DOES VALUE OR HISTORY DRIVE HABITUAL CHOICE?

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ABSTRACT

This thesis aims to investigate the relative contributions of frequency and value in driving habitual choices. The thesis defines habit as a learned behaviour that is repeated regularly and tends to occur unconsciously. It distinguishes between goal-directed and habitual decision making, which differ in terms of the underlying cognitive and neural processes involved. The study will test the question of whether value or history drives habitual choice, by overtraining different values and examining the resulting choices in an online two-day task. In the study, participants had to choose between two stimuli with fixed values and earn points. The stimuli were gorillas in different colours, with values between 1 and 8, that were learned through trial and error in two contexts: a low value context and a high value context. The analysis used a repeated measures design, with blocks (time) and trained pairs (type of pair presented to the participant) as independent variables and reaction time (RT) and accuracy as dependent variables. The study found that value seems to drive responses more than mere frequency, potentially illuminating the respective roles of frequency and value in habitual responding.

Keywords: habitual choices, frequency, value, goal-directed decision making, cognitive processes, overtraining, online task

ABSTRACT

Deze thesis heeft als doel de relatieve bijdragen van frequentie en waarde te onderzoeken bij het sturen van gewoontematige keuzes. De thesis definieert gewoonte als een aangeleerd gedrag dat regelmatig wordt herhaald en vaak onbewust optreedt. Er wordt onderscheid gemaakt tussen doelgerichte en gewoontematige besluitvorming, die verschillen in termen van de onderliggende cognitieve en neurale processen die erbij betrokken zijn. De studie zal de vraag onderzoeken of waarde of frequentie gewoontematige keuzes bepaalt door verschillende waarden te overtrainen en de resulterende keuzes te onderzoeken aan de hand van een online taak over twee dagen heen. In de studie moesten de deelnemers kiezen tussen twee stimuli met vaste waarden en punten verdienen. De stimuli waren gorilla's in verschillende kleuren, met waarden tussen 1 en 8, die werden aangeleerd door middel van trial and error in twee contexten: een context met lage waarden en een context met hoge waarden. De analyse gebruikte een design met herhaalde metingen, waarbij blokken (tijd) en getrainde paren (het type paar dat aan de deelnemer werd gepresenteerd) als onafhankelijke variabelen werden gebruikt, en reactietijd (RT) en accuraatheid als afhankelijke variabelen. De studie vond dat waarde gewoontematige keuzes meer lijkt te bepalen dan louter frequentie, wat mogelijk inzicht geeft in de respectieve rollen van frequentie en waarde bij gewoontematige reacties.

Trefwoorden: gewoontematige keuzes, frequentie, waarde, doelgerichte besluitvorming, cognitieve processen, overtraining, online taak

PREWORD

First of all I would like to thank Dr. Elise Lesage for her guidance and the many meetings we had to discuss this thesis. You introduced me to a subject I knew little about and you broadened my knowledge in the subject. Despite the difficulties, you remained positive and motivated me to persevere. I appreciate the opportunity you have given me to discover and express myself over the two years. Secondly, I would like to thank Prof. Dr. Tom Verguts for taking over the workload from Dr Lesage and guiding me further in finalizing my thesis. Prof. Verguts' involvement and support were instrumental in my journey, providing me with the strength and motivation necessary to navigate the challenges without losing my focus. Lastly, I would like to extend my appreciation to my dear ones. My friends, I am grateful to you for showing me that life is full of significance, and for engaging in conversations with me without any barriers. To my amazing boyfriend, I cannot thank you enough for adding joy and excitement to my life and being my emotional support during times of need. Their contributions have played an integral role in shaping the outcome of this thesis, and for that, I am immensely grateful.

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1 INTRODUCTION

In this thesis, we aim to shed light on the nature of habitual systems, which are believed to take over from goal-based systems over time. Although this transition has been widely acknowledged, the specifics of how this occurs remain unclear. To address this question, we draw on the work of Miller et al. (2019), who propose two competing views of how habits are formed. The traditional view posits that frequency is the key factor, with actions that are performed more frequently becoming more deeply ingrained in the cognitive system through Hebbian learning. The common computational view, in contrast, emphasizes the role of value-based learning, where actions are reinforced based on their outcomes. To distinguish between these two accounts empirically, we manipulated both frequency and value in a training design. Frequency was manipulated by comparing old (high-frequency) pairs with new (low-frequency) pairs in a mixed phase, while value was manipulated by assigning stimuli to a value scale from 1 to 8. By doing so, we can examine the relative importance of these two factors in shaping habitual behaviour. Overall, this study provides a novel approach to understanding the cognitive and computational mechanisms underlying habitual systems, which has important implications for both theoretical and practical domains.

2 LITERATURE STUDY

2.1 What is a habit?

Many of our daily decisions are habitual (James, 2007). Everyone is familiar with both bad and good habits. From choosing the same sandwich every time, to smoking, to brushing your teeth. An example of a habit could be an individual consistently choosing to eat the same kind of food for lunch every day. For instance, they may habitually choose to eat a turkey sandwich on whole wheat bread with lettuce, tomato, and mustard, along with a piece of fruit and a bottle of water. This behaviour may have started as a conscious decision, but over time, the individual may have formed a habit of choosing this particular meal without even thinking about it. They may not even consider other options or consider trying something new, as they are so used to choosing this particular meal. This habit of choosing the same kind of food every day could be influenced by various factors, such as taste preferences, convenience, or a desire for a healthy meal. However, it could also become a rut that limits the individual's dietary variety and potential enjoyment of other foods. Breaking this habit and trying new foods could lead to a more diverse and satisfying diet. Habits are automatic, repetitive behaviours that are triggered by contextual cues or environmental stimuli. While habits can be beneficial for conserving cognitive resources and promoting efficiency in daily life, they can also be detrimental when they lead to maladaptive or unhealthy behaviours.

Behavioural psychologists Skinner and Thorndike conducted research on habits and their role in shaping behaviour. Both Skinner and Thorndike believed that habits were formed through the reinforcement of certain behaviours over time. They argued that behaviour was not determined by internal factors such as thoughts or emotions, but rather by external factors such as environmental cues and rewards (DiBlasi & Waters, 2017).

In addition to *Thorndike's Law of Effect*, which states that behaviours followed by positive consequences are more likely to be repeated, there is also the *Law of Exercise* (Hearst, 1999), which highlights the role of frequency in habit formation. The *Law of Exercise* suggests that the more frequently a behaviour is repeated, the more likely it is to become habitual.

Consider the example of an individual habitually choosing to eat the same turkey sandwich for lunch every day. This behaviour may have initially started as a conscious decision, but over time, it became a habit due to various factors. The positive consequences of this behaviour, such as feeling full and satisfied after lunch, the convenience of having a pre-prepared meal, and the comfort of knowing what to expect in terms of taste and quality, contribute to its repetition in the future. Moreover, the frequency of engaging in this behaviour plays a significant role in the formation and solidification of the habit.

Thorndike also proposed the concept of *instrumental conditioning*, in which an individual learns to associate a particular behaviour with a particular outcome or reward. Skinner's work further built on Thorndike's principles and focused on the role of reinforcement in shaping behaviour. Skinner introduced the concept of *operant conditioning*, involving the reinforcement of desired behaviours and the discouragement of undesired behaviours through the use of rewards and punishments (Thorndike, 1911; Skinner, 1961).

In the example of the individual's lunch habit, the behaviour of choosing the turkey sandwich could be reinforced in various ways. For instance, if the individual finds that they feel more productive or energized after eating this particular lunch, it serves as a form of positive reinforcement that encourages them to continue choosing this meal. Conversely, if the individual once tried a different lunch option and found it less satisfying or less convenient, this could act as a form of negative reinforcement that discourages them from trying something new in the future.

Overall, Skinner and Thorndike's research suggests that habits are formed through a process of trial and error, where individuals repeatedly engage in a particular behaviour and learn to associate it with specific outcomes. Reinforcement, including positive consequences, rewards, and the frequency of engaging in the behaviour, plays a crucial role in habit formation. With repetition and reinforcement, behaviours that lead to positive outcomes become more likely to become automatic and difficult to change, resulting in the formation of habits.

Later writers have emphasized the role of cues in habit formation. Neal et al. (2006) suggest that habits are formed through a process of reinforcement learning, where the association between a cue and a particular behaviour is repeatedly reinforced through positive or negative feedback. These cues can be external or internal and take various forms, such as a specific time of day, a location, a social context, or an emotional state. Once a habit has been formed, Neal et al. suggest that it becomes an automatic response to the cue, requiring little or no conscious thought. This can be both beneficial, as it conserves mental energy, and problematic, as it can lead to unwanted behaviours. Thus, Neal et al.'s work highlights the role of cues in habit formation and the potential for modifying habits through deliberate practice and reinforcement of new behaviours.

Building on this perspective, Wood and Neal (2007) further emphasize the importance of learned stimulus-response associations in habit formation and behaviour change. They argue that habits are developed through repeated exposure to stimulus-response associations, where the strength of the association and the frequency of activation are key factors. The strength of the association is determined by the extent to which the response reliably follows the stimulus, while the frequency of activation is determined by the number of times the association is activated in response to the stimulus. Wood and Neal describe habit formation as a shift from controlled and intentional behaviour to automatic and habitual behaviour. This shift occurs as the learned stimulus-response association becomes stronger and more automatic, requiring less conscious effort to initiate the behaviour. Importantly, Wood and Neal also suggest that learned stimulus-response associations can be modified through repeated exposure to new stimuli or responses. This process of habit modification involves breaking existing associations and forming new ones through repeated practice and reinforcement. Overall, Wood and Neal's work on learned stimulus-response associations emphasizes the importance of reinforcement learning in habit formation and the potential for modifying habits through deliberate practice and reinforcement of new behaviours.

Similarly, Nir Eyal (2014) defines habits as "actions performed with little or no conscious thought" and emphasizes the role of cues in habit formation. Cues, which can be environmental or internal triggers that signal the brain to initiate a particular behaviour. These cues become deeply ingrained through repeated exposure and serve as powerful triggers for habitual behaviour. Eyal acknowledges that habits can be challenging to change because they are deeply ingrained in our neural pathways and require conscious effort to modify. To change a habit, Eyal suggests identifying the cue that triggers the behaviour and then modifying the subsequent routine or behaviour. By substituting a new behaviour for the old one, and reinforcing it through repetition, it is possible to form a new habit that is more desirable and better suited to our goals and values.

Gardner (2015) defines habit as "a recurrent, often unconscious, pattern of behaviour that is acquired through frequent repetition." This definition is similar to the psychological definition of habit, which emphasizes the role of reinforcement and repetition in shaping behaviour. Gardner's definition of habit is also similar to Thorndike's and Skinner's in that it emphasizes the role of repetition and reinforcement in shaping behaviour.

Recent research (Wood & Rünger, 2016) suggests that habitual choices may be driven by two distinct processes: the history of past experiences and learning, and the value or consequences of the behaviour. Both frequency-driven and value-driven models proposes that habits are formed through a process of reinforcement learning. The difference between both frequency-driven and value-driven models lays in what exactly is learned. In a frequency-driven model the repeated pairing of a particular cue with a particular response leads to the automatic activation of that response in the presence of the cue, regardless of the value or consequences of the behaviour. In contrast, the value-driven model suggests that habitual choices are influenced by evaluation of the value or consequences of the behaviour, and that behaviours that are perceived as more valuable or rewarding are more likely to become habitual.

In conclusion, building upon recent research by Wood and Rünger (2016), this thesis aims to empirically disentangle the contributions of frequency-driven and value-driven processes in habitual choices.

2.2 Traditional model vs common model

2.2.1 Computational model of Miller et al. (2019)

In the previous section, we discussed two key ideas regarding how habits are formed. These ideas have also been implemented in computational models, which provide valuable insights into the underlying mechanisms of habit formation. In this section, we will briefly describe both computational approaches and their contributions to our understanding of habitual behaviour.

The computational model proposed by Miller et al. (2019) builds upon the notion that habit can be understood as a form of frequency-based behaviour. In other words, the more frequently we perform a specific action in a given context, the more likely it becomes a habitual response. When we engage in a behaviour that leads to a rewarding outcome repeatedly, the association between the behaviour and the reward strengthens. Over time, this association becomes encoded in our neural pathways, making the behaviour more automatic and less dependent on conscious deliberation.

The model also considers the influence of contextual cues, as highlighted by Neal et al. (2006). These cues provide information about the likelihood of receiving a reward for a specific behaviour in each situation. When we encounter a familiar context, the associated cues trigger the learned habit, leading to a habitual response.

The computational model incorporates two separate value functions to capture the balance between model-based and model-free control in decision-making. The value function associated with the model-based system relies on a cognitive representation (model) of the environment and considers the current state, available options, and desired goals. It evaluates different actions and their potential consequences. On the other hand, the value function associated with the model-free system relies on learned associations between actions and rewards or punishments. It is based on reinforcement learning, where the value of an action is updated based on the received feedback. This system is more focused on immediate rewards and learned associations, rather than explicitly considering the environment's structure or the long-term consequences of actions.

By having two separate value functions, the model allows for the integration of both model-based and model-free decision-making processes. The relative importance of these systems is determined by a gating parameter that varies between 0 and 1, which can dynamically adjust the balance between the two based on the task complexity and predictability of rewards. When the gating parameter is set to 1, the model-based system is fully engaged, while when the gating parameter is set to 0, the model-free system is fully engaged. This flexible weighting mechanism enables the model to capture different decision-making scenarios and adapt to different task demands.

In the model (Figure 1), there are three modules: the habitual controller, the goal-directed controller, and the arbiter. The habitual controller is responsive to past actions and tends to repeat frequently taken actions. This is referred to as model-free or habitual learning. For example, if you have consistently chosen a turkey sandwich before and had positive experiences, the habitual controller would suggest selecting it again. It relies on the learned association between being in the grocery store and choosing the turkey sandwich based on past habits.

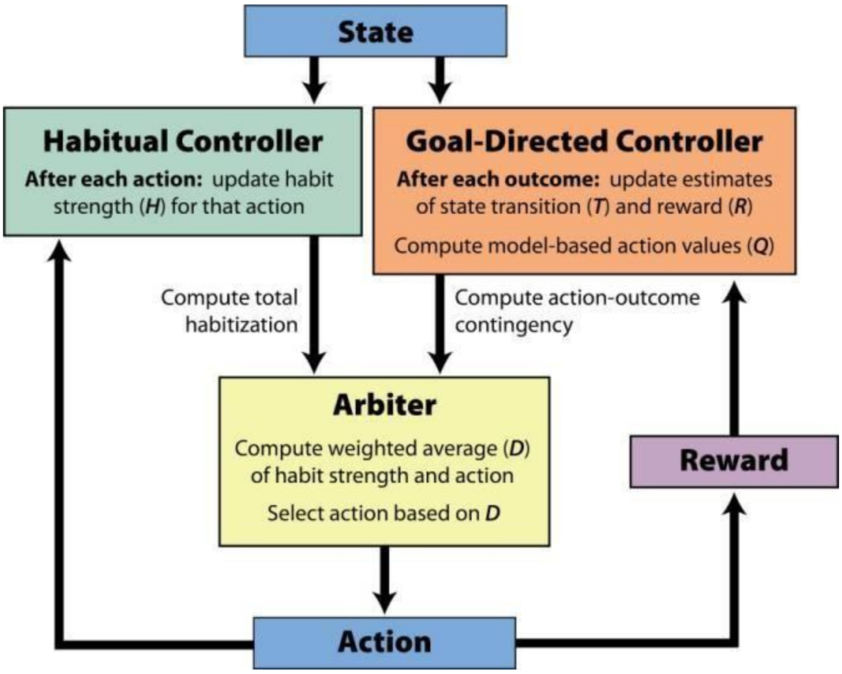
The goal-directed controller, on the other hand, is responsive to outcomes that have high value. This is known as model-based or goal-directed learning. When deciding on a turkey sandwich, the goal-directed controller considers factors like hunger, taste preferences, and health goals. It evaluates the potential satisfaction and healthiness of choosing the turkey sandwich compared to other options. If it determines that the turkey sandwich aligns with your desired outcomes and preferences, it suggests choosing it. The goal-directed controller initially plays a more prominent role as you consciously weigh various factors.

