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Embodied decision biases during walking

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Grießbach, E., Herbort, O. & Cañal-Bruland, R. (2022). Wechselwirkung von motorischen und kognitiven Prozessen in hierarchisch organisiertem Verhalten. In S. Klatt & B. Strauß (Hrsg.), *Kognition und Motorik – Sportpsychologische Grundlagenforschung und Anwendung im Sport* (S. 46 - 58). Göttingen, Hogrefe Verlag.

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Abbreviations

CoM	Center of Mass
BoS	Base of Support
MoS	Margins of Stability
SLE	Swing Leg Effect
OFC	Optimal Feedback Control
CrI	Credible Interval
CI	Confidence Interval
OR	Odds Ratio
TWWT	Turning-While-Walking-Task
MLTT	Multilane-Tracking-Task

Zusammenfassung

Viele Jahre lang hat die psychologische Forschung *Kognition* als einen sequenziellen und modularen Prozess betrachtet, bei dem die Motorik nur das Ergebnis eines kognitiven Prozesses auf höherer Ebene ist. Dies ist jedoch ein Problem bei der Untersuchung von alltäglichem Entscheidungsverhalten, wo die motorische Kontrolle auf niedrigerer Ebene (z. B. beim Gehen) oft gleichzeitig mit Entscheidungsprozessen auf höherer Ebene erfolgen muss (z. B. beim Ausweichen vor einem Hindernis nach links oder rechts). Unter diesen Umständen deutet Forschung in den Bereichen des Multitasking, Embodiments sowie zum motorischen Entscheidungsverhalten darauf hin, dass die Informationsverarbeitung auf der Ebene der motorischen Kontrolle die Entscheidungsfindung durch Crosstalk zwischen den Prozessen und paralleles Feedback der motorischen Kosten beeinflussen kann. Dies würde die traditionelle Sichtweise des Entscheidungsverhaltens als modularen und sequenziellen Prozess in Frage stellen.

Ziel dieser Arbeit ist es, die vermuteten motorischen Einflüsse auf niedrigerer Ebene auf Entscheidungen auf höherer Ebene zu untersuchen, wenn Handlung und Entscheidungsfindung gleichzeitig ablaufen müssen. Dazu wurde zunächst eine neuartige experimentelle Aufgabe zur Untersuchung von Entscheidungsverhalten während des Gehens validiert. In der Aufgabe sollten die Teilnehmenden auf ein Hindernis zugehen und sich gleichzeitig für ein linkes oder rechtes Ziel für Belohnung entscheiden. Wir manipulierten die Bewegung zu den Zielen, indem wir das Schwungbein für die Drehung vor dem Hindernis beeinflussten. Die Ergebnisse bestätigten, dass die Bewegungsdynamik des Gehens die Entscheidungsfindung beeinflusste. Genauer gesagt zogen die Teilnehmenden es vor, sich zu dem Ziel in Richtung der Seite ihres Schwungbeins zu bewegen, auch wenn sie dafür weniger Belohnung erhielten.

Nach der ersten Validierung des experimentellen Designs fuhren wir fort, die Art des motorischen Einflusses zu untersuchen, welcher bei der Gehaufgabe auftritt. Dabei konzentrierten wir uns auf die sich ändernden motorischen Kosten während der Bewegung. Sollte der Entscheidungsprozess parallel Feedback über die motorischen Kosten erhalten, sollten Manipulation der motorischen Kosten während der Bewegung das Entscheidungsverhalten beeinflussen. In vier Experimenten manipulierten wir die Kosten des Umgehens des Hindernisses zum linken oder rechten Ziel unter verschiedenen Bedingungen. Die Annahme von parallelem Feedback bestätigend, beeinflusste die Manipulation der sich ändernden motorischen Kosten das Entscheidungsverhalten während der Bewegung. Die Teilnehmenden bevorzugten dabei generell die Entscheidung mit weniger motorischen Kosten.

Schließlich untersuchten wir, ob der motorische Einfluss auf Entscheidungen beim Gehen auf manuelle Bewegungen übertragbar ist. Die Teilnehmer führten sowohl die Gangaufgabe als auch eine computergestützte Version dieser Aufgabe durch. Die Ergebnisse deuteten nicht nur auf paralleles Feedback der Handlungskosten hin, sondern auch auf einen kostenunabhängigen Einfluss, welcher für Crosstalk spricht. Die Stärke dieser Einflüsse korrelierte jedoch nicht zwischen den beiden Aufgaben für die einzelnen Teilnehmenden. Dies deutet darauf hin, dass die interindividuellen Unterschiede für motorische Einflüsse auf Entscheidungen in unserer Gangaufgabe aufgabenspezifisch sind.

Übergreifend konnten wir demnach in mehreren Experimenten zeigen, dass Entscheidungsfindung und Handlung eng miteinander verwoben sind. Dies steht im Gegensatz zu einer modularen und sequenziellen Sichtweise für Entscheidungen, welche in der Bewegung stattfinden müssen. Stattdessen unterstützen diese Ergebnisse Modelle, die paralleles Feedback der Kostendynamik während der Bewegung, aber auch Crosstalk zwischen motorischer Kontrolle und Entscheidungsverhalten beinhalten.

Summary

For many years, research of psychology has viewed *cognition* as a sequential and modular process, with action being only as the output of a higher-level cognitive process. This is a problem when studying decision-making in everyday behavior, where lower-level motor control (such as walking) often needs to occur at the same time as higher-level decision processes (such as avoiding an obstacle to the left or right). For these situations, research in multitasking, embodiment, and specifically embodied decision-making suggests that information-processing at the level of motor control can influence decision-making through crosstalk between the processes and parallel feedback of action costs. This challenges the traditional view of decision-making as a modular and sequential process. Thus, we set out to investigate the assumed influences of lower-level actions on higher-level decisions when action and decision-making must run concurrently.

To do that, we first implemented a novel experimental paradigm for studying decision-making during the whole-body movement of walking. Participants were asked to walk toward an obstacle and to concurrently decide to turn toward a target on the left or right for reward. We manipulated the action of walking toward the obstacle by predetermining the swing leg before turning in front of the obstacle. Results revealed that the body dynamics of concurrent action influenced decision-making. More specifically, participants preferred turning toward the side of the swing leg, even at the expense of receiving less reward.

After validating the experimental paradigm, we investigated the type of embodied decision bias present in the walking task. Thereby, we focused on the bias by action costs during action. If the decision process receives parallel feedback during movement, the cost dynamics during movement should influence decision-making. In four experiments, we manipulated the action costs of turning under various conditions. As hypothesized by parallel feedback, the action cost dynamics during movement moderated the effect of action on decision-making. Participants generally preferred decisions with less action costs during action.

Finally, we investigated whether the embodied decision biases for walking generalize to manual movements. Participants did both the walking task and a computerized version of it. Results provided evidence not only for feedback of action cost, but also for a cost-independent influence, indicating crosstalk. However, the strength of these biases did not correlate between both tasks for individual participants. This indicates that the interindividual differences of embodied decision-biases in our walking task are rather task-specific.

Altogether, our results show that decision-making and action are closely intertwined. This opposes a modular and sequential framework of hierarchical decision-making for embodied decisions. Instead, these results support models which include parallel feedback of the cost dynamics during action but also crosstalk between motor control and decision-making.

Chapter 1

Introduction

1. Introduction

1.1. Sequential and modular information processing in cognitive psychology

How do we process the information to manage our behavior in everyday life? For many years, the most widely accepted answer to this question proposed two main assumptions (see Fig. 1-1, and Fodor, 1983, Newell & Simon, 1972). First, information processing was presumed to consist of modules like *perception*, *cognition,* and *action* which process information independent of each other. Second, these modules were hypothesized to operate sequentially, that is information processing only starts when it is completed by the previous stage. In this process, higher-order cognitive processes like decision-making were postulated to operate after perception but before action. Hence, information processing would be unidirectional.

The idea behind these assumptions comes from the idea in cognitive psychology that the mind works like a computer, and that cognition is essentially the process of performing computations on mental representations, similar to how a computer processes data (van Gelder, 1998). In this context, computation refers to a set of instructions specifying basic operations (like Boolean Logic, or Arithmetic Operations) while representations are considered abstract and discrete tokens emerging from a perceptual layer. The computer metaphor had strong conceptual benefits in cognitive psychology: The assumption of modularity and sequentiality enabled research paradigms to theorize about and investigate underlying mental processes, like object recognition, memory, attention, logical thinking, or decision-making. It was thereby essential for the transition from a behavioral to a cognitive perspective on mental functions (Anderson, 2020). For the first time, cognition was not treated as a black box, but as an empirically approachable construct.

However, in this modular framework, one aspect of everyday behavior has been severely neglected: Action. Being only regarded as the output of the computational layer of cognition, action merely played a subordinate role for a long time (Cisek, 2019; Rosenbaum, 2005). As a result, many experimental tasks in cognitive psychology were structured sequentially with action being trivialized to simple button presses. That is, experiments often followed a sequential trial-based composition of the task – ending shortly after action has only begun (Gordon et al., 2021).

Fig. 1-1. Modular and sequential view of cognition. Cognition is presumed to process information independently of action and prior to planning and implementing an action.

1.2. The pitfalls of neglecting actions

The neglect of action in cognitive psychology is in severe contrast to many phenomena of everyday life in which action plays a central role, like participating in sport games, driving a car, or just casually walking to work. In fact, according to Cisek (2019), it is also in contrast with the environment we evolved in, in which animals had to enact decisions quickly while already in action in order to survive (e.g., fleeing from a predator). From an evolutionary perspective, one might even argue that the reverse is true: Organisms need to act in order to survive, and cognition, serves the purpose of finding the appropriate actions that will ensure their survival and reproductive success (Fine & Hayden, 2022). A similar argument can be made for perception (Hoffman et al., 2015; Proffitt, 2006).

