Noname manuscript No.
(will be inserted by the editor)

The effects of directed and free self-monitoring on goal-directed and habitual decision-making

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Received: DD Month YEAR / Accepted: DD Month YEAR

Abstract Many studies on humans and animals have provided evidence for the contribution of goal-directed and habitual valuation systems in learning and decision-making. However, how the arbitration between these two systems is affected by other cognitive processes is not well known. Here, we study the effects of directed and free self-monitoring of one's decisions on this arbitration. In our experiments, in a within-subject design, the subjects participated in a control and a two modified versions of the Two-step decision-making task, where we could measure each system's contribution to decisions. We had two

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modified tasks. In both, every few trials subjects had to think about what they have experienced in the past trials in one of the two days. In one task, they had to designate which action was better and then report their confidence about this decision (directed self-monitoring task). In the other modification of task, they had to explain what had happened in the past few trials by talking (free self-monitoring task). We hypnotized that in both modified tasks, the behavior of the participants would shift toward goal-directed behavior because they need to think more about the structure of the task. Our experimental results showed that subjects indeed became more goal-directed in the directed self-monitoring task, but in the free self-monitoring task, they became more habitual. We would discuss the underlying reasons for these shifts in the behavior.

1 Introduction

Decision-making and its ingredients are among the most prominent and intriguing challenges throughout the history of thinking, albeit with different approaches in different disciplines. In the past few decades, cognitive science has taken a keen interest in this question. What has been unearthed is that the decision-making process can be explained by a dual system model (Dickinson, 1985; Kahneman, 2011; Gilovich et al., 2002). Although there are some incompatibilities between different theories, the consensus is that the decision-making system is comprised of two systems; one is reflexive and habitual, and only relies on past experiences to form a decision. The other system is reflective and goal-directed. This system not only incorporates the past experiences in the decision-making process but also utilizes complete knowledge of the environment, which contains information about each actions' prospective outcomes.

One celebrated dual system model stems from the work of Gläscher et al. (2010), also Daw et al. (2011). The theory states that one system of decision-making is based on the model-free strategy, which infers values for each action on the basis of experience. The other system is based on the model-based strategy, which at its heart engages in planning. The model-based system will make decisions according to the structure of the environment and will use this structure in tandem with its experience of the actions. In theory, the model-based system is optimal, and gains more reward relative to the model-free system (Sutton and Barto, 2018). In addition, there are some studies that show higher performance of model-based system relative to model-free system in empirical data (Kool et al., 2016). The dual system theory, named after the two systems, model-free and model-based, can explain many facets of decision-making (Gershman et al., 2014; Otto et al., 2013a; Worbe et al., 2016; Moran et al., 2021).

How arbitration and integration is handled between these two systems is a question of the utmost importance. Not only does it have implications on a computational level, but it also has many practical implications. A common thread that emerges from work on computational psychiatry works in this area is that many psychological disorders like OCD, schizophrenia, eating disorders, and different types of addiction are all linked to a deficit in exerting model-based control (Gillan et al., 2016; Voon et al., 2017; Heller et al., 2018; Vaghi et al., 2017; Janssen et al., 2020). These findings are a strong set of incentives to search for what could affect and possibly change the arbitration between the model-based and model-free systems, especially if we can find a way to increase the model-based system's contribution to decisions. People can become more model-based if we increase the incentive by increasing the amount of available payoff (Patzelt et al., 2019). Also model-based behavior can be manipulated through drug administration in Wunderlich et al. (2012); Deserno et al. (2021). It is questionable whether increasing model-based behavior is possible via a more self-dependent method without extra financial costs and without drugs.

