The Effects of Arousal on Multi-Attribute Decision Making

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Abstract

The effects of arousal on decision making are widely studied. However, less is known about the relationship between arousal and more complex multi-attribute decision making. In this study, I used a probabilistic inference task to test the effects of manipulated arousal on decision strategy use. Furthermore, I tested the influence of information structure, trait anxiety and valence of affect on this relationship. Behavioral effects were analyzed on three distinct aspects of information search: importance of information, quantity of information, and integration of information. The results supported an increasing effect of arousal on the quantity of used information. Trait anxiety affected this relationship: Higher scores on trait anxiety decreased the effect of arousal on the quantity of used information. It is argued that combining an idiographic and nomothetic approach increases detection of effects given large inter-individual variability, and its varying susceptibility to environmental factors.

The Effects of Arousal on Multi-Attribute Decision Making

Central arousal state is unremittingly affecting human decision making, via systematic fluctuation (De Gee et al., 2017) or induced by external stimuli (Nieuwenhuis, de Geus, & Aston-Jones, 2011). An arousing environmental event elicits a response in the peripheral nervous system, and concomitant activation in neuromodulatory nuclei in the midbrain and brainstem mediates the cortical arousal state (Sara & Bouret, 2012). This way, environmental stimuli affect arousal, essential for cognitive functioning, and therefore decision making, which is fundamental to everyday human life (Pfaff, 2006). Effects of arousal on decision making are widely studied in domains of perceptual decision making in detection tasks (e.g. De Gee et al., 2017; Nieuwenhuis, Aston-Jones, & Cohen, 2005), and in relatively simple decision making tasks governing risk taking (e.g. Preuschoff, ’t Hart, & Einhauser, 2011), which has tremendously increased our understanding of effects and underlying mechanisms. However, sometimes people are required to make more complex decisions, based on multiple attributes. Less is known about the effect of arousal on decision strategy use in multi-attribute decisions. In this study, I aimed to investigate the relationship between arousal and decision strategy use in a probabilistic inference task, and the personal and environmental factors that might influence this relationship. Adaptation of decision strategy to the information structure of the task (Kerstholt, 1992; Marewski & Schooler, 2011) might be affected by a higher state of arousal. Furthermore, arousal induced by a positive affective state could have different effects on decision making than arousal induced by a negative affective state. Lastly, the effect of arousal on decision strategy use might be different for people with higher trait anxiety.

In this paper, I will first discuss classification of decision strategies. Second, I provide an overview of previous work on arousal and decision making. Subsequently, I explain the value of consideration of (individual) information search patterns. Before describing the experimental design, I propose possible effects of arousal on three distinct aspects of decision strategies.

Decision Strategies

People make many decisions every day. In order to predict the value of different options, decisions often depend on multiple attributes that contribute to possible future outcomes (Payne, Bettman, & Johnson, 1993). For example, when choosing a new car, one can compare power, price, design, et cetera. In this 'multi-attribute decision problem', not every cue predicts the best outcome with the same probability. When people make a probabilistic inference, they try to make a decision based on their perception of which option has the highest probability of being the best option (Rieskamp & Hoffrage, 2008). To do so, different decision strategies can be used. In research on this subject, decision strategies are generally classified in compensatory decision strategies and noncompensatory decision strategies. Compensatory decision strategies are based on the assumption that people make rational decisions (Bryant, 2014). For a perfectly rational decision, all cues would be evaluated, and all gathered information, including the validity and values of the cues, are integrated into one decision (Payne, Bettman, & Johnson, 1988; Rieskamp & Otto, 2006). Heuristic models of human decision making, in contrast, assume that people often rely on more simple rules to avoid the costly search for information (Korhonen & Wallenius, 1986; Payne et al., 1988).

Heuristic decision strategies can be noncompensatory, which means that cue validity and/or cue value information is not integrated into a decision (Rieskamp & Otto, 2006). Furthermore, heuristic decision strategies are typically characterized by the use of a subset of the available information (Betsch & Glöckner, 2010). Although many researchers differentiate between noncompensatory heuristic strategies and compensatory rational decision strategies (Bryant, 2014; Wichary, Mata, & Rieskamp, 2016), it is important to note that a decision maker can use a simplified heuristic decision strategy and a subset of the information, and integrate the information of that subset at the same time.

An example of a compensatory decision strategy is the weighted additive strategy (WADD). In this strategy, the decision maker calculates for each option the sum of all cue validities multiplied by all cue values, and selects the option with the highest sum (Rieskamp & Hoffrage, 2008). WADD is the ultimate rational compensatory strategy, and is also known as ‘Franklin’s Rule’ (Bröder & Schiffer, 2003; Gigerenzer, Todd, & the ABC Research Group, 1999), or ‘additive difference model’ (Tversky, 1969). A more simple compensatory decision strategy is tallying (TAL), in which the decision maker tallies the number of positive cue values for all cues for each option, and selects the option with the highest sum of positive cue values (Gigerenzer & Goldstein, 1996). Similar to the WADD strategy, tallying integrates cue values, but does not include cue validities in the decision. In the weighted tallying strategy (WTAL), both cue values and cue validities are integrated. The decision maker tallies the cue validities of each positive cue value for each option, and selects the option with the highest sum (Gigerenzer & Goldstein, 1996).

Prominently available in decision literature is the heuristic decision strategy ‘Take the Best’ (TTB; Gigerenzer & Goldstein, 1996). In this strategy, people select the cue with the highest validity and if this cue discriminates between the options, the option with the highest value on this cue is selected. If the cue with the highest validity does not discriminate, the cue with the second-highest validity is evaluated, and so forth, until the discriminating cue with the highest validity is found (Rieskamp & Hoffrage, 2008). The TTB strategy is a noncompensatory decision strategy: Values on the best discriminating cue determine the decision, and these values cannot be compensated by values on less valid cues. However, the TTB strategy often leads to a performance similar to compensatory decision strategies that do allow for integration of cue values (Gigerenzer & Goldstein, 1996).

The amount of information used to make a decision is an important determinant for classification of decision strategies. If WADD strategy, using all information, is on one side of the spectrum, one could say that pure guessing, not using any information, is on the other end. In the decision strategy ‘random choice rule’ (RAN) the decision-maker selects a random option (Payne et al., 1988).