In general, neglecting action might be problematic for three not mutually exclusive reasons: 1. As Rosenbaum (2005) nicely framed it, with actions being *The Cinderella of psychology,* it is not subject in the majority of experimental tasks in cognitive psychology and as a result, there is a gap between research and many phenomena of everyday life. 2. The sequential and modular metaphor of cognition as a computer is misleading when designing models for embodied situations. Alternatively, control models with parallel feedback could provide a more appropriate framework for embodied situations (Pezzulo & Cisek, 2016). 3. The assumption of modularity and sequentiality of perception, action, and cognition became more and more challenged as tasks that were thought to involve action only (e.g., walking) interfered with cognitive tasks (Patel et al., 2014). Additionally, the same is true for action and perception, that is, there is evidence that action penetrates perceptual processes (Hommel et al., 2001; Müsseler & Hommel, 1997). Finally, decision-making requires profound feedback from action like constraints or costs to enable us to maneuver our bodies through the numerous requirements of everyday tasks (Gordon et al., 2021; Lepora & Pezzulo, 2015).

1.3. Chapter preview

All of the aforementioned problems specifically arise in research on decision-making which will be outlined in Chapter 2. Decision-making generally describes the process of selecting one action among several alternative options. It is thought to comprise a higher-level cognitive process that evaluates the value (Rangel et al., 2008) or evidence (Heekeren et al., 2008) of choice options and provides goals as output for lower-level motor control.

In contrast to this sequential view, Chapter 2 argues that action and decisions often have to run concurrently in everyday behavior – a fact that has been mostly neglected by the tasks used to study decision-making so far. Because action requirements and constraints are dynamically changing under these situations, feedback control models that have often been used to describe motor control processes suggest parallel processing of decision-making and action execution. In addition to parallel feedback, the chapter resumes by highlighting that there is ample evidence from a plethora of different research areas advocating the idea that lower-level motor control interferes with higher-level decision processes (*crosstalk*), which might speak against the modular processing of action and decisions. As a result, the chapter concludes with in a working model which includes parallel feedback and crosstalk between action and decision-making.

Based on these considerations, this dissertation aims to scrutinize the influence of action on decision-making. Chapter 3 picks up this challenge by providing a general overview of the methodological design used in the empirical part of this dissertation while illustrating the general and specific research questions. To address these questions, we designed a new paradigm in which higher-level reward-based decisions had to be made during ongoing actions, more specifically walking. After establishing the experimental paradigm, the empirical investigations first and foremost focused on examining the influence of action by the feedback of costs. Chapters 4 to 6 comprise the empirical work of this dissertation. Chapter 4 (Study 1) focuses on a first validation of the experimental design and tested whether and when action influences decision-making. However, it remained uncertain which aspects of action influence decision-making.

Accordingly, Chapter 5 (Study 2) focuses on the influence of action by parallel feedback of motor costs. To strengthen the claim that motor cost dynamics might play a role in the embodied decision bias, motor costs were manipulated in various ways within four experiments.

Within the first two studies (Chapters 4 and 5), large interindividual differences have been observed. That is, while some of participants' decisions were only weakly affected by their concurrent action, some were highly affected. In order to investigate these differences between individuals, Chapter 6 (Study 3) focused on examining whether the size of embodied decision biases is consistent across tasks for individual people.

Finally, Chapter 7 provides a general overview of the empirical results and discusses whether we were indeed able to extend the construct of decision-making by addressing the role of action and whether the action perspective was filling the gap we hoped to address. At the end of the chapter, some remaining challenges as well as suggestions on how to approach them will be addressed.

Chapter 2

Conceptual introduction – Crosstalk and feedback in hierarchical tasks

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2.1. Hierarchical structure of (everyday) behavior

Many tasks in everyday life are more complex than they appear at first sight. For example, consider the following situation in soccer: The player with the ball crosses a player of the opponent team. While the player coordinates the running movement with the ball (motor process), a decision of whether to pass the ball or to risk a goal shot has to be made (cognitive process). In order to realize the higher-level objective, for example, winning the game, cognitive and motor processes take place not only simultaneously but also in a direct, *nested* dependency. On the one hand, without a decision, no further movement for the pass or goal shot takes place and the objective of the task is not achieved. On the other hand, the decision also depends on whether the simultaneous movement is executed adequately. If, for example, the ball bounces or the player slips, many decisions are no longer feasible or more difficult to make so that the objective of the action may also not be achieved.

The dependency of cognitive on motor processes has been mostly represented in hierarchically organized models so far (e.g., Cooper & Shallice, 2000; Merel et al., 2019). In these hierarchically organized models, *higher-level* decisions arise based on the objective of the task and sensory input (see Fig. 1-1). The decision (e.g., pass) is then transferred to

[1] This chapter is by and large a literal translation of the German book chapter, translated to English by the author of this thesis. Changes were made to fit the overall narrative of the dissertation in keeping with previously introduced concepts. That is, the title of this chapter has been changed. In addition, the term *peripheral crosstalk* has been changed to *parallel feedback*. In case it incorporates feedback, the term *crosstalk* has been changed to *embodied decision biases*. Moreover, as this thesis conceptually relies on feedback control models, these models were described in more detail in Box 1 *Feedback control models in motor control*.

lower-level motor processes, which translate the decision into movement (e.g., swing movement of the right leg).

Previous models have been based on two fundamental assumptions: First, those motor processes are initiated sequentially only after deciding and completing associated cognitive processes. That is, cognitive processes are superordinate to motor processes per se. Second, information processing is characterized to be independent between levels of the hierarchy. This means that the information processing for the movement of the swing leg to execute a pass is processed independently of the information processing of the decision of the pass.

This theoretical introduction aims to present three different research approaches and their respective empirical results which indicate that there is reason to question the two assumptions of previous hierarchical models for the described tasks. As a matter of fact, previous research advocates the existence of crosstalk and parallel feedback between cognitive and motor processes during movement. These corresponding areas of research concern 1. research on multitasking, 2. approaches from the field of embodied cognition, and 3. research on decision behavior. Based on a discussion of these three approaches, we propose a revised theoretical model for hierarchical tasks that integrates and specifies three different ways in which motor and cognitive processes might interact (see Fig. 2-1).

2.2. Evidence for crosstalk from the field of multitasking

The first relevant research approach in which a reciprocal relationship between motor and cognitive processes can be observed comes from the field of multitasking. In multitasking, two or more tasks have to be performed simultaneously or in short temporal succession, for example, recognizing a sound and a visually presented letter, which commonly leads to a decline in performance in at least one of the two tasks (for a review, see Koch et al., 2018). With respect to our empirical endeavor, dual tasks that combine a predominantly motor task with a predominantly cognitive task appear to be of particular relevance (e.g., Patel et al., 2014). Patel et al. (2014) investigated the influence of walking on the simultaneous performance of different cognitive tests, such as a Stroop task, counting down, or a visual response task. As a comparison condition, the tasks were performed in a sitting position. Results showed that the subjects in the walking condition performed worse on each cognitive task when compared to the subjects in the seated condition. Furthermore, walking speed decreased as soon as the cognitive tests had to be performed simultaneously. The results illustrate that both cognitive and motor performance deteriorate when performed simultaneously. The decline in performance on the tasks in the walking condition may be due to the limited cognitive resources being shared between the two tasks. In other words, if both tasks require some of the same resources for processing information, attempting to do them at the same time may cause one or both tasks to suffer from a drop in performance or be delayed when the capacity of these resources is exceeded (Koch et al., 2018).

At this point, we want to emphasize that the considered tasks in multitasking are mostly independent rather than hierarchically dependent. In contrast to hierarchical tasks, in which decision options depend on concurrent movement execution, cognitive tasks did not depend on the gait task in the example by Patel et al. (2014). In turn, the gait task also did not depend on the cognitive tasks.

If the results from multitasking research can be transferred to hierarchical tasks, then more *resource-intensive* movements, which are performed simultaneously, should lead to unfavorable decisions more frequently. If true, the difficulty of dribbling the ball in the initial example would limit the simultaneous decision-making ability, and the player with the ball would run the risk of passing the ball, even if a goal shot would have been the better alternative. On the other hand, if the decision is difficult to make because there are various options (Churchland et al., 2008), the dribbling of the ball could also suffer, and the player could lose the ball. Thus, cognitive and motor processes influence each other as one or both processes can experience limitations, depending on the distribution of the available cognitive resources.

2.3. Evidence for crosstalk from embodiment approaches

In contrast to traditional models that suggest independent information processing between motor and cognitive processes, a variety of findings and theoretical approaches that contradict this initial assumption have emerged in the recent years. These research approaches are classified under the overarching term of *Embodied Cognition* (Shapiro, 2019). In brief, Embodied Cognition emphasizes the role of the body and sensorimotor processes for information processing. Accordingly, it is expected that perceptive processes, cognition, and motor control are not separable but affect each other. This assumption is supported by numerous empirical findings suggesting that motor processes influence, for example, perception (Cañal-Bruland & van der Kamp, 2009), language processing (Liepelt et al., 2012), or problem-solving strategies (Thomas, 2013) probably due to an overlap between cognitive and motor processes with respect to specific representations causing crosstalk between tasks. In contrast to multitasking (see above), crosstalk does not emerge unspecifically, but depends on the content of the motor process in the overlapping representations. This distinction should be emphasized here since empirical work in the field has also frequently relied on a multitasking design. However, there is no general degradation between the pairing of cognitive and motor tasks but a representation-specific influence (positive or negative priming effect) between both motor processes and cognitive processes. To explain this relationship in more detail, we will focus on two representative areas of research: the influence of motor processes 1. on perception and 2. on cognitive problem-solving strategies.

