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An abstract of
a thesis submitted to the Faculty of Emory College of Arts and Sciences
of Emory University in partial fulfillment
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Abstract

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Previous research has revealed we often make decisions by relying more or less on deliberate cognition. Human decision-making about choosing between options of unspecified value demonstrates our preferences. The present study focuses on the influence of either greater deliberate processing or greater automatic processing on emotionally salient preferential decisions. By presenting 11 participants with preferential tasks under manipulations that increase reliance on these processing systems, it is revealed that we may utilize rationalizations of automatic decision-making to inform our elaborated evaluation of stimuli, and that influencing motivation is important for manipulating deliberate cognition. Finally, through modeling these decision tasks with deep reinforcement learning models, we discovered that these preliminary model-free deep Q approaches are more similar to performance under deliberate cognition rather than automatic cognition, contradicting our predictions. This research may further our understanding by demonstrating how these aspects of decision-making influence our actual choices and informs how researchers should utilize these machine learning approaches for future research.

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Dual Systems Influence on Preference Based Decision Making

Preferences are our inclinations to seek out one concept, idea, or experience over others given the choice. This judgement of our environment shapes both our automatic responses and our conscious judgement. Preferences are fundamental to our decision-making about emotionally charged stimuli. Therefore, it is important to understand the mechanisms behind this concept as disruptions to normal decision-making processes can lead to life-threatening conditions, or impairment to quality of life. Our preferences have been demonstrated to be influenced by conscious input, as well as our implicit biases (Berridge & Kringelbach, 2008) Broadly speaking, decision-making has been theorized to be influenced by two distinct processes: a rapid, automatic process (referred to as "System 1") and an effortful, deliberate system ("System 2"; Glockner & Witteman, 2010; Mauss, Bunge, & Gross, 2007) Machine learning approaches have effectively modeled decision-making in many contexts and approaches, such as model-free Reinforcement Learning (RL), seem to follow a similar organization to rapid, "System 1" processing. (Peterson et. al, 2021) Though reinforcement learning has been used to model dual systems theories before, and has been used to predict preferential behavior, this approach has yet to be applied complex, emotionally charged, generalizable stimuli. In the present research, we investigated the impact of dual systems manipulations on decision-making as well as the predictive power of RL models to preferential behavior of naturalistic, emotionally valent stimuli.

Emotion and Preference

Valence—or the degree to which an emotional experience is either positive or negative—plays a vital role in our decision-making. Our incentives to make decisions are driven by reward and punishment, which are often the result of either positive or negative emotional experiences.

These emotional experiences are classically viewed as automatic processes that are not influenced by conscious effort. However, recent findings have demonstrated that deliberate cognitive actions such as logical reasoning about the causes of emotional events (O'Rorke & Ortony, 1994), attentional constraints (MacLeod et. al., 2002), and deliberative regulation of emotion (Gross, 2002) can influence the nature of emotional experience. Therefore, the valence of an experience is determined by automatic and deliberate processes.

Though it was once posited by economists that decisions were made through purely rational influences, modern approaches have accepted the strong influence of emotions and bias in human decision making. These early approaches to decision making, such as expected utility theory, were replaced by more psychologically accurate theories (Starmer, 2000). A principal example of this development is prospect theory, formulated by Kahneman and Tversky, which posits that our subjective value judgements are distinct from objective utility (1979). As these approaches have been demonstrated to be more accurate, it became clear that the decisions we make are guided by our emotional experience (Levy, 1992).

Preference, or the inclination to choose one stimulus over others given the opportunity, is therefore driven by our emotional experiences. The unconscious associations we have, surrounding context, and our subjective liking of a concept all define our specific preference for it. Our emotional experiences which produce this subjective context for our choices provide this basis for preference, and therefore decision-making in many circumstances (Leder, Tinio & Bar, 2011).

Decision-Making

The mode in which humans make decisions about probabilistic events, and about situations that may result in either reward or punishment, determine a great number of outcomes in an individual life. In extreme cases, impairments in decision-making can derail an individual's ability to live freely and healthily. For example, individuals with Parkinson's disorder have been found to display less profitable decision-making and impaired executive functioning (Mimura, Oeda & Kawamura, 2006) which can lead to devastating financial damage, and disrupted relationships. In many cases, decision-making interventions are developed to aid individuals who have impaired functioning, as remaining untreated can result in dangerous and risky behavior (Janis & Mann, 1976). For these individuals, it is important to determine the mechanisms that drive normal decision-making, in order to produce techniques that can address these extreme cases.

The preference that shapes our choices about emotionally relevant information is driven by this fundamental decision-making processes. While some elements of our preferences may be implicit evaluations of situations—such as deciding whether or not you enjoy a flavor of ice cream—there are also examples where we express these preferences by explicitly selecting choices. Examples for this aspect of preferential decision-making include how often you are to actually buy that flavor of ice-cream, which may be unrelated to how you consciously feel about flavor. These aspects of preference are both driven by our reaction to emotional stimuli, but they result in differing behaviors, and can be driven by separate processes.

Decision-making is often studied in settings with rigid control over the environment. In these cases, individuals have little experience of true risk or personal reward, and therefore these conditions can limit what can be determined about natural decision-making. For example, some approaches to investigating decision-making include very contrived scenarios such as games with a reported monetary value (e.g., *Choose one option and get $3, choose another and you have a chance to gain 10$*; Steinberg, 2010). While these approaches allow for precise control, they are very dissimilar from real world examples of decision-making. Organic examples often have unclear rewards, emotional relevance, time pressure, and less explicit stimuli. The influences over these decisions are far from exclusively rational, top-down understanding inhibiting low level impulses, but instead are often determined by these more rapid inclinations. In natural cases, the ability to make deliberate decisions is often unavailable due to limited motivation or ability. When these constraints are present, rather than considering the role of the rational self-interest that leads to decisions, our choices are dictated by this automatic, rapid thought process.