Arousal and Decision Strategy Use

An arousing event leads to an adaptive behavioral response via two main biological mechanisms. Arousal state is mediated in the body by responses in the peripheral nervous system elicited by arousing stimuli (Sara & Bouret, 2012). An external arousing event immediately activates the sympathetic adrenal medullary system, resulting in secretion of catecholamines into the bloodstream (Gazzaniga, Ivry, & Mangun, 2019). Concomitantly, arousal state is mediated in the central nervous system by activation in neuromodulatory neurons in the midbrain and brainstem in response to arousing stimuli (Sara & Bouret, 2012). The locus coeruleus (LC) is a neuromodulatory nucleus in the brainstem with many projections to all other neuromodulatory serotonergic, dopaminergic and cholinergic nuclei in the midbrain and brainstem, as well as (sub)cortical regions. The LC is the sole source of norepinephrine (NE) to limbic and cerebral cortical structures (Sara, 2009). Therefore, the LC plays an important role in the modulation of central arousal state. Together, peripheral and central arousal facilitate an organism to respond to an arousing event with adapted behavior. Noradrenergic projections to the forebrain are of particular importance for shifts in attention in response to an arousing event (Sara & Bouret, 2012). The LC-NE system induces a signal to the ventral frontoparietal network (Bouret & Sara, 2005), resulting in the detection of salient stimuli. The ventral network subsequently interrupts the ongoing activity in the dorsal frontoparietal network, causing a reset of attention (Corbetta, Patel, & Shulman, 2008; Shulman et al., 2002). How could this ‘circuit breaking’ affect behavioral adjustment?

In literature about the effects of arousal on cognition in general, cognitive narrowing is frequently discussed. Interestingly, cognitive narrowing is used as a concept to account for behavioral effects in a wide range of studies in domains of for example perceptual attention, (social) categorization, ergonomics, safety and human-computer interactions. Cognitive narrowing often refers to a reduction of the attentional scope (attentional narrowing). Cognitive narrowing can also refer to a reduction of scope on a more conceptual level, for example in a study where heightened arousal led to more exclusiveness when subjects were asked to categorize items (Gable, Poole, & Harmon-Jones, 2015).

When addressing the question what the behavioral effects of cognitive narrowing as a result of arousal would imply for decision strategy use in a probabilistic inference task, it is important to consider that decision strategies can differ on various aspects. However, in the field of decision making, it is common to compare effects for two or more decision strategies. The researcher uses multiple regression to infer the used strategy from the outcome of the decision. The classification often entails differentiating between a compensatory and noncompensatory strategy (Bröder, 2000b). Besides that it is argued that structural modeling can reliably distinguish between these characteristics (Bröder, 2000b), it also omits to take into account the patterns of information search. Although computational models of decision strategies are important for empirical purposes, the applicability to actual psychological behavior might become questionable (Bröder, 2000a; Hanoch & Vitouch, 2004; Newell & Shanks, 2003). Therefore in the current study, I will consider the outcome of the decision, as well as search patterns for classification. Furthermore, I will take individual response patterns into account. Adding an idiographic approach prevents failing to detect systematic variation in individual decision strategy use due to aggregation of information search data (Bröder, 2000b; Einhorn, 1970; Rieskamp & Otto, 2006). Although including the decision process in analyses still involves making an inference about the used decision strategy that not necessarily has to be correct (a subject may for example search for additional information but not use it in the final decision (Rieskamp & Hoffrage, 1999), it does have the advantage of allowing for discriminating between aspects of information search and decision strategies. This is important, because increased arousal state might affect various aspects of the use of information that underlie the defining of a decision strategy. These aspects of information search, which will be discussed below, are: importance of information, quantity of information, and integration of information.

A common view regarding the effect of increased arousal involves narrowing of attention towards important information. Early research on this topic focused on allocation of attention in the visual field, and found that higher levels of arousal resulted in decreased utilization of cues displayed in the periphery of the perceptive field. Easterbrook (1959) refers to this phenomenon as ‘reduced range of cue utilization’, arguing that adjustment of the range of cue utilization serves the maintenance of performance under emotional distress. The well-known inverted U-shape of the relationship between arousal and human performance (Yerkes & Dodson, 1908) could be explained by the idea of an optimal attention for and utilization of relevant cues under the optimal level of arousal. Nevertheless, Easterbrook (1959) emphasizes that elevated arousal does not per se facilitate or deteriorate performance: The result of a reduced range of cue utilization on performance depends on the task at hand. When increased arousal results in decreased utilization of cues displayed in the periphery of the perceptive field, performance depends on the number of cues required to perform the task successfully (Easterbrook, 1959). Does arousal enhance allocation of attention towards centrally located information, or does arousal enhance the use of (central) relevant information, when peripheral information is perceived as irrelevant to the task? To answer this question, Cornsweet (1969) designed a task with task-relevant peripheral cues. In the arousal condition, the use of peripheral cues was enhanced. These results suggested that arousal narrows attention towards more relevant information, regardless of the location of this information.

In consecutive decades, abundant research with dual task paradigms followed. The dual task paradigm involves performance of two tasks concurrently, for example tapping the finger while performing a more cognitive demanding task. When arousal increases, performance on the central task is typically maintained at the expense of the secondary task (Navon & Gopher, 1979). The effect of ‘attentional narrowing’ in a higher state of arousal seems evolutionary plausible given that an organism in distress does not have the time to gather all information. Instead, decisions need to be made faster, based on a subset of information. This process is supported when heightened arousal changes the allocation of attention towards (behaviorally) important cues, and less attention is towards less important cues in the search for information.