The arbiter weighs the influence of each controller on behaviour. It favours goal-directed control when there is a strong relationship between actions and outcomes, and it favours habitual control when habits are well-established. As the behaviour of choosing the turkey sandwich becomes more familiar and repeated, the habitual controller gains strength, influencing the decision based on past habits and associations. Some actions may be rewarding, which can lead to more goal-directed control. For the turkey sandwich, positive experiences and rewards influence the balance between goal-directed and habitual control. A rewarding experience with the turkey sandwich reinforces the idea that selecting it leads to a positive outcome, strengthening goal-directed thinking. Conversely, developing a habit of always choosing the turkey sandwich reinforces habitual learning, making it more challenging to break that habit (Miller et al., 2019).

The Miller et al. (2019) model has been shown to capture human decision-making behaviour in various tasks. It provides a framework for understanding how the brain integrates information from different sources to make decisions and how the balance between different decision-making systems can be adjusted based on the demands of the task.

Figure 1

Computational Model of Habit Formation and Goal-Directed Control (Miller et al., 2016)



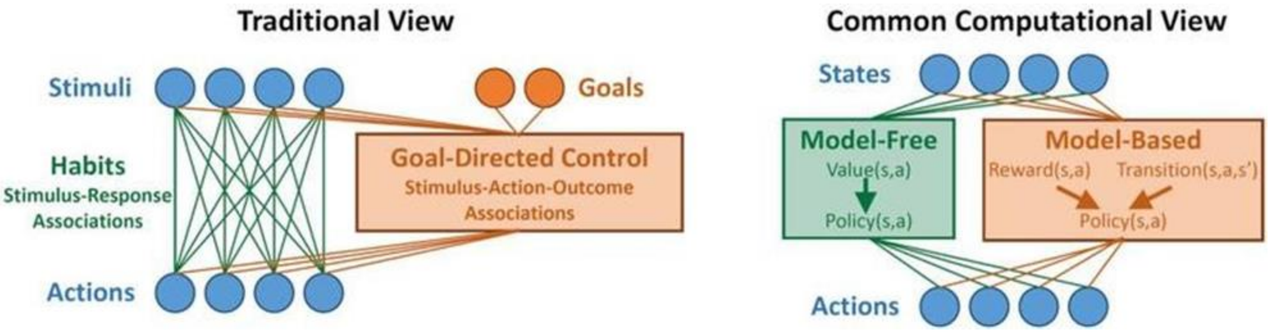
Note. The figure above is deducted from Miller et al.'s paper (2016) and represents a schematic description of their computational model. The scheme shows the interaction between the model components and their description. It has three modules: the habitual controller, the goal-directed controller and the arbiter. The habitual controller reacts when a state reminds of actions done in the past, which will lead to more chance to redo the same action. The goal-directed controller reacts when different options are being considered. The arbiter makes the balance between the habitual controller and the goal-directed controller. When one of the two is stronger than the other, the action will be made based on it. Which on his turn can reinforce the habitual controller or the goal-directed controller through reward. See main text for more details and examples.

2.2.2 Common computational model

Next to the Miller traditional computational view (Miller et al., 2019) there is the common computational model, which is more modern and proposes that habits are mediated by outcome-sensitive reinforcement learning mechanisms. In this view, habits are not solely dependent on frequency or repetition but are instead influenced by the value or desirability of the outcomes associated with certain actions. The model suggests that individuals learn to associate actions with specific outcomes based on the expected value of those outcomes, and habits are formed when actions with high expected value become automatic and reflexive. On figure 2 a comparison between the modern common computational model and the traditional computational model are visualised (figure 2).

Figure 2

Contrasting Perspectives on Goal-Directed and Habitual Learning



Note. The figure above with the comparison between the traditional view and common computational view regarding goal-directed and habitual learning is deducted from Miller et al.'s (2019) paper. The figure from Miller et al.'s (2019) paper illustrates this comparison. Left: the traditional view; habitual learning is the stimuli that leads to certain actions based on habits formed through stimulus-response associations and goal-directed control include knowledge of action-outcome relationships as well as goals guiding the choices. Right: the common computational view; habitual learning/model-free learning happens through learning the value over actions and states, while goal-directed learning/model-based learning happens through the learning of the structure of the task.

2.3 Goal directed and habitual choices

We have already talked about habits, but it’s also important to talk about goal-directed actions as another possible approach to decision-making. Goal-directed actions are taken with the intention of achieving a desired outcome or goal. In the example of habitually choosing to eat a specific lunch, the desired outcome or goal could be maintaining a healthy diet. However, if the individual's goal were to try new foods, then habitually choosing to eat the same meal every day would not be goal-directed. In this case, the individual would need to consciously make an effort to try new foods in order to achieve their goal. Overall, whether an action is considered goal-directed or habitual depends on the underlying intention or goal of the individual performing the action (Wood & Rünger, 2016).

Research suggests that goal-directed and habitual choices are mediated by different neural systems, and that they can be influenced by a variety of factors, including prior experience, reinforcement, and the presence of cues in the environment. Overall, understanding the mechanisms underlying goal-directed and habitual choices can shed light on the processes by which individuals make decisions, and can have important implications for promoting behaviour change and improving health outcomes (Dolan & Dayan, 2013; Wood & Rünger, 2016).

There are several frameworks that capture the difference between goal-directed and habitual decision making or choice. For this thesis, relevant frameworks are discussed to get a better understanding of goal directed and habitual choices.

2.3.1 Dual-Process Theory

The Dual-Process Theory is a framework that suggests that decision making is mediated by two distinct processes: a fast, automatic, and unconscious process (associated with habitual behaviour), and a slower, deliberative, and conscious process (associated with goal-directed behaviour) (Strack & Deutsch, 2004). According to this theory, habitual behaviour is driven by stimulus-response associations that are learned through repeated experience, whereas goal-directed behaviour is driven by the individual's conscious evaluation of the expected outcomes of different actions. Using the example of habitually choosing to eat a turkey sandwich, the fast, automatic, and unconscious process is triggered by a cue in the environment, such as feeling hungry at lunchtime. This process leads to a habitual response of choosing the turkey sandwich without much conscious thought or evaluation. On the other hand, if the individual decides to choose a different type of lunch, they will need to engage in a slower, more deliberative, and conscious process of decision-making. They would need to evaluate different options and consider their expected outcomes in order to choose a lunch that aligns with their specific goals, such as trying to eat healthier or having more variety in their diet. The dual-process theory suggests that these two types of decision making are mediated by distinct neural systems, and that habitual behaviour is relatively inflexible and resistant to change, while goal-directed behaviour is more flexible and adaptable to changing circumstances.

2.3.2 Model-based vs model-free framework

The model-based vs. model-free framework emphasizes the role of cognitive representations of the environment (i.e., "models") in guiding decision making (Daw et al., 2005). According to this framework, model-based decision making involves using a cognitive map or mental model of the environment to simulate different possible outcomes of a decision. This allows for flexible, context-dependent decision making that considers the current state of the environment and the desired outcome. In contrast, the model-free framework does not rely on an explicit internal model of the environment. Instead, it emphasizes learning through trial and error, without explicitly representing the underlying structure of the environment. Model-free approaches often involve reinforcement learning algorithms that learn from interactions with the environment to associate actions with rewards or punishments. When we rely on a model-free approach, there is a higher likelihood of falling back on habitual or automatic responses. This is because model-free algorithms tend to learn through repetition and reinforcement of specific actions, without actively considering the current state of the environment or long-term goals. These learned behaviours become automatic and may not always be the optimal choice in every situation. Dolan and Dayan (2019) propose that these two systems interact dynamically in the brain, with the model-based system providing top-down control over the model-free system. This allows for a balance between flexible, context-dependent decision making and efficient, automatic decision making based on previously learned associations.

Overall, according to Dolan and Dayan (2019) the model-based vs. model-free framework offers a more nuanced and integrative view of goal-directed and habitual decision making, emphasizing the importance of both cognitive representations and associative learning in guiding behaviour. Suppose you are at a local grocery store, and you see a turkey sandwich on whole wheat bread with lettuce, tomato, and mustard. You decide to buy it because you remember that you enjoyed it the last time you had it. This decision-making process involves both model-based and model-free components. The model-based component involves your mental representation of the sandwich and the context in which it is presented. You may have a mental model of the grocery store and the various foods that are available there, including the turkey sandwich. Using this model, you simulate the possible outcomes of choosing the sandwich, such as the taste, the satisfaction you might feel after eating it, and the cost. You also consider the current context, such as your hunger level and the time of day, which might influence your decision. All of these factors are integrated to generate a decision that is tailored to the specific situation. The model-free component involves the associative learning mechanisms that link the sandwich with positive outcomes based on previous experiences. If you have eaten the sandwich before and enjoyed it, your brain has formed an association between the sandwich and the positive experience, and this association influences your decision-making process. This component is less flexible than the model-based component, as it relies on pre-existing associations rather than taking into account the current context. Overall, the decision to buy the turkey sandwich involves a dynamic interplay between these two components, with the model-based system providing top-down control over the model-free system. This allows for a balance between flexible, context-dependent decision making and efficient, automatic decision making based on previously learned associations.

To summarize, both the model-based and model-free approaches can sometimes lead us to act out of habit or automatically. However, the model-free approach is more likely to rely on these automatic responses because it learns from past experiences without really thinking about the current situation. On the other hand, the model-based approach is better at adapting to different situations because it has an internal model of the environment that helps it simulate and evaluate different actions and their outcomes. So, the model-based approach allows for more flexible decision-making that takes into account what's happening right now.

2.3.3 Habit-Goal Framework

The *Habit-Goal Framework* suggests that habitual behaviour and goal-directed behaviour are two endpoints on a continuum of behaviour. At one end of the continuum, behaviours are automatic, triggered by cues in the environment, and relatively inflexible (characteristic of habitual behaviour). At the other end of the continuum, behaviours are consciously controlled, flexible, and goal-oriented (characteristic of goal-directed behaviour) (Wood & Rünger, 2016). Behaviours can shift along this continuum depending on factors such as motivation, attention, and the salience of environmental cues. The turkey sandwich for example is a part of a person's daily routine, where they buy it from the local grocery store every day on their way to work without much thought. This is an example of habitual behaviour, where the person's decision to buy the turkey sandwich is triggered by a cue (i.e., passing by the grocery store) and is automatic and inflexible. However, if the person decides to switch to a healthier lunch option, such as a salad, they may have to consciously control their behaviour and make a goal-directed decision to choose the salad over the turkey sandwich. This shift in behaviour from habitual to goal-directed can be influenced by factors such as motivation, attention, and the salience of environmental cues. For example, if the person is motivated to eat healthier or if the grocery store starts offering healthier lunch options, they may be more likely to make a goal-directed decision to choose the salad.

These frameworks offer different ways of conceptualizing the difference between goal-directed and habitual behaviour. In conclusion, goal-directed and habitual decision making are two distinct modes of decision making that differ in terms of the underlying cognitive and neural processes involved (which will be discussed later on). Goal-directed decision making is a more flexible and intentional mode of decision making that involves considering multiple options and choosing the option that best achieves a desired outcome or goal. In contrast, habitual decision making is a more automatic and less conscious mode of decision making that involves repeating a learned response based on cues from the environment. The same action can be taken under either habitual control or goal-directed control in different circumstances (Miller et al., 2019). However, it is worth mentioning that the concept of habit is still not completely clear-cut. There is ongoing debate about whether habit refers to a specific action or simply the frequency of occurrence. Therefore, more research is needed to fully understand the nature of habits in decision making. By understanding the differences between goal-directed and habitual decision making, we can make more informed choices in different situations. It helps us recognize when we should consciously deliberate and when we can rely on automatic responses.

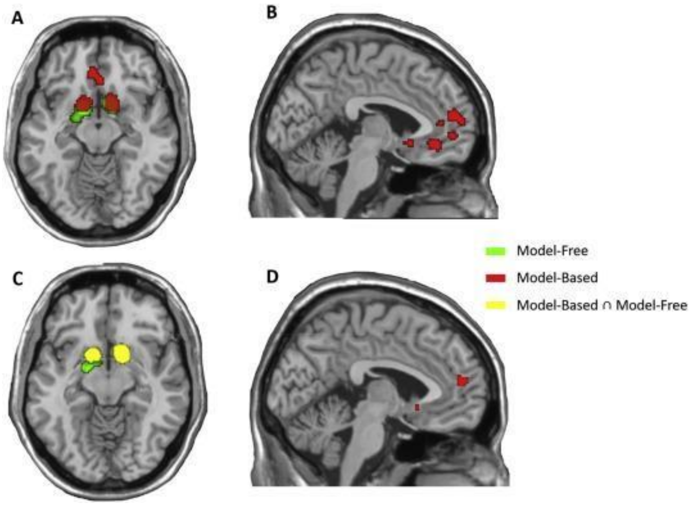
There are some side notes to the comparison between ‘model-based/goal-directed’ behaviour and ‘model-free/habitual’ behaviour. In recent studies researchers have used a test called "The Fabulous Fruit Game" to examine the effect of devaluing goals on these behaviours (Buabang et al., 2021). Interestingly, when goals were devalued, it was found that model-based behaviour decreased, but model-free behaviour did not increase (Robbins & Costa, 2017). This means that the balance between the two types of behaviours did not change as expected. So, just because there was a decrease in goal-directed behaviour, it doesn't necessarily mean that habitual control took over. There is also a debate about whether "model-free" behaviour only refers to habit-based behaviour or if it includes general reinforcement learning (Robbins & Costa, 2017). Some studies suggest that both goal-directed and habitual learning happen simultaneously when an action leads to a certain outcome, but habitual learning tends to dominate over goal-directed learning. However, this doesn't mean that goal-directed behaviour is completely absent (Wood & Neal, 2007). In fact, researchers have discovered a neural difference between goal-directed and habitual learning, supporting the idea that they are distinct processes (more on this in the following paragraph). Overall, the studies suggest that there are complexities and nuances in the relationship between goal-directed and habitual behaviour. The presence of one does not automatically mean the absence of the other, and there are ongoing discussions about the specific nature of these behaviours and their underlying neural mechanisms.

2.3.4 Neural determinants of goal-directed and habitual control

In neuroimaging research studies of Huang et al. (2020) different findings were made that can help us to improve our understanding of how model-based/goal-directed and model-free/habitual learning represented in the brain. Here are some interesting findings: first, both goal-directed and habitual control activate ventral striatum. Second, model-based/goal-directed learning activates the orbital frontal cortex and the medial prefrontal cortex. Last, model-free/habitual learning specifically activates the left globus pallidus and right caudate head. As conclusion Huang et al. (2020) suggests that goal-directed and habitual decision make use of overlapping yet different neural regions. In figure 3, the model-free and model-based regions are being illustrated in the brain (figure 3). Other studies repeatedly show that the dorsomedial striatum (DMS) is implicated in goal-directed behaviour whereas related studies demonstrate that the dorsolateral striatum (DLS) is implicated in habitual learning. Besides, there is evidence for the transfer from dorsomedial to dorsolateral over the course of training (Dayan, 2013).

Figure 3

Activation Patterns of Model-Free and Model-Based Brain Regions



Note. The activation patterns of model-free and model-based processes in the brain, as shown in the figure, are based on research conducted by Huang et al. (2020) and the figure is conducted from the paper of Huang et al (2020). A&B: simultaneous activity for model- free (green) and model based (red) processes. C: The bilateral ventral striatum for both model-based and model-free processes (yellow) and the globus pallidus for model-free learning. D: anterior cingulate and ventromedial prefrontal cortex for model-based learning.