We propose that adding a self monitoring step to decisions can enhance reliance on the model-based system. Frith and Frith (2012) have proposed that communication about self-monitoring is a meta-cognitive process which enhances the learning strategy and pushes it toward the more optimal strategy. As they explained, meta-cognition is the ability to monitor ourselves and describe our behavior to others. Taking a step apart from our behavior is required for self-monitoring, which is called a mental "decoupling" (Leslie, 1987). There are more studies that show the influence of self-monitoring on learning the optimal behavior (Drugowitsch et al., 2019; Guggenmos et al., 2016; Lee and Daunizeau, 2021). Accordingly, we hypothesized that communication of self-monitoring about goal-directed behavior changes behavior toward the optimal, model-based strategy, and it does so via a meta-cognitive process and also increases motivation through communication. The above proposal is in line with Frith and Frith (2012)'s discussion about exertion of control over automatic behavior via meta-cognitive processes. Ershadmanesh et al. (2019)'s result confirm our proposal, too. They show a positive relationship between the proportion of model-based relative to model-free behavior and self-monitoring ability. Therefore, we expect higher model-based behavior when people are instructed to communicate about self-monitoring.

In this exploratory study, we asked people to share what they think about their behavior while achieving a goal, every few trials. Like this, we aimed to tip the balance of the two systems in favor of the model-based system. We hypothesize that the mentioned manipulation will engage the meta-cognitive process and would lead to higher model-based behavior. Our experiment is based on the task designed by Daw et al. (2011) . Their task can demonstrate the effects of the model-based and model-free system on behavior in a manner that enables one to decompose the contribution of each system and weigh them against each other. One controversial characteristic of Daw and colleagues (2011)'s original two-step decision-making task is that model-based and model-free systems perform equally well on it (Kool et al., 2016). We used this two-step decision-making task and added a self-evaluation segment to it in which subjects were asked to share their self-monitoring about reaching the goal, either by talking, which we will refer to as free communication, or by rating their confidence about their actions, which we will refer to as directed communication. With this manipulation, people need to think about the goal-directed behavior in a more profound way. According to our hypothesis, this should lead to a change in arbitration in favor of the model-based system.

2 Methods

In our study, we measured subjects' behavior in two versions of the two-step decision-making task (Daw et al., 2011). One similar to the original version of the task (Daw et al., 2011) and a modified version in which subjects were asked to evaluate their decisions every few trials (self-monitoring task). We implemented Two variations of this self-monitoring task. One in which self-monitoring was with talking and the one with reporting the best choice in previous trials and reporting confidence about it.

So our study consists of two experiments based on the aforementioned self-monitoring tasks, each with a within-subject design. The goal of both experiments was to see if subjects behave differently in the self-monitoring task compares to their behavior in the original version of the task. We hypothesize that their behavior will shift toward model-based behavior. The changes in subjects' behavior were evaluated by measuring the differences in behavioral parameters. Since the results of this experiment were surprising and not entirely in line with our original hypothesis, we repeated the experiments keeping everything the same. Here we are going to introduce the original two-step decision-making task, self-monitoring versions of this task, and our data analysis and participants recruitment methods which were the same in both experiments and their replications.

2.1 Two-Step Decision-Making Task

Two-step decision-making task was used in both experiments and was the basis for both modified tasks. Here, we are going to discuss the details of this task. As it is shown in Figure 1, each trial of the task consists of two consecutive binary decision steps, made to bring the subjects to the second step in which they could attain a unit reward. Any of the second-step choices has its own probability of giving rewards; this probability changes over time with a Gaussian random walk. Subjects needed to use their experiences to track these changes to make optimal decisions. They had 2s for each of their decisions. After the first-step decisions, there was a 300 MS inter-stimulus interval and after second-step decisions a 500 MS inter-trial interval.

Because of the task structure, experience has a different effect on model-based and model-free evaluations. This is due to the existence of rare transitions. Following a rare transition, a model-based agent can appropriately update its belief on the first-step actions. The reason is that this agent can rightfully attribute the outcome, whether a reward was acquired or not, to the action that was not chosen in the first step. In contrast, a model-free agent only evaluates first-step actions in light of whether a reward was acquired or not, regardless of the transition that occurred during the trial. We can assess the behavior of subjects following trials with a rare transition to gain an insight into how they arbitrated control between these two systems. This task was used in both experiments to measure the baseline arbitration level of the subjects. Both experiments had a within-subject design, and this base level of arbitration level was compared to the arbitration level in the modified version of the task. These modified versions are going to be discussed in directed and free self-monitoring experiments.