According to the ideomotor principle, there is a direct, bidirectional connection between perception and motor processes (Shin et al., 2010). This connection is closely intertwined with the notion that every movement is coupled with a sensory consequence. For example, pressing a light switch (usually) leads to the sensory consequence that the room is illuminated. Following the ideomotor principle, this association between movement and the sensory consequence is established in both directions. The anticipated sensory consequence (of the room being lit) can trigger movement toward the light switch (Shin et al., 2010), and hence can be used for the goal-directed control of actions. The *common-coding approach* (Prinz, 1997) and the *theory of event coding* (Hommel et al., 2001), which is based on the former, are enrooted in this bidirectional connection between perception and action. These theoretical approaches assume a common representation of perception and the anticipated sensory consequence of action. If true, motor processes should influence perception on the level of common representations. Intriguingly, this issue has been addressed by Müsseler and Hommel (1997). In this study, subjects had to recognize a partially covered arrow pointing to the left or the right, whereas a second task required a key press to the left or the right. The side of the key press affected the perception of the arrow: Subjects tended to perceive the direction of the arrow opposite to the side of the keypress (negative priming, see Müsseler and Hommel, 1997).

It is commonly stated that the spatial correspondence (left or right) between motor planning and the stimulus is used by both processes. Because the motor process blocks this representation at the time of the perceptual task, this representation cannot be used by perception, and accordingly, the arrow is perceived in the opposite direction more frequently. However, the overlapping representations are not exclusively limited to spatial characteristics. Priming effects of motor processes can also be based on other sensory representations such as colors (Hommel, 1998).

Similar effects seem to apply to motor processes and *cognitive* problem-solving strategies, such as the radiation problem in the study by Thomas (2013). In this study, a fictional central tumor is ought to be destroyed using multiple lasers without damaging surrounding tissue. The solution of destroying the tumor with multiple weak lasers from different directions is usually rarely found. However, if participants were forced to align their eye movements in accordance with presented visual targets (i.e., smooth pursuit from the inside to the outside of the tumor), the probability of solving the problem increased drastically. With respect to the finding, it is assumed that the resulting eye movements overlapped representationally with the solution to the problem of irradiating the tumor from multiple directions, thereby positively influencing it.

As discussed in more detail in the respective section on multitasking, the findings of crosstalk in embodied cognition research are also not based on hierarchical tasks but on independent tasks. In contrast to multitasking, crosstalk between processes is dependent on the content of the shared representation. If the approaches on Embodied Cognition can be verified for hierarchical tasks, it can be assumed that motor processes have a content-specific effect on cognitive processes whenever representations are shared between motor and cognitive processes. For example, it is conceivable that dribbling the ball with the right foot could cause a pre-activation for decisions to the right side. In turn, this could make a pass or turn to the right side more likely to occur, irrespective of the estimated success or effort of the action.

2.4. Evidence for parallel processing from decision research

The third and final approach, which indicates that motor and cognitive processes are mutually interrelated, origins from decision research. In research on decision behavior, it can often be observed that decisions represent a trade-off between rewards, costs, and risks (Kahneman & Tversky, 1979). In this respect, it’s important to note that the amount of effort required to perform different actions (action costs) can significantly influence the decision-making process, with individuals tending to favor options that require less physical effort (Cos et al., 2014; Herbort & Rosenbaum, 2014). If a decision has to be made during movement, the costs of the action alternatives may change with the dynamic body state. Recalling the initial example of the soccer player who changes his/her position in relation to the opponent while dribbling the ball, the costs of playing around and executing both movement options vary depending on whether the opponent's new position obstructs the pass or the goal shot. In the worst case, the ball is lost while running and completely new action alternatives must be considered.

The influence of the dynamic body state during movement has been recently investigated (Cos et al., 2021; Grießbach et al., 2021; Griessbach et al., 2022; Kurtzer et al., 2020), and can be computationally modeled by feedback control (see Box 1).

Box 1. Feedback control models in motor control

Considering the dynamical nature of the decision-process during action, feedback control models might be particularly valuable to study situation where decisions have to be made concurrent to actions (Diedrichsen et al., 2010). Feedback control models are comprised of an agent (i.e., controller) implementing actions to transition between states based on state estimation by sensory input (arrow C in Fig. 2-1). A state can be defined, for example, as the position or velocity of a body part like the hand. The goal of the agent is to take control with action to stay or get towards a desired state (e.g., reach towards a glass). Because many actions can lead towards the desired goal state (redundancy, see Bernstein, 1966), the problem of which action to select arises. *Optimal feedback control* argues that actions are selected by minimizing a cost function (Todorov & Jordan, 2002). Hence, it is a normative model, prescribing how humans should behave and is successfully used to model motor control in humans. For instance, it can account for temporal aspects of movement (Harris & Wolpert, 1998), and muscle activation patterns including synergies of coactivation (Todorov & Jordan, 2002). Identifying a parsimonious cost function is the endeavor of Optimal Feedback Control. This cost function classically comprises a state error (i.e., difference in current state and the desired state) and the sum of the squared motor commands. But it could also include other factors related to action costs like energetic demands (Diedrichsen et al., 2010), jerk (Flash & Hogan, 1985; Hoff & Arbib, 1993), time (Shadmehr et al., 2016), or integrated torque change (Uno et al., 1989).

In this respect, it has also been shown that less costly action alternatives are preferred during movement. For example, in the first study of this thesis (Grießbach et al., 2021), participants were asked to make reward-based decisions while walking. During walking, the stance leg (left/right) alternates and so does the effort required to change direction. When the left foot is on the ground, a lateral step to the right is more stable than a cross-step to the left. In the respective study, reward-based decisions involving a change of direction to the right or left depended on the stance foot. Participants preferred the side affording the *easier* lateral step outward. Thus, the findings provide evidence that motor processes can influence decisions via concomitant changes in action costs.

The question whether motor and cognitive processes occur in parallel or sequentially in this process, and whether these processes overlap, is currently controversially debated (Wispinski et al., 2020). *Good-based* models, similar to hierarchical models, state that decision-making processes form an abstract decision first, independently of motor processes, and sequentially translate it into an appropriate movement (Padoa-Schioppa, 2011). Because movement execution is a subsequent product of the decision, information about movement requirements (e.g., costs) is not directly available. Consequently, action costs for choice options must be learned associatively from the movement goal and body state. In contrast, *action-based* models assume that decisions form at the level of sensorimotor representations (Cisek, 2007). In this case, an abstract *cognitive* level of decision-making would be omitted, and movement options would directly compete with each other in sensorimotor areas, allowing for a parallel processing of action execution and decision-making. Additionally, action costs would directly affect decision formation because movement information is already incorporated into the decision.

Action-based and good-based models make opposing predictions, and both types of models are supported by empirical evidence (for a review see Wispinski et al., 2020). In this regard, the nature of the decision seems to be of particular importance. That is, while abstract decisions, such as buying a house, occur at a separate decision level independent of motor processes, concrete movement decisions such as in the soccer example seem to take place on the level of sensorimotor processes. Thus, decisions could take place on multiple hierarchical levels (Cisek, 2012). Accordingly, whether and how motor processes influence decision processes depend on the type of decision. At least for movement decisions like in the soccer example, concurrent motor processes might have a parallel influence on decision behavior via dynamic costs. Respectively, as the success and action cost of choice options dynamically changes during action so does the preference to choose.

2.5. Cognitive-motor crosstalk in hierarchical tasks - A model proposal

Previous models of hierarchical tasks propose a hierarchical manner of information processing in which objectives are sequentially passed on at different stages (e.g., scoring a goal, passing the ball, moving the swing leg). The task thereby leads to motor processes (e.g., dribbling the ball), which, however, often occur simultaneously with higher-level decision processes. Until recently, it has been commonly assumed that the underlying processes are independent of each other. However, three different approaches were identified that argue against the sequential processing of cognitive and motor processes and predict a direct interaction between the processes: research from the field of multitasking, embodied cognition, and decision-making. Consecutively, three distinct types of interactions emerge from these approaches. Fig. 2-1 depicts our proposed extended model of hierarchical tasks. In addition to the traditional model consisting of sequential unidirectional processing stages, three different types of interactions with action were added to the model. The respective types of interactions will be discussed more thoroughly below.