Methods for Investigating Decision-Making

The primary approach to investigating decision-making is through behavioral choice tasks. In these approaches, participants are offered options that have some level of subjective value, and their choices are recorded for each trial. These investigations can reveal what factors change our decisions, such as level of uncertainty, degree of reward or punishment, type of reward, and how the information is presented. These tasks can then be analyzed using statistical approaches, or more recently through the use of computational modeling.

One of the primary approaches used for modeling decision-making is the use of machine learning, which runs a program designed to take an input and produce an output, changing the weights within the model to create a more and more accurate outcome according to the desired output—therefore resembling the learning process humans use. These approaches have been used to train the computer to replicate the behavior of participants and attain highly accurate predictions of their decisions. These models can then be investigated by analyzing their structure to understand the theoretical organization of the neural circuitry that may be involved in the same process in humans. This approach has been used to investigate general decision making, decisions in social situations, (Kishida & Montague, 2012) and moral decision making. (Crockett, 2016). One machine learning approach, called “reinforcement learning,” trains these models by reinforcing or punishing elements of the model according to the accuracy of the output, improving performance through trials, and therefore “learning” (Sutton & Barto, 1998). This model is theoretically similar to low-level conditioning learning, as it has less to do with higher order context and simply trains the model on correct or incorrect outputs. In recent years, larger datasets have been increasingly used resulting in these models having much greater accuracy in predicting human decision making, allowing for a deeper and more accurate analysis of human decision making (Peterson et. al., 2021). As these approaches have become more utilized, we are discovering that the different types of models are better able to predict specific aspects of neural circuitry, therefore suggesting that the choice of model used must be guided by knowledge of the type of cognition being studied.

Dual Systems Theories

According to Kahneman and Tversky’ dual system theory of decision-making, we make decisions by relying on a combination of two processes, which they term “System 1” and “System 2” (Frankish, 2010; Glöckner & Witteman, 2010). System 1 decision-making is influenced by rapid, biased, but extremely efficient processes. These influences often employ heuristics, stereotypes, and generalizations which are based on the surface level features of stimuli rather than surrounding context or detailed information. “System 2,” on the other hand, is a slow, deliberate, often very rational influence on decisions, leading to conclusions to be drawn according to context and the full detail of information presented. Both of these systems work together to influence behavior, and individuals can rely more or less on either a deliberate process or an automatic one.

This theory of decision-making has been thoroughly demonstrated in research (Lubashevsky et. al., 2019). Across the field of economics, it was previously believed that decisions were made due to the rational influence of objective value and self-interest, however this account could not predict the influence of factors such as bias, limited intellectual resources, and affective inclinations which were accounted for in the dual systems approach (Opaluch & Segerson, 1989).

These theories suggest that, perhaps, those hyper-controlled laboratory conditions and unrealistically explicit rewards in previous decision-making research may incline individuals to think in a more rational, "System 2" influenced way. It may also be possible that these highly explicit forms of rewards lead to less time spent interpreting the stimuli, therefore leading to a more automatic, "System 1" form of processing. Either way, this type of reward used in research may have an impact on the style of decision-making participants rely on. Additionally, preferences about emotional content may also be influenced by both our implicit rapid inclinations, as well as our deliberate understanding of the context of a situation and choice. Research has demonstrated that emotional valence of stimuli has a large impact on eventual decision making (Katahara, 2011). However, it is not fully clear in what ways naturalistic emotional stimuli impact a greater reliance on either of the dual processes. Most decisions we make are heavily biased by our emotions, and often are not purely neutral information such as how many dollars a choice will earn us, or theoretical points scored. Given that our interpretation of emotional stimuli is impacted by either our reliance on deliberate or automatic processing, it is therefore important to frame our understanding of decision making based on emotional stimuli around this dual process approach.

We know that we think using more deliberate as well as more rational processing, but this simple fact has deep implications for our experience of reality. The deepest psychological question—of understanding our conscious experience of reality—is intrinsically tied to these dual processes. Our ability to be aware of stimuli consciously, is the process that makes our decisions either deliberate or automatic. If we intend to understand how our conscious attention changes our reaction to stimuli that elicit a reaction from us, either due to threat or due to reward, we must investigate the role of our deliberate cognitions on decision making. This work will therefore allow us to understand to what degree our conscious attention impacts our preferences.

Modeling Dual Processes

An important modern approach to investigating preference-based decision making, is through the use of Deep Reinforcement Learning. These models have been shown to successfully model these decision processes (Diederich & Trueblood, 2018). Research reveals that preferences seem to be driven less by the content of images, as they were driven by aesthetic evaluations, which are less determined by higher order, deliberate, “system 2” decision-making. Investigations such as these emphasize the distinction between modeling a rapid and a deliberate process. More recent research has demonstrated that the use of “model free” reinforcement learning may reflect a more rapid approach than “model based” reinforcement learning, which has a greater theoretical similarity to deliberate processing (Peterson et. al., 2021). additionally, quantitative, and statistical modeling has successfully distinguished between these two processing approaches (Milli, Lieder & Griffiths, 2021). As with so many other examples of cognition, utilizing these machine learning models to examine previous cognitive theories helps us analyze more specifically the structural differences in neural circuitry, but also the specifics of the cognitive processing. While these models have been able to model dual processes in cognition, they often have been specifically compared against performance on unrealistic, abstract rewards rather than naturalistic ones (Plonsky & Erev, 2021).

Current Study

Previous research into the dual systems influence on decision making focused primarily on using less naturalistic, more simplistic stimuli. Specifically, the rewards used are often unnaturally explicit and abstract, whereas natural choices are often based on emotional salient stimuli. While this makes the impact of these systems easier to observe, it weakens the generalizability of the findings. Additionally, many of the presumed approaches to manipulate the reliance on either deliberate or automatic decision-making lack thorough investigation into the impact on these naturalistic stimuli. Finally, the machine learning models that can predict this influence have been applied to other instances of dual systems approaches but may not have been understood for naturalistic stimuli. This study aims to integrate these gaps in the literature by utilizing naturalistic stimuli under common manipulations for the dual systems approaches, and then model these influences with deep reinforcement learning.