In many studies in the field of decision making, researchers emphasize the aspect of importance of information when they make a distinction between heuristic or rational strategies, or between compensatory or noncompensatory strategies. A classification in either a complete rational compensatory strategy using all available information, or a noncompensatory lexicographic heuristic. I think it is important to acknowledge that a decision-maker can use a compensatory strategy while not using all available cues (i.e. take validities into account on a subset of information). Even so, a heuristic can be used where all available cues are used, while the exact validities are not taken into account (for example in the tallying heuristic). Moreover, in a multi-attribute dilemma, in real life as well as in a laboratory setting, cue validity dispersion can be low. When attentional narrowing leads to more attention towards the most important information, what happens when importance of information is close to equal over different cues? Many studies that manipulated arousal report a lower quantity of used cues in the high arousal condition. For example, Rieskamp and Hoffrage (2008) performed an experiment with a probabilistic inference task with consecutive cue search. In this experiment, fewer information boxes were opened in the condition with time pressure, which induces arousal (Svenson & Maule, 1993). Also in experiments without time pressure, where arousal was induced by perceived threat, fewer cues were used (Keinan, 1987). In a literature review on the effects of arousal on cognition, Staal (2004) concluded that in decision making, arousal leads to reduced search for information. To summarize: Although studies have different methods and report different outcomes related to strategy use, a consistent (secondary) outcome is the decreased quantity of information use. Therefore, it is argued that in order to validly test the use of heuristics and information search, it is important that the design of an experiment involves successive cue activation and not present all information on screen simultaneously (Gigerenzer et al., 1999).

A third aspect that distinguishes decision strategies is integration of information. Many researchers use this aspect to differentiate between compensatory and noncompensatory decision strategies. A change in the amount of integration of information in a higher state of arousal, would implicate not using other (more important) information, nor using less information, but using the information in a different way. Perhaps in a more simple way. Research suggests that in a high arousal condition, people tend to use more noncompensatory decision strategies: less integration of information (Rieskamp & Hoffrage, 2008; Wichary et al., 2016). The underlying explanation stems from the idea that rational computational strategies are cognitively more demanding than the use of a more simple heuristic (Gigerenzer & Selten, 2002; Simon, 1955). People tend to select a strategy that minimizes costs (Dieckmann & Rieskamp, 2007), so in arousing situations, people would choose a simple heuristic strategy that is less costly in time and effort. However, this line of thought assumes the conventional idea that a noncompensatory decision strategy (such as the TTB strategy), is less cognitive demanding than a compensatory strategy (for example the

WADD strategy). Interestingly, recent studies suggest that this might not be straightforwardly the case. Glöckner and Betsch (2008) suggest that noncompensatory and compensatory decision strategies rely on a underlying distinction between automatic and deliberate processes. The use of heuristic decision strategies is a deliberate rule-based processing, and a integration of cues in a compensatory decision strategy relies on automatic processes. Glöckner and Betsch (2008) argue that participants can respond according to a WADD strategy in an amount of time (1.1 second) that indicates automatic process of integration of information, instead of a complex, deliberate calculation with high cognitive demand. Even under time pressure, the majority of participants responded according to this compensatory decision strategy. Bryant (2014) provides further evidence for a certain automatic integration of information, and a deliberate application of heuristic decision rules. In his experiment, he manipulated cognitive demand by adding a secondary task to a decision-making task. Indicated by response time, results suggest that the secondary task interfered more when a heuristic strategy was used than when a compensatory strategy was used. Furthermore, it did not affect the proportion of participants using both compensatory or noncompensatory strategies. The relevance of the cue did affect strategy use: If one cue stands out and has a higher validity, the likelihood that a TTB strategy will be used increases. Bryant (2014) concludes that the use of heuristics can involve deliberate processes and that the use of compensatory strategies can involve automatic processes.

The outcomes of Bryant (2014) and Glöckner and Betsch (2008) are based on calculations of response time and models that predict the used strategy based on the decision outcome. Results (such as proportion of people using one strategy) are mainly based on aggregated data, which might cover individual patterns. Furthermore, Bryant (2014) considers all heuristics noncompensatory, while the unweighted additive rule could be considered compensatory as well as a heuristic, as mentioned earlier. Glöckner and Betsch

(2008) consider a comparable equal weight rule a heuristic. Despite these comments, the suggestion to argue the general assumption that arousal would lead to a less cognitive demanding strategy and thus a higher use of heuristics is interesting, considering that the use of a compensatory decision strategy might follow an automatic integration process, and the use of a heuristic might follow a deliberate application of a decision rule.

The aim of this study is to disentangle the behavioral effects of arousal on various aspects of decision strategies in a multi-attribute decision problem, using a probabilistic inference task and manipulation of arousal using affective pictures from IAPS (Lang, Bradley, & Cuthbert, 2008). Cues are displayed by means of successive cue activation. I tested the effects of arousal on three aspects of decision strategies: importance of information, quantity of information and integration of information. In the decision strategy ‘random choice rule’ (RAN), no cue is used, with no integration of information. In the decision strategy ‘take the best’ (TTB), 1-3 cues are used (depending on the position of the first discriminating cue), with no integration of information. In the decision strategy ‘partial tallying’ (PTAL), cue values are integrated on a subset of information. In the decision strategy ‘weighted tallying’ (WTAL) all cues are used, with integration of both cue validity and cue value.

Information Structure

Research suggests that environmental characteristics of the task affect the selection of decision strategies (Bryant, 2014; Marewski & Schooler, 2011; Rieskamp & Hoffrage, 2008). People tend to select a strategy that is perceived to have the best cost-benefit trade off: less cognitive effort with relatively high accuracy (Dieckmann & Rieskamp, 2007). Information structure of the task seems an important factor. When dispersion of cue validities is high, a relative high accuracy can be achieved by using the most important (high validity) cues, while ignoring less important cues. This is probably why many studies find an increase of

TTB usage when the information structure of the task encourages the use of lexicographic heuristics (Bröder, 2003; Gigerenzer et al., 1999; Marewski & Schooler, 2011). This is relevant for the current research because including a condition of high vs low cue validity dispersion (HVD vs LVD) allows to compare the effect of arousal on the aspects of importance and quantity of information. If the effect of arousal on the quantity of used cues is larger in the HVD condition than in the LVD condition, it means that the aspect of importance of information is crucial for the attentional narrowing effect on decision strategy use. If the effect of arousal on the quantity of used cues is similar in HVD condition and LVD condition, it means that the aspect of quantity of information is crucial for the attentional narrowing effect of decision strategy use.

Trait Anxiety

Individual factors can also influence decision strategy use. Individuals with a predisposition for anxiety are associated with increased activity of the LC, which increases cortical arousal (Howells, Stein, & Russell, 2012). Trait anxiety seems to have an effect on attentional narrowing (Pacheco-Unguetti, Acosta, Callejas, & Lupianez, 2010) and decision making (Werner, Duschek, & Schandry, 2009; Zhang, Wang, Zhu, Yu, & Chen, 2015). Therefore, trait anxiety will be measured and included in analyses to control for confounding effects on the relationship between arousal and decision strategy use.