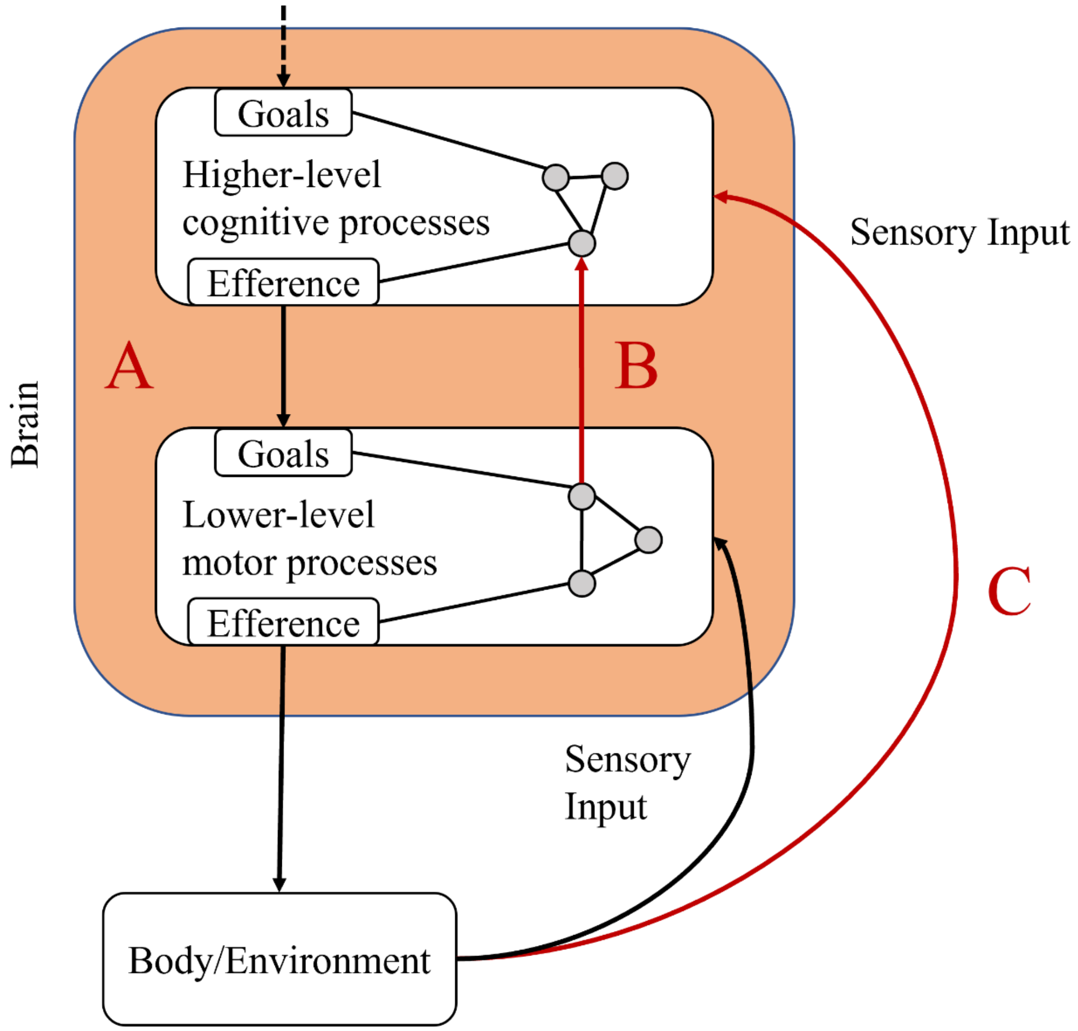

Fig. 2-1. Working model for hierarchical tasks with three types of embodied decision biases. A: Unspecific crosstalk. B: Specific crosstalk and C: Parallel feedback.

A) Unspecific crosstalk: Research from the field of multitasking has shown that performing (independent) motor and cognitive tasks simultaneously can lead to performance decrements in one or both tasks (Patel et al., 2014) as both motor processes and cognitive processes might share the same limited resources (Koch et al., 2018). Once information processing resources are exhausted, deterioration occurs at one or both levels. This limitation causes decisions to become more independent of task success overall, or slower, and/or concurrent movement execution suffers. We call this type of crosstalk *unspecific* because it does not depend on the content of the motor or cognitive processes. In terms of the soccer example, it would mean that the difficulty of dribbling the ball determines whether and how quickly future decisions are made successfully. If more resources must be devoted to controlling ball dribbling, successful game decisions become slower and/or less frequent.

B) Specific crosstalk: research from the field of embodied cognition has shown that motor tasks influence perception and cognitive processes in overlapping dimensions (Hommel, 1998; Prinz, 1997; Thomas, 2013). Here, it is hypothesized that motor and cognitive processes overlap at the representational level. Due to the content-specific overlap, motor processes can have a positive or negative effect on cognitive processes. Hence, this type of crosstalk is called *specific*. In terms of the soccer example, it might be possible that running while dribbling the ball primes certain game decisions. For example, a change of direction with the ball to the right side could prime a passing situation to the right side (i.e., overlap in spatial representation). This effect would be independent of whether the play decision is beneficial to the player, as opposed to the following type of crosstalk.

C) Parallel feedback: Research from the field of decision behavior has shown that less effortful choice options are preferred (Cos et al., 2014; Herbort & Rosenbaum, 2014). During simultaneous movement execution, the relationship of one's body position in regard to the task goal changes dynamically. Accordingly, the costs for action options changes with the movement, and so does the decision (Grießbach et al., 2021; Griessbach et al., 2022; Nashed et al., 2014). The dynamics of body position and environment are peripheral to the information processing of the central nervous system and provide feedback, thereby explaining the name for this type of embodied decision bias. Here in particular, action-based models would predict that decisions are formed at the sensorimotor level and therefore naturally entail parallel processing with movement execution (Wispinski et al., 2020). The distinction between cognitive and motor processes partially dissolves here and implies a mutual influence. This type of bias seems to be of special importance in decisions with a strong motor component. For the soccer example, it would be conceivable that the decision to run around an opponent to the left or the right depends on the current foot on the ground. Changes of direction to the left side are more stable and thus less effortful if the right foot serves as the momentary footing while running (Grießbach et al., 2021; Moraes et al., 2007). When the right foot is on the ground, the left swing leg can be guided outwards to run to the left, rather than crossing centrally to run to the right.

Our model of hierarchical decision tasks extended by crosstalk and feedback represents a proposal to integrate findings from different research directions. Based on the presented literature and the extended model, different challenges for future research emerge. For specific and unspecific crosstalk, this concerns the validation of findings for hierarchical tasks. To date, previous studies have almost exclusively conducted experiments with independent (non-hierarchical) combinations of motor and cognitive tasks (Hommel, 1998; Patel et al., 2014; Thomas, 2013). Thus, future research would be well-advised to apply findings from multitasking and embodied cognition research to hierarchical actions. In this regard, recent literature provides a good basis for further experimentation. For example, to manipulate unspecific crosstalk, the control requirements of the motor task could be manipulated. This could be done by manipulating the stability or walking speed of the motor task (Patel et al., 2014). For validation within hierarchical tasks, the secondary cognitive task (e.g., a decision task) should be designed as a function of the motor process (e.g., turning left or right while walking to meet an objective) in which the action requirements to implement the decision change with the movement.

When examining specific crosstalk and parallel feedback of action costs, it should be noted that both types of interaction can be confounded with each other as both feedback and specific crosstalk result in a specific change in the decision, for example, a right swing leg might share a representation with the decision to execute a directional change to the right but also might cost less due to enabling a lateral step. To disentangle these two types of crosstalk, the costs would have to be manipulated independently from the concurrent motor control (see Study 2). On the other hand, experiments might also reverse the mapping of costs and motion execution to discriminate between these effects (Raßbach et al., 2021).

Further, whether embodied decision biases can be avoided by specific strategies might be another interesting question of future studies. For unspecific crosstalk, it would be conceivable that the control effort of motor processes for time points at which decisions must occur would be reduced or altered if pre-planning is possible (McIlroy et al., 1999). Additionally, for feedback of action costs, the cost differences of alternative movement options can be reduced by considering multiple action alternatives during movement execution. This phenomenon can be observed in reaching experiments in which multiple reaching targets are displayed and the final reaching target is not determined until after the movement (Chapman et al., 2010). In this case, if participants would move their arm toward one target, the costs (i.e., distance) to opt for the other target would increase. To balance this increase in costs, the movement between the reaching targets is averaged to keep both movement options eligible (Wong & Haith, 2017). Furthermore, in the long term, training and experience in hierarchical tasks might have an impact on the different types of crosstalk by reducing its impact (Koch et al., 2018).

In sum, many everyday tasks are organized hierarchically with motor and cognitive processes occurring simultaneously. Nevertheless, previous models have assumed sequential and independent information processing between these processes. However, in this chapter, we were able to show that different research directions suggest crosstalk or parallel feedback between motor and cognitive processes. Based on existing research, we identified three different types of so-called embodied decision biases. As a result, we proposed an extended model of hierarchical task control. The validation of the model poses new challenges to previous research approaches. Especially due to the many open questions in the field and the possibilities of crosstalk between levels of information processing, hierarchical tasks are not only a promising object of investigation for future research - but also for our empirical endeavor.

Chapter 3

Research questions, paradigm, and work program

Psychological research has been neglecting the role of action for cognitive processes for many years (Rosenbaum, 2005) as information processing has been commonly assumed to be sequential and modular (Fodor, 1983). However, especially with respect to embodied decision-making in which lower-level motor control processes frequently occur simultaneous with higher-level decision processes, this perspective could be detrimental for further progress in research (see Chapter 2). As a matter of fact, multiple lines of research (Janczyk et al., 2014; Liepelt et al., 2012; Gordon et al., 2021; Lepora & Pezzulo, 2015) suggest that action affects decision-making via parallel feedback of cost dynamics and/or crosstalk between both processes (see Fig. 2-1) thereby questioning the sequential and modular view on decision-making (see Chapter 2).

In keeping with these deliberations, this dissertation aspired to investigate whether action is indeed part of the decision-process in a three-step trajectory (see Fig. 3-1). If it is true that action affects the decision process, we expected that manipulations of concurrent action, by means of specific crosstalk and/or cost dynamics, would bias decision-making.[2]

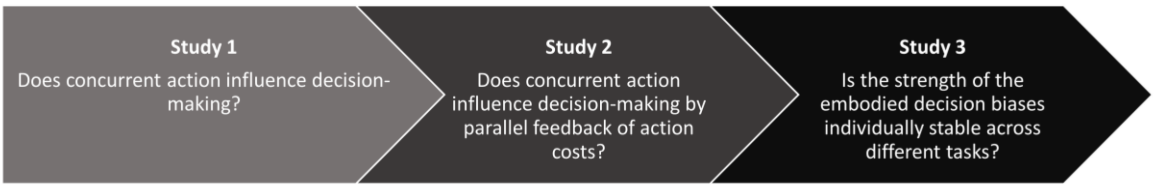

Fig. 3-1. Trajectory of research questions addressed in the dissertation.

