles was presented in matrix layout in separate halves of the screen. Eye movements were recorded and choice behaviour was measured. Different strategies derived from Cumulative Prospect Theory (Tversky & Kahneman, 1992), Priority Heuristic (Brandstätter, Gigerenzer, & Hertwig, 2006) and Decision Field Theory (Busemeyer & Townsend, 1993) were tested. More compensatory (within alternative) than non-compensatory (between alternative) search behaviour was observed (a result well in line with, e.g., Johnson, Schulte-Mecklenbeck, and Willemsen, 2008). Interesting for our purpose was that results were best explained by models that, at least partially, are claimed to rely on intuitive components in the decision making process (Decision Field Theory and Parallel Constraint Satisfaction (PCS) Models, e.g., Glöckner & Betsch, 2008c; Thagard & Millgram, 1995). For example, analysis of fixation patterns (the number of fixations and the duration of fixations in each AOI) indicated that most of the observed fixations were rather fast (< 250ms) indicating short inspections. Long fixations (>500 ms) were found only seldom indicating only few deliberate processing steps. Additionally there was a tendency for participants to make within-gamble comparisons and to show an unequal distribution of fixations over gambles, which were also taken to reflect automatic processing.

How does this study address the possible dissociation between objective and subjective measures that would indicate that the basis of the decision was unconscious? One objective measure might be visual attention shifts. There are several examples showing that visual attention shifts, measured by eye-tracking, can indicate a preference for a certain decision alternative before a conscious preference has evolved (see e.g., Bridgeman, 1992; Holm, Eriksson, & Andersson, 2008; Ryan & Cohen, 2004). Eye movements can be seen as a type of objective measurement that also reflects non-intentional characteristics of behaviour (see Seth, Dienes, Cleeremans, Overgaard, & Pessoa, 2008, for further discussion about objective and subjective measures). Because these studies also applied subjective report measures of participants' conscious preferences, these examples illustrate the type of dissociation between objective and subjective measures that would be needed to indicate that participants were not consciously aware of the basis of their decision.

Glöckner and Herbolds (2008) actually explored this question. They found that participants attended relatively more to the option they later chose than to the other option, before the actual choice was made. This was taken as additional evidence that the decision relied on intuitive processes.

Eye tracking also allows for measurement of pupil dilation, which is an indicator of autonomic activation. In principle, differences in autonomic activation toward different options before a conscious preference has developed could be seen as another indicator of intuitive processing. In implicit cognition research, it has been found that implicit learning of a complex stimulus pattern can be predicted by pupil dilation preceding each of a series of classification judgements (Bierman, 2004). However, we are not aware of examples applying pupil dilation measures in this way in more traditional decision research.

In conclusion, Glöckner and Herbold's (2008) study suggests that attention shifts as measured by eye tracking can be sensitive (objective) measures of intuitive decision processes, because they sometimes precede conscious preferences measured by explicit choice behaviour (i.e., a subjective measure). Whether pupil dilation can be an equally valid dependent (objective) measure remains to be shown.

Discussion and critical remarks

We now address some general concerns related to the measurement of intuitive processes in decision making, and their relevance for the empirical studies we have described.

As pointed out in the introduction, intuitive decision making is most often equated with the involvement of automatic processes. Automaticity in this context implies the unintentional application of complex knowledge structures, and/or lack of conscious awareness of the details of these knowledge structures. We suggested that a starting point for exploring this would be to apply a fundamental criterion of consciousness, namely dissociation between objective and subjective measures that supposedly reflect the same underlying knowledge.

In this chapter we wanted to explore whether two well-established process tracing tools, namely Mouselab and eye-tracking, could be used to study intuitive decision making. To illustrate their applicability we summarised some central findings from a series of studies by Glöckner and Betsch (2008a, 2008b) and Glöckner and Herbold

(2008). A wide variety of objective behavioural measures were used in these studies, including fixation times, opening length, information search patterns and response times. Our focus was mainly on those objective measures that would indicate an unconscious preference for the to-be-chosen option before a conscious preference for this option had evolved.