The present study was conducted using a sample from the general metro-Atlanta population. We administered a Cognitive Reflection Test questionnaire, and a 1-hour preference-based decision-making task constructed using naturalistic images from the Stanford Dog Dataset, naturalistic spider images from the GBIF database, altered images which were created using *DeepDream* for a trained model on each of the animal types, and coded using the *PsychoPy* software. We recorded participant's choices under each pairing of options between high threat dog images, low threat dog images, high threat spider images, and low threat spider images, to determine if these deliberate/automatic manipulations may change the preference choices of individuals for these stimuli by relying more or less on species or true threat level. We also recorded their self-reported mood for anxiety, excitement, and arousal after key choices. We hypothesized that choice behavior would match self-report data according to the expected relationship under deliberate manipulations, and that it would not match self-report on automatic manipulations (Match an expected relationship can be defined as participants choosing options less frequently if they report feeling unpleasant after viewing it). Second, we hypothesize that model-free Reinforcement Learning is worse at predicting choice behavior under deliberate manipulations than under automatic manipulations.

Methods

Participants

Participants (*N* = 11, 2 males and 9 females) were adults (*M* = 48.18, *SD* = 13.2) from near Atlanta, Georgia, and surrounding metro area. The sample's racial and ethnic breakdown showed 90.91% were Caucasian, 9.09% were Asian. The participants were recruited through the subject pool data base called the Emory SONA system of the psychology department, as well as online advertisements through Smartform. The participants were directed to complete a prescreening questionnaire and then were contacted through email if they were eligible. Participants were able to withdraw at any time, though none withdrew. Potential participants that were not adults, were cognitively impaired, prisoners, or not fluent in English did not meet the inclusion criteria to participate.

Materials and Measures

Sociodemographic Questionnaire

We asked the participants to complete a list of primary demographic, education, and social status questions—which were all merely metrics to better understand the representativeness of our sample.

Baseline Questionnaires

We administered multiple frequently used questionnaires in order to ensure our sample fell within typical scores across relevant traits (Speilberger, 1983; Narrow, 2013; Kroenke, Spitzer & Williams, 2001). We administered the State-trait Anxiety Inventory (STAI-S) which measured the state anxiety before self-report and experimental manipulations (Frederick, 2005).

Cognitive Reflection Test

The Cognitive Reflection Test (CRT) is a 3-item questionnaire that asks participants to answer questions that require effortful and deliberate consideration to correctly answer. (For example: "A bat costs $1 more than a ball, and they both cost $1.10 together. How much does the ball cost?", the correct answer being $.05, with the trick answer being $.10) This measure is designed to test how likely participants are to rely on deliberate thinking and is a well-established measure in decision-making research. The questions are scored based on sum of correct answers. This measure has been shown to have high inter-item reliability (r = .7; Stagnaro, Pennycook & Rand, 2018).

Visual Stimuli

The images presented were a subset of the Stanford Dog dataset (Khosla et. al., 2011*)* selected based rates of fatal bites per year, and visual similarity across threat levels. Additionally, we used a set of naturalistic spider images from the GBIF database, similarly selected for based on clinically significant bites, and visual similarity between species detected by a convolutional neural net trained to distinguish between species of spiders (GBIF.org, 2021). We selected

American Staffordshire Terrier (Pitbull) and Chow-Chows as the high threat dog breeds, Golden Retrievers and Boxers as the low threat dog breeds due to their reported bite frequency (Sacks et. al., 2000). Additionally, we selected the Brown Recluse (*Loxosceles Reclusa*) and the False Widow (*Steatoda Borealis*) as the high threat spiders, and we selected the Jumping Spider (*Saitis Barbipes)* and the Southern House Spider (*Kukulcania Hibernalis*) as our low threat spiders, due to the clinical significance of their bite (Wong, Hughes & Voorhees, 1987). For one set of manipulations, we created a new set of 18 images per set of naturalistic images that were digitally altered to project the low-level features of these images (for each onto neutral background (eg. A grassy hillside), using *DeepDream* on convolutional neural networks trained to classify images of dogs and spiders in terms of their breed and species, respectively. (Human AI Collaboration, 2021; *See Figure 4*).

Behavioral Task Software

The behavioral task was conducted on PsychoPy software, which displayed two of four possible squares with a neutral corresponding color for each decision trial. When a neutral cue was selected, an image from the corresponding data set of either high-threat spiders, low-threat spiders, high-threat dogs, and low-threat dogs, was displayed. This baseline behavioral condition was altered in 3 ways: duration restriction, addition of information (which revealed the true threat level of each species beside the image), and/or *DeepDream* low-level image manipulation. (*See Figure 3*).

Procedure

We aimed to understand if decision-making was impacted by rapid or deliberate modes of processing. To test this, we manipulated the duration of choices presented before a decision task, the feature level of the images, and the information presented. We then recorded the choices our participants made, the output of the deep reinforcement learning models, and participant self-reports of pleasure, excitement, and anxiety. By comparing the performance of deep reinforcement learning models, we assessed how well these tasks are likely to influence rapid or deliberate thinking and estimate the organization for how that decision making process occurs through the models. Additionally, by comparing the differences between the manipulations we may investigate how these dual systems influence preferential decision-making.

We first invited the participants in the lab and asked for their consent on the study and administered the set of questionnaires and recorded their payment information. This process took around 30 minutes. Next, we presented them with PsychoPy tasks in the lab, which displayed the image choice task. During each trail, the participants were presented with 2 of 4 possible neutral-colored squares. Each of these options, when picked, displayed images from one of four groups of naturalistic images, each corresponding to one of the shapes: 2 species of “non-threatening” spiders, 2 species of “threatening” spiders, 2 breeds of “non-threatening” dogs, and 2 breeds of “threatening” dogs (*See Figure 3*). For each block of trials, one pairing of choices will have a self-report questionnaire presented, 6 at every block, totaling to totaling in 48 during the entire process. These self-reports allowed the participants to record to what degree they feel pleasure, excitement, or anxiety by moving a point along a slider with their mouse.