To address these questions, we had to design a study that met three requirements. Firstly, the study had to involve participants making decisions while they were performing an action. We decided to use value-based decision-making, where participants had to collect rewards while they were walking. We chose walking as the action for our task for several reasons: Firstly, walking is essential in many situations in everyday behavior and is one of the most used behaviors to cover short distances. Secondly, arm movements, which could have been used as an alternative everyday action, were the focus of another PhD thesis within the same research project (Raßbach et al., 2021) and have also been studied in other related research (Marti-Marca et al., 2020; Michalski et al., 2020; Nashed et al., 2014). Thirdly,

[2] In the following, we will refer *to biases of action on decision-making* as *embodied decision biases*.

control aspects of walking have already been investigated (Bruijn & van Dieen, 2018; Mirelman et al., 2018; Patla et al., 1991), which was necessary for the second requirement of the study: In order to examine how concurrent feedback of action affects decision-making, the task had to include choices that varied in action cost based on the concurrent action being performed. Finally, the third requirement was to elicit specific crosstalk between action and decision-making, so it was necessary for both to share specific characteristics, that are known to influence each other, such as spatial qualities (Hommel, 1998; Simon et al., 1970). To create a task with both dynamic action costs requiring feedback and provoking crosstalk during walking, we took advantage of the fact that turning while walking requires different actions based on the side of the current swing leg (Patla et al., 1991). Concerning specific crosstalk, both, the side of the swing leg (e.g., left) and the side of turning (e.g., right) have spatial characteristics which can be congruent and incongruent to each other. Concerning feedback processes, the costs of turning during walking varies with the current swing leg, which will be described more in depth within the following subchapter.

3.1. The costs of turning during walking

Walking can be thought of as an inverted pendulum (Winter, 1995) which is by nature instable (i.e., it tips over if not in balance) and hence requires control to be stabilized. To stabilize our Center of Mass (CoM) and prevent ourselves from falling, we must bring a base of support below the CoM and create moments in such a way, that the moment created by gravity gets balanced out. The feet take over this stabilizing role when standing (Winter, 1995) and walking (Bruijn & van Dieen, 2018). While the CoM just needs to be stabilized statically in a standing position, it needs to be moved to another location during walking. This requires dynamic stabilization which can be achieved by temporarily bringing the CoM outside the base of support and as a result tipping it over (Winter, 1995). To prevent falling, the swing leg is positioned at a new position so that it *catches* the shortly falling CoM at a new position and extending the base of support to this location. If the CoM falls outside the base of support because the feet are positioned incorrectly, the CoM is instable and could be falling over (Hof et al., 2005). In terms of stability, it can be differentiated between anterior-posterior stability and mediolateral stability. The more instable mediolateral direction (McAndrew et al., 2011) was focus in our experiments. During straight walking, the feet are positioned outside the mediolateral swaying CoM. The CoM typically falls in the opposite direction of the leg that is supporting the body's weight (stance leg). The other leg (swing leg) is positioned laterally to the stance leg in order to catch and support the CoM as it falls (Bruijn & van Dieen, 2018).

Now, to turn while walking requires different stepping strategies and action costs based on the current swing leg and the direction to turn. If the turn is towards the side of the swing leg, a lateral step can be taken similar to normal walking. The CoM does not need to leave the base of support in this case (Moraes et al., 2007; Taylor et al., 2005). However, to turn to the opposite side of the current swing leg, you have to push your CoM temporarily outside the base of support and cross the stance leg with the swing leg to intercept the CoM. These crossing requirements have been shown to be more instable (Moraes et al., 2007; Taylor et al., 2005) and hence be more costly compared to the lateral stepping strategy.

In sum, turning requires different strategies based on the current swing leg which differ in their stability thereby offering two options with dynamic costs during walking: An easier lateral step when walking toward the side of the swing leg and a more effortful cross-over step when walking opposite of the side of the current swing leg.

3.2. Paradigm and work program

As building up in the previous subchapters, turning while walking seems to be a suitable candidate to investigate whether concurrent action affects decision-making. Based on this, we constructed a new paradigm in which participants had to walk toward an intersection and chose to turn toward one of two lateral targets for reward. The rewards were displayed during walking toward the intersection. The turning requirements were manipulated by predetermining the side of the first step. As a result, participant's swing leg changed accordingly before turning, and with that the stepping requirement to opt for either target. For instance, if the swing leg was left before turning, an easier lateral step could be taken toward the left side, but a more effortful cross-over step had to be taken to walk toward the right side. Vice versa applied to the right swing leg.

Accordingly, we expected that the swing leg (i.e., lower-level motor control) would influence the higher-level reward-based decision to turn toward either target. Based on the cost difference but possibly also due to specific crosstalk (i.e., left swing leg representation could bias leftward decision independent of costs), we hypothesized that participants would be biased to walk toward the side of their swing leg with a lateral step.

Given this basic paradigm, Study 1 (Chapter 4) aimed to validate our methodological approach and investigated whether and when the current swing leg influences the reward-based decision. In three experiments, we first validated the claim that a lateral step is preferred when rewards are shown before walking is initiated. Then, based on the cost difference for turning (McNarry et al., 2017; Wilson et al., 2013) or specific crosstalk (Janczyk et al., 2014), experiment 2 investigated whether the swing leg influences decision-making when presented shortly before turning. In the third experiment, we investigated the timing of the SLE by providing reward information at different time points before turning.

As Study 1 did not differentiate between an embodied decision bias by feedback from cost dynamics or specific crosstalk, Study 2 (Chapter 5) extended this work by focusing on the cost dynamics as a potential mechanism for the SLE. In four different experiments, the action costs to turn were manipulated in addition or interaction with the swing leg before turning.

Finally, we found evidence of embodied decision biases not only during walking. As a matter of fact, an additional study of ours which is not part of this dissertation found similar biases in a computerized version of the task but with manual movement (Raßbach et al., 2021). In both paradigms, large interindividual differences in the size of the embodied decision biases were present. Study 3 (Chapter 5) investigated whether the strength of embodied decision biases for individual participants observed in walking are task-specific or generalize to manual movements.

The following chapters (Chapters 4 to 6) will now present the three scientific peer-reviewed published or submitted articles comprising the empirical studies which addressed the research questions of this dissertation.

Chapter 4:

Body dynamics of gait influence value-based decisions

Published as:

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Abstract

Choosing among different options typically entails weighing their anticipated costs and benefits. Previous research has predominantly focused on situations, where the costs and benefits of choices are known before an action is effectuated. Yet many decisions in daily life are made on the fly, for instance, making a snack choice while walking through the grocery store. Notably, the costs of actions change dynamically while moving. Therefore, in this study we examined whether the concurrent action dynamics of gait form part of and affect value-based decisions. In three experiments, participants had to decide which lateral (left vs. right) target (associated with different rewards) they would go to, while they were already walking. Results showed that the target choice was biased by the alternating stepping behavior, even at the expense of receiving less reward. These findings provide evidence that whole-body action dynamics affect value-based decisions.

Keywords: embodied choices, gait, reward, decision-making

4.1. Introduction

Imagine yourself walking through the grocery store. While walking down the aisle in the candy section, you start having an appetite for candy. To your left you see your favorite liquorice. Somewhat closer to your right you see your favorite fruit gums. Which snack will you go for? Value-based decision-making is often considered to be a cognitive weighing process between costs and benefits (Pyke et al., 1977; Schoemaker, 1982). In this scenario, the benefit would perhaps be reflected by the caloric intake or tastiness of either of the two snacks, and the costs might include the cost of the action itself, here the physical effort it may take to walk to the liquorice, which is farther away than the fruit gums. There is empirical evidence supporting the claim that the costs of action play a significant role in decision-making (Cos et al., 2011; Hagura et al., 2017; Hartmann et al., 2013; Klein-Flugge et al., 2015; Solomon, 1948).

However, the majority of this research investigates just a snapshot of human decisions, namely situations in which choices and actions can be implemented sequentially. Per definition, in sequential decisions, cost and reward information is available before an action is initiated. Only after weighing the options, the action is executed. Theories of sequential decision-making such as good-based models (Padoa-Schioppa, 2011) and evidence accumulation models (Gold & Shadlen, 2007) assume that costs and rewards are being weighted independently of actions. Good-based models focus on where the competition between action choices occurs (Cisek, 2007; Padoa-Schioppa, 2011). They assume that the comparison of choice options takes place at an abstract level independent of sensorimotor representations. As such, decision and action are separate, sequentially unfolding modules. Only after reaching a decision boundary modeled as competition between abstract choice options, the decision is accomplished and implemented by a respective sensorimotor action.

Evidence accumulation models focus on a formal specification of how selection occurs (Gold & Shadlen, 2007; Wispinski et al., 2020). More specifically, evidence is sampled in a sequential manner until one choice option reaches a threshold. Similar to good-based models, only afterwards an action is initiated. It follows that in these theories the flow of information is modeled in a unidirectional manner: the choice governs the action (Gold & Shadlen, 2007; Padoa-Schioppa, 2011).