2.2 Two-Step Decision-Making Task with directed self-monitoring

What was added to the two-step decision-making task was a new section which happened every 20th trials and required subjects to share their experience. The subjects were told that their inputs would be used to help another subject doing the exact same task. For the first experiment, the self-monitoring section was implemented in a way that subjects needed to share their experience by communicating through their confidence about the first step actions. They were asked to designate which of the two first-step actions was better during the last 20th trials and subsequently requested to communicate their confidence about the best first-step action. The details of this section can be seen in Figure 1. To compensate for the time spent on the self-monitoring segment, we added 30 seconds of resting time every 20th trial in the original two-step decision-making task. This will rule out the possibility that the changes in behavior was due to the added idle time and not the self-monitoring itself. We also limited the reward probabilities generated by the random walks to two pre-defined versions, each assigned to one of the sessions of directed self-monitoring experiment. This assignment was done in a counterbalanced way.

2.3 Two-Step Decision-Making Task with free self-monitoring

The subjects in this experiment participated in the same two-step decision-making task as experiment A, but their required method for self-monitoring was different. In this experiment, the self-monitoring was implemented with sections that popped up every 20th trial in which subjects were instructed to talk about their experience in the past 20 trials in a manner that would help a new participant that would take on the exact same task (Figure 1). Just like the main experiment the added time due to this section was compensated in the original two-step decision-making task, and the reward probabilities generated by random walks was restricted to two versions and assigned to each subject's sessions in a counterbalanced manner.

2.4 Participants.

Each experiment (both main experiments and replication experiments) conducted from 23 subjects, 10-12 females, aged between 19 and 30, from the University of Tehran. All subjects had at least a high school diploma and were native Persian speakers. The two-step decision-making task was introduced to subjects via a detailed instruction manual. After reading the manual to ensure that subjects comprehended, they were asked some questions about the figure used in task and their whereabouts. If any of the questions were answered incorrectly, the subject instructed to go back to read the instruction once more. Finally, they were shown a PowerPoint presentation of the task. The experiment and its procedure were approved by the Tehran University of Medical Sciences (TUMS). All participants signed informed consent for the usage of their data. The subjects were paid a fixed amount of money (150k Rial) for their participation and up to 150k Rial for their performance in the task. There was at least one week break between the two tasks and the order was counterbalanced.

2.5 Data Analyses

We used Probability of Stay analysis as an almost pure behavioral analysis that benefits from being theory agnostic. This analysis helps us to study the effects of the last trial on the current first-step action. The events in the previous trial are, whether a rare transition happened or a common one, and whether a reward was acquired or not. These two events were combined to create a total of four situations; common transition occurrence in tandem with a reward, which can be called Rewarded Common (RC) for short. The other three are unrewarded common (OC), rewarded uncommon (RU), and unrewarded uncommon (OU). The probability of staying with the same first-stage choice as the last trial with regards to these four conditions is used to formulate model-based and model-free indices. These indices indicate the degree to which each of these two systems were potent in decision-making.

The model-free index is the difference between the probabilities of staying when a reward was gained and the probabilities of staying when no reward was gained. This index captures a good measure of model-free behavior because model-free agents don't account transition into their decisions and only care about the reward. On the other hand, the model-based index distinguishes between types of transition and cares for the compounded effect of reward and transition. So, the probability of stay for a rare transition that didn't result in a reward will look more like a stay probability after a rewarded common transition trial. And, stay probability after a trial with a rare transition that ended up with reward would be more like when no reward was gained, and the transition was common. Hence, to determine the model-based index, stay probability is grouped into two groups, a group consists of RC and UR conditions and a group consisting of RR and UC conditions. And, the difference between these two groups is as a measure of model-based behavior(Miller et al., 2016).