This task was broken into 6 sections, a total of 293 trials, containing 3 independent manipulations throughout the experiment. In the first block, participants were given unaltered behavioral tasks presented along with duration restricted trails. During these time-restricted trials, the participants were given 1 second to make their decisions between cues, which is intended to result in more rapid decision-making. Additionally, in this first block the participants were presented with visually manipulated images of the dogs and spiders in place of the naturalistic images, that combine low level features of the images with a neutral background (for example, a grassy hill) using *DeepDream* (*See Figure 4*). This therefore altered the visual features for the dogs or spiders, allowing us to influence whether participants could readily use semantic information about the images (i.e., the specific type of animal presented), theoretically increasing reliance on more rapid decision-making. These low-level trails were additionally split into limited duration and normal duration trials.

In the second block, the participants were administered unaltered trials, duration restricted trials, and additionally, trials in which participants were presented with information on how dangerous species are at the beginning of the section. Then within each of these information manipulation trials; the participants were shown a figure displaying the true threat level for each species beside the naturalistic images (*See Figure 5*). This was performed to influence the participants to think in a more deliberate way. Finally, we debriefed the participants on the intention of the study and compensated each of them.

Data Preparation

The choices for each participant given the two options present in each trial were recorded, along with the pair of options available, and the manipulation during the trial. This was used to calculate if the threatening option was selected (1 if yes, 0 if no), and if the spider was chosen (1 if yes, 0 if no). Additionally, each mood rating was recorded along with the options available in the trial before the self-report recorded (a scale from 0 to 100). From these, average scores of choosing threat, choosing spider, and self-reported pleasure was calculated from the set of data. The cognitive reflection test was scored by either receiving a 1 or a 0 if the participant correctly answered the question, and the score was summed across all questions (Total of 3 possible).

Design, Scoring and Analysis

The present study is a cross sectional, experimental study. Independent variables used were duration of choice presented (*duration*), complexity of visual features of stimuli (*low level vs holistic*) and presented information to the participants (*present or not*). The dependent variables measured were choice behavior from the participants (*Chose threat* and *chose animal type*), choice behavior from deep Q networks trained to emulate human behavior, and self-report of pleasure, excitement, and anxiety from the participants. We used factorial within subjects ANOVAs to determine the relationship between the manipulations and choice behavior of the participants, behavior of the artificial neural network models, and self-report of the participants.

The deep Q networks are deep model-free reinforcement learning models that emulate human behavior. They are computer models that make selections about input that is either rewarded or punished based on accuracy according to reward schemas. It takes as inputs the images of the cue pairs, and then after a selection it takes as input the naturalistic images, which it then judges according to the reward schema. The decisions it then records as an output, and we analyze the average score of the rewards to determine if learning occurred. The Deep Q Reinforcement Learning model was trained using 3 reward schemas: punishing threat, punishing animal type, and mixed punishment, such that the model would train itself to either avoid choosing stimuli if it was either threatening, a spider, or both. Over many trials (300 epochs of 100 trials each), the model eventually sufficiently learned to make consistent decisions, which we then compared the performance of participant behavior in each condition and recorded the R^2 value for each subject.

To examine the first and second hypotheses that choice behavior will be inconsistent with self-report data under “rapid” manipulations, and consistent with self-report data under "deliberate" conditions, we first analyzed the choice data and the self-report data to determine if any significant interactions were present. We performed two repeated measures ANOVAs to compare each of the manipulations (image features, duration, information) for both self-reported pleasure and choice of threat, along with multiple interactions. Additionally, we compared the mean differences between the conditions for choice and self-report data.

Results

Descriptive Statistics for Measures of Interest

Our sample consisted of (2) male and (9) females, (n = 11). Our participants reported being 90.91% Caucasian, 9.09% Asian. The mean age for the participants was 48.18 years old, with a standard deviation of 13.2. Participants reported their mood being generally positive, with variation. (Pleasure Intercept = 41.733, Standard Error = 11.80) 36.4% of participants succeeded across all of the cognitive reflection test questions, with a mean score of 1.64 out of 3.

Across the manipulations, participants reported having a positive mood in response to images of dogs. In all conditions, (natural or features, slow or fast) the mean score was near or above 50% for preference of dog images. Additionally, nearly all conditions showed a below 50% mean pleasure report in response to spider images. (What was chosen for dogs preference and show figure or numbers). Peculiarly, there seemed to be a tendency to report high pleasure in response to spiders under the slow, altered features condition. This pleasure report was similar to the reports in response to dog images, unlike in the fast altered features images (*See Figure 1*).

Tests of Main Hypotheses

Among our ANOVAs results which investigated if there were consistent patterns between self-report and behavioral data across manipulations, we found that there was a statistically significant 3-way interaction between duration, image type, and animal type difference on choice of threat, such that all groups except short duration low-level feature images showed differences between animal types in choosing threat (Parameter Estimate = 0.98, Standard Error = .049, z = 1.98, p = .048). Additionally, we found a significant interaction between image type and animal type for reported pleasure, such that in low-level features, participants rated spiders as more pleasurable than in naturalistic trials (Parameter estimate = -5.68, Standard Error = 2.03, t_{82} = -2.79, p = .0065). This revealed that across the entire study, there was consistency for the causes of both self-report data and behavioral choice data, being a relationship between the image type and animal type.