4. Body dynamics of gait influence value-based decisions

According to Lepora and Pezzulo (2015), when a decision is made and only afterwards an action is initiated, by definition the action dynamics - evolving a posteriori - cannot influence the already made decision without feedback from action dynamics. Consequently, sequential decision-making theories (Gold & Shadlen, 2007; Padoa-Schioppa, 2011) cannot account for many situations in which decisions have to be made during action execution, be it in sports (e.g., when deciding whether to pass a defender on the left or right while dribbling the ball), work environments (e.g., when navigating through a construction site), or other everyday situations (e.g., when making a snack choice while walking). In such situations costs of actions change dynamically and hence may need to be continuously updated and integrated into the decision process, a process not covered by sequential decision-making models.

Therefore, alternative theoretical approaches have been proposed, including the embodied choice framework (Lepora & Pezzulo, 2015) and action-based models (Cisek, 2007; Wispinski et al., 2020; Wunderlich et al., 2009). These approaches do integrate dynamic action costs in decision-making. The embodied choice framework assumes bidirectional, continuous feedback between the action and the decision process (Lepora & Pezzulo, 2015). This entails feedback about dynamic action costs that are continuously fed back into the decision. Action-based models propose that the degree of activation between competing actions reflects the weighing of costs and rewards, thereby arguing that action and decision processes form an inseparable unity (Cisek, 2007; Wispinski et al., 2020; Wunderlich et al., 2009).

While these theoretical approaches have received support from neurophysiological studies (Cisek & Kalaska, 2010; Wunderlich et al., 2009), there are only a handful of behavioral studies that examined the impact of concurrent action dynamics (Bakker et al., 2017; Burk et al., 2014; Michalski et al., 2020; van Maarseveen et al., 2018). These studies, however, tend to report rather mixed evidence. On the one hand, Burk et al. (2014) showed that perceptual decisions are influenced by dynamic action costs in a reaching task. On the other hand, Michalski et al. (2020) provided evidence that in a finger tracking task the dynamic action cost was only integrated into the decision process when the demands of continuous tracking were removed. Therefore, a first open question that remains to be answered is whether dynamic action costs are integrated into behavioral decisions, and if so, whether this effect translates to whole-body movements (going beyond reaching and pointing), thereby generalizing to a broad range of ecological choices in daily situations.

A second open question concerns the time course of action cost integration. In this regard, Bakker et al. (2017) provided initial evidence that when dynamic action costs are integrated into a reaching task, this is based on the immediate body state rather than the anticipated body state that per definition lies in the future and is bound to change continuously. However, given that this study applied a paradigm that only included passive motions (Bakker et al., 2017), the time course of action cost integration in decisions during active movements such as when walking through the aisle of the grocery store to buy candy is yet to be determined.

To recap, if indeed dynamic changes of body state (i.e., dynamic action costs) are part of the decision process in daily human behaviors, then the decision in the introductory example to choose between the liquorice or the fruit gums should be influenced by the concurrent stepping (i.e., walking) behavior. To test this, here we examined how walking, a complex whole-body movement, affects value-based decision-making in three experiments in which reward options appeared to the left or right side during walking (see Fig. 4-1). During walking the body state alternates between the left and right foot supporting the body. Based on the foot on the ground, the action costs of making a directional change vary dynamically. That is, if the left foot is currently on the ground and we intend to walk towards a target at the right, the swing leg (right) can make a lateral step towards the right. If in the same scenario, we intend to walk towards a target at the left, the right swing leg would have to make a cross-over step towards the left side (see Fig. 4-1). Prior work showed a preference for the lateral stepping strategy over cross-over steps when avoiding a planar obstacle on the ground (Moraes et al., 2007; Moraes & Patla, 2006). More specifically, a cross-over step was more unstable than a lateral step because of a reduced area on the ground to stabilize the laterally swaying center of mass. When participants were free to choose a directional change towards the left or right side, participants had a higher success rate and preference to change the direction towards the side which enabled a lateral step and avoided the cross-over step (Patla et al., 1991). This finding confirms that a directional change by making a cross-over step is costlier than a lateral step. Costlier is defined quite liberally here (i.e., is not limited to bioenergetic costs only; see Dominguez-

Zamora & Marigold, 2019; Moraes & Patla, 2006), denoting any difference of characteristics between actions (including e.g., stability, see Moraes et al., 2007)) that render one action preferable or more likely than the other.

To validate that in our walking paradigm (see Fig. 4-1) the cross-over step was indeed costlier than a lateral step, in Exp. 1, we examined the preference for either stepping strategy in sequential decision-making, that is, when cost and reward information was available before the first step was initiated. Knowing that in sequential decision tasks participants typically adapt their coordination pattern to assume body states that facilitate the realization of their decision (Cowie et al., 2010; van der Wel & Rosenbaum, 2007), we predicted a preference for the lateral rather than the cross-over stepping strategy. Results confirmed this prediction.

This validation allowed us to subsequently address the two main questions highlighted above. First, based on the embodied choice framework (Lepora & Pezzulo, 2015) and action-based models (Cisek, 2007; Wispinski et al., 2020; Wunderlich et al., 2009), we examined whether the dynamic action costs during walking influence value-based decisions. Second, we aimed at scrutinizing the time course of such action cost integration. Given previous evidence from research on reaching tasks indicating that dynamic action costs of immediate body states rather than anticipated body states are integrated into the decision process (Bakker et al., 2017), in Exp. 2, we first tested whether this prediction proved robust for whole-body movements such as displayed in our walking paradigm (see Fig. 4-1). To this end, we presented the reward information so late that the immediate body state would necessarily dictate the subsequent lateral or cross-over step. In other words, if participants were to integrate dynamic action costs, in this condition this could be only achieved by integrating the immediate (but not anticipated) body states due to the temporal demands of the task. It follows that based on the embodied choice framework (Lepora & Pezzulo, 2015) and action-based models (Cisek, 2007; Wispinski et al., 2020; Wunderlich et al., 2009), in Exp. 2 we predicted that participants would be biased towards a lateral stepping strategy, even at the expense of getting lower rewards.

Because Exp. 2 did not differentiate between the integration of the dynamic action costs of immediate vs. anticipated body states, we conducted a third experiment. Exp. 3 allowed us to scrutinize the time course of action cost integration in value-based decisions in a more fine-grained manner. That is, we systematically manipulated three time points of displaying the reward information during walking, including earlier reward presentation conditions that gave participants more time to potentially anticipate the final body state mandating the lateral or cross-over step. We hypothesized that if it was indeed the immediate body state at the time of reward presentation (and not the anticipated body state) that affects the value-based decision, then the immediate body state would predict the final stepping direction regardless of the anticipated body state dictating a lateral step. This should hence be observable independent of congruency or incongruency between the immediate and anticipated body states, even when resulting in lower rewards at higher action costs.

4.2. Results

4.2.1. Adaptation of stepping behavior enables a lateral step in sequential decision-making.

As in the introductory grocery store example, we chose a task in which participants were walking while reward options appeared on the left or right side (see Fig. 4-1A). To get the reward, participants had to step with at least one foot into a designated zone in front of a central obstacle and bypass it to its left or right to walk to one of the lateral targets. As rewards different combinations of points were displayed at the left and right lateral target (e.g., 60 points left and 40 points right). The points always summed up to 100. To first assess and control whether participants would indeed prefer a lateral stepping strategy compared to a cross-over step (see Fig. 4-1B and Fig. 4-1C), in Exp. 1 the rewards were displayed before participants started walking. That is, cost and reward information were available before an action was initiated. Participants started a trial in a neutral position with the feet next to each other. The stepping behavior was measured kinematically by attaching reflective markers on the shoes and measuring their position with a 3D-infrared camera system (see methods).