Positive and Negative Valence

Valence of arousal can be negative or positive. In research on the topic of decision making, often positive and/or negative affect is compared to neutral affect. However, the outcomes are contradictory. Some studies find evidence for an increase in the use of heuristic decision strategies in positive mood (Bohner, Chaiken, & Hunyadi, 1994; Park & Banaji, 2000) and an increase of rational compensatory decision strategies in negative mood (Park & Banaji, 2000).

Others predict an increase in the use of heuristic strategies during negative mood and more compensatory strategies in positive mood (Bolte, Goschke, & Kuhl, 2003; Fredrickson & Branigan, 2005; Friedman & Förster, 2010). Results of Steenbergen, Band, and Hommel (2011) show that only arousal with negative valence leads to attentional narrowing, and not arousal with positive valence. They argue that arousal in general is not the regulating source of attentional narrowing. To take these contradictory views into account in the current study, manipulation of arousal will include positive and negative valence.

To investigate the effect of arousal on decision strategy use, I conducted an experiment with a 2 (information structure: HVD / LVD) x 3 (arousal: positive / negative / neutral) within subjects design. Analyses will include a combination of an idiographic and nomothetic approach.

Methods

Participants

Twenty-five participants took part in this experiment. All participants, regardless accuracy or performance on the task, are included for analysis, as decided beforehand. Trait anxiety scores are missing for 1 participant. The final sample for analysis of behavioral data consisted of 25 participants: 20 female, 2 left-handed, aged 18-27 (M = 23.1, SD = 2.6). All participants reported normal or corrected-to-normal vision, and absence of neurological or psychiatric disorders and use of psychoactive drugs. Participants confirmed that they did not consume alcohol 12 hours prior to the study, and no caffeine 3 hours prior to the study. All participants signed informed consent prior to testing. Participants received € 47,00 for participation in two experiments[1]. Participants were recruited through a recruitment website, most participants were international students from various departments. The study was approved by the Leiden University Ethics Committee.

[1] The current study was part of a larger project. Subjects participated in two sessions, where EEG and eyetracking was recorded. For the current study, behavioral data from the second session was used.

Procedures

Participants were told that the aim of the experiment was to study the effect of arousal on decision making, and that the task involved making choices about which diamond is the most valuable. They were also explained that they would see pictures that can elicit emotions, and that they could stop at any moment. After giving the opportunity to ask questions, participants signed an informed consent form. Participants were seated at 70 cm distance from the screen, in a room with dim light. In the instructions presented on screen, as well as verbally emphasized by the experimenter, participants were instructed to pay attention to the percentages that indicated the probability of each cue to accurately predict the best option. Participants were also instructed to respond as accurately as possible, and they were promised a bonus of € 3 for accuracy above 65%. After performing a training of 3 trials, participants performed the first block of 36 trials. After this first block an opportunity was given for a short break of 5 minutes, followed by the second block of 36 trials. The task duration was approximately one hour. Each block started with 8 trials with positive or negative pictures (see counterbalancing), followed by 8 trials of neutral affect pictures, and ended with 8 trials of negative or positive pictures. Before every trial block with pictures, 4 trials with a blank screen (no pictures) were presented to avoid residual arousal from previous trial blocks.

Counterbalancing

Participants were sequentially assigned to 4 groups. Group 1 and 2 started each block with positive affective pictures, followed by neutral pictures, and ended with negative affective pictures. Group 3 and 4 started each block with negative affective pictures, followed by neutral pictures, and ended with positive affective pictures. Group 1 and 3 had an LVD information structure in the first block, and an HVD information structure in the second block. Group 2 and 4 had an HVD information structure in the first block, and an LVD information structure in the second block.

Task

Participants performed a multi-attribute decision task adapted from Wichary et al. (2016). Participants had to make a decision about which of two diamonds had the highest value. Information about the diamonds was given in 6 cues: size, clarity, shape, color, brilliance and proportions. Cue values of these cues were indicated with 0 or 1, with 1 meaning a higher value on this cue than 0. In the LVD condition, cue validities were: 71%, 69%, 67% 65%, 62%, 60%. In the HVD condition, cue validities were: 93%, 69%, 64%, 62%, 62%, 58%. Cue validities were described to participants as “the probability of making a correct choice based only on that cue”. Cue validities were presented in the instructions before the start of the task. Participants had to actively acquire successive cues, which were always presented in decreasing order of validity (as above). In each trial, the left button on the keyboard was a choice for diamond A, the middle button was a choice for a successive cue, and the right button was a choice for diamond B. On every trial, the keys on the keyboard to respond with switched between keys z-x-c (left hand) and 1-2-3 (right hand), as indicated on screen and with labels on the keyboard.

Every trial started with a fixation cross with a duration of 2000 ms, followed by a neutral or affective picture, or a blank screen for the duration of 3000 ms. Subsequently, participants were asked the questions ‘what is your current arousal?’ and ‘what is your current mood?’, accompanied by a slide bar to indicate the answers on a scale of 0-100. Next, a screen appeared that prompted the participant to make a choice between A and B or to acquire a (successive) cue. When the participant chose for a cue, a blank screen was presented for a jittered duration between 900 and 1200 ms, followed by the presentation of the cue values for 3000 ms and another blank screen for a jittered duration between 900 and 1200 ms. The trial ended when the participant made a choice for A or B, after which feedback appeared on screen for 2000 ms.

Arousal Manipulation

For the manipulation of arousal, 24 affective pictures were drawn from the International Affective Picture System (Lang et al., 2008)[2]. IAPS is a system with a set of affective stimuli, including normative ratings for arousal and valence on a scale between 1 and 9. The 8 pictures in the negative trial block had a mean arousal rating of 6.2 and a mean valence rating of 1.73. The 8 pictures in the positive trial block had a mean arousal rating of 6.14, and a mean valence rating of 6.91. The 8 pictures in the neutral trial block had a mean arousal rating of 3.57, and a mean valence rating of 4.86. Pictures were presented in gray scale[1] (Bradley, Miccoli, Escrig, & Lang, 2008).