In a study by Yin et al. (2004), the roles of the dorsomedial striatum (DMS) (analogue of the caudate), and the dorsolateral striatum (DLS) (analogue of the putamen) are examined in habit expression and habit formation. Yin and colleagues used a devaluation paradigm and taught rats to press a lever to obtain a sucrose solution as reward. Lesions were induced by using muscimol. In a first study, researchers have looked at the DLS and induced the lesion prior to training. As a result of this study, rats with an intact DLS became habitual, while the lesioned rats no longer pressed the lever after outcome devaluation. When the DLS is removed, the rats were not able to form a habit. Following that, the researchers induced lesions in the DMS after the rats had undergone overtraining. The results demonstrated that rats with a DMS lesion could still react based on habits, showing that the DLS plays a significant role in habit learning and that the DMS is important for goal-directed learning (Yin, Knowlton & Balleine, 2004).

These studies may offer a better understanding of neural findings and shows that structures associated with goal-directed/model-based learning and habitual/model-free learning tend to overlap, whereas lesion studies show differences between structures associated with habitual learning and goal-directed learning (Miller et al., 2019). While significant progress has been made in understanding the neural basis of goal-directed and habitual behaviour, there is still much to learn about how these processes work in the brain.

2.4 Overtraining choices

Now that we have a better understanding of the processes and different theories in decision making, we can take a closer look to overtraining choices and how this impact decision making and the transition from goal-directed to habitual processes. In the context of this thesis on whether habits are based on frequency or value, it is important to consider the concept of overtraining and its effects on decision making. By investigating the effects of overtraining, we can specifically focus on the impact of frequency, or the sheer number of repetitions, on the formation and strength of habits. This is relevant to this thesis as it directly addresses the question of whether habits primarily arise from the frequency of behaviour or from the subjective value associated with the behaviour.

Overtraining refers to a scenario where an individual repeatedly performs a task beyond the point of mastery. Research has shown that choices made during overtraining can have a lasting impact on subsequent behaviour (Dolan & Dayan, 2013). One key finding is that choices made during overtraining can bias subsequent behaviour towards a habitual or a goal-directed mode of control. For example, if an individual repeatedly performs a task with a consistent reward feedback, such as pressing a button that always delivers a reward, the individual may develop a habitual response pattern that is insensitive to changes in the reward contingencies. On the other hand, if the task is complex and the reward feedback is unpredictable, the individual may rely more on a goal-directed mode of control (Dolan & Dayan, 2013).

Another finding is that choices made during overtraining can influence the neural systems that underlie decision-making. Studies using neuroimaging techniques have shown that overtraining can lead to changes in the structure and function of the striatum, a brain region that is involved in habit formation and goal-directed behaviour (Dolan & Dayan, 2013). For example, overtraining on a task that promotes habitual responding has been shown to increase the volume of the dorsolateral striatum, while overtraining on a task that promotes goal-directed responding has been shown to increase the volume of the ventromedial prefrontal cortex. Overall, the study of choices in overtraining provides insights into how behaviour is shaped by experience and how different decision-making systems interact to control behaviour.

2.5 Research question

The classic view about habit is the fact that after a lot of repetitions, choices become independent of the outcome (de Wit et al., 2018). The more used we are to certain choices (habits), the more likely we are to repeat them. However, it remains unclear how habitual choices are reinforced or represented. As explained before, habit formation has two opposing views regarding its representation. The traditional view that suggests that habit formation is primarily driven by the frequency of performing a specific action in response to a particular stimulus. In contrast, the common computational view that proposes that habits are formed based on the expected value of outcomes associated with specific actions. To empirically distinguish between these views, our study will manipulate both frequency and value. According to the traditional view (also espoused by Miller et al., as discussed above), frequency plays a crucial role, while the common computational view highlights the importance of value. We will manipulate frequency through a training design that compares high-frequency pairs (old pairs) with low-frequency pairs (new pairs). Value manipulation will involve placing stimuli on a value scale from 1 to 8. This design will help determine the relative importance off frequency and value.

Based on those two opposing views, two hypotheses are formulated, the frequency-driven and the value-driven hypothesis. The frequency-driven habit formation hypothesis suggests that habits primarily develop based on the reinforcement history. Extensive overtraining leads to automatic and habitual choices that have been consistently reinforced. The frequency of reinforcement strengthens the association between the choice and the expected outcome, causing the choices to occur automatically, independent of their current value. In contrast, the value-driven habit formation hypothesis suggests that habits form based on the value associated with choices, regardless of the reinforcement history. Through repetition and exposure to different choices, individuals learn the subjective value of each option. This familiarity with value leads to faster and more automatic decision-making. According to this hypothesis, the repeated computation of value drives the formation of habits.

Through the experiment, we seek to test both hypotheses and analyse the data in light of these perspectives. This research contributes to a deeper understanding of habit formation by addressing the main question: Does value or history drive habitual choice? Exploring these factors provides valuable insights into the underlying mechanisms of habit formation. It is important to note that the precise conditions or duration of training required for habits to form are still subjects of debate among researchers.

3 METHOD

3.1 Participants

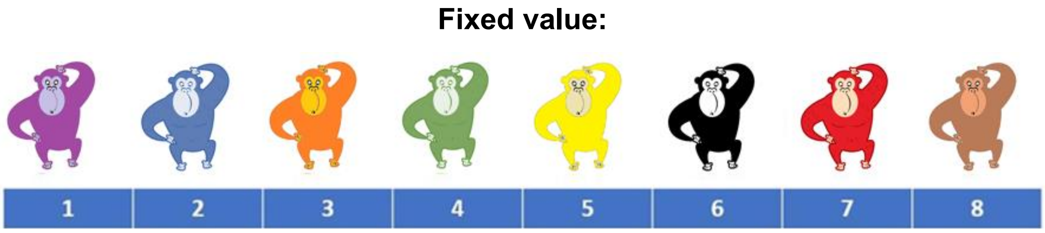
A total of fifty-one participants participated in the experiment, with one individual being excluded from the analysis due to non-compliance with the experimental protocol. They all participated in turn for monetary compensation, which was 20 euros. All participants were recruited through Sona. They were reminded that they could stop participating in the study at any time and an informed consent was obtained (approved by the ethical committee, in line with declaration of Helsinki).

3.2 Stimuli and experiment

The study consists of two parts conducted over two days. The experiment is programmed using the Gorilla Experiment Platform, specifically the Gorilla Experiment Builder. Participants engage in an online task, so they could perform it at home. On each trial, they are presented with a choice between two stimuli with a fixed value. To make a choice, participants press the "F" key to select the left stimulus and the "J" key to select the right stimulus. The stimuli that are used are gorillas presented in eight different colours (purple, blue, orange, green, yellow, black, red and brown; figure 4). When participants make a choice between the two stimuli, the value of the selected stimulus is visually represented by showing a chest with the corresponding number of coins that represents the value assigned to that particular gorilla. As the experiment progresses, participants learn the values associated with each gorilla through trial and error. Initially, participants may randomly choose a stimulus, but as they continue the experiment, they gradually discover the value of each gorilla by observing the outcomes and the number of coins displayed in the chest. It is explicitly stated in the instructions that participants should aim to collect as many points (coins) as possible, highlighting the importance of learning the value of each gorilla stimulus through their choices and subsequent feedback. The values assigned to the gorilla stimuli range between 1 and 8, giving a range of potential outcomes for participants to explore and learn from. With each trial, participants have a time limit of 3000 ms to respond. If they are too late in making a choice, no points are given for that trial. This time limit encourages participants to make quick and automatic decisions, aiming to tap into the formation of habits that rely less on deliberate thinking processes. In figure 5 an example of different trials is showed.

Figure 4

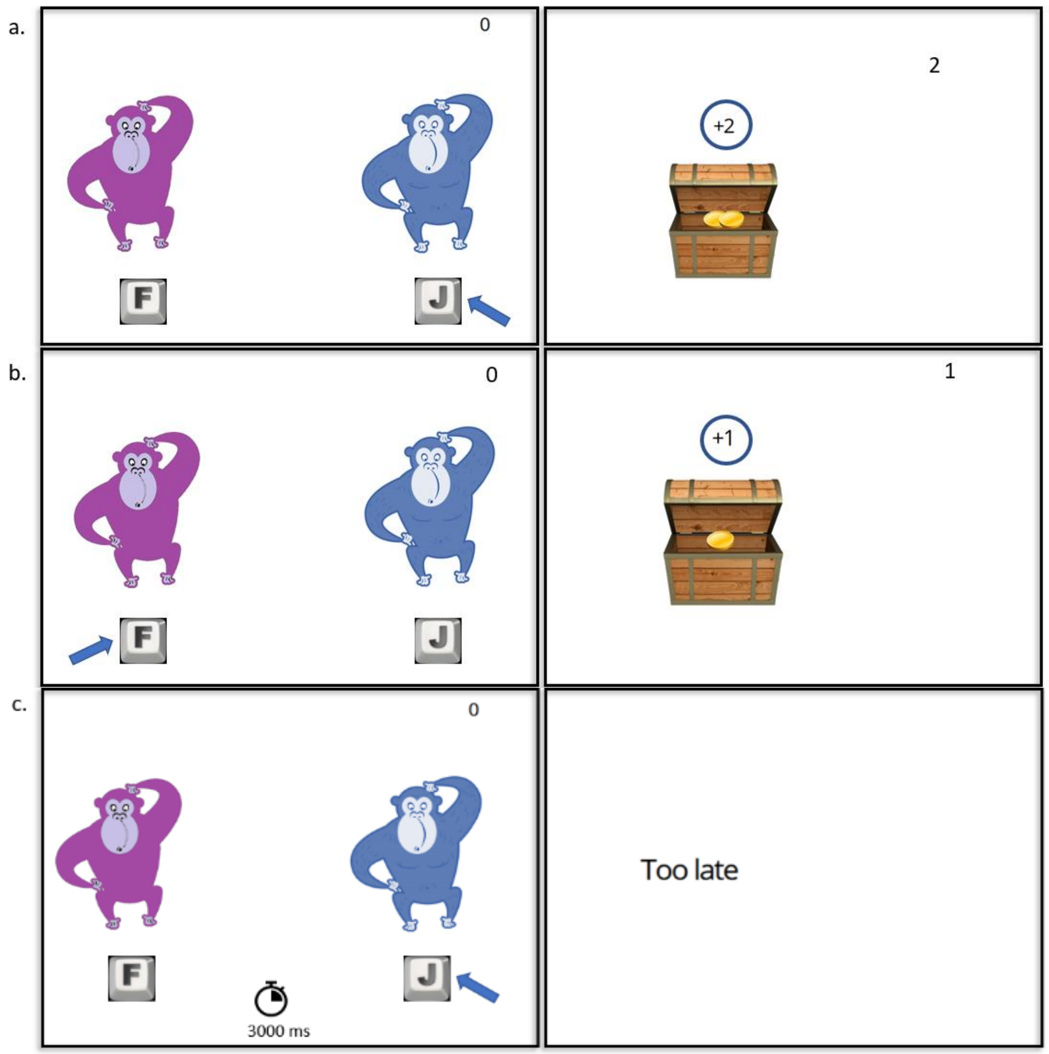
Fixed Value Stimuli: Learning through Trial and Error



Note. The different stimuli with their fixed value. The fixed values are not given beforehand but are learned through trial and error. The fixed values of the different colours are randomized per participant so that we can eliminate the hypothesis of the influence of the colour.

Figure 5

Illustration of Stimulus Value Learning: Trial Examples and Time Limit



Note. This example demonstrates a series of trials in which participants learn the value of different gorillas by making choices. During each trial, participants are presented with a pair of gorillas. When participants select a gorilla (illustrated by a blue arrow), they receive a chest displaying the number of coins that gorilla is worth. To illustrate, in trial a, participants select the blue gorilla by pressing “J” and then get the reward of 2 points, so they can learn that the blue gorilla has the value of 2. In trial b, participants select the purple gorilla by pressing “F” and then get the reward of 1 point, now they learned that the purple gorilla has the value of 1. The number displayed in the right corner represents the cumulative points the participant has earned by choosing gorillas. In trial c, it is demonstrated that if a participant fails to decide within 3000 milliseconds (ms), no points are awarded, and a delayed display *too late* will be shown.

The experiment consists of a total of 38 blocks, distributed across two days. In order to create habitual responses, participants will extensively overtrain on this task over two days (Lesage & Verguts, 2021). The first day, participants receive a welcome and information block followed by a training phase with a total of 18 blocks divided into 2 contexts, differentiating a low-value (with values ranging 1 to 4) and a high value-context (with values ranging from 5 to 8). Hence, there are 9 low-value blocks and 9 high-value blocks. The order of these blocks is randomized, meaning that participants may encounter a sequence of low-value blocks followed by high-value blocks, or vice versa. Each block consists of 100 trials, resulting in a total of 100 pairs of stimuli.

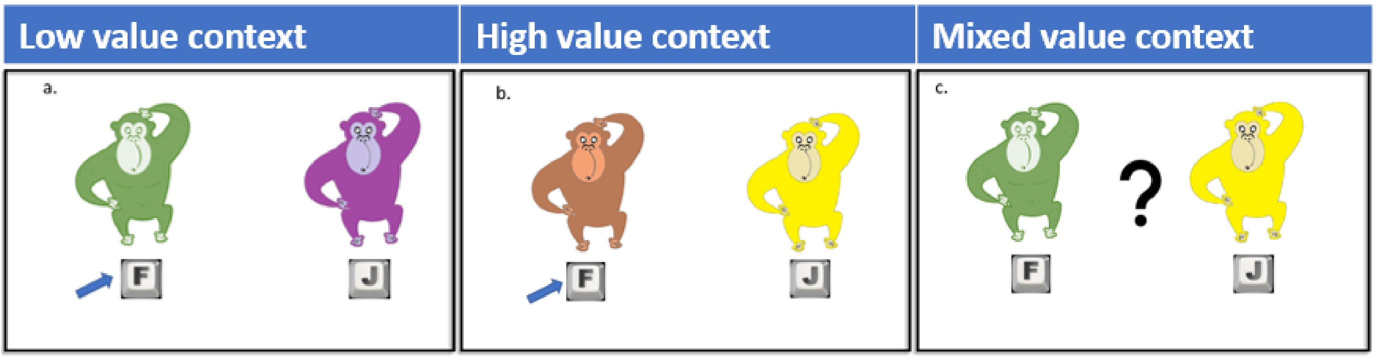
On the second day the trained phase continues followed by the test phase of the study. Participants again receive blocks that differentiate between low-value and high-value contexts. On the second day, there are 7 blocks in low-value context and 7 blocks in high-value. Again, the order of these blocks is randomized. Following these context-specific blocks, participants will enter a mixed condition. In this mixed condition (with values ranging from 1-8), participants will encounter 6 blocks, each again consisting of 100 trials. In this mixed condition, low-value and high-value stimuli are randomly mixed and paired, offering a varied range of values for participants to encounter and respond to. Upon completion, a message was presented in which the full purpose of the experimental design was explained. Then the payment and thanks were given for participating in the study.

This design allows for a comprehensive exploration of habit formation across different value contexts and the potential influence of value on participants' choices. Let us consider an example of one trial within these various contexts (Figure 6). The contexts consist of low value, high value, and mixed value scenarios, each containing stimulus pairs with specific fixed values. In the low value context, the stimuli have values ranging from 1 to 4. Through trial and error, participants learn that the green gorilla holds the highest value within this context, specifically a value of 4. Similarly, in the high value context, with stimuli ranging from 5 to 8, participants learn that the brown gorilla possesses the highest value of 8. Now, in the mixed value context, where stimuli span values from 1 to 8, we can study the interaction between history and value in determining habitual choices. By comparing the gorilla that participants are accustomed to choosing in the low value context (in this example, the green gorilla with a value of 4) to a gorilla that is typically not chosen in the high value context (in this example, the yellow gorilla with a value of 5), we can explore whether history or value plays a more significant role in habitual decision-making. If, in the mixed value context, participants opt for the yellow gorilla (see Figure 6; with a higher value but not their usual choice), it suggests that the habitual choice is primarily driven by value considerations. Conversely, if participants still choose the green gorilla (despite its lower value) in the mixed value context, it indicates that the habitual choice is more influenced by historical patterns rather than immediate value.