Additionally, we investigated the responses to choosing spider under each of the conditions (naturalistic and altered features, fast and slow) as well as the reports for pleasure across each condition, to determine if these outcomes matched under each condition, to investigate our first hypotheses. We discovered that in each condition, when they reported lower pleasure for spiders, they chose spiders less frequently (*See Figures 1 & 2*). This was consistent with the expected relationship between self-report, and choice data, which we would classify as “matching” results. While this confirmed the first part of our hypothesis, it disconfirmed the second part. Specifically, that self-report data would match with choice data under deliberate manipulations was shown to be accurate, but that self-report data would be inconsistent with choice data under automatic manipulations was inconsistent. However, as we have not yet completed collection of the full planned sample for this study, these results do not have enough power to be statistically significant differences. We plan to continue to collect and analyze more participants to determine if these differences are statistically significant with adequate sample size and power.

To examine the final hypothesis, we determined the accuracy of the reinforcement learning model under the multiple manipulations for each subject. Additionally, we investigated multiple reward systems to train the model, including a reward schema that is punished purely on threat, a schema that is punished purely based on spider images, and one that is punished partially based on threat and partially based on spider images, in order to understand the similarity between this approach and the theoretical processing the participants are using. We found that for the threat reward schema, there were 3 subjects for which the model's predictive ability for the behavioral data was greater than $R^2 = 0.2$, all were in the slow information manipulations. For the spider reward schema, there was one participant for which the model's R^2 was greater than 0.2, also in the slow information manipulation. Finally, in the mixed reward schema, there were 2 subjects for which the model's R^2 was greater than 0.2 in the slow information manipulation, and one in the fast information manipulation. This reveals that the model most accurately predicted the performance of participants in the deliberate manipulations (slow and information presented), which was contrary to our second hypothesis.

Discussion

The current study investigated if manipulations of deliberate and automatic processing would influence decision-making and self-reported affective experience. We found that choice behavior matched self-report data under both deliberate manipulations and under automatic manipulations, and additionally that model free reinforcement learning is better at predicting choice behavior under deliberate manipulations than under automatic ones. While these manipulations of deliberate and automatic processes have been previously used as classic examples (such as using less duration to suggest more rapid processing, or using more information presented to suggest a greater reliance on deliberate processing, etc.) they have not been evaluated in the context of complex, naturalistic emotional stimuli for preferential decision-making (Glöckner & Witteman, 2010). Without experiments of this kind, the findings cannot be fully generalized to understand natural examples of relying on deliberate or automatic processing.

Finally, the structure of this dual system influence on preferential decisions theoretically shares similar structure to less context dependent learning models (such as model-free learning) in automatic processing, however this theoretical similarity has not been fully demonstrated. In order to construct treatments that may influence maladaptive decision-making, the structure of the relevant processes must be investigated to understand how to improve a more rational and deliberate decision-making approach.

Due to this unexplored aspect of preferential decision-making, this work aimed to demonstrate which aspects of decision-making are impacted by deliberate or automatic processes. Findings from the current paper add to previous literature by investigating the impact of these classical dual process manipulations under more varied naturalistic rewards, and through examining the predictive power of model-free deep learning on these decision tasks. Results revealed that self-report data had the similar relationships with choice-behavior under rapid conditions, as well as under deliberate conditions. Secondly, that under rapid low-level feature manipulations participants could distinguish between spiders and non-spiders (which was not found in slow low-level feature manipulations). Finally, these findings reveal that the deep Q learning models we employed are more similar to human performance in deliberate cases despite the theoretical similarity to lower-order processing.

Overall, we found that participants' self-report matched with their choice behavior during manipulations designed to engage "deliberate" and "automatic" processing of stimuli. These results were inconsistent with our first hypothesis, confirming that choice behavior would match self-report data according to the expected relationship on deliberate manipulations, (Hypothesis 1a) but failed to support the second aspect of our hypothesis that choice behavior would not match self-report on automatic manipulations (Hypothesis 1b). This relationship was consistent with prior work, demonstrating that our descriptions of our preferences are often justifications for behavior rather than elements that lead to behavioral outcomes (Jarcho, Berkman & Lieberman, 2011). However, these results were inconsistent with the theoretical understanding of deliberate processing, which interprets deliberate processing as more reliant on and influential to our conscious evaluation (Größler, Rouwette & Vennix, 2016). This deliberate processing is opposed to rapid cognitions, which are presumably less accessible to conscious awareness.

Since these findings showed that under more deliberate conditions, participant's self-reported evaluation was unchanged as compared to the automatic conditions, this suggests that participants may have been using the same quick judgments to influence their conscious evaluation of preference in both conditions. While this may be a demonstration of conscious report being a rationalization for more automatic behavior, it may also be due to individuals not having a motivation to rely on deliberate processing, though they are given the opportunity to do so. This may suggest that we determine our conscious evaluations of situations post-hoc, though more analysis is needed to reject any alternate hypotheses for this behavior (Mishra, Allen & Pearman, 2015).

One surprising observation was that in the conditions which allowed the participants to take more time to make decisions (theoretically allowing for use of deliberate processing), and in which the participants viewed the altered, lower-level feature images (theoretically less context-based stimuli)—spider images and dog images were associated with similar levels of subjective pleasure. This stands in contrast to effects observed in the fast condition, their reports showed a difference in pleasure reporting, as demonstrated in the ANOVA results (see *Figure 1*). This may suggest that having more opportunity to think in a deliberate manner can inhibit the automatic interpretation of events. In other words, perhaps stimuli with very little context can have a clearer interpretation under more rapid or automatic processing, as opposed to interpretations through the use of deliberate processing.

The interpretation that some stimuli are better learned and understood using automatic processing as opposed to deliberate processing sheds light on the relationship between different systems involved in decision making. Individuals may make better decisions by taking less time to consider a decision when it is less dependent on higher order context, as in this case participants seemed to demonstrate an improved consistent decision-making only under the rapid condition. While more analysis is needed to directly test this effect, it raises the possibility of evolutionary and proximal utility for rapid processing (Cosmides, & Tooby, 2000).