Analyses

A decision on a trial was counted as TTB if a correct choice was made on the first cue that discriminated between both options. If an incorrect choice was made on the first discriminating cue, or a choice was made on a cue before a discriminating cue, the trial was counted as RAN. TTB and RAN were considered noncompensatory strategy use. A decision confirmed the use of a compensatory strategy if a choice was made for a subsequent cue after a cue that discriminated between both options. A decision was counted as PTAL when a choice was made for a subsequent cue after a discriminating cue, and fewer than 6 cues were used. A decision was counted as WTAL when all cues were used. To test differences in integration of information between arousal conditions, I conducted a multilevel logistic mixed model with clustered bootstrap. The dependent variable was integration: compensatory / noncompensatory. To test differences in quantity of information and importance of information between arousal conditions, I used a multilevel linear mixed model with a clustered bootstrap.

[2] The IAPS stimuli used in this study are:
Negative: 2800, 3015, 3030, 3053, 3100, 3170, 3180, 3181. Neutral: 2278, 2383, 2393, 2410, 2441, 2514, 2579, 2620. Positive: 4640, 4650, 4653, 4658, 4659, 4689, 5621, 8041.

Results

Manipulation Check

The effectiveness of the arousal and mood manipulation was tested with paired *t*-tests. Subjective arousal scores were somewhat higher in trial blocks with affective pictures (M_{high} = 55.13, *SD* = 15.08) than in blocks with neutral pictures (M_{low} = 51.51, *SD* = 15.4), $t(24)$ = 2.972, p = .007, Cohen's d = 0.24, 95% CI [1.11-6.13], indicating that the arousal manipulation was effective. The difference between the positive (M_{neg} = 52.45, *SD* = 18.86) and negative blocks (M_{pos} = 57.81, *SD* = 15.44) was not statistically significant, $t(24)$ = -1.608, p = .12. Subjective arousal scores in neutral blocks differed with those in positive blocks, $t(24)$ = 2.943, p = .007, Cohen's d = .41, 95% CI [1.88, 10.72], but not with those in negative blocks, $t(24)$ = .473, p = .64.

Subjective mood scores were higher in positive blocks (M = 58.08, *SD* = 14.26) than in neutral blocks (M = 53.14, *SD* = 13.55), $t(24)$ = 3.891, p = .001, Cohen's d = .35, 95% CI [2.32, 7.56]), and lower in negative blocks (M = 42.85, *SD* = 15.25) than in neutral blocks, ($t(24)$ = -6.042, p < .001, Cohen's d = 0.71, 95% CI [-13.80, -6.77]), indicating that the mood manipulation was effective.

Quantity of Information

To test the effect of arousal on quantity of information (QUANT) I conducted a multilevel linear mixed models analysis (MLM) with the amount of used information in each trial as the dependent variable, using the lme4 package in R (Bates, Mächler, Bolker, & Walker, 2015). MLM is an appropriate method since the measurements are nested within subjects (Haverkamp & Beauducel, 2017). MLM is superior over repeated measures ANOVA in decreasing error variability by accounting for between-subject heterogeneity, leading to increased power to detect effects, especially in relatively small sample sizes (Goedert, Boston, & Barrett, 2013). To account for biased estimates of standard errors due to the within-subject dependency of measurements, I conducted a clustered bootstrap using the ClusterBootstrap package in R (Deen & de Rooij, 2019). I used full maximum likelihood estimation to estimate random and fixed effects. For the comparison of the models, I used the likelihood ratio test.

Model 1 was an unconditional means model that estimated within-subject and between-subject variance in the dependent variable, without any explanatory variables. The intercept was fixed and represented the mean number of used cues in neutral blocks. The results of all models are summarized in Table 1. The intra-class correlation was .537, which means that 53.7% of variance in quantity of information was explained by differences between subjects. A multilevel model is required to account for these dependencies.

In model 2, the level 1 predictors AROUSAL and INFO were added to the fixed effects of model 1. Given that differentiating between positive and negative affect did not lead to a better fit of the model (deviance = 4380.3, AIC = 4390.3, BIC = 4415.8), I decided to continue with a variable AROUSAL, representing the contrast between the condition of low arousal (blocks with neutral pictures) vs high arousal (blocks with affective pictures). INFO represents information structure, where 0 = HVD and 1 = LVD. In model 2, only the intercepts were random. The two level 1 predictors together explained 4.9% of the within-subject variation (AROUSAL 0.03% and INFO 4.6%).

In model 3, AROUSAL and INFO were added to the random effects of model 2. The variance in slope between subjects is $\hat{\sigma}_1^2$ = 0.06 for AROUSAL, and $\hat{\sigma}_2^2$ = 1.45 for INFO. Variance in intercept between subjects is higher ($\hat{\sigma}_0^2$=2.28). In model 4, the interaction of INFO and AROUSAL was added to the fixed effects of model 3. Model 4 did not outperform model 3, $\chi^2(5) = 4.50$, $p = .48$: There is no interaction effect between INFO and AROUSAL. Therefore, I continued with the more parsimonious model 3. In model 5, the (centered) variable trait anxiety (ANX) and the interaction of ANX and AROUSAL was added to the fixed effects of model 3. In model 6, which did not outperform model 5 ($\chi^2(2) = 1.27$, p = .53), gender and its interaction with AROUSAL was added to the fixed effects of model 5. In model 7, I added the fixed effect of counterbalance condition to the fixed effects of model 5, to test for order effects. Adding counterbalance conditions to the model did not improve model 5 ($\chi^2(3) = 3.15$, p = .37), which means that there was no difference in the number of used cues between beginning both blocks of trials with positive pictures and beginning both blocks of trials with negative pictures, or between beginning a block in the LVD condition and beginning a block in the HVD condition.

Comparison of all models is summarized in Table 2. I conducted a linear regression analysis with clustered bootstrap to model 5, using an α of .05 and 10.000 bootstrap samples. Results are summarized in Table 3. The final model explained 23% of the variance within subjects. The average number of used cues in the low arousal condition with HVD information structure is 2.31 (95% CI [1.79, 2.81]). Arousal and information structure both had significant effects on quantity of information. The number of used cues increased with 0.16 (95% CI [0.02, 0.29]) in the high arousal condition compared to the low arousal condition. In the information structure LVD, the number of used cues was 0.61 (95% CI [0.19, 1.03]) higher compared to the HVD condition. The significant interaction between arousal and trait anxiety suggests that an increase in trait anxiety leads to a reduction of 0.03 (95% CI [-0.05, -0.02]) of the increase of number of used cues in the high arousal condition.