The experiment aims to find out which gorilla participants choose when faced with different values. By observing their choices, valuable insights can be gained regarding the factors that influence their habitual decision-making. Of particular interest is whether individuals are more likely to be drawn to gorillas with higher values, even if it contradicts their usual habits. Additionally, examine if they stick to their habits based on past experiences, even if the immediate rewards are lower.

Figure 6

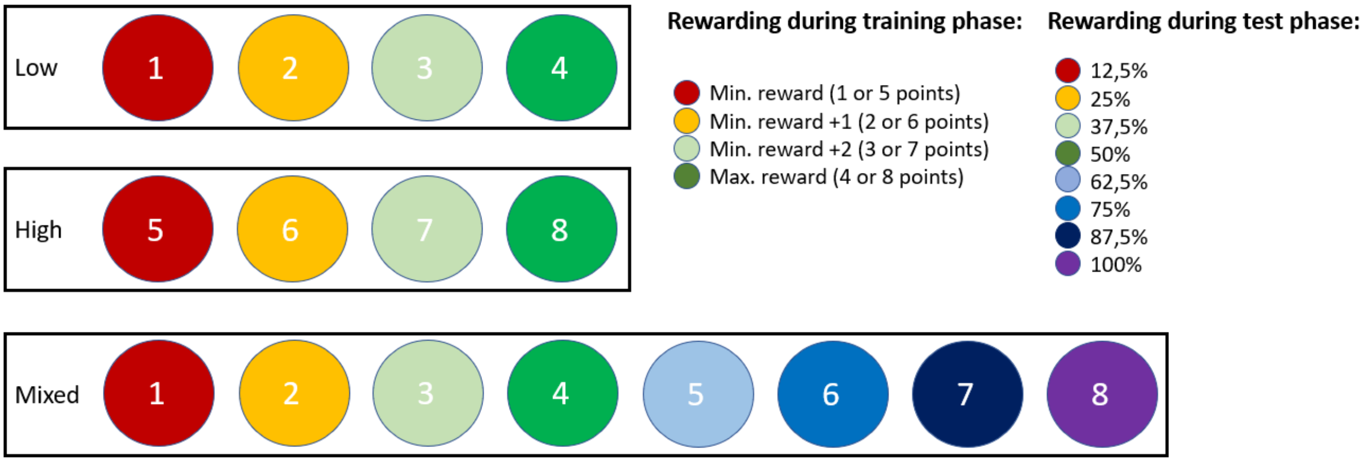
Trials of Stimulus Choices in Different Contexts: Low, High, and Mixed Value



Note. An example of one trial in the different contexts. Trial a is an example of a trial in the low value context where stimuli have fixed values between 1-4. Trial b is an example of a trial in the high value context where stimuli have fixed values between 5-8. Trial c is an example of a trial in the mixed value context where stimuli have fixed values between 1-8. In the low context participants learn through trial and error that the green gorilla has the highest value (value 4, illustrated with the blue arrow) and in the high context that the brown gorilla has the highest value (value 8, illustrated with the blue arrow). When the gorilla that the participant is used to choose in the low context (in this example, the green gorilla with value 4) is compared to a gorilla that is not used to be chosen in the high value context (in this example, the yellow gorilla with value 5) then, a question mark arises, prompting us to ponder: What gorilla will be chosen?

Figure 7

Reward Distribution for Different Value Conditions: Low and High and Percentage of Received Rewards by Chosen Stimuli based on Trial and Error in the Mixed Condition



Note. The different values within conditions low/high and their reward during the training phase and the percentage based on trial and error received reward according to the chosen stimuli in the mixed condition during the test phase are illustrated in figure 7. The minimal reward in low condition is 1 point and in high condition 5 points. The maximal reward in low condition is 4 points and in high condition 8 points.

3.2.1 Trained pairs

In this section, the stimulus pairs used in the experiment are divided into four distinct categories representing different types of pairs.

1. *Old* are the pairs: 1-2, 1-3, 1-4, 2-3, 2-4, 3-4, 5-6, 5-7, 5-8, 6-7, 6-8, 7-8. The *Old (overtrained)* pairs are the pairs that are presented in the training phase and test phase. For example, a trial where you have to choose between a blue gorilla with value 1 or a puple gorilla with value 2.
2. *New_congruent* are the pairs: 1-6, 1-7, 1-8, 2-7, 2-8, 3-8. The *New_congruent* pairs are only presented in the test phase and represent new pairs with two values that never were compared to each other before but are congruent which means that the stimulus as before needs to be chosen to maximise value. For example, a trial where you have to choose between a blue gorilla with value 1 or a black gorilla with value 6.
3. *New_incongruent* are the pairs: 2-5, 3-5, 3-6, 4-5, 4-6, 4-7. The *New_incongruent* pairs are only presented in the test phase and represent new pairs with two values that never were compared before to each other but are incongruent which means that a different stimulus than before needs to be chosen to maximise value. For example,

a trial where you have to choose between a purple gorilla with value 2 or a yellow gorilla with value 5.

4. *New_same* are the pairs: 1-5, 2-6, 3-7, 4-8. The *New_same (neutral)* pairs are only presented in the test phase and represent new pairs with two values that were on the same place of value during a low-value or high-value context. For example, a trial where you have to choose between a blue gorilla with value 1 or a yellow gorilla with value 5.

3.3 Design

A repeated measures (within-subject) design has been used. This design allowed for testing the same participants repeatedly while measuring their reaction time (RT) and accuracy. The study consists of two main phases: a training phase and a test phase. During the training phase, the participants underwent extensive training on the task. This phase was primarily focused on training the participants and familiarizing them with the stimuli and their values. The data collected during this phase were mainly used for training purposes and were not extensively analyzed.

Our analysis focuses on the mixed phase.The independent variables in the study are the blocks (representing time) and the trained pair (referring to the type of pair presented to the participant). The blocks variable is used to investigate the effects of time and habituation on participants' performance. The trained pairs variable is used to examine potential differences in accuracy and RT based on the specific pair presented to the participants. The dependent variables are the RT and accuracy.

3.4 Predictions

The thesis explores two competing hypotheses regarding the determinants of habitual choice: history and value. These hypotheses generate distinct predictions regarding the participants' accuracy and RT.

Let us first consider the predictions of a frequency-based theory of habitual choices. In this case, it is predicted that the highest accuracy and fastest RTs will be observed in the *Old* pairs. These pairs have been extensively overtrained and therefore became strongly ingrained habits. The *congruent pairs* are also expected to yield relatively high accuracy and fast RT, as the association between the stimuli and their values is consistent. The stimuli in these pairs consistently represent a particular value, without any conflicting or contradictory information. This alignment between the stimuli and their values simplifies the decision-making process for participants. When the association between the stimuli and their values is consistent, participants can rely on their learned knowledge and previous experiences to quickly and accurately determine the value associated with each stimulus. The absence of conflicting associations or ambiguity reduces the cognitive load and decision complexity, facilitating faster and more accurate responses. The incongruent pairs are predicted to have the lowest accuracy and slowest RTs due to the conflicting associations between the stimuli and their responses. This inconsistency poses a challenge for participants as they need to override or suppress their pre-existing associations or habits to make a correct choice. As a result, participants may experience difficulty in accurately responding in incongruent pairs, leading to lower accuracy rates. Additionally, the need to resolve the conflicting associations and make a decision may delay their response, resulting in slower RTs.

Let us now consider, what one predicts under a value-based theory, that is, if value primarily drives habitual choices. Here, it is predicted that the highest accuracy and fastest RTs will be observed in the *congruent* pairs. When stimulus values in a pair are *congruent*, the association between the stimuli and their values is consistent and straightforward. As a result, participants find it easier to make accurate choices and respond quickly. The clear alignment between the stimuli and their values allows them to easily figure out which option is more valuable. So, in these congruent pairs, participants are expected to perform well, with high accuracy and fast RTs. In the *new_same* pairs, both stimuli have new values that participants haven't seen before. But even though the values are new and unfamiliar, participants are still expected to do well because value matters In this theory, and the value computation of which stimulus is the best, should be relatively easy. They are likely to make accurate choices and respond quickly.

In particular, the value-based theory must take into account the distance between the values within a pair. When the distance between the values of the stimuli in a pair is greater, it becomes easier for participants to make decisions based on value (Moyer & Landauer, 1967). This is because the contrast between the options is more noticeable and pronounced. When there is a clear distinction between the values, participants can more clearly identify the preferred option and make a value-based decision. Therefore, in pairs where the distance between the values is greater, participants are expected to demonstrate higher accuracy and faster RTs in making their choices, particularly in the *congruent pairs*.

On the other hand, in pairs where the values are closer together, the differentiation between the stimuli becomes less distinct. This can lead to greater ambiguity in determining the preferred option based on value alone. Consequently, the *old* pairs, which involve pairs with only values within a low-value or within a high-value context, may have lower accuracy and slower RTs compared to the other pairs. This because the distance between the values in pairs is never more than 3. It is hypothesized that both the *Congruent* and *Incongruent* pairs will yield higher accuracy and faster RTs compared to the old stimuli. Indeed, the value associated with the stimuli influences participants' choices more significantly.

3.5 Statistical analysis

The first step of data collection was conducting an online experiment. A two-day experiment began, representing the actual data collection. The link to the study was then deactivated, and the complete dataset was downloaded. In the next chapter, the results obtained are presented and evaluated in light of the research hypotheses using R.Studio. First, the main effect was examined. For this purpose, a dependent samples t-test was performed to reject the null hypothesis if necessary. Equal variances were checked using Levene's Test for Equality of Variances. The p-value should be greater than $\alpha = .01$ for rejecting the null hypothesis. Possible interaction effects were measured using Two-way Analysis of Variance (ANOVA).

4 RESULTS

4.1 Assumptions

Before we can analyse the data, we need to make sure certain conditions are met for conducting t-tests and ANOVA.

For t-tests, there is a focus on two main assumptions: normality and independence. Normality means that (in the paired-samples case) the differences between the paired observations should roughly follow a bell-shaped curve. A test called the Shapiro-Wilk test is used to check if this condition is met. The second condition, independence, means that the paired observations should not be influenced by each other.

On the other hand, for the ANOVA test, there is a focus on three assumptions: normality, homogeneity, and independence. Normality relates to how the residuals (the differences between the observed values and the predicted values) are distributed. It is checked if the residuals follow a normal distribution. Homogeneity, or homogeneity of variance, means that the variances of the residuals are roughly equal across the different groups or conditions being compared. A test called Levene's test is used to assess this assumption. Finally, independence means that the observations within each group or condition are not affected by each other.

4.1.1 T-tests assumptions

The normality assumption was assessed for the RT and accuracy t-tests using the Shapiro-Wilk test on the differences between paired observations. Table 1 provides an overview of the assessment of the normality assumption for each comparison.

Table 1

Assessment of Normality Assumption for t-Tests

Comparison	RT (p-value)	Accuracy (p-value)
New_same vs. New_congruent	.001***	.001***
New_incongruent vs. New_congruent	.011*	.03*
Old vs. New_congruent	.63	.17
New_incongruent vs. New_same	.03*	.09
Old vs. New_same	.67	.37
Old vs. New_incongruent	.55	.14

*** p < .01, * p < .05

Because some of the p-values are small (see Table 1), the assumption of normality may not hold for certain t-test comparisons involving both RT and accuracy. Therefore, it is important to exercise caution when interpreting the results and selecting appropriate statistical methods, taking into account the potential non-normality of the data.

Table 2

Assessment of Normality Assumption for Paired t-Tests at Different Distances of Value between Pairs

Distance	RT (p-value)	Accuracy (p-value)
1	.17	.06
2	.008***	.12
3	.002***	.66

*** p < .01

The normality assumption was evaluated for the paired t-tests comparing accuracy and RT between the *Old* and *New_incongruent* pairs at different distances. The Shapiro-Wilk test was conducted on the differences between the paired observations.

The independence assumption is reasonably met for the RT and accuracy t-tests of the pairs. Indeed, the differences between pairs come from different individuals, and it is reasonable to assume that data from different individuals are independent.

4.1.2 ANOVA assumptions

To assess the normality assumption for the ANOVA on accuracy and block, the residuals of the model were examined, and the Shapiro-Wilk test was conducted on each error term. In Table 3, the results for the residuals of each error term are shown.

Table 3

Assessment of Normality Assumption for Residuals of Error Terms in the ANOVA

Error Term	W	p-value
"factor(Participant.Private.ID)"	.98	.57
"factor(Participant.Private.ID):factor (D_mixed_abs)"	.99	.12
"factor(Participant.Private.ID):factor (Block)"	.97	4.415e-05***
"factor(Participant.Private.ID):factor (D_mixed_abs):factor(Block)"	.98	4.415e-05***

***p < .01.

To summarize, the residuals of "factor(Participant.Private.ID)" and "factor(Participant.Private.ID):factor(D_mixed_abs)" conform to a normal distribution, satisfying the assumption of normality. However, the residuals of "factor(Participant.Private.ID):factor(Block)" and "factor(Participant.Private.ID):factor(D_mixed_abs):factor(Block)" deviate from normality.

By examining the residuals and conducting the Shapiro-Wilk tests, it was determined that the assumption of normality is violated for certain error terms. The violation of the normality assumption suggests that caution should be exercised when interpreting the results of the ANOVA model. When the residuals in a model do not follow a normal distribution, it can affect the reliability of the statistical conclusions we draw from the model. It's important to understand that deviations from normality don't automatically mean that the ANOVA results are completely invalid. However, they can affect the accuracy and dependability of the statistical conclusions. So, it's crucial to consider these deviations when interpreting the results of the analysis.

To test the homogeneity assumption, a statistical test called Levene's test is used. The results of this test showed that there is no strong evidence to suggest that the variances of the residuals differ significantly across the different levels of the "Block" factor in the ANOVA analysis for accuracy ($p = .96$). This means that the assumption of equal variances is supported, indicating that the differences in residuals are roughly the same across the different levels of "Block" in the accuracy analysis. However, in the ANOVA analysis for RT, the results of Levene's test indicated a significant violation of the assumption ($p = .0002$). This suggests that the variances of RTs are not equal across the different levels of the independent variable "Block." It's important to take this violation into account when interpreting the results of the ANOVA for RT.

In this case, since the data is organized by individual participants, the assumption of independence across participants can be assumed to hold.

In summary, the assumptions necessary for t-tests and ANOVA were examined to ensure valid and reliable statistical inferences. Violations of the normality assumption were observed in some t-test comparisons, indicating caution is needed when interpreting the results. The assumption of independence was reasonably met. When it comes to ANOVA, we found violations of the normality assumption, which might have an impact on how we interpret the results. It's important to be aware of this potential impact. The homogeneity assumption was held for accuracy but was violated for RT.

4.2 Training data

4.2.1 Accuracy

Understanding the effect of blocks on participants' accuracy is crucial as it aligns with the primary objective of this study, which is to explore the formation of habits through learning. Examining the impact of blocks on accuracy allows us to determine whether participants improve their performance over time, indicating the acquisition of skills and the development of habitual behaviour. Conversely, if no effect of blocks is observed, it would suggest a lack of learning effect, indicating that participants do not improve their task performance, thus undermining the purpose of this study.