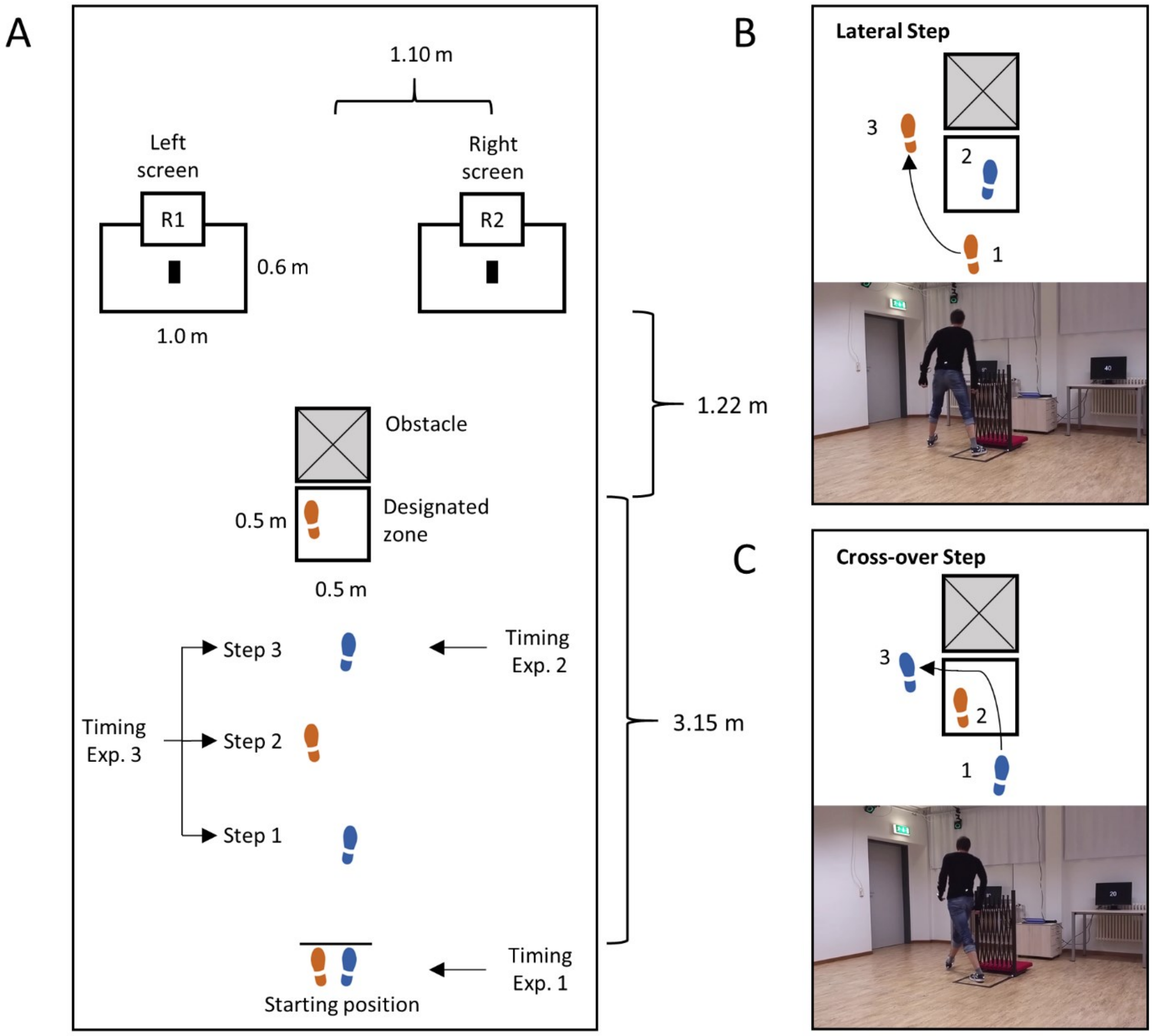

Fig. 4-1. Experimental setup and exemplary stepping behavior to bypass the obstacle. A. Dimensions of the experimental setup. Proportions are scaled to closely fit the real setup in this figure. Participants started a trial with the feet next to each other (Exp. 1) or a prespecified foot was placed at the starting line and the other foot was positioned behind, thereby determining the first step and stepping behavior towards the obstacle (Exp. 2 and 3, not shown in the figure). Rewards were displayed on the left and right screens before walking towards the obstacle (Exp. 1) or while walking towards the obstacle (Exp. 2 and 3). To determine the timing of the reward presentation the positions of the shoes were measured kinematically with a 3D infrared camera system in real-time and the time point of the touch-down for each step was estimated(Banks et al., 2015). Rewards were displayed at the touch-down one step (Exp. 2) or between three to one steps (Exp. 3) before stepping into the designated zone. To get to the reward, participants were instructed to step into the designated zone before bypassing the obstacle. Participants ended a trial by touching the black rectangle on either desk with one hand. B. Example for the lateral step. Here the right foot stepped into the designated zone before walking towards the left target C. Example for the cross-over step. Here the left foot stepped into the designated zone before walking towards the left target. For convenience, the left foot is displayed in orange, and the right foot in blue. R1 = Reward left side, R2 = Reward right side.

In the sequential decision-making task of Exp. 1, participants followed the instruction and almost always went toward the side with higher rewards (99.9 %). Only when there was no reward difference, choices were more variable (see Appendix Fig. 8-1).

Regarding the stepping strategy, participants adapted the final step into the zone to enable a lateral step (see Fig. 4-2).

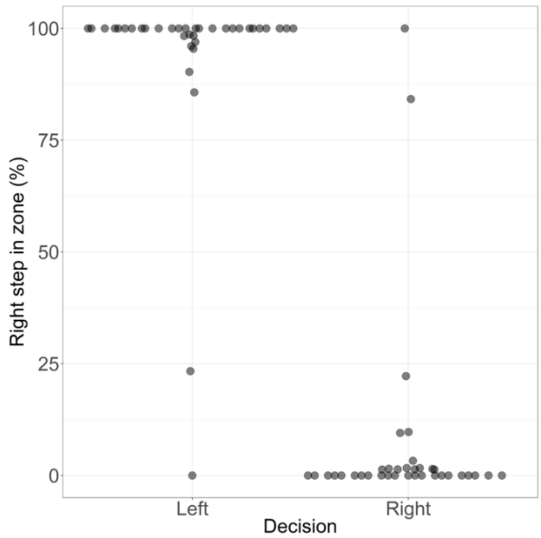

Fig. 4-2. Adaptation of the step into the zone enabling a lateral step. When participants walked towards the left side, they stepped more frequently into the zone with the right foot and vice versa. This shows the preference for a lateral step over the cross-over step, thereby confirming that the cross-over step is indeed costlier. Each dot displays the probability for individual subjects of making a step with the right foot into the zone. Zero percent indicates that participants always made a left step into the zone. Dots are jittered for better visual inspection.

Specifically, when participants walked to the reward presented at the right side, they more frequently stepped with the left foot into the designated zone and vice versa (χ^2 (1) = 59.30, p < 0.001, OR = 0.00010, 95 % CI [0.00001, 0.00020]). To examine whether participants took into account the cost information before the first step was initiated, we additionally analyzed if participants already adapted their first step based on the decision they finally effectuated. Results showed that participants indeed varied the leg to start walking with or the step length to enable a final lateral stepping strategy (see Appendix, Fig. 8-2), indicating that the cost information was taken into account before action initiation.
The adaptation of the stepping strategy validated that in our walking paradigm the cross-over step was indeed costlier than a lateral step when cost and reward information was available before the first step was initiated, that is, in sequential decision-making.

Following this validation, in Exp. 2 we then tested whether that dynamic action costs of immediate body states are integrated into the decision process (see Fig. 4-1) as predicted by research on reaching (Bakker et al., 2017). To this end, we presented the reward information late so that the immediate body state would inexorably dictate the subsequent lateral or cross-over step. Based on the embodied choice framework (Lepora & Pezzulo,

2015) and action-based models (Cisek, 2007; Wispinski et al., 2020; Wunderlich et al., 2009), we hypothesized a bias towards a lateral stepping strategy, even at the expense of receiving less rewards.

4.2.2. Dynamic action costs influence immediate value-based decisions.

In Exp. 2, rewards were displayed while participants were approaching and close to the obstacle. Specifically, the reward information was displayed at the kinematically estimated touch-down (first contact of the foot with the ground, see Banks et al., 2015) one step before stepping into the designated zone. The localization of this step was determined based on Exp. 1. It typically concerned the third step which took on average 490 ms (sd = 111 ms) until the touch-down of the final step into the zone. To control the final step into the zone (dictating either a lateral or cross-over step) and its combination with the reward information (e.g., 60 points left vs. 40 points right), we manipulated the starting position (left or right leg in front, resulting in a first step with the right or left foot, respectively) randomly on each trial. Additionally, to regulate the difficulty of the task, we constrained the temporal demands of reaching the target. Based on the data of Exp. 1, we included a 'regular walking' condition (6 s) and a 'time pressure' condition (4 s). If participants integrated dynamic action costs based on the body states assumed when stepping into the zone, then we hypothesized a bias towards a lateral stepping strategy, independent of and hence even at the expense of receiving less rewards.

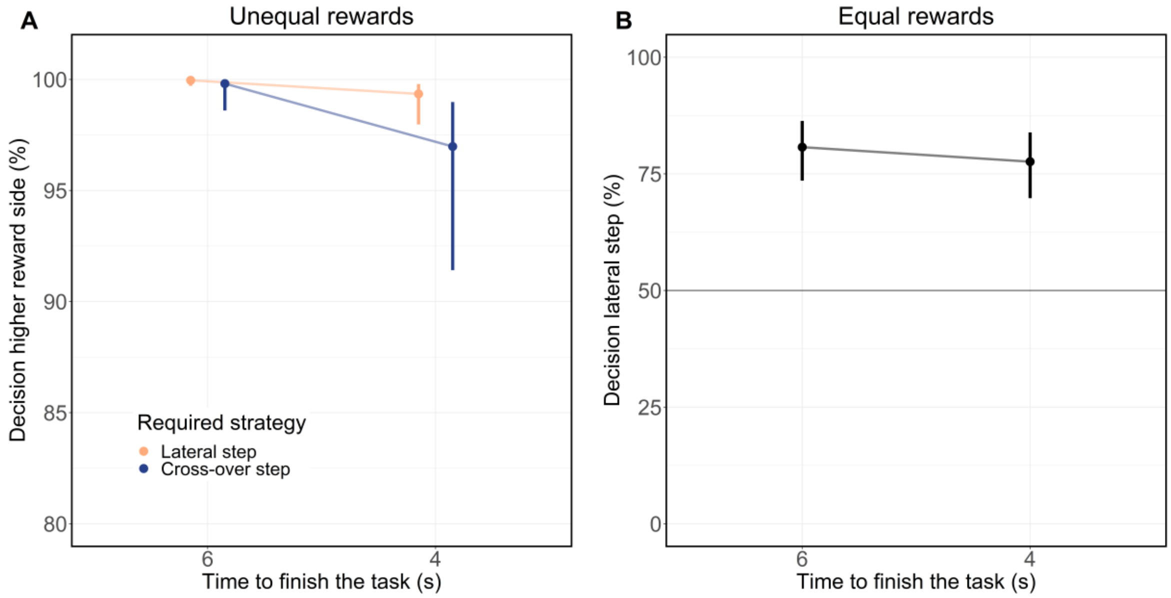

Fig. 4-3. Influence of the step into the zone on decision-making in Exp. 2. Displayed are the estimates and 95 % CI (Wald) of the respective GLMM. Note that the scale on the y-axis differs between both plots. A) Effect of the step into the zone and time constraints on decisions for unequal rewards (e.g., 40/60 points left/right). If the step into the zone was incongruent to the side with higher reward (e.g., left step in the zone and higher rewards on the right side), this required a lateral stepping strategy to achieve higher rewards (orange circles). If the step into the zone was congruent to the side with higher reward (e.g., right step in the zone and higher rewards on the right side), this required a cross-over strategy to achieve higher rewards (blue circles). Participants walked more often to the side displaying lower rewards when a cross-over step was required, independent of the time to finish the task. B) Probability to choose the side enabling a lateral step for equal rewards (50/50 points left/right) within both time conditions. A decision for a lateral step indicated that participants walked towards the incongruent side of the step in the zone. Participants went more frequently than chance level towards the side which enabled a lateral step independent of the time constraint.