3 Results

3.1 The Main Experiments

3.1.1 Model-based and model-free contribution to decisions

First, we examined whether the subjects incorporated the evaluations of both systems in their decision or not. To do this, we amalgamated the two sessions of the experiment for each subject and looked at their trial-by-trial behavior. We fitted a mixed-effects regression model to predict the probability of staying with the same first-step choice in any given trial with regards to events in the previous trial. The first regressor was the reward, which represents the model-free contribution to decision-making. Interaction between reward and transition was another regressor that represents model-based contribution. The third regressor was the type of transition, which has been used in the previous works(Gillan et al., 2016). The lme4 package in R was used to implement this model. The Result shows a clear contribution of both systems to decisions (main effect of reward: $F(1, 45) = 23.7$, $p = 5 \times 10^{-5}$, interaction between reward and transition: $F(1, 45) = 14.63$, $p = 0.0005$).

3.1.2 Directed Experiment

Subjects completed two sessions of two-step decision-making tasks. One like the original experiment and the other one with the self-monitoring segment. Each session comprised of 201 trials. In the main experiment, the self-monitoring was designed so that subjects had to report their confidence about which the first-step choice was superior. The reported confidences were numbers between 1 and 6, 6 being the highest level of confidence.

Behavioral analysis. To assess whether subjects utilized different mixtures of model-based and model-free strategies in two sessions of two-step decision-making task, we applied repeated-measures ANOVA on their behavioral data (Wunderlich et al., 2012). The behavior in question is the probability of staying with the first-step choice depending on three factors: 1) Session: the type of experimental session; the original version, or the self-monitoring version. 2) Reward: the reward acquisition statues on the previous trial. 3) Transition: the type of transition in the previous trial. Also, in this model, the constant conveys the information about subjects' bias to repeat their previous action regardless of anything. We found that the interaction between Session, Reward and Transition was significant F (1, 23) = 4.85, p-value = 0.04. This result shows an increase in the model-based behavior of subjects in the self-monitoring session. Session:Reward, Session:Transition and Session

Factors were not significant. These results show that subjects' model-free behavior and action bias were not affected by self-monitoring. You can see the result in Figures 3.

3.1.3 Free self-monitoring Experiment

The outline of the free self-monitoring experiment is the same as the directed self-monitoring experiment. Subjects completed two sessions of two-step decision-making task. One like the original experiment and the other one with the self-monitoring segment attached to it. The specific characteristic of the replication experiment was that self-monitoring was implemented so that subjects must talk about what was their experience in the last 20 trials. They were told that another subject would take on the exact same experiment, and their speech would be used to help that subject. The AVONA was used to analyze the behavioral data, with factors Reward, Transition, and Session, like the main experiment. We found that the interaction of session and reward was significant $F(1,23) = 12.14$, $p = 0.002$. This result shows an increase in the model-free behavior in subjects in the self-monitoring experiment. You can see the results in Figure 4.

This result was the exact opposite of the directed self-monitoring experiment, where the model-based component of decision-making changed in the self-monitoring session. We did not find any significant changes in other parameters. We also did not find any changes in behavior due to the order of the sessions.

3.2 The Replication Experiments

The hypothesis of this paper was that self-monitoring would make people more model-based. This was the case when participants were asked to evaluate their experiences and share them by expressing confidence (experiment A). But, when the medium in which participants used to share their evaluation of their experiences changed to talking in experiment B, participants became more model-free. Since this result was unexpected, we replicated both experiments to make sure our results were reliable.

3.2.1 Model-based and model-free contribution to decisions

First, just like the main experiment, we examined if subjects utilized the evaluations of both systems in their decision or not. And just like the main experiment we confirmed the presents of both systems in participants' decisions (main effect of reward: $F(1, 45) = 22.1$, $p = 1.5 \times 10^{-5}$, interaction between reward and transition: $F(1, 45) = 16.37$, $p = 0.0002$).

3.2.2 directed self-monitoring Experiment

We used the same analysis as the main experiment. Our results, again, shows an increase in model-based behavior. The interaction between Session, Reward and Transition was significant ($F(1, 23) = 5.35$, $p = 0.03$).