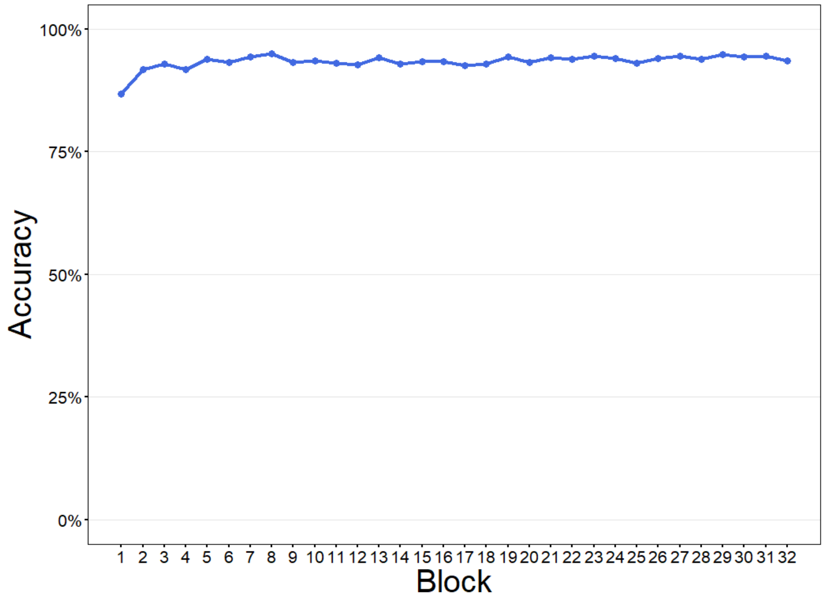
To examine the effect of blocks (time) on participants' accuracy during the training phase, a graph (figure 8) is made with the (training) data from the experiment. Figure 9 shows that participants in the study became better at making accurate choices as they went through the training phase. This could mean that they learned from their previous choices and adjusted their decision-making strategies to make better decisions over time. By practicing and gaining more exposure to the task, participants became more skilled at making accurate choices and earning more points, with accuracy being higher on average in Block 32 ($M= 0.93$; $SD= 0.25$) compared to Block 1 ($M= 0.87$; $SD= 0.34$).

To analyse the effect of blocks on participants' accuracy during the training phase, several statistical tests can be employed. These tests will help determine the significance of the observed differences and provide insights into the impact of blocks on accuracy. Based on the results obtained from the ANOVA analysis, we can conclude that the analysis reveals a significant effect of the "Block" variable on the "Accuracy" variable ($F\ (31, 1550) = 6.26$, $p < .01$). The p-value is less than .01, suggesting that the observed difference is unlikely to occur by chance. However, the effect size of the observed differences in accuracy is small ($\eta^2= .11$).

In summary, the ANOVA analysis demonstrates a statistically significant overall effect of blocks on accuracy during the training phase. Additionally, a paired-samples t-test is conducted to compare accuracy between block 1 and block 32. This analysis determines if there is a significant difference in accuracy between the first and final block, providing more detailed insights into the effect of blocks on accuracy. Based on the t-test output ($t = 5.18$, $df = 50$, $p < .01$), we can conclude that there is a significant difference in accuracy between Block 1 and Block 32. The p-value is less than .01, suggesting that the observed difference is unlikely to occur by chance. Therefore, we reject the null hypothesis and conclude that there is a significant difference in accuracy between Block 1 and Block 32. In summary, based on these t-test results, we can conclude that there is a significant difference in accuracy between Block 1 and Block 32. Overall, the findings in the ANOVA and t-tests support the idea that repeated practice contributes to improved decision-making. These results help validate the observed trends in the data and provide statistical evidence for the presence of a significant effect of blocks on accuracy during the training phase.

Figure 8

Improvement of Accuracy Across Blocks during Training Phase: A Learning Effect in Decision-Making



Note. The graph illustrates the relationship between accuracy and the progression of blocks in the experiment during the training phase. The x-axis represents the blocks 1 to 32 from the training phase. The y-axis represents the accuracy for correct answers which varies between 0% and 100%. A higher value on the y-axis indicates more accuracy. The line depicted on the graph showcases the trend of accuracy as the blocks progress. It reveals that as the experiment advances, individuals become more accurate at making choices that result in the highest number of points.

4.2.2 Reaction time

Understanding the impact of blocks on participants' RT is crucial as it aligns with the primary objective of this study, which is to explore the effects of practice and learning on decision-making. Examining the influence of blocks on RT allows us to determine whether participants become faster in making decisions over time, indicating the acquisition of skills and the improvement of decision-making efficiency. Conversely, if no effect of blocks is observed, it would suggest a lack of learning and skill development, undermining the purpose of this study.

To examine the effect of blocks (time) on participants' RT during the training phase, we analysed the data and generated a graph (see Figure 9). The graph illustrates how participants' RT changed as they progressed through the training phase. Initially, their RT was longer, presumably because they were still becoming familiar with the task and its requirements. However, as they practiced more and gained experience, their RT gradually decreased, indicating quicker decision-making.

This improvement in RT suggests that participants became more efficient in decision-making. These findings highlight the importance of practice and training in improving decision-making skills, allowing individuals to make faster and more accurate choices as they become more familiar with the task. Additionally, to provide a clearer illustration of the effect of blocks on RT, a statistical comparison of the RT is made between the initial block, block 1, and the final block of the training phase, block 32. This comparison further emphasizes the significant impact of blocks on RT, as the distinct difference in RT becomes evident.

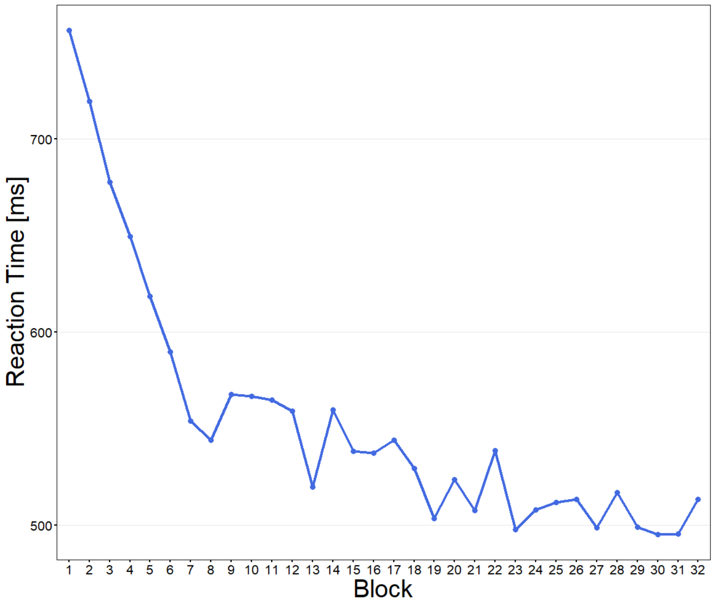
To investigate the improvement of participants' RTs throughout the training phase, a statistical analysis was conducted using a one-way repeated measures ANOVA and a paired-samples t-test. These analyses aimed to examine the effect of block progression on RTs and determine if there was a significant improvement in performance as participants gained more experience with the task.

The mean RT in Block 32 ($M = 513.45$ ms; $SD = 198.76$ ms) was significantly faster than in Block 1 ($M = 756.28$ ms; $SD = 348.56$ ms). Based on the ANOVA analysis, the present study reveals a significant effect of the Block factor on participants' RT, ($F(31, 1550) = 46.92$, $p < 2e-16$). The extremely small p-value, less than 2e-16, indicates that the observed difference in means between the blocks is highly significant and unlikely to occur by chance. Furthermore, the effect size of the observed differences in accuracy is large ($\eta^2 = .48$).

In summary, the findings from this ANOVA analysis demonstrate a substantial and highly significant effect of the Block factor on participants' RT. Additionally, a paired-samples t-test is conducted to compare RT between block 1 and block 32. This analysis determines if there is a significant difference in accuracy between the first and final block, providing more detailed insights into the effect of blocks on RT. Based on the t-test output ($t = 10.15$, $df = 50$, $p < .01$), we conclude that there is a significant difference in RTs between the initial block (Block 1) and the final block (Block 32) of the training phase. The p-value of less than .01 provides strong evidence that the observed difference is unlikely to occur by chance. Therefore, we reject the null hypothesis and conclude that there is a significant difference in RTs between Block 1 and Block 32. In summary, based on these t-test results, we can conclude that there is a significant improvement in decision-making efficiency as participants progressed from Block 1 to Block 32. Overall, the findings in the ANOVA and t-tests support the idea that repeated practice contributes to improved decision-making. These results help validate the observed trends in the data and provide statistical evidence for the presence of a significant effect of blocks on RT during the training phase.

Figure 9

Improvement of Reaction Times Across Blocks during Training Phase: A Learning Effect in Decision-Making



Note. The graph illustrates the relationship between RT and the progression of blocks in the experiment during the training phase on day 1. The x-axis represents the blocks 1 to 32 from the training phase. This indicates the passage of time throughout the experiment, as higher block numbers correspond to later stages. The y-axis represents the RT in milliseconds (ms) for correct answers. The line depicted on the graph showcases the trend of RT as the blocks progress.

4.3 Test data

4.3.1 Accuracy

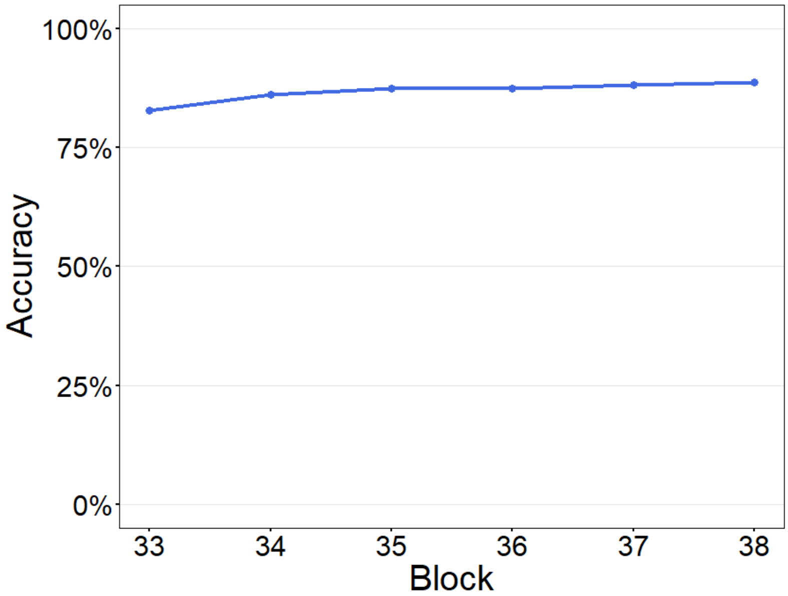
This section presents the results investigating the accuracy improvement of participants as they advanced through the test phase which represents blocks 33 to 38. The findings reveal a clear positive trend, indicating that participants' accuracy gradually increased over time (Figure 10). Initially, accuracy may have been relatively lower as participants familiarized themselves with the task and its underlying rules during the early blocks. However, as they gained experience and became more familiar with the task, their accuracy gradually increased over time. The upward trend suggests that participants refined their decision-making strategies and became more efficient and skilled at making choices that resulted in the highest number of points. Participants demonstrated a higher level of accuracy in Block 38 ($M= 0.89$; $SD= 0.32$) compared to Block 33 ($M=0.82$; $SD=0.37$). This improvement in accuracy reflects a continuing learning effect, where individuals optimized their decision strategies to maximize their points. As participants gained more exposure and practice with the task, their ability to make accurate choices improved.

To determine the significance of the observed trend, a one-way repeated measures ANOVA was conducted to assess the differences in accuracy across the blocks during the test phase. The results revealed a high significant improvement in accuracy over time ($F(5, 250) = 16.88$, $p < .001$). Post-hoc pairwise comparisons using paired t-tests confirmed significant differences between the first block (block 33) and the last block (block 38) of the test phase, indicating a progressive increase in accuracy as participants advanced through the experiment.

Based on the paired t-test conducted between Block 33 and Block 38 there is a significant difference in accuracy between Block 33 and Block 38 ($t = 6.27$, $df = 50$, $p < .01$). Therefore, it is unlikely that the difference occurred by chance. The mean difference in accuracy between Block 33 and Block 38 is estimated to be 0.0582. This suggests that, on average, participants had a higher accuracy in Block 38 compared to Block 33. These findings suggest that as the experiment progressed, participants became more accurate in making choices, indicating a continuing learning effect in the test phase.

Figure 10

Improvement of Accuracy Across Blocks during Test Phase: A Learning Effect in Decision-Making



Note. The graph illustrates the relationship between accuracy and the progression of blocks in the experiment during the test phase. The x-axis represents the blocks 33 to 38 from the test phase. The y-axis represents the accuracy for correct answers which varies between 0 and 1. The line depicted on the graph showcases the trend of accuracy as the blocks progress.

We next turn to the crucial results of the accuracy of participants across different pair types over time in the test phase. Figure 11 shows a graph where different pair types are compared in terms of how accurately participants scored over time in the test phase.

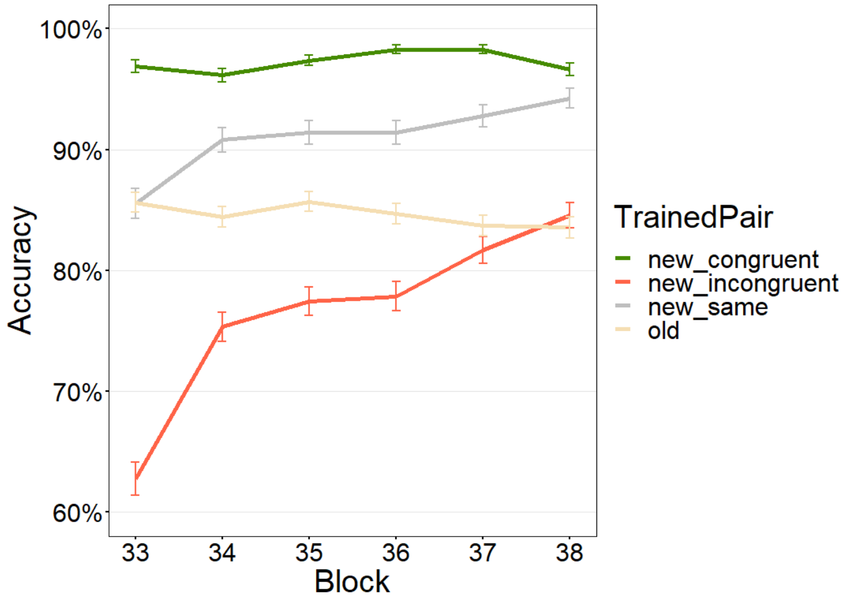
To further investigate the observed patterns and differences in accuracy, a statistical analysis using ANOVA was conducted. The ANOVA results indicate significant main effects of the factor Trained pair ($F(3, 150) = 85.5$, $p < .01$), the factor Block ($F(5, 250) = 21.76$, $p < .01$), and a significant interaction effect between Trained pair and Block ($F(15, 750) = 14.37$, $p < .01$). These results confirm the presence of meaningful differences in accuracy across different pair types and over time. Specifically, the analysis reveals that initially, the *New_incongruent* pairs show lower accuracy, but as the blocks progress, participants' accuracy for these pairs improves significantly, surpassing the accuracy of the old pairs. This suggests that participants learn to override or suppress pre-existing associations or habits, leading to better accuracy in making correct choices for the *New_incongruent* pairs. The *Old* pairs, which represent extensively trained and ingrained habits, consistently show an average accuracy across the blocks, suggesting the influence of past experiences. This pattern is in line with the frequency-driven habits, because of the frequency of past choices. However, when considering the interaction with the *New_incongruent* pairs, their accuracy initially appears relatively high but decreases towards the end. This observation aligns with the value- based habits that eventually seems to overrule the habits due to frequency. On the other hand, the *New_same* pairs consistently show above-average accuracy throughout the blocks, suggesting that participants may rely on the value associated with these pairs, drawing from their prior positive experiences and outcomes. The *New_congruent* pairs consistently maintain a high level of accuracy throughout the blocks, suggesting that decisions based on value have a strong influence from the beginning. This finding aligns with the expectation that these pairs, which are associated with higher value, should perform well.