Especially the study using eye-tracking (Glöckner & Herbold, 2008) illustrates how attention shifts sometimes indicate a preference toward one option before this option is explicitly chosen. However, how do we know that this reflects *intuitive* decision making rather than more deliberate processing? More precisely, how do we know that the intuitive preference developed independently of, faster than, or in the absence of, a more conscious preference that could be reflected on subjective measures? The answer is that we do not know as long as explicit choice, the only subjective measure included, was always measured after the various objective measures. In principle, a conscious preference for a certain option could have developed in parallel with, or before participants started to show a selective attentional preference for this option. Therefore, a better procedure would be to collect subjective measures of preferences (e.g., explicit choice) at regular intervals while the person is considering the different options. This would more closely parallel procedures used in implicit cognition research. For example, in the classic study by Bowers et al. (1990), subjective awareness measures always preceded objective forced-choice measures, and intuitive preferences indicated by forced-choice were only measured for the subset of trials for which the participant had reported no explicit solution.

For the sake of simplicity, we so far only discussed one criterion for unconscious cognition, namely dissociation between objective and subjective measurements. In the decision making experiments we have discussed, a subjective measure of preference is the actual choice behaviour, i.e., indicating one's choice by saying or writing down which response alternative one prefers. However, no single forced choice measure is process-pure in the sense that it reflects only conscious (or unconscious) knowledge or processes, but is likely to be influenced by a mixture of these (Destrebecqz & Cleeremans, 2001). One solution is to combine the measurement of choice behaviour with another measurement of conscious awareness with confidence ratings. The use of confidence ratings in the area of implicit cognition derives from higher-order thought theories, according to which a mental state is conscious if the person is metacognitively aware of being in that state (see Dienes & Perner, 1999, for a more detailed discussion). Let us take an example of how confidence ratings are used in implicit cognition research. In the training phase of an implicit learning experiment, participants acquire knowledge about a complex rule (e.g., an artificial grammar structure) by passive exposure to a series of stimuli that follow this rule. In a test phase, participants are presented with a series of novel stimuli, and have to decide whether each of these follow the rule or not. It is common to ask people to indicate their subjective confidence in each of these decisions. Learning is regarded as implicit if confidence is unrelated to accuracy (i.e., the zero-correlation criterion, Dienes, Altmann, Kwan, & Goode, 1995), or if classification accuracy is above chance when the participant claims to be guessing (i.e., the guessing criterion, Dienes et al., 1995). Although confidence judgements are sometimes included in studies of intuitive decision making they are used for a different purpose than in the implicit learning literature.

The central aim of this chapter was to show how the presented methods can be used to decide whether a certain decision is predominantly influenced by controlled/conscious processes or automatic/unconscious processes. However, we are aware that this approach might represent an over-simplification. In line with Hammond et al. (1987) we think that the distinction between deliberate and intuitive forms of processing might not be clear-cut. An assumption that is receiving increased popularity is that implicit cognition often gives rise to consciously experienced, “intuitive” feelings that reflect these implicit processes, sometimes referred to as cognitive feelings (Price & Norman, in press) or fringe consciousness (Norman, Price, Duff, & Mentzoni, 2007). The study of cognitive feelings in decision making is associated with yet another set of methodological challenges (see Price & Norman, 2008).

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Table 1

Influential Mouselab studies based on their citation count

Publication	Citation count	Area
Payne, Bettman & Johnson (1988)	372	Gambles, multi-variate
Costa-Gomes, Crawford, and Broseta (2001)	67	Gambles
Bröder (2003)	44	Heuristics
Levin, Huneke, and Jasper (2000)	37	Consumer decision making
Lohse and Johnson (1996)	32	Method comparison
Dhar, Nowlis, and Sherman (1999)	26	Consumer decision making
Dhar, Nowlis, and Sherman (2000)	24	Consumer decision making
Lurie (2004)	17	Consumer decision making

Table 2

Influential eye-tracking studies based on their citation count

Publication	Citation count	Area
Russo and Dosher (1983)	200	Gambles
Lohse and Johnson (1996)	32	Method comparison
Russo and Leclerc (1994)	22	Consumer Research
Pieters, Rosbergen, and Wedel (1999)	22	Consumer Research
Pieters and Warlop (1999)	18	Consumer Research