3.2.3 Free self-monitoring Experiment

For this part again, we did the same behavioral analysis. We saw an increase in model-free behavior (the interaction of session and reward was significant $F(1, 23) = 7.88$, $p = 0.01$), Figure 4.

4 Discussion

The well-established dual system of decision-making theory is a successful and under development (da Silva and Hare, 2020; Moran et al., 2021), framework for explaining a variety of humans' and animals' behaviors (Daw et al., 2011). The theory posits that two systems with distinct features contribute to the decision-making process; one system solely draws on past experiences to reach the goal of achieving reward, known as the model-free system, while the other systems, known as the model-based system, also incorporates the information about the environment with the added cost of more cognitive computation (Dolan and Dayan, 2013). How people arbitrate between these two systems is of utmost importance, since the extra reliance on one system has been associated with drug abuse and some psychiatric dysfunction (Gillan et al., 2016; Voon et al., 2017; Heller et al., 2018; Vaghi et al., 2017). In this study, we investigated the effects of self-monitoring on this arbitration. We designed two experiments to see the difference in decision-making in the two-step decision-making task when subjects were required to monitor their decision-making process in reaching the goal every few trials. We used directed self-monitoring (in the form of confidence sharing about the best choice) in one experiment, and free self-monitoring (in the form of talking about experiences) in another. We hypothesized that self-monitoring changes the people behavior toward the goal-directed, model-based, behavior through engaging the meta-cognitive process (Frith and Frith, 2012) and increasing the motivation for communication about reaching to the goal . Our result showed that people become more model-based when they were in our directed self-monitoring experiment. But, surprisingly, in the free self-monitoring experiment, the result showed a shift towards model-free behavior. Since our result was surprising and not entirely in line with our initial hypothesis, we replicated both experiments and got the same results. In the following paragraphs, we discuss the possible explanations for the result we saw; these explanations may lead to further research as well.

To interpret our result from directed self-monitoring, we discuss the manipulation which we applied. We asked about a more rewarding option which is a common motivation between both model-based and model-free systems.

These systems have different strategies to achieve reward, the model-free strategy by repeating the option which has been rewarding more previously and model-based strategy through utilizing both the task structure and previous experiences. Based on theory and behavioral data (Kool et al., 2016), between these two methods of achieving reward the model-based strategy is optimal (more rewarding) relative to model-free strategy (Sutton and Barto, 2018). Thus, the result from our directed self-monitoring was in line with our hypothesis, asking about more rewarding options and reporting confidence about it, increased the model-based behavior. As a direct result, subjects' ability to monitor their behavior in goal gaining was enhanced and their behavior moved toward the goal-directed strategy, model-based strategy.

About the above result, one may ask whether subjects could achieve more reward via changing their behavior toward the optimal strategy or not. This question is related to an important challenge about two-step original task (Daw et al., 2011) in the literature (Kool et al., 2016), which the model-based and model-free strategies achieve the same amount of reward, close to chance level (Akam et al., 2015). Also Wunderlich et al. (2012) showed that increasing the Dopamine level in this task enhances the model-based behavior, the optimal strategy, while the achieved reward via this strategy is the same as model-free strategy. This issue in the literature is the case also about our study, participants increased their model-based behavior via more thinking about the optimal choices while the optimal strategy, in theory, did not increase their performance. A possible explanation about our result is that in daily life the model-based strategy has been the optimal strategy in the cases in which people have had enough motivation (enough money or communication about their experiences) to pay the costs of this strategy. This prior has encouraged them to rely more on the model-based system. One may ask why subjects did not decrease the model-based behavior during trials when they experienced the same achieved reward via increasing the model-based behavior. This is an important question in the literature and future studies are necessary to answer it. Perhaps people have a strong prior about using the model-based strategy as an optimal strategy and they should experience the two-step original task so many times to understand that model-based behavior is not an optimal behavior in this task. Although, it is just a speculation and it is an open question for next steps.

About our result from free self-monitoring, when the self-monitoring was in the form of talking, the results were in contradiction with our hypothesis. This manipulation led to increased model-free weight in decisions. This was a surprising finding for us and it could be hard to interpret the result with only behavioral data, but here we provide some possible explanation for it.