Additionally, post-hoc tests in the form of paired t-tests were conducted to further explore the pairwise differences in accuracy among the different pair types during the test phase (blocks 33 to 38), when all pairs were presented. The results of these tests indicate that all mean differences in the "Accuracy" scores between the pair types are statistically significant, providing meaningful insights into the distinctions between them. Significant differences were observed in the "Accuracy" scores between the following pair types: *New_congruent* and *New_same* pairs ($t = 7.74$, $df = 50$, $p < .01$), *New_congruent* and *New_incongruent* pairs ($t = 11.71$, $df = 50$, $p < .01$), *New_congruent* and *Old* pairs ($t = 15.38$, $df = 50$, $p < .01$), *New_same* and *New_incongruent* pairs ($t = 11.21$, $df = 50$, $p < .01$), *New_same* and *Old* pairs ($t = 6.44$, $df = 50$, $p < .01$), and *New_incongruent* and *Old* pairs ($t = 4.05$, $df = 50$, $p < .01$).

Overall, the statistical findings align with and reinforce the observed patterns in Figure 11, providing empirical evidence that there are meaningful differences in accuracy between each of these pair types. The statistical findings provide support for the primary role of value-based decision making in achieving accuracy. The higher accuracy in the *New_congruent* and *New_same* pairs, compared to the New_incongruent and *Old* pairs, suggests that participants prioritize value when making accurate choices. The interplay between history and value is evident, as both factors contribute to the observed accuracy differences among pair types. The initial relatively high performance of the *Old* pairs, followed by a decrease towards the later stages, suggests the influence of frequency in decision-making processes, particularly during the early stages of the test phase. This indicates that frequency also plays a significant role in shaping decision-making, alongside the impact of value.

Figure 11

Accuracy of Different Pair Types Across Blocks during Test Phase



Note. In the graph above, the x-axis represents blocks 33 to 38, indicating the passage of time during the test phase of day 2. The y-axis represents accuracy, ranging 0% to 100%. The graph displays four distinct lines, each corresponding to a different pair type within those blocks. The accuracy is assessed across the blocks based on the pair types. This analysis highlights the impact of pair types on accuracy across the blocks, illustrating the varying levels of accuracy and the improvements over time

In our next set of analyses, we take into account the role of (value) distance between stimuli in a pair. Specifically, we explore the connection between the distances in value of two stimuli in pairs and how accurately people make decisions. We were guided by the hypothesis of value-based decision making, which proposes that when there are big differences in value, it becomes easier to make choices because the value gap is more apparent. To dive deeper into this theory, we carefully organized our data, taking into account the distance between the values of the stimuli. We focused on the eight different values present in the experiment. Thus, we have value distances from 1 to 7 in the presented pairs.

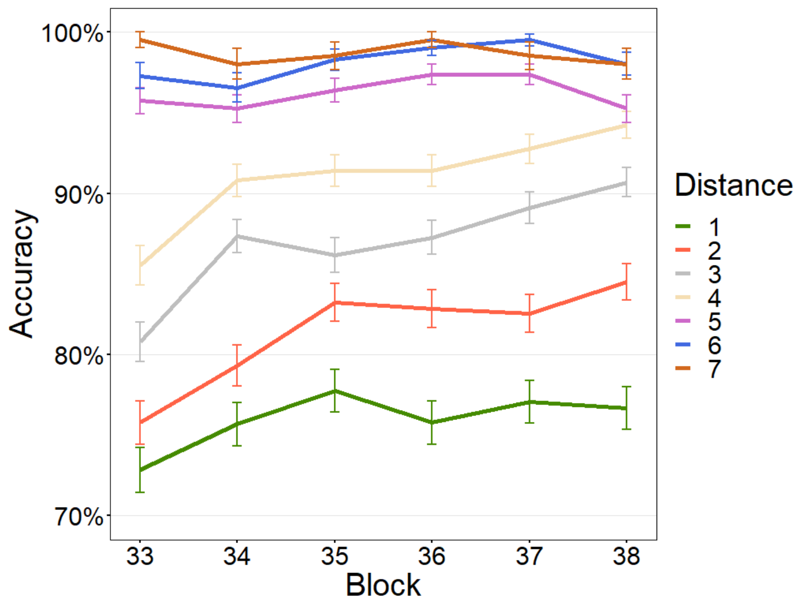
First, the following analysis examines the effects of pair value distances on accuracy in the test phase over a specific time range (blocks 33 to 38). Figure 12 graphically represents the obtained results. The findings from the graph supports the idea that our choices are influenced by the value of options. When there is a bigger difference in value between two stimuli, people tend to make more accurate decisions, a finding in line with a large literature on numerical cognition (e.g., Moyer & Landauer, 1967). As the distance in values between the stimuli in pairs increases, participants' accuracy also increases. This means that the size of the difference in value affects how well people can make accurate choices. The order of distances, from highest to lowest accuracy, follows the pattern: 7, 6, 5, 4, 3, 2, 1, confirming the value-based hypothesis.

In addition, a mixed-design ANOVA was conducted to investigate the effects of pair value distance and block on accuracy. The analysis revealed significant main effects for both "Pair Value Distance" ($F(6, 300) = 185.8$, $p < 2e-16$) and "Block" ($F(5, 250) = 13.88$, $p = 5.65e-12$), indicating that there are significant differences in accuracy scores across different pair value distances and blocks, respectively. Furthermore, a significant interaction effect between "Pair Value Distance" and "Block" was observed ($F(30, 1500) = 3.036$, $p < 8.57e-08$), suggesting that the influence of pair value distance on accuracy varies across different blocks.

Overall, these findings suggest that both pair value distances and blocks (time) have significant effects on accuracy. Moreover, the significant interaction highlights the dynamic nature of the influence of pair value distances on accuracy over time. The statistical analysis supports the notion that value plays a significant role in determining participants' choices.

Figure 12

Effects of Pair Value Distances on Accuracy in the Test Phase



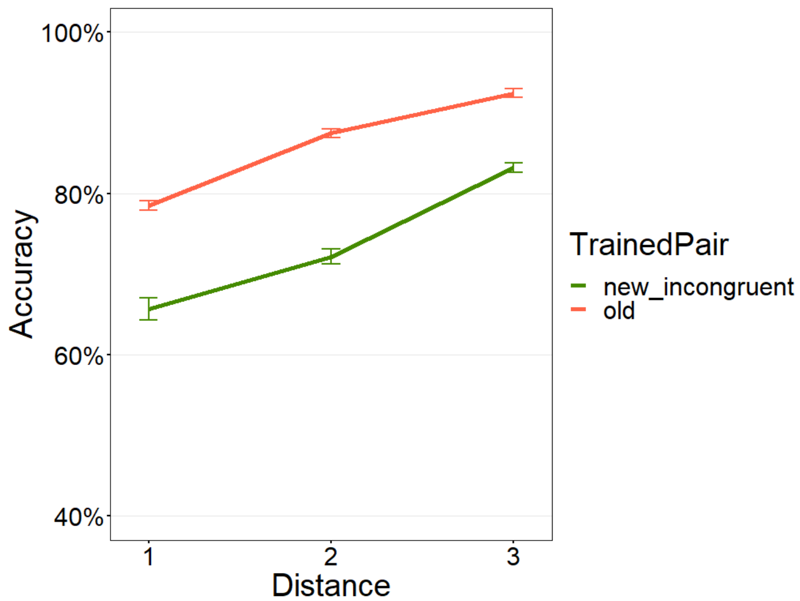
Note. In the figure above, the y-axis represents accuracy, while the x-axis represents the block number. Specifically, the graph displays data from blocks 33 to 36, corresponding to the test phase. Each line in the graph represents a different distance between the values of stimulus pairs.

In figure 13 a closer look is taken at the effect of pair type on accuracy for trained pairs with same distances. The detailed analysis of the graph sheds light on the influence of pair type, despite sharing the same distances between the stimuli within the pairs. The graph reveals distinct characteristics between the *Old* and *New_congruent* pairs. The *Old* pairs demonstrate higher accuracy than the *New_congruent* pairs. According to the hypothesis of value-based decision making, it is expected that the Old pairs would exhibit lower accuracy than the *New_incongruent* pairs. The observed better performance of the Old pairs contradicts this expectation. It is important to note that these observations and conclusions specifically pertain to the *New_incongruent* and *Old* pairs, as the analysis focused solely on pairs with the same distances of value between stimuli. Comparisons between other pairs with varying distances are not possible within this analysis.

Further research and analysis are necessary to explore the potential influences of history, frequency, and other factors on decision-making processes across different pair types. By considering additional factors, a more comprehensive understanding of the complex interplay between value-based and history-based decision making can be achieved.

Figure 13

Effect of Pair Type on Accuracy for Trained Pairs with Same Distances



Note. The figure above provides a detailed analysis of the trained pairs, *New_incongruent* and *Old* because these pairs are the only ones with the same distances between the values of the stimuli in their pair, namely 1, 2, and 3. This eliminates the difference in distance, allowing us to examine whether the pair type has an effect despite the same distance the pairs share. On the x-axis, the distance between the stimuli within a pair can be read, namely 1, 2, or 3. The y-axis shows the accuracy between 0-1. The lines show the trained pairs: *New_incongruent* and *Old*.

In figure 14, a panel of 3 graphs is illustrated with a closer look at the accuracy per distance in a type of pair across the test phase. In the first graph, which explores distance 1, there is a noticeable difference in accuracy between the *Old* and *New_congruent* pairs. However, as the blocks progress, this accuracy gap gradually fades away. This highlights an important point regarding the interaction mentioned earlier (pair * block) and its relationship to the distance variable. The crucial observation is that this interaction remains significant even when the distance variable is held constant. This finding indicates that the previous interaction between pair and block is not a confounding factor influenced by the varying distances among different pairs. Therefore, it strengthens the validity of the observed effects and supports the interpretation of the results.

The *Old* pairs consistently maintain a stable accuracy throughout, while the *New_congruent* pairs show a significant improvement over time, eventually reaching similar levels of accuracy. Moving on to the second graph, which explores distance 2, we observe an interesting interaction between pair and distance. While the *Old* pairs still display slightly better accuracy compared to the *New_congruent* pairs, it is important to note that this difference varies depending on the distance. This suggests that the historical knowledge acquired during training may contribute differently to the performance of *Old* and *New_congruent* pairs at various distances. Similarly, in the third graph representing distance 3, we continue to observe a similar pattern of interaction. The *Old* pairs maintain a slight advantage in accuracy over the *New_congruent* pairs, with the magnitude of this difference varying with distance. These findings highlight that both the *Old* and *New_congruent* pairs show increased accuracy as the blocks progress. However, the *Old* pairs consistently outperform the *New_congruent* pairs.

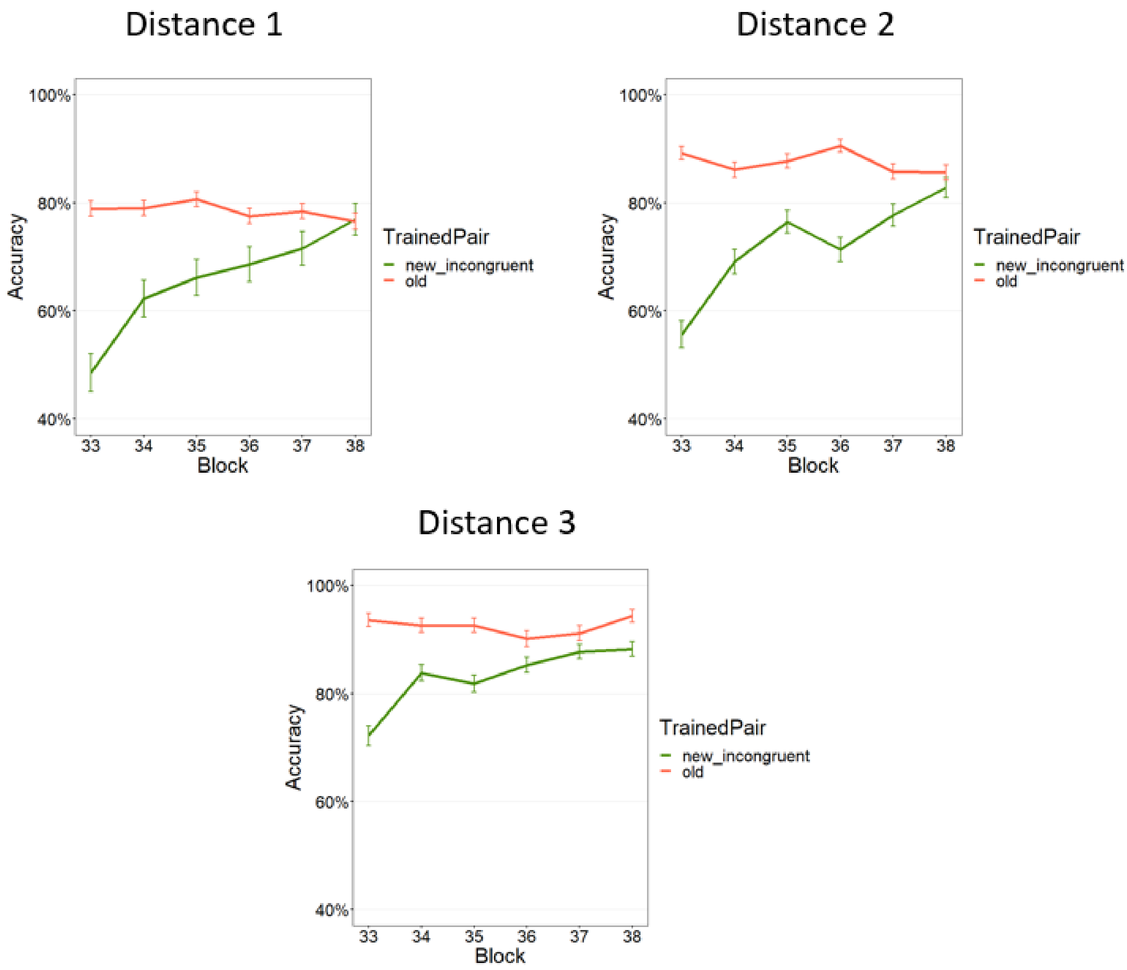
These results align with the earlier graph 12, which illustrated the better accuracy of the *Old* pairs compared to the *New_incongruent* pairs. This performance difference is likely due to the influence of prior training and history-based choices, where the previously established associations in the *Old* pairs give them an advantage.

The analysis employed the ANOVA MIXED procedure to investigate the effects of the factors "Trained Pair" and "Distance" on accuracy during the test phase. The model included the interaction between these two factors and accounted for the variability associated with individual participants. The results of the ANOVA indicated significant effects for both the "Trained Pair" factor ($F(1, 50) = 33.67$, $p < .001$) and the "Distance" factor ($F(2, 100) = 101.4$, $p < .001$). Additionally, there was a significant interaction between "Trained Pair" and "Distance" ($F(2, 100) = 3.374$, $p = 0.04$). Overall, these findings demonstrate that both the type of pair and the distance between stimuli significantly impact accuracy during the test phase. The interaction effect further emphasizes the nuanced nature of these relationships, highlighting the importance of considering both factors when interpreting the accuracy outcomes.