Finally, the data derived from the deep RL model revealed that a reward function that punished threat was most accurate, and that it was specifically accurate under the slow information manipulations. This follows from a functional perspective as without being able to extract this information, participants would have no ability to distinguish between which species were threatening and non-threatening. However, the inability of any model to predict participant behavior in any of the automatic manipulations may suggest that these model-free approaches may not be as similar to automatic processing as previously expected. We note that these models are preliminary, and further work is needed to explore other options in modeling to undermine the existing theoretical connection, but these results do suggest the connection may not be as strong as previously believed.

Implications

The findings of the current study reexamine the some of the classical manipulations of deliberate and automatic processing (Deck, Jahedi & Sheremeta, 2017), but additionally reveal more specifics about what aspects of decision making are determined by these separate processes. The present study revealed evidence that simply increasing the time to make decisions does not lead to decisions being more informed by deliberate evaluations. It instead revealed that these evaluations may be primarily rationalizations for more automatic behavior. Additionally, these findings may suggest that individuals engaging in rapid processing may have processing advantages for stimuli that is less context dependent. This also suggests that there may be cases in which rapid processing provides more useful decision-making than in circumstances with less restricted processing.

While previous research revealed that dual systems influence many aspects of decision making, and play a role in interpreting emotional information, this study utilized more naturalistic reinforcement to understand the influence of these dual processes on preferential decision making (Glöckner & Witteman, 2010; Frankish, 2010). This suggests that decision-making interventions must consider more than just increasing reliance on deliberate processing, but that automatic processing has utility over deliberate cognition in some cases. Additionally, these findings may indicate that simply increasing the amount of time individuals have to make decisions may not increase their reliance on deliberate processing, but that motivation is also an important factor that may influence this. Moreover, these results suggest that conscious evaluations will readily be determined by automatic processing, without influence of motivation. In short, this may show that factors at each level of the decision-making process are impacted by the dual processes differently, and that deliberate cognition is not a superior form of processing in all circumstances.

Finally, the results of the deep RL models reveal that, at least according to the preliminary set of models evaluated, model-free RL does not show greater accuracy for deliberate decision-making than automatic. This may suggest that perhaps automatic processing relies on more contextual information, such as associations and instinctual reactions, whereas deliberate cognitions may have less contextual information as it is more reliant on abstract thinking. Finally, it also revealed that the threat differences, rather than species differences, were more predictable by these models. This result may suggest that the preliminary modeling work requires different approaches to successfully model the true behavior of these participants.

Limitations

The results of this paper must be considered given the following limitations. Most importantly, while this set of pilot data allows us to analyze general trends of the results, the sample size is small and estimates of effect size are highly variable. As we continue to collect data, we intend to add in a larger sample for this study to determine if these effects are robust. Additionally, while the stimuli used were more naturalistic than previous research, the task could be extended to be more ecologically valid. The decision-making task contained no context about what situation individuals may find these images in, which may have reduced their need to utilize deliberate processing, as no relevant context could be considered. The task additionally could utilize manipulations of motivation for the participants, to ensure more reliance on deliberate processing in the conditions. Because the sample was small, there was little diversity in demographics of the sample. While there is no indication that this would have an effect on decision-making, it limits the scope of the findings greatly. Finally, the modeling approach utilized was simplistic, as accurately predicting human behavior requires much more nuanced approaches, which is difficult to attain in this single study.

Future Directions

The results of the current study potentially reveal that specific aspects of decision-making (such as perception of emotionally relevant stimuli, and interpretation of preference) are differentially influenced by dual processes. Future investigations should determine how these aspects of decision-making interact with one another. Specifically, focusing on manipulations that may change the way individuals self-report their preferences to be less impacted by their automatic behavior and more based on deliberate considerations. Future research should utilize more context based decision-making tasks, to increase generalizability. Additionally, examining how emotional regulation techniques may impact reliance on deliberate or automatic cognition would be an important next step in understanding how interventions may be developed to impact decision-making and utilizing the dual systems perspective to improve outcomes.

The present results suggest that there may be advantages in automatic processing over deliberate processing in perception of low context stimuli. While this finding has fascinating implications, more research should be conducted to identify when and to what extent this conclusion is accurate. It is important to investigate how reliance on deliberate processing may be enabled through the use of motivational manipulations, which may lead to a more accurate control of deliberate cognition. It would also be important to analyze the performance of other models, such as Bayesian models, to understand how different types of statistical learning compare to model-free associative learning implemented in deep RL. Additionally, it will be important to explore different architectures and objective functions than those utilized for deep RL in the present study. This may allow for a deeper investigation into the structural similarity between complex learning models, and simpler ones in relation to automatic and deliberate processes. Finally, these findings require replication to ensure that they are more than mere superficial relationships.

Conclusion

While these results require further analysis and a larger sample of data for sufficient power, the findings suggest that preferential decision making is influenced differentially by the dual systems at each component of the decision-making process. They seem to suggest that evaluations of preference are often inclined to be constructed based on automatic behavior, as rationalizations. Additionally, it may be the case that perception of low context complex stimuli is more accurately interpreted using rapid processing. These findings also reveal that model-free approaches are less similar to automatic decision-making than previously theorized. It seems that these classical manipulations of dual systems processing require a greater focus on motivation as a factor to be sufficiently effective manipulations. These findings are consistent with previous research revealing that rationalizations are commonly interpretations of automatic behavior, and the theoretical perspective that there are alternate advantages to processing in automatic approaches that deliberate cognitive perspectives don't allow. Finally, these findings suggest that interventions must incorporate the important role of utilizing automatic processing rather than merely emphasizing a greater use of deliberate processing, and that researchers must consider the motivation of the individual to influence their reliance on dual systems, more so than merely opportunity.