First, this result might be caused because of cognitive load. Otto and colleagues demonstrated that subjects under working memory load relied less on the model-based system (Otto et al., 2013a). Here, subjects needed to think about what they wanted to say, which can be a form of cognitive load and hence caused the shift toward model-free behavior. But there are some crucial differences between our work and Otto et al. (2013a). In the mentioned study, the result showed a decrease in the model-based component of decision-making while here we observed an increase in model-free behavior. These two results are not inherently inconsistent, as Lee et al. (2014) discussed arbitration between two systems may result in model-based system strengthening via model-free weakening, but the reason for this apparent difference needs more study in future.

Second, talking about a difficult task, chance level performance, could cause people to be more stressful. As Otto et al. (2013b) showed stress decreases the model-based behavior proportional to working memory capacity. Our result was also in the same line but we saw an increase in model-free behavior. The difference between our result and Otto et al. (2013b) may root in different kinds of stress which were applied in our experiments. They shocked the participants via cold water while the stress in our task was a result of high cognitive load and low performance. Certainly, a more exact interpretation about the difference between the results needs future studies.

To understand what the subjects had in mind in the free self-monitoring task, we listened to the participants' speeches, most of the subjects mentioned some sort of conspiratorial rules for their decisions, things like: "if you get two consecutive rewards from a decision, change it. It will not reward you the third time". One could hypothesize that making people talk about a process that they do not understand, made them stressful and as a result, they generated heuristic rules, which in turn change their behavior. Of course, this theory needs further examination and other experiments to be confirmed. The second interpretation for the above sentences may root in sense-making motivation studied by Chater and Loewenstein (2016). According to their study, subjects told some stories about their non-clear experiences to make sense for them. As the authors discussed, sense-making could be a strong motivation that may cause the above heuristic rules in a condition that the task was difficult for subjects and they were instructed to talk about it.

Third, it has been shown in different studies in Ajzen (2005) that there is a decrease in the correlation between attitude and behavior when people are asked to list their reasons for their attitudes. They argued that focusing on one's attitude will temporarily disrupt that attitude. Here, a similar kind of disruption could have happened.

We saw that there is a correlation between subjects' average confidences and their reliance on the model-free system. People with lower average confidence had a weaker model-free contribution to their decisions. This is consistent with findings in Ershadmanesh et al. (2019), where authors showed that there is a negative correlation between the model-free component of decision and memory meta-metacognition. Since the two-step decision-making task is designed in a way that you could not have a better than random performance (Akam et al., 2015; Kool et al., 2016), it can be argued that people with lower confidence understood this fact better and were more meta-cognitive.

Our result has some interesting implications for psychological disorders related to arbitration between the model-based and model-free systems. Works like Gillan et al. (2016); Voon et al. (2017); Heller et al. (2018); Vaghi et al.

(2017); Janssen et al. (2020) showed that there is a correlation between disorders such as OCD, addiction, schizophrenia, and eating disorders and less reliance on the model-based system. So, finding ways that could shift the arbitration towards the model-based system could prove beneficial for helping these patients. Our directed self-monitoring experiment was successful in doing so. Further study could tackle how useful this manipulation is for the patients with the disorders mentioned above. Furthermore, the difference between the directed and free self-monitoring results could have some critical implications for education studies and any sort of qualification exams. Making sure we evaluate people in a clear, direct and less noisy way could help them to think in a more structured way which is an optimal way of thinking. This result could prove beneficial in many different fields.

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5 Acknowledgements

6 Author contributions statement

M.M., S.E., A.V. and M.N. conceived the study and designed the experiment. S.E. and M.M. performed the experiments. M.M. and S.E. developed the mathematical models and analysed the data. S.E., M.M., A.V. and M.N. discussed the results and wrote the manuscript. A.V and M.N. supervised the study.

7 Competing interests

The authors declare no competing interests.