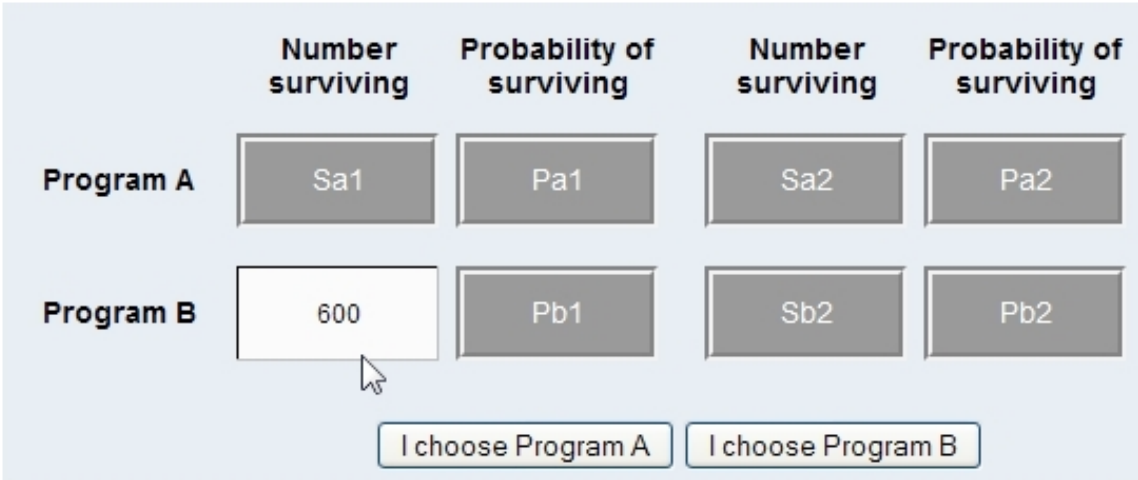
Figure Captions

Figure 1. Example of a MouselabWeb setup in a framing study. There are eight cells, with different labels, of which seven are closed and one open, displaying a value of 600. At the bottom of the figure the participant can select the option he prefers.

Figure 2. MouselabWeb Designer

Figure 3. Types of information-selection

Figure 4. Remote mounted system with the camera underneath the presentation monitor (top part), Head mounted system with the camera built into the helmet (bottom part)


Number surviving
Probability of surviving
Number surviving
Probability of surviving
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Pa1
Sa2
Pa2
Program B
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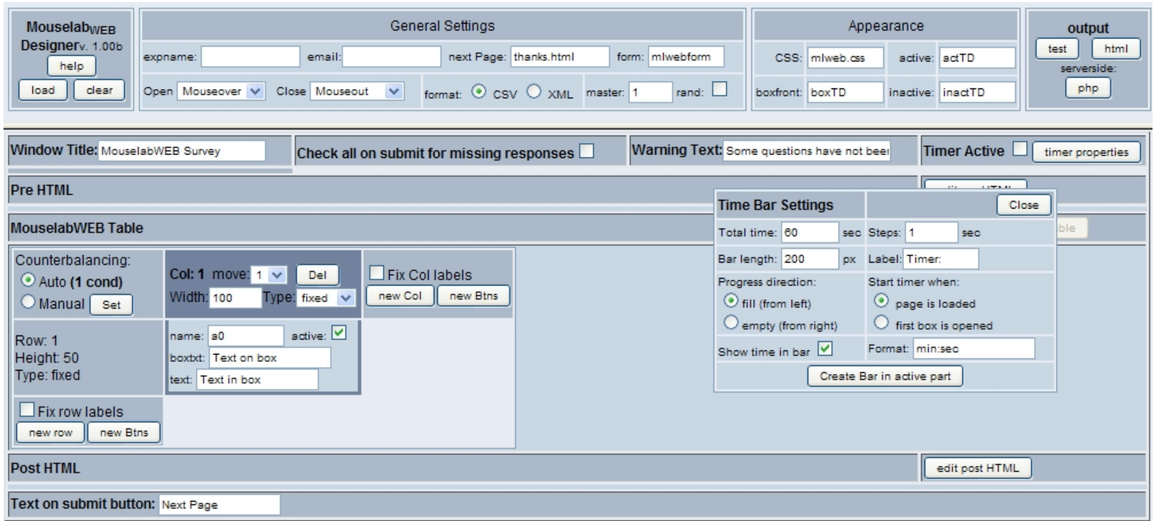
Pb1
Sb2
Pb2
I choose Program A
I choose Program B