Table 1

Results of Multilevel Models for Quantity of Information

Parameter	Model1	Model2	Model3	Model4	Model5
Intercept	2.72	2.31	2.31	2.28	2.31
AROUSAL		0.16	0.16	0.20	0.16
INFO		0.61	0.61	0.68	0.61
ANX					0.05
ANX * AROUSAL					-0.03
INFO * AROUSAL				-0.09	
$\hat{\sigma}_e^2$	2.08	1.98	1.60	1.58	1.60
$\hat{\sigma}_0^2$	2.42	2.42	2.28	2.21	2.16
$\hat{\sigma}_1^2$			0.06	0.12	0.01
$\hat{\sigma}_2^2$			1.45	1.00	1.44
$\hat{\rho}_{01}$			-0.41	-.024	-0.48
$\hat{\rho}_{02}$			-0.02	0.10	-0.04
LogLikelihood	-2192.3	-2162.9	-2069.8	-2067.5	-2066.7
Deviance	4384.7	4325.8	4139.6	4135.1	4133.3
$df_{residuals}$	1197	1195	1190	1185	1188
AIC	4390.7	4335.8	4159.6	4165.1	4157.3
BIC	4405.9	4361.3	4210.5	4241.4	4218.4

Table 2

Likelihood Ratio Tests for Quantity of Information

Model	*df*	LogLikelihood	Deviance	χ^2	$df\ \chi^2$
Model 1	3	-2192.3	4384.7		
Model 2	5	-2162.9	4325.8	58.865 ***	2
Model 3	10	-2069.8	4139.6	186.214***	5
Model 4	15	-2067.6	4135.1	4.450	5
Model 5	12	-2066.7	4133.3	6.278*	2
Model 6	14	-2066.0	4132.0	1.268	2
Model 7	15	-2065.1	4130.2	3.147	3

Note. ***$p < .001$, *$p < .05$

Table 3

95% CI Linear Regression with Bootstrap for Quantity of Information

	non-parametric	
	5%	95%
Intercept	1.79	2.81
AROUSAL	0.02	0.29
INFO	0.19	1.03
ANX	-0.07	0.12
AROUSAL*ANX	-0.05	-0.02

Integration of Information

On average, a noncompensatory strategy was used in 50.2% of trials. In the high arousal condition, a noncompensatory strategy was used in 51.2% of trials, compared to 49.8% in the low arousal condition. In the HVD condition, a noncompensatory strategy was used in 58.2% compared to 42.3% in the LVD condition. To test the effects of AROUSAL and INFO on the binary variable INT (integration of information), I conducted a multilevel logistic mixed models analysis with clustered bootstrap. The specification of the models was identical to analyses of quantity of information. Model 3, which included AROUSAL and INFO in fixed and random effects, outperformed model 1 and 2 ($\chi^2(5) = 149.07$, p <.001, see Table 4). None of the successive models, which included AROUSAL*INFO interaction (model 4), AROUSAL*ANX interaction (model 5), gender (model 6) and counterbalance condition (model 7) outperformed model 3. Statistics of comparisons are listed in Table 5. Differentiating between positive and negative affect did not lead to a better fit of model 3 (($\chi^2(5) = 6.59$, $p = 0.25$, AIC = 867.91, BIC = 939.17, deviance = 839.91). A logistic regression analysis with clustered bootstrap was conducted for model 3 (see Table 6). Results showed a significant effect of information structure on integration of information: $b = 0.64$, 95% CI [0.16, 1.16], $z = 5.46$, $p < .001$. In the LVD condition, the odds of using a compensatory strategy increase by a factor of 1.89, 95% CI [1.174, 3.177]. There was no effect of arousal on integration of information: *b* = .06, 95% CI [-0.09, 0.23], *z* = 0.50, *p* = .62.

Table 4

Results of Multilevel Models for Integration of Information

Parameter	Model1	Model2	Model3	Model4	Model5
Intercept	-0.32	-1.04	-1.26	-1.25	-1.19
AROUSAL		0.12	0.30	0.28	0.23
INFO		1.25	1.88	1.67	1.86
ANX					-0.01
ANX * AROUSAL					-0.05
INFO * AROUSAL				2.93	
$\hat{\sigma}_0^2$	9.86	10.98	16.70	20.72	16.50
$\hat{\sigma}_1^2$			1.16	2.38	0.97
$\hat{\sigma}_2^2$			15.53	13.33	16.17
$\hat{\rho}_{01}$			-0.92	-1.00	-0.95
$\hat{\rho}_{02}$			-0.42	0.06	0.45
LogLikelihood	-526.9	-497.8	-423.3	-421.5	-421.8
Deviance	1053.9	995.6	846.5	843.0	843.7
$df_{residuals}$	1198	1196	1191	1186	1189
AIC	1057.9	1003.6	864.5	871.0	865.7
BIC	1068.0	1023.9	910.3	942.3	921.7

Table 5

Likelihood Ratio Tests for Integration of Information

Model	*df*	LogLikelihood	Deviance	χ^2	$df\,\chi^2$
Model 1	2	-526.93	1053.86		
Model 2	4	-497.79	995.57	58.284 ***	2
Model 3	9	-423.25	846.5	149.070***	5
Model 4	14	-421.5	843.01	3.497	5
Model 5	11	-421.85	843.69	2.812	2
Model 6	11	-423.24	846.48	0.022	2
Model 7	12	-421.56	843.12	3.382	3

Note. ***$p < .001$

Strategy Use

On average, participants used a noncompensatory strategy in 50.3% of trials, of which RAN was used in 22.6% of trials, and TTB in 27.7% of trials. A compensatory strategy was used in 49.8% of trials, of which PTAL was used in 31.8% of trials and WTAL in 18.0% of trials. Figure 1 shows the percentages of strategy use across the conditions of arousal (low/high) and information structure (HVD/LVD). The proportions of RAN and PTAL use were consistent across conditions. A difference was present for the use of TTB and WTAL. The use of TTB was lower in the LVD condition (19.8%) than in the HVD condition (35.5%), while the use of WTAL was higher in the LVD condition (24.8%) than in the HVD condition (11.2%). As expected, the use of TTB strategy is higher in an information structure with high validity dispersion, and the use of WTAL strategy is higher in an information structure with low validity dispersion. However, this effect is similar in both arousal conditions. Comparison of aggregated data of strategy use does not reveal an effect of arousal.