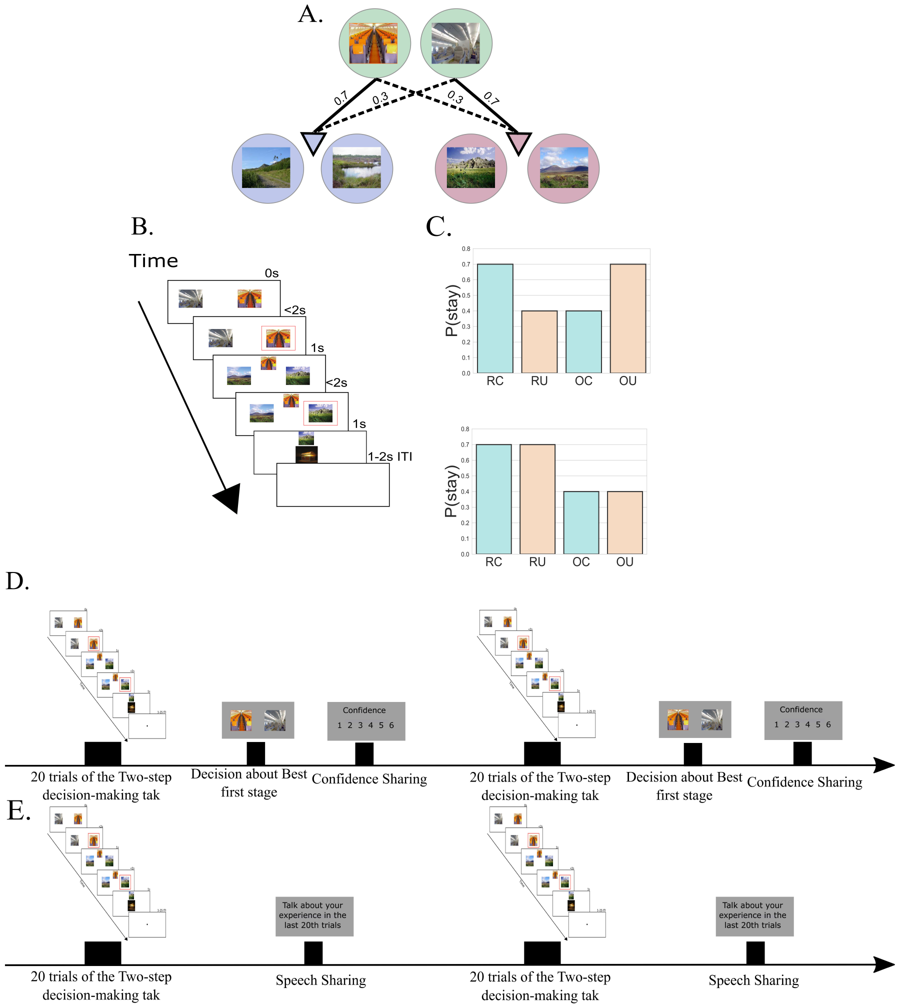

Fig. 1 Two-step decision-making task. A) Each first-step action was commonly associated with the transition to one of the second-step states. Although, it also could lead to the other second-step state, but rarely. B) The timing of a single trial: a choice in the first step, followed by a choice in the second step. The second choice was reinforced by the reward. C) Left, model-free RL predicts a high probability of repeating (stay probability) the first-step action of the previous trial if it is rewarded. Type of transition, common or rare, does not have an influence on stay probability in this case. Right, model-based RL predicts that the type of transition influences the stay probabilities. Thus model-based learning is influenced by the interaction of reward and transition. D & E) Flow for self-monitoring tasks, after 20 trials of the two-step decision-making task, (D) subjects were asked to designate which of the first-stage choices yielded more reward and how confident they are in their selection.Or, (E)instructed to talk about their experiences in the past trials in a way that would be beneficial to another subject in a similar situation.