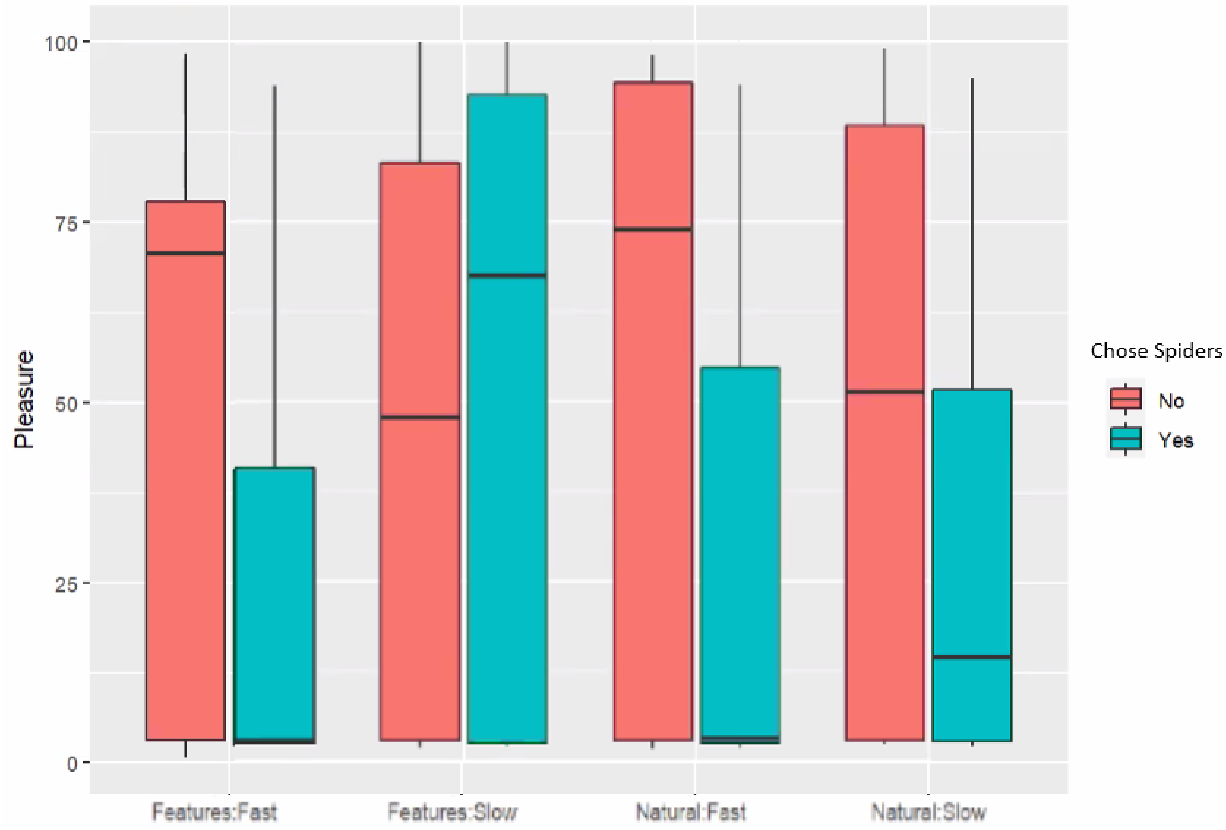

Figure 1. Bar graph of Image Type by Duration by Pleasure Report, Broken down Across Animal Type. The Y axis represents how high the participants reported their pleasure, and across the X axis are the different conditions. Which species they chose (spider or not) is represented as the two colors.

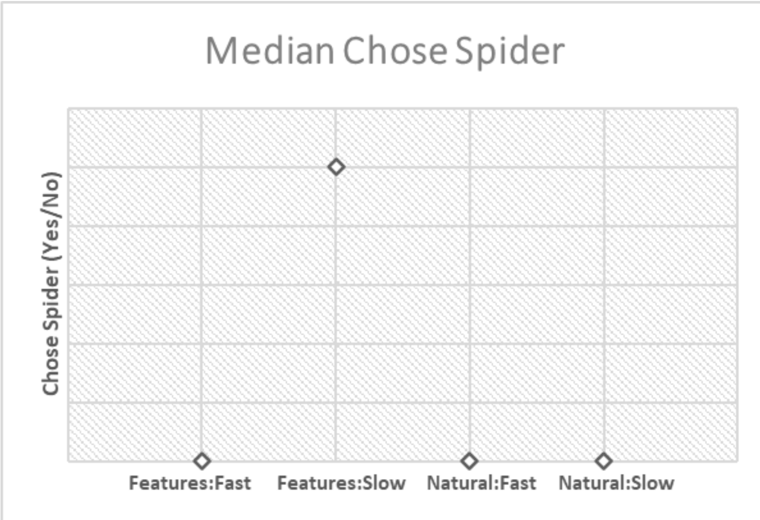

Figure 2. Plot of Median Animal Type Choice Across Image Type by Duration. The Y axis represents if the median choice for that condition was for either spider (higher) or dog (lower), and across the X axis are the different conditions.