Further analysis using paired t-tests within each distance revealed significant differences in accuracy between the *Old* and *New_incongruent* pairs across all three distances. At distance 1, the *Old* pairs exhibited higher accuracy compared to the *New_incongruent* pairs ($t = 4.12$, $df = 50$, $p < .01$). At distance 2, there was also a significant difference in accuracy scores between the two pair types ($t = 6.40$, $df = 50$, $p < .01$). Once again, the *Old* pairs demonstrated higher accuracy compared to the *New_incongruent* pairs, indicating a consistent pattern of better performance for the *Old* pairs as the value difference increased. Similarly, at distance 3, there was a significant difference in accuracy scores between the *Old* and *New_incongruent* pairs ($t = 4.67$, $df = 50$, $p < .01$). The *Old* pairs maintained their superiority in decision accuracy compared to the *New_incongruent* pairs even at this larger value difference.

Figure 14

Comparison of Accuracy for Trained Pairs with Varying Distances: New_congruent vs. Old



Note. The three panels, each illustrate the trained pairs *New_congruent* and *Old* with varying distances. The x-axis represents the blocks 33 to 36, corresponding to the test phase on day 2. The y-axis represents accuracy ranging from 0% to 100%.

4.3.2 Reaction time

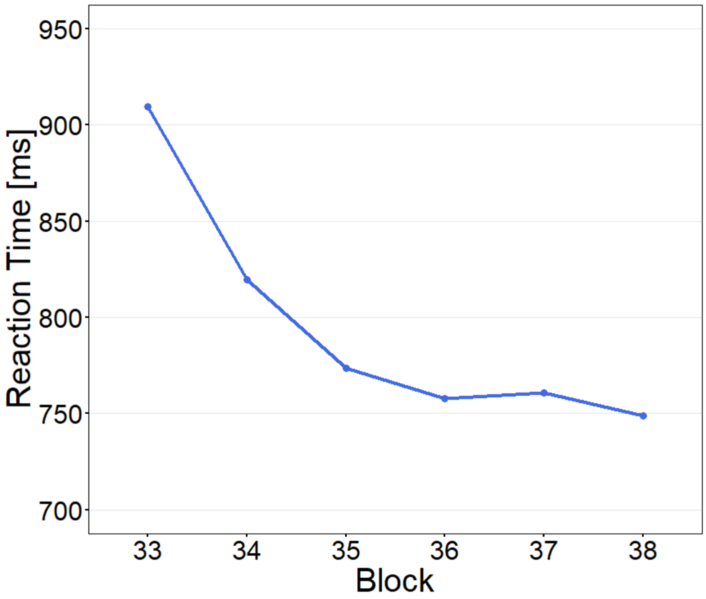
Based on the data shown in Figure 15, there is a clear positive trend in RT improvement as participants progressed through the test phase. Initially, participants' RT may have been relatively longer as they familiarized themselves with the task and its underlying rules during the early blocks. However, as they gained experience and became acquainted with the task, their RT gradually decreased over time. The downward trend in RT suggests that participants became more efficient and skilled at making choices. The improvement in RT reflects a learning effect, where participants optimized their decision strategies to make faster and more accurate choices, resulting in improved RTs. This finding provides further evidence for the impact of experience and familiarity in enhancing decision-making skills. This supports the notion that experience and familiarity play crucial roles in optimizing decision-making skills.

The ANOVA conducted on the RT data shows a significant effect of block ($F(5, 250) = 30.36$, $p < .001$). This indicates that the block, has a significant influence on participants' RTs. The analysis suggests that RTs vary across different blocks, suggesting changes in decision-making processes or task performance as participants progress through the experiment.

Post-hoc pairwise comparisons using paired t-tests confirmed significant differences between the first block (block 33) and the last block (block 38) of the test phase, indicating a progressive increase in accuracy as participants advanced through the experiment. Participants demonstrated a higher level of RT in Block 38 ($M= 748.88$; $SD= 337.33$) compared to Block 33 ($M= 909.56$; $SD= 401.02$). Based on the paired t-test conducted between Block 33 and Block 38 there is a significant difference in RT between Block 33 and Block 38 ($t = 7.45$, $df = 50$, $p < .01$). This suggests that, on average, participants had a faster RT in Block 38 compared to Block 33. In summary, based on these t-test results, it can be concluded that there is a significant improvement in RT from Block 33 to Block 38.

Figure 15

Progression of Reaction Time Across Blocks in the Test Phase: Evidence of Improving Performance



Note. The graph shows the relationship between RT and the progression of blocks in the experiment during the test phase. The x-axis represents the blocks 33 to 38 from the test phase. The y-axis represents the RT in milliseconds (ms), reflecting the time taken by participants to respond to stimuli. The line plotted on the graph demonstrates the trend of RT as the blocks progress. It reveals that participants tend to improve their RT over time, with the duration of their responses gradually decreasing. This indicates that participants become faster in making choices as they gain experience and familiarity with the task.

This section presents the RT results across different pair types over time in the test phase. Figure 16 presents an analysis of RT variation across blocks 33 to 38, specifically examining the influence of different pair types. The *New_congruent* pairs consistently show the fastest RTs, suggesting that the congruence between stimulus values facilitates quicker decision-making. Conversely, the *New_incongruent* pairs exhibit slower RTs, possibly due to the incongruent nature of their stimulus values. The *Old* pairs and *New_same* pairs fall in between, with the *Old* demonstrating a faster RT than the *New_same* pairs. These observations highlight the influence of pair types on RT during the test phase. The varying patterns observed across the different pair types indicate that the congruence or incongruence between stimulus values can impact the speed of decision-making. The observation that the *New_congruent* pairs consistently maintain the fastest RTs across the blocks supports the value-based theory. According to the value-based theory, individuals make decisions based on the perceived value or desirability of the stimuli. In this context, the congruence between stimulus values in the *New_congruent* pairs likely enhances their perceived value, leading to quicker decision-making. This finding suggests that when stimulus values align and are congruent, individuals are more efficient in processing and responding to them, supporting the notion that value influences decision-making processes.

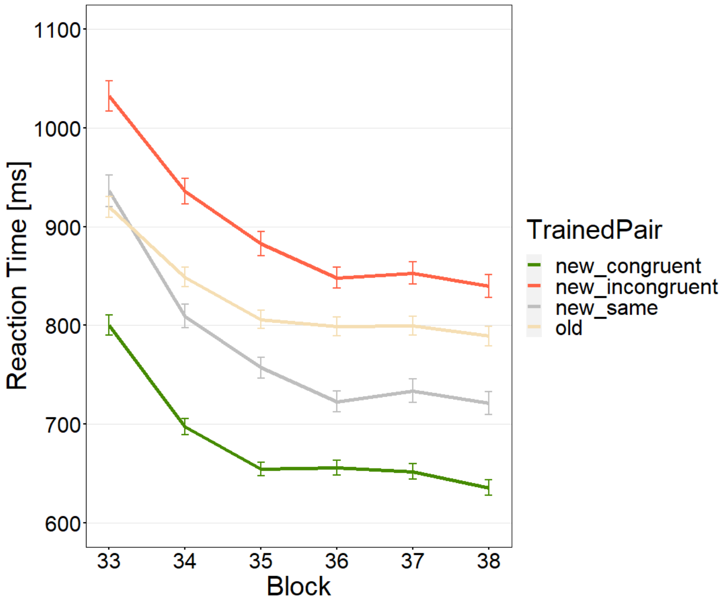
The ANOVA conducted on the RT data revealed significant differences among the different Trained pair conditions ($F(3, 150) = 93.3$, $p < .001$). This finding indicates that the specific pairings or combinations of stimuli in the Trained pair variable significantly influence participants' RTs. The results suggest that the Trained pair condition plays a crucial role in determining the speed at which participants make decisions or respond to stimuli during the experiment.

Statistical analysis using post-hoc tests, specifically paired t-tests, was conducted to explore the pairwise differences in RT among the different pair types. The results of these tests indicate that all mean RT differences between the pair types are statistically significant. The mean differences in the RT between the *New_congruent* and *New_same* pairs were significant ($t =11.65$, $df = 50$, $p < .01$), as well as between the *New_congruent* and *New_incongruent* pairs ($t =11.63$, $df = 50$ $p < .01$), the *New_congruent* and *Old* pairs ($t =14.03$, $df = 50$, $p < .01$), the *New_same* and *New_incongruent* pairs ($t =8.05$, $df = 50$, $p < .01$), the *New_same* and *Old* pairs ($t =4.87$, $df = 50$, $p < .01$), the *New_incongruent* and *Old* pairs ($t =4.42$, $df = 50$, $p < .01$).

In conclusion, the findings from the ANOVA and post-hoc tests provide compelling evidence of the significant influence of the Trained pair condition on participants' RTs. The ANOVA results demonstrated that the specific pairings or combinations of stimuli in the Trained pair variable yielded notable differences in RTs, highlighting the importance of this factor in decision making. Furthermore, the post-hoc tests revealed statistically significant mean differences in RT between all pair types, emphasizing the distinct nature of each pair.

Figure 16

Reaction Time Variation Across Blocks: Influence of Trained pair



Note. In the graph above, the x-axis represents blocks 33 to 38 from the test phase of day 2. The y-axis represents RT in milliseconds (ms). The graph displays four distinct lines, each corresponding to a different pair type within those blocks.

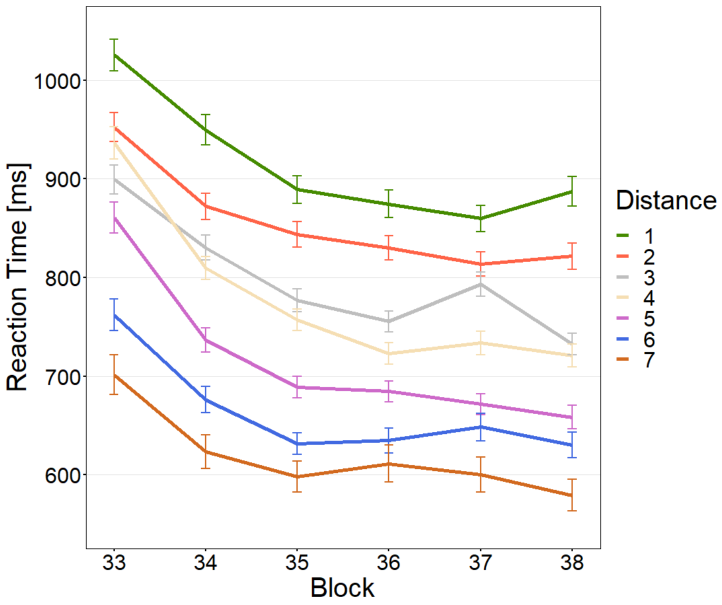
Figure 17 provides insights into the effects of pair value distances on RTs during the test phase. The graph illustrates the relationship between RT and the distances between the values of stimuli within pairs. The results support the hypothesis that choices are influenced by the value of the stimuli. The graph demonstrates that as the distance between the values of two stimuli in a pair increases, participants exhibit faster RTs. This finding suggests that larger differences in value facilitate quicker responses, indicating that individuals are sensitive to variations in value when making decisions. The observed pattern aligns with the value-based decision-making hypothesis. The order of the distances, from best to worst in terms of RTs, confirms this trend: 7, 6, 5, 4, 3, 2, 1. The larger the difference in value between stimuli, the faster participants react, supporting the notion that value influences decision-making processes. However, there are a few deviations from this pattern for distances 3 and 4 during the first blocks of the test phase. Contrary to the expected order, participants exhibited faster RTs for distance 4 compared to distance 3. It is worth noting that occasional deviations from the expected patterns can occur, which is why statistical analysis is employed to identify reliable signals amidst the noise. Additionally, there is a sudden decline in RT speed for distance 3 on block 37, followed by an upward trend. These anomalies could be explained by the relative neutral value of distances 3 and 4, creating confusion and difficulty for participants in making rapid decisions. Overall, the graph provides evidence for the role of value in determining choices.

The ANOVA revealed several significant effects. Firstly, there was a significant main effect of pair distance on RTs ($F(6, 300) = 142.8$, $p < .001$), indicating that the distance between the values of stimuli within a pair significantly influenced participants' RTs. This suggests that different pair distances led to variations in RTs. Secondly, a significant main effect of block on RTs was found ($F(5, 250) = 32.41$, $p < .001$). This indicates that the specific blocks in which the stimuli were presented had a significant impact on participants' RTs. Lastly, there was a significant interaction between pair distance and block ($F(30, 1500) = 2.51$, $p < .001$), indicating that the influence of pair distance on RTs differed across different blocks. The relationship between pair distance and RTs was not consistent across all blocks.

In summary, these findings demonstrate that both the distance between stimulus values within a pair and the specific block in which stimuli were presented had significant effects on participants' RTs.

Figure 17

Effects of Pair Value Distances on Reaction Times in a Test Phase



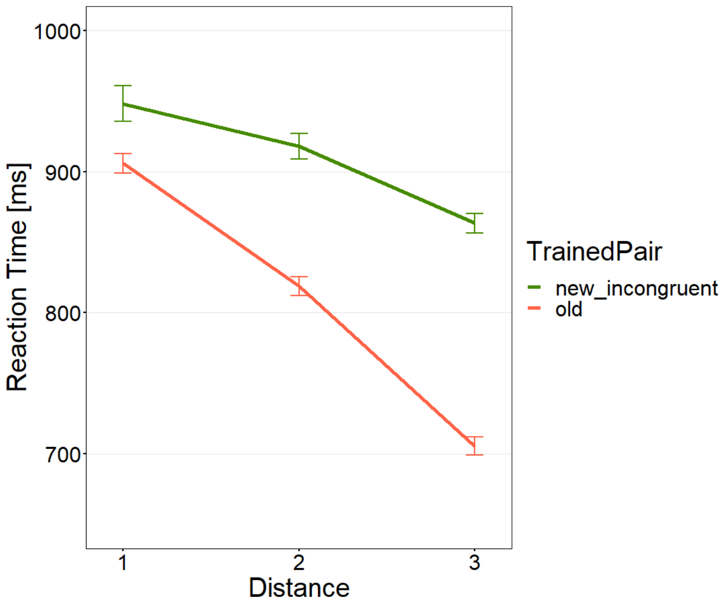
Note. In the figure above the RT in milliseconds (ms) is displayed on the y-axis and the blocks on the x-axis. Specifically, the blocks represented in the figure are 33 to 36, which correspond to the test phase of day 2. The different lines in the graph represent the various distances between the values of the stimuli in the pairs.

Figure 18 offers insights into the effects of pair type on RT for trained pairs with the same distances between stimuli. The graph specifically focuses on the *New_incongruent* and *Old* pairs, as they share identical distances of 1, 2, and 3. By eliminating the difference in distance, we can examine whether the pair type has an effect on RT. The graph clearly demonstrates that there is indeed a difference in RT between the two pair types. The *Old* pairs show faster RTs compared to the *New_incongruent* pairs, which require a longer RT. According to the hypothesis of value-based decision making, it is expected that the Old pairs would show a faster reaction rime than the *New_incongruent* pairs. The observed better performance of the Old pairs aligns with this expectation. It is important to note that these observations and conclusions specifically pertain to the *New_incongruent* and *Old* pairs, as the analysis focused solely on pairs with the same distances of value between stimuli. Comparisons between other pairs with varying distances are not possible within this analysis.

The results of the ANOVA conducted on the RT data indicate a significant effect of Trained pair on participants' RTs ($F(3, 20) = 10.51$, $p < .001$). This finding reveals that the specific pairings or combinations of stimuli in the Trained pair variable have a noteworthy influence on the speed at which participants make decisions or respond to stimuli. In conclusion, the results of this study highlight the significance of Trained pair in influencing participants' RTs.

Figure 18

Effect of Pair Type on Reaction Time for Trained Pairs with Same Distances



Note. In the figure above, a detailed look at the trained pairs: *New_incongruent* and *Old* are illustrated because these pairs are the only ones with the same distances between the values of the stimuli in their pair, namely 1, 2, and 3. This eliminates the difference in distance, allowing us to examine whether the pair type has an effect despite the same distance the pairs share. On the x-axis, the distance between the stimuli within a pair can be read, namely 1, 2, or 3. The y-axis shows the RT in milliseconds (ms). The lines show the trained pairs: *New_incongruent* and *Old*. From this, we can conclude that there is indeed a difference in pair type despite the same distance. We can see that the *Old* pairs require less RT and are therefore better than the *New_incongruent* pairs, which have a higher RT.