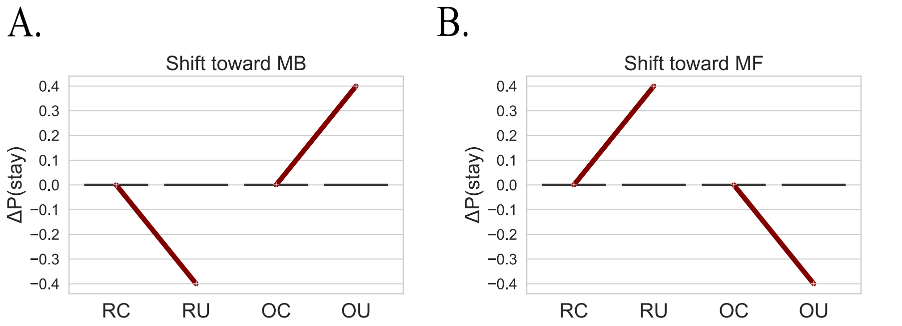

Fig. 2 Trials after rare transitions (second and fourth bar) are discriminatory between model-free and model-based choices, whereas both strategies make equal predictions for trials after common transitions (A) A shift toward model-based control is expressed by enhanced sensitivity to the task structure. (B) A shift toward model-free control would be indicated by an increased propensity to stay with the chosen pattern after uncommon rewarded trials and an increase in switching after uncommon unrewarded trials.

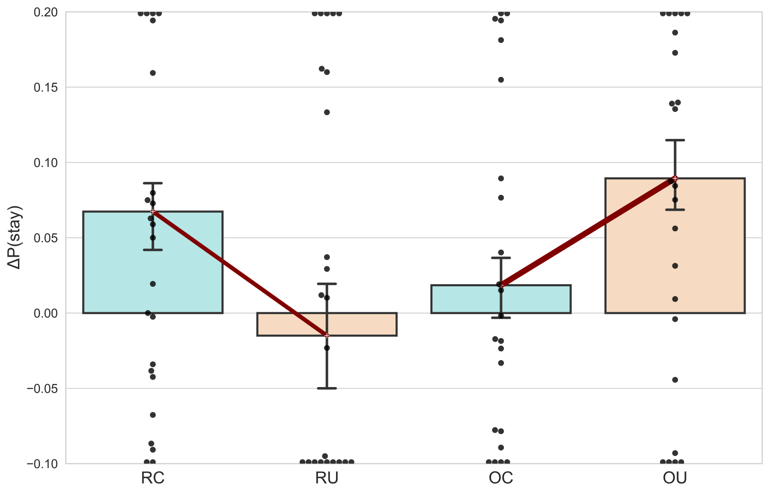

Fig. 3 The difference in stay probability between confidence and control condition is shown in this plot. The observed interaction indicates a shift toward model-based choice.

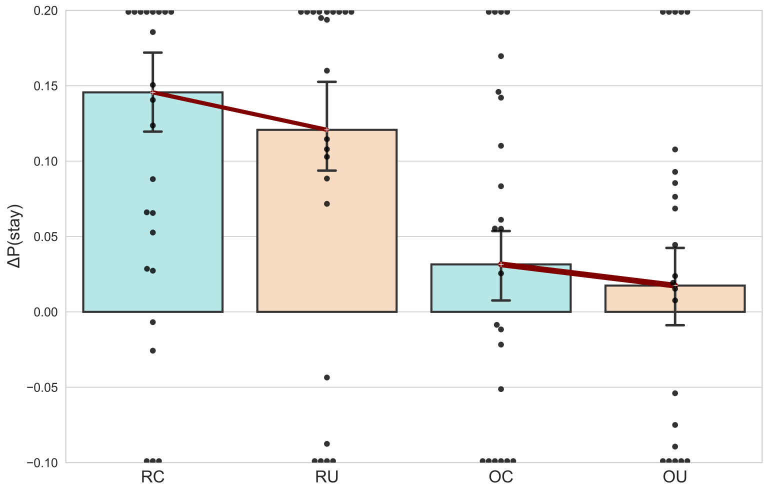

Fig. 4 The difference in stay probability between talk and control condition is shown in this plot. The observed interaction indicates a shift toward model-free choice.