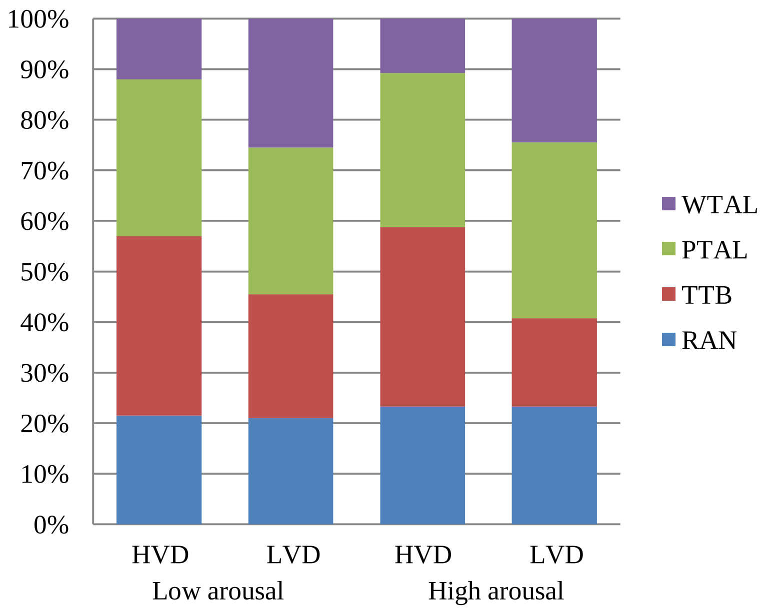

Figure 1. Strategy use across all participants.

Individual Patterns

Based on the majority of decision strategy use, all participants were classified as specific strategy users. Of all participants, 5 participants (20.0%) were classified as RAN users, 7 (28.0%) were TTB users, 9 (36.0%) participants were PTAL users, and 4 (16.0%) were WTAL users. This classification was different between the low and high arousal condition for only 2 participants: one participant mainly used WTAL in the low arousal condition and PTAL in the high arousal condition, and another participant mainly used TTB in the low arousal condition and compensatory (PTAL/WTAL) strategies in the high arousal condition. These findings confirm the absence of an effect of arousal on integration of information.

Accuracy was based on the proportion of responses equal to the correct response in accordance with WTAL strategy. Mean accuracy for all participants was 66.8%. The mean accuracy for RAN, TTB, PTAL and WTAL users was 56.2%, 64.3%, 70.9%, and 74.6% respectively.

An interesting pattern appeared when quantity of information was plotted against arousal conditions for each individual subject (see Figure 2). A declining effect of more than .3 was present only for participants #6, #9, #22, and #25. These 4 participants were all classified as WTAL users. Furthermore, WTAL users had a mean trait anxiety score of 45.5. This was higher than the average score across all participants (M = 39.1), and higher than the average score of other strategy users (M_{RAN} = 36.0, M_{TTB} = 40.7, M_{PTAL} = 36.6). Although confirmation is required for inferences, these observations support the recommendation to take individual patterns into account, and may reveal possible effects of arousal and trait anxiety on decision strategy use.

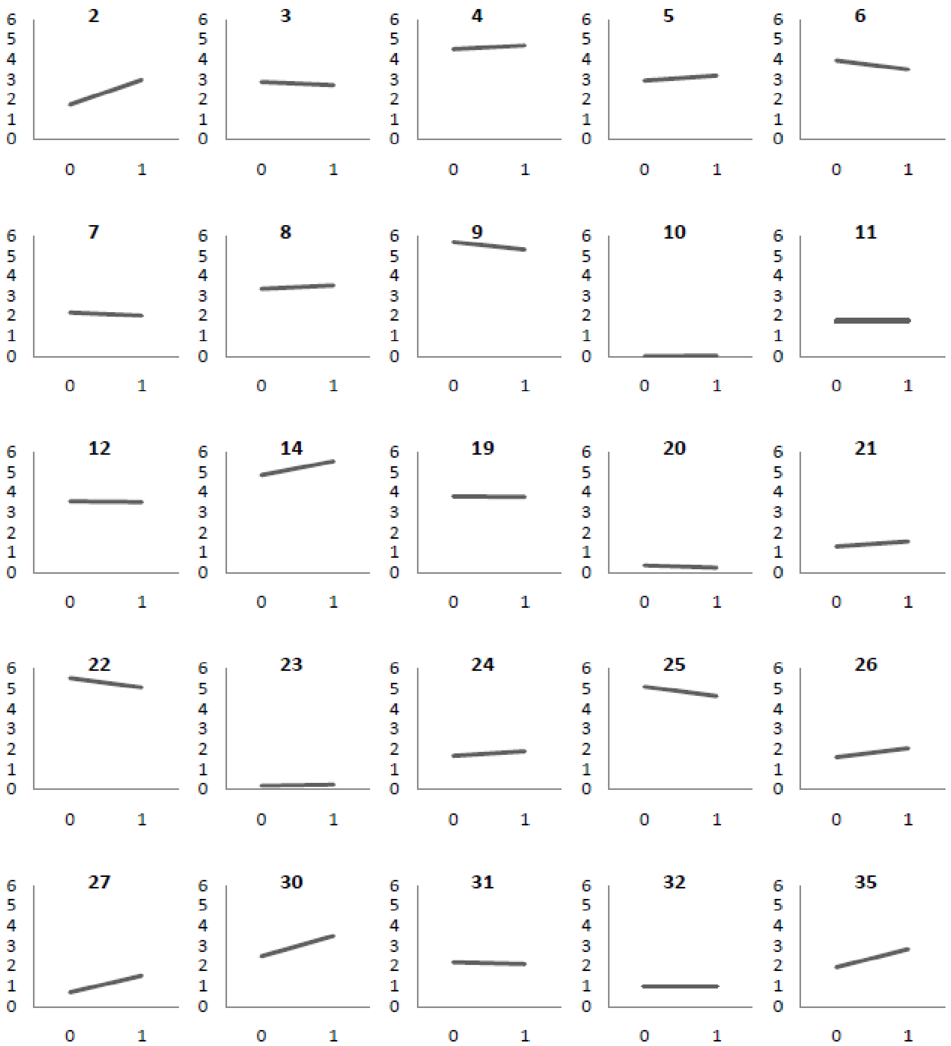

Figure 2. Quantity of information (y axis) in each arousal condition (x axis, 0=low arousal, 1 = high arousal) for all individual subjects.