Figure 19 provides a comparison of RTs for trained pairs when distance is kept constant, specifically examining the pairs *New_congruent* and *Old*. The three graphs in the panel showcase the RTs for distances 1, 2, and 3. In the first graph, which focuses on distance 1, it is evident that despite having the same distance of 1, the trained pair *Old* consistently exhibits faster RTs compared to the *New_congruent* pair. This finding indicates that factors other than the distance between stimuli influence the participants' RTs. Moving on to the second graph, which explores distance 2, we observe a similar pattern. Once again, despite the same distance of 2, the *Old* pair consistently outperforms the *New_congruent* pair in terms of RTs. This suggests that factors beyond the distance between stimuli contribute to the observed differences in RTs. In the third graph, analysing distance 3, we observe a parallel trend. Despite having the same distance of 3, the *Old* pair consistently demonstrates faster RTs compared to the *New_congruent* pair. These consistent findings across varying distances highlight the advantage of the *Old* pair in terms of RTs. These observations emphasize that even with fixed distances between stimuli, the *Old* pairs consistently show faster RTs compared to the *New_congruent* pairs. These results suggest that factors such as historical knowledge, previous experiences, or other cognitive mechanisms play a significant role in influencing RTs, independent of the specific distances between stimuli.

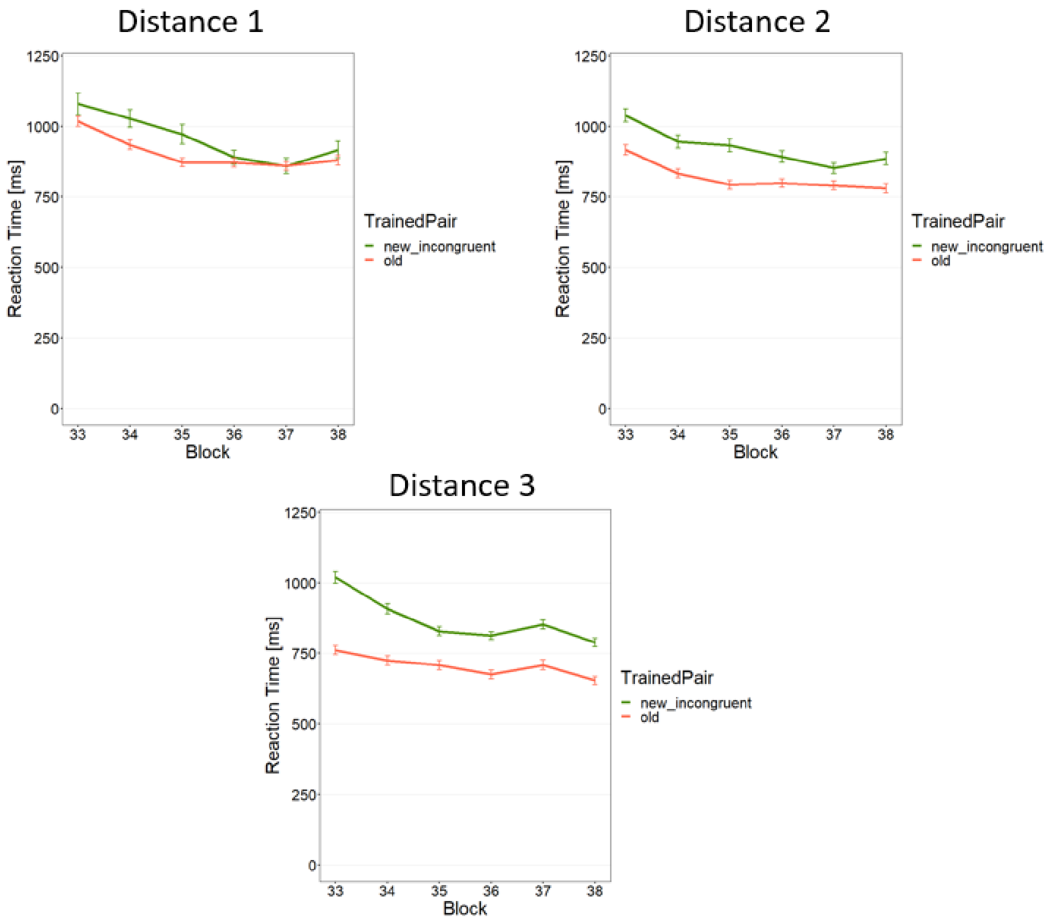
The ANOVA MIXED procedure was employed to investigate the impact of the factors "Trained Pair" and "Distance" on reaction time (RT) during the mixed phase. The results of the ANOVA revealed significant effects for both the "Trained Pair" factor ($F(1, 50) = 38.87$, $p < .001$) and the "Distance" factor ($F(2, 100) = 97.41$, $p < .001$) on reaction time. Furthermore, a noteworthy interaction effect emerged between "Trained Pair" and "Distance" ($F(2, 100) = 16.29$, $p < .001$). Overall, these findings underscore the significance of both the pair type and the distance between stimuli in influencing reaction time during the test phase. Moreover, the interaction effect emphasizes these associations, implying that the impact of pair type on reaction time depends on the particular distance.

Further analysis using paired t-tests within each distance revealed significant differences in RT between the *Old* and *New_incongruent* pairs across all three distances. At distance 1, the

Old pairs exhibited a faster RT compared to the *New_incongruent* pairs (t = 2.32, df = 50, p < .01). At distance 2, there was also a significant difference in RT scores between the two pair types (t = 4.52, df = 50, p < .01). Once again, the *Old* pairs demonstrated higher accuracy compared to the *New_incongruent* pairs, indicating a consistent pattern of faster and more accurate performance for the *Old* pairs as the value difference increased. Similarly, at distance 3 (t= 7.60, df = 50, p < .01) there was a significant difference in RT scores between the *Old* and *New_incongruent.*

Figure 19

Comparison of Reaction Times for Trained Pairs with Varying Distances: New_congruent vs. Old



Note. In the above panel, three graphs are presented, each illustrating the trained pairs *New_congruent* and *Old* with varying distances. The x-axis represents the blocks 33 to 36, corresponding to the test phase on day 2. The y-axis represents RT in milliseconds (ms). These findings indicate that while both the *Old* and *New_congruent* pairs show increased RTs as blocks progress, the *Old* pairs consistently outperform the *New_congruent* pairs.

5 DISCUSSION

The present study aimed to determine the primary driver of habitual choices, whether it is value or history. Based on the literature (Miller et al., 2019), two contrasting hypotheses were formulated: the value-driven habit formation hypothesis and the frequency-driven habit formation hypothesis. According to the value-driven habit formation hypothesis, habit formation entails the computation (and subsequent use) of (stimulus, response) values.

In contrast, the frequency-driven habit formation hypothesis suggests that extensive overtraining leads to automatic and habitual choices that have been consistently reinforced. The frequency of training a particular (stimulus, response) pair strengthens the association between the stimulus and the response, causing the choices to occur automatically, independent of their current value. By manipulating both frequency and value in the experimental design, the study aimed to test these hypotheses and analyse the data in light of these perspectives.

We conducted an online two-day experiment where participants had to make choices between two stimuli with different values in different conditions. The results revealed a notable improvement in accuracy and a decrease in RT as participants progressed through the blocks, indicating the beneficial effects of practice and experience on decision-making. During the test phase, the analysis focused on examining the accuracy and RT across different pair types, as well as the influence of pair value distances on these measures. The findings unveiled significant differences in accuracy and RT among pair types, with *New_congruent* and *New_same* pairs showing higher accuracy and faster RTs compared to *New_incongruent* and *Old* pairs. This suggests that participants prioritize value when making accurate choices.

Besides, the analysis provided evidence of a clear relationship between pair value distances and both accuracy and RT. Participants demonstrated higher accuracy and faster RT as the value differences between stimulus pairs increased. This finding aligns with the hypothesis of value-based decision making, indicating that the choices individuals make are influenced by the inherent value of the available options. These findings were supported by statistical analyses, which confirmed the significant effects of blocks, pair value distances, and trained pairs on accuracy and RT.

Based on the results obtained from the experiment, we can confirm the hypothesis of value-driven habit formation. However, it is important to note that findings revealed that there is also an effect of frequency. Specifically, *Old* pairs performed significantly better, particularly in the early stages, compared to what would be predicted based solely on their distance. Thus, the role of frequency should be considered in addition to value.

The results consistently demonstrated a clear preference for options with higher subjective value, even after prolonged overtraining. This suggests that value plays a significant role in driving responses. However, it is important to exercise caution when interpreting the results of the t-tests and ANOVA in this study. It should be noted that not all assumptions underlying these statistical tests were met. Deviations from these assumptions can potentially affect the validity and reliability of the findings.

The present study is not without limitations that should be considered when interpreting the results. Firstly, the sample size of this study was relatively small, with a final participant count of fifty-one after excluding one participant due to non-compliance. While efforts were made to recruit participants through Sona and obtain a diverse sample, the limited sample size may affect the generalizability of the findings. Future research should aim for larger and more diverse samples to enhance the external validity of the study.

Secondly, the experiment was conducted online using the Gorilla Experiment Platform. While online experiments offer convenience and accessibility, they may introduce certain limitations. The lack of direct supervision during the task could potentially lead to variations in participants' engagement and compliance (American Psychological Association, 2020). Additionally, the reliance on participants' self-report measures and online data collection may introduce response biases or technical issues that could impact the validity and reliability of the results. It is important to acknowledge these potential limitations and consider their impact on the study's findings.

Furthermore, the experiment was relatively short, consisting of only two days, with 33 blocks of training spread over 2 executive days and only 6 blocks of testing in a mixed condition. The inclusion of only six blocks of the mixed condition on the second day might not have been sufficient to fully capture the potential effects of habit formation. As habits typically develop over an extended period, it is possible that a longer experiment duration or a more prolonged exposure to the mixed condition would provide a clearer understanding of the stability or evolution of the observed effects over time (Research Guides: Organizing Your Social Sciences Research Paper: Limitations of the Study, 2023). Future research could consider extending the experiment duration or increasing the length of the mixed condition to investigate whether the patterns of behaviour and decision-making remain consistent or undergo any changes as habit formation progresses. By doing so, researchers would gain valuable insights into the temporal dynamics of habit formation and its influence on decision-making processes.

Moreover, the study primarily focused on the influence of history and value on habitual choices, neglecting other potential factors that could contribute to participants' decision-making processes. Variables such as individual differences, cognitive strategies, and environmental cues were not explicitly considered in the study. Including a broader range of variables in future research could provide a more comprehensive understanding of the determinants of habitual choice.

Lastly, it is important to note that the study's generalizability is limited to the specific context and stimuli used in the experiment. The stimuli consisted of gorillas presented in different colours, and the values assigned to the stimuli ranged from 1 to 8. The specific characteristics of the stimuli and task design may have influenced participants' decision-making processes in unique ways. Replicating the study with different stimuli or tasks could help assess the generalizability of the findings across diverse contexts. Despite these limitations, the present study contributes valuable insights into the determinants of habitual choice. The findings provide a foundation for future research to further investigate these factors and expand our understanding of the cognitive processes underlying habitual decision-making.

Although the notion of value (1 to 8) looks straightforward in the current experiment, how exactly value is represented, has been debated. Existing neuroeconomic theory (Kahneman & Tversky, 1979) suggests that the value we place on a particular item or experience is not fixed but rather depends on the context in which it is presented. This context-dependence can manifest in several ways, including scaling effects and anchoring effects. The theory of context-dependent valuation raises the question of whether the values we assign to items or experiences are truly reflective of their inherent worth or whether they depend on contextual factors (Palminteri et al., 2015). In other words, if the value we place on an item can be influenced by factors such as scaling and anchoring effects, can we really say that the value we assign to it is an accurate reflection of its objective worth?

Scaling effects refer to the way in which the perceived value of an item changes depending on the range of values presented alongside it. For example, if a consumer is presented with two options, one priced at 50 euros and one priced at 100 euros, they may perceive the 50 euros item as a better value than they would if it were presented alongside an item priced at 25 euros. This scaling effect can lead to consumers overvaluing certain items simply because they are presented alongside more expensive options. Anchoring effects, on the other hand, refer to the way in which our initial impressions of an item can influence our subsequent valuations of it (Tversky & Kahneman, 1974). For example, if a consumer is told that a particular item is priced at 100 euros, they may be more likely to perceive it as valuable than if they were told it was priced at 50 euros. This anchoring effect can be particularly strong when we have limited information about the item in question and are relying primarily on external cues such as price to make our valuation. Both scaling effects and anchoring effects are thought to operate in the brain through the interplay between regions involved in valuation (such as the ventromedial prefrontal cortex) and regions involved in sensory processing and attention (such as the visual cortex). Through this interaction, our perceptions of value can be shaped by a variety of contextual factors, from the range of options presented alongside an item to the cues we receive about its price or quality.

In the context of the discussion about context-dependent valuation, overtraining refers to the possibility that repeated exposure to a particular stimulus or decision could lead to the formation of habitual responses, which are then automatically triggered in response to that stimulus. This process is thought to involve different brain structures, such as the basal ganglia and prefrontal cortex, which play a role in habit formation and decision-making (Solway & Botvinick, 2012). However, the RTs observed in the mixed condition do not suggest that any of the decisions made in this condition are habitual. This implies that even with repeated exposure to the stimuli, participants did not form strong habitual responses and instead continued to engage in more deliberate decision-making processes. These findings align with the research conducted by de Wit et al. (2018), highlighting the difficulty in experimentally inducing habits in healthy humans. Numerous studies have successfully induced habits in healthy rats through overtraining stimulus-response behaviours. However, there is a lack of similar research in humans, and only one study has shown how extensive training can affect habit formation in humans. In their study, de Wit et al. (2018) report five failed attempts to demonstrate that overtraining instrumental behaviour leads to the development of inflexible habits in humans. These findings indicate that the outcome devaluation procedures used in these studies may be insensitive to the duration of stimulus-response training in humans. This and the current study raise questions about the role of overtraining in shaping habitual responses and highlights the need for further research to better understand the conditions under which overtraining leads to habitual responses and when it does not.

Altogether, the discussion of overtraining and habitual responses highlights the complex interaction between neural processes and behaviour and underlines the importance of considering both theoretical and empirical factors in our understanding of decision-making and valuation. To gain a more nuanced understanding of the role of value in habitual choices, further analyses should be conducted by comparing models that differentiate between value differences based on the number of repetitions versus value differences based on the intrinsic value of the stimuli themselves. This would allow researchers to examine whether certain stimuli become habitual simply because they are encountered frequently, or whether their intrinsic value plays a more significant role. Additionally, further analyses could also explore the impact of large versus small discrepancies in value on habitual choices. By comparing the choices made in situations where the values of the stimuli are very different versus situations where the values are only slightly different, researchers may be able to gain a better understanding of how the magnitude of value differences influences habitual responding. Overall, these further analyses could provide important insights into the complex processes that underlie habitual choices and could inform the development of more effective interventions for promoting behaviour change and influencing consumer choices.

In conclusion, this study contributes to the existing knowledge on habit formation and provides a foundation for further investigation into the factors that drive habitual choices. The findings not only highlight the role of value in habit formation but also suggest that frequency of repetition plays an influential role in shaping habitual behaviour. The results of this study support the hypothesis of value-driven habit formation, suggesting that repeated exposure to stimuli alone may not be sufficient to induce strong habitual responses. Instead, the interaction between value-based processes and the frequency of repetition appears to be crucial in determining the development of habits in human behaviour.

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