MouselabWEB Designer v. 1.00b
help
load
clear
General Settings
expname:
email:
next Page: thanks.html
form: mlwebform
Open Mouseover
Close Mouseout
format: CSV XML
master: 1
rand:
Appearance
CSS: mlweb.css
active: actTD
boxfront: boxTD
inactive: inactTD
output
test
html
serverside:
php
Window Title: MouselabWEB Survey
Check all on submit for missing responses
Warning Text: Some questions have not beer
Timer Active
timer properties
Pre HTML
MouselabWEB Table
Time Bar Settings
Close
Total time: 60 sec
Steps: 1 sec
Bar length: 200 px
Label: Timer:
Progress direction:
fill (from left)
empty (from right)
Start timer when:
page is loaded
first box is opened
Show time in bar
Format: min:sec
Create Bar in active part
Counterbalancing:
Auto (1 cond)
Manual
Set
Col: 1 move: 1
Del
Width: 100
Type: fixed
Fix Col labels
new Col
new Btns
Row: 1
Height: 50
Type: fixed
name: a0
active:
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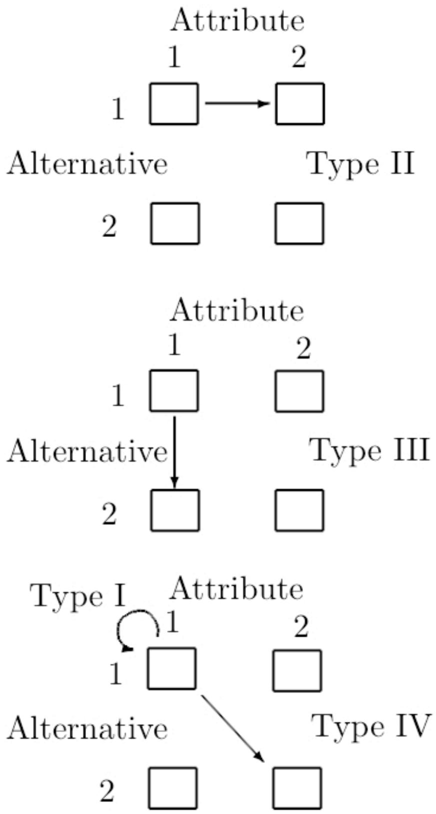
text: Text in box
Fix row labels
new row
new Btns
Post HTML
edit post HTML
Text on submit button: Next Page


Attribute
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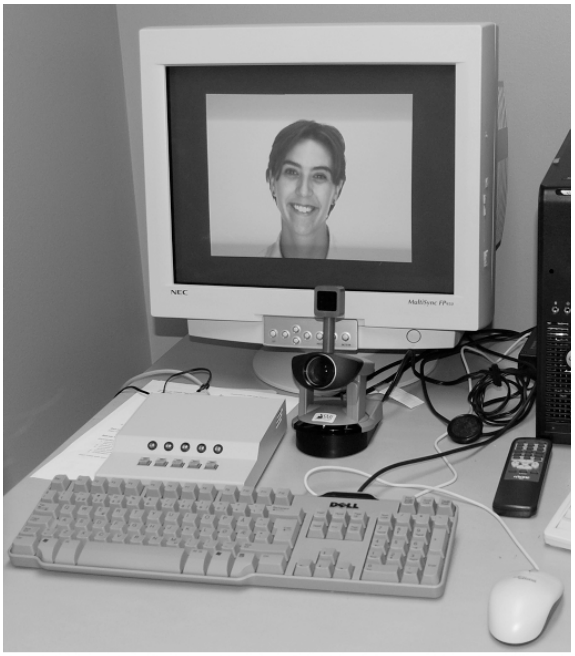
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DELL


SMI

Footnote

[1]Thanks to Martjin Willemsen for pointing this out to us.