Discussion

The purpose of this study was to investigate the effects of arousal on multi-attribute decision making. To answer the question which aspect of information search is affected by arousal, I used a probabilistic inference task with successive cue activation, and manipulation of arousal by means of affective pictures. Arousal had a small but significant increasing effect on the quantity of used information. Higher scores on trait anxiety reduced and ultimately reversed this effect. Arousal did not lead to a change in integration of information, nor did it lead to an alternated bias towards more important information. Information structure affected information search: Low validity dispersion increased quantity and integration of information. However, this effect was present regardless of the degree of arousal.

These findings do not confirm a general narrowing of attention in a state of higher arousal. The absence of an effect of arousal on integration of information is surprising, since many studies focus on this aspect of decision making when comparing the use of compensatory and noncompensatory strategies (e.g. Bröder, 2002; Shevchenko & Bröder, 2018; Wichary et al., 2016). The general idea is that according to the attentional narrowing hypothesis, arousal should lead to increased focus on more important information and increased use of simple, noncompensatory heuristics. The absence of this effect in this study is not likely to be caused by the used classification method, which included strictly defined criteria based on information search patterns that matched expected data patterns from the cognitive models of decision strategies. After all, an effect of arousal on integration of information was absent in analyses of aggregated strategy use, in individual classification of strategy-users, and in comparison of compensatory vs noncompensatory decisions on trials. Furthermore, I specifically addressed an important assumption of the attentional narrowing hypothesis: an allocation of attention towards more important information. The effect of arousal on this aspect of information search was not reflected in the results of this study either. However, an arousing environmental event did affect the amount of searched information, while the direction depended on the individual trait of anxiety. Therefore I argue that cue-utilization in multi-attribute decision making depends on an interplay of individual and environmental factors, which complicates ascribing a generalized effect on decision strategy use to arousal.

The influence of trait anxiety on the relationship between arousal and information search was evident and expectable, since high trait anxiety is related to increased tonic LC activity (Howells et al., 2012) and increased emotional reactivity in decision making (Miu, Heilman, & Houser, 2008). Performance on a task is highly related to LC-NE modulation, and levels of arousal affect task engagement following an inverted U-shape (Aston-Jones & Cohen, 2005; Yerkes & Dodson, 1908). This means that individuals with high baseline arousal and/or high arousal reactivity can react differently to induced arousal than individuals with low baseline arousal. In a multi-attribute decision task, this might imply that for an individual with low baseline LC activity, task-engagement will increase by the purported moderate increase in tonic LC activity in the high arousal condition, leading to an increase of information search. Conversely, an individual with higher baseline LC activity (e.g., due to trait anxiety), may move towards high tonic LC activity in the high arousal condition, resulting in task-disengagement and a decrease of information search. This might explain the effect of trait anxiety on the relationship between arousal and the quantity of used information, found in the current study. Results in this study also cautiously suggest that high trait anxiety individuals use the WTAL strategy more often. This is in line with the previous findings that anxiety can promote effortful processing (Tiedens & Linton, 2001). However, these results in the current study were not anticipated a priori, and found in a small number of subjects. Future research should confirm this relationship for multi-attribute decision making in a new and larger sample.

This study reflects the importance of individual factors in multi-attribute decision making. The differences between participants were larger than differences within participants across arousal conditions. The inter-individual differences cannot be explained by trait anxiety alone. There are more individual factors that may have an effect on the relationship between arousal and decision making. For example, individuals with a high need for closure are subject to increased arousal before making a final decision (Roets & van Hiel, 2008) and tend to use less information in order to reduce uncertainty (Jaśko, Czernatowicz-Kukuczka, Kossowska, & Czarna, 2015). This example illustrates that all (unmeasured) individual differences that may affect arousal, decision making, or an underlying modulating factor, potentially affect outcomes when studying the effect of arousal on multi-attribute decision making.

In a real-life situation, it is likely that an individual invests more effort in finding the correct solution to a multi-attribute problem, when the outcome is important to him or her. A limitation of this study is that participants might not have been highly motivated to respond accurately. Rewards for accuracy were relatively low, and information search was costly in time (60 s per trial for WTAL versus 20 s per trial for RAN), while cost-benefit tradeoffs tend to influence strategy choice (Dieckmann & Rieskamp, 2007). Most importantly, the feedback given after each trial did not correspond to either TTB or WTAL calculations of the correct response. This may have demotivated participants to invest mental effort in more complex integration of information. Furthermore, it may have increased uncertainty about task-related goals which might have influenced arousal in participants (Berenbaum, Bredemeier, & Thompson, 2008). Since motivational significance of information is positively related to phasic LC activity (Nieuwenhuis et al., 2005), it is possible that the motivational aspects of this study have influenced task performance or effects of arousal. I speculate that high motivation for accurate performance on a task will increase the likelihood of finding an effect of arousal on the aspects of integration and importance of information. Therefore I recommend to vary the levels of incentives in a future study on arousal and multi-attribute decision making. I also recommend to increase sample size in order to have a sufficient and balanced representation of possible stratifications of baseline anxiety. Anxiety may in turn influence sensitivity to incentives (Miu et al., 2008).

The results of the current study support an effect of arousal on quantity of used information, and demonstrate that an arousing environmental event can influence decision making in more complex multi-attribute decision problems. In this study, I proposed a novel way of addressing behavioral effects on the use of decision strategies. By investigating distinct aspects of information search as opposed to categorized decision strategies, I demonstrated that important effects on information search can be detected that would have been unrecognized otherwise. Furthermore, this study underlines the value of an idiographic approach, given the large individual variability in strategy use. The effect of arousal on multi-attribute decision making reflects a complex interaction of individual factors with contradictory responses to environmental factors.

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