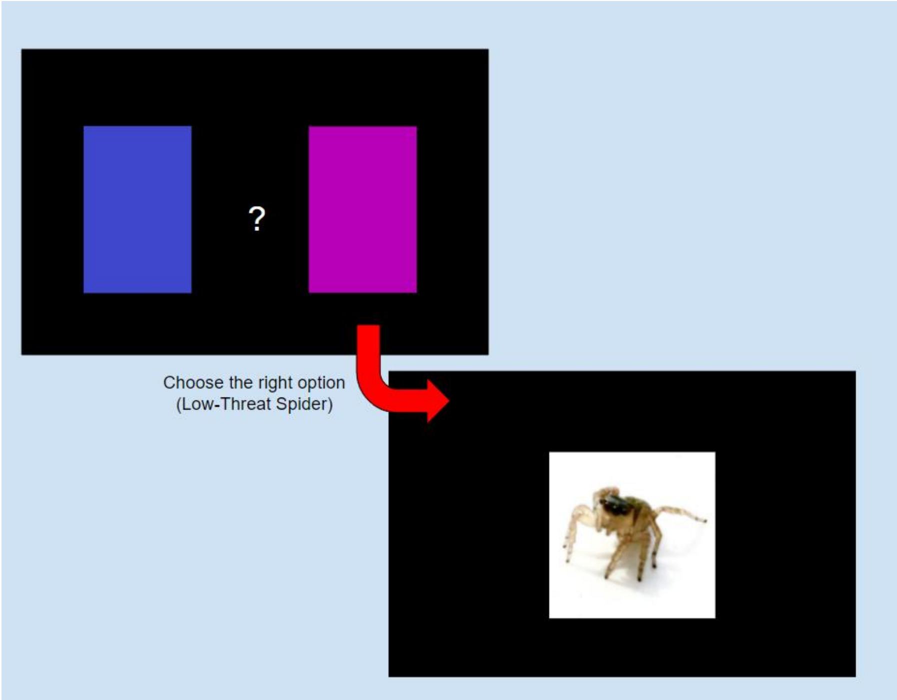

Figure 3. Choice Behavior Task Example. This figure represents the task that the participants engaged in. They were asked to choose either left or right with their arrow keys, and each color was associated with a set of images, that were then displayed to them after their choice.

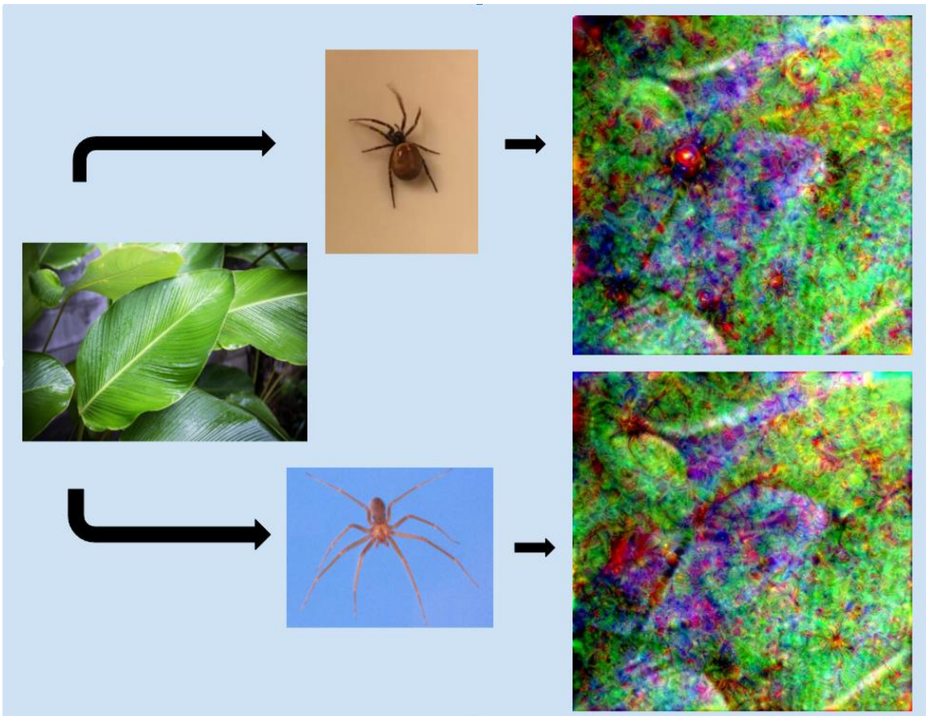

Figure 4. *DeepDream* Image Creation Example. This figure displays an example of how the *DeepDream* software takes a neutral image and alters it according to the features derived from an animal type, creating a different image for each species.

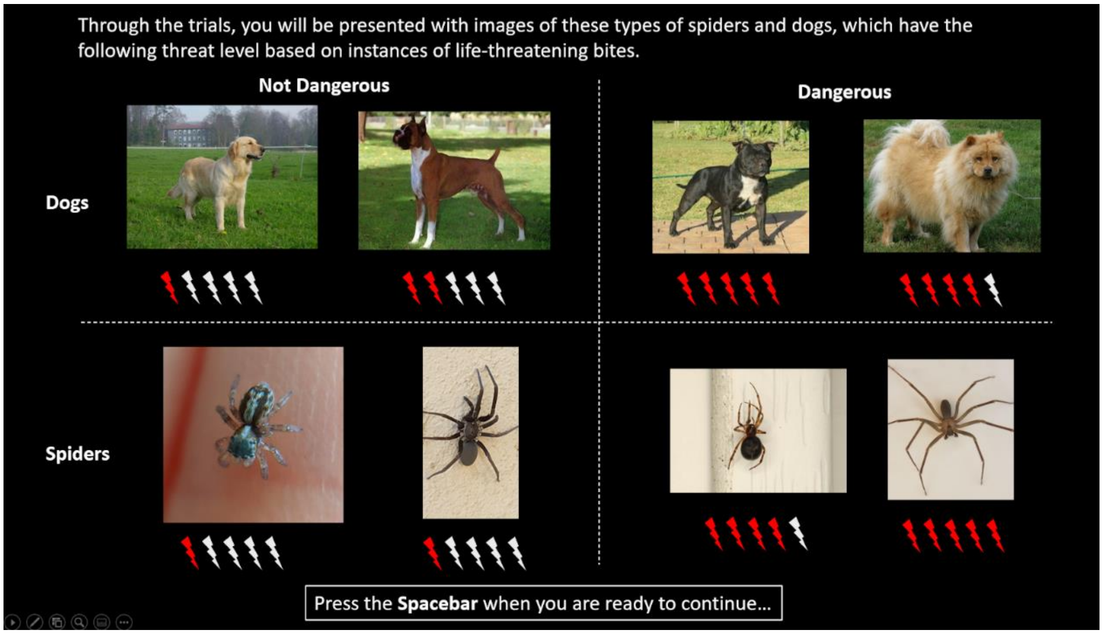

Figure 5. Information Presented to Participants Example. This slide of information on the threat-level for each species was presented to participants, and during the information manipulation the ranking of threat-level was displayed next to the images with the red lightning bolts.

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