For the unequal reward combinations (e.g., 60 points left vs. 40 points right, see Fig. 4-3A) participants less frequently walked towards the side with higher rewards when a cross-over step was dictated by the step into the zone (χ^2 (1) = 6.55, *p* = 0.01, OR = 0.20, 95 % CI [0.07, 0.63]).

Similarly, for the equal reward combination (50 points left/ 50 points right, see Fig. 4-3B), participants walked significantly more often than chance towards the side enabling a lateral step dictated by the step into the zone (Z = 7.41, p < 0.001, OR = 3.81, 95 % CI [2.67, 5.43]). The different time constraints did not moderate the preference to walk towards the side enabling a lateral step, neither for unequal rewards (χ^2 (1) = 0.01, *p* = 0.90, OR = 1.07, 95 % CI [0.36, 3.17]) nor equal rewards (χ^2 (1) = 0.78, *p* = 0.38, OR = 0.83, 95 % CI [0.55, 1.24]). Additional model specifications and other estimations not related to the stepping strategy are presented in the SI (see Appendix Table 8-1 and Table 8-2).

To summarize, the results of Exp. 2 showed that the step into the zone and consequently the immediate body state at the time of reward information presentation influenced the value-based decision. Participants more frequently walked towards the side which afforded a lateral step and avoided the side of a costlier cross-over step even at the expense of receiving less reward. This result confirms that the dynamic action costs of the immediate body state are integrated into the decision, as proposed by action-based models (Wispinski et al., 2020) and the embodied choice (Lepora & Pezzulo, 2015) framework.

Despite showing that dynamic action costs are integrated into the decision, Exp. 2 was not designed to address the second main question of our study regarding the time course of action cost integration in value-based decisions. Therefore, in Exp. 3, next to the late presentation of reward information administered in Exp. 2, we systematically added two earlier time points of displaying the reward information during walking that potentially allowed participants to anticipate the final body state dictating the lateral or cross-over step. If the immediate body state at the time of reward presentation (and not the anticipated body state) affects the value-based decision, then the immediate body state should predict the final stepping direction independent of whether the immediate and anticipated body states were congruent or incongruent, even when resulting in lower rewards at higher action costs.

4.2.3. The anticipated rather than the immediate body state influenced decision-making

To examine the time course of action cost integration in value-based decisions, in Exp. 3 the rewards were displayed at three different time points: the touch-down of the last step (identical to Exp. 2), the second-last step, and the third-last step before stepping into the zone. Because in Exp. 2 participants predominantly made four steps until reaching the zone, these time points corresponding to their first, second, and third step after initiating each trial (see methods for how we ensured the four steps criterion). As a result, the different steps (i.e., immediate body states) at the time of reward presentation would differently affect lateral vs. cross-over stepping strategies. For instance, a third step making touch-down with the left foot, thereby enacting a corresponding swing with the right leg for the final touch-down in the designated zone, would consequently lead to a lateral step to the left (see Exp. 2). In contrast, a second step making touch-down with the right foot, thereby enacting a corresponding swing with left leg, would lead to a lateral step to the right. It follows that if the immediate body states accounted for a lateral vs. a cross-over stepping strategy, these would be different if predicted by the second step vs. the third step (see the previous example). However, if participants' decisions were influenced by the anticipated body state when stepping into the zone, the direction of this effect should be independent of the time point and step (i.e., immediate body state) at which the rewards were presented. Note that such an anticipatory strategy may also be effectuated by means of stepping behavior adaptations, thereby reducing the influence of the body state on decisions. Consequently, Exp. 3 allowed us to differentiate between the integration of the dynamic action costs of immediate vs. anticipated body states (see Fig. 4-4A and Fig. 4-4B), and hence to scrutinize the time course of dynamic action cost integration.

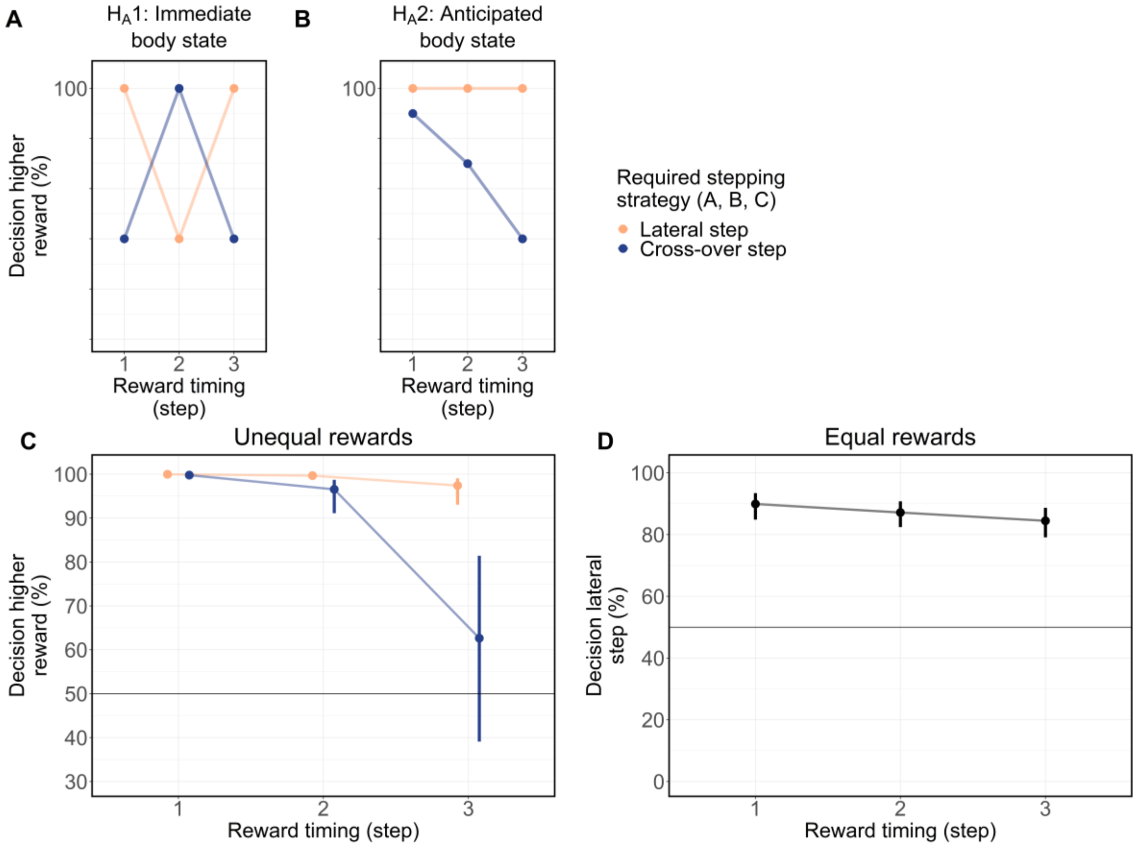

Fig. 4-4. Alternative hypothesis and results for the influence of the stepping strategy and the timing of reward presentation on decision-making in Exp. 3. Reward timing (step) refers to the first (earliest presentation), second or third step after trial start. A) Predicted results if the immediate step at reward presentation influences decisions. B) Predicted results if the anticipated step into the zone influences decisions. C) Estimates and 95 % CI for decisions with unequal rewards (e.g., 60 vs. 40 points). Participants walked more often to the side displaying lower rewards when a cross-over step was required., independent of the time to finish the task. This effect descriptively increased when rewards were displayed later. D) Estimates and 95 % CI for decisions to walk to the side enabling a lateral step for equal rewards (50 vs. 50 points). Participants went more often than chance level towards the side which enabled a lateral step. The frequency to walk towards the side enabling a lateral step decreased when rewards were presented later.

As illustrated in Fig. 4-4C, for unequal reward combinations, independent of the time the reward information was presented, participants less frequently walked towards the side with higher rewards when a cross-over step was required by the final (anticipated) step into the zone (χ^2 (1) = 24.61, p < 0.001, OR = 0.07, 95% CI = 0.02 – 0.20). Likewise, for the equal reward combination (see Fig. 4-4D), participants walked significantly more often than chance towards the side enabling a lateral step that was dictated by the anticipated step into the zone (Z = 10.96, p < 0.001, OR = 6.91, 95 % CI [4.89, 9.76]). Together, these two findings support the hypothesis that the anticipated and not the immediate body state influenced decision-making (Fig. 4-4B).

Given that, in addition, the interaction between reward presentation and required stepping strategy also almost attained significance for unequal reward combinations (χ^2 (2) = 5.03, p = 0.08, first step vs. second step: Z = -0.99, p = 0.32, OR = 0.58, 95% CI [0.20, 1.69], second step vs. third step: Z = -1.72, p = 0.09, OR = 0.45, 95% CI [0.18, 1.12]), we argue that the effect of the anticipated body state on decision-making was likely effectuated by means of step adaptations (see Fig. 4-4C). To test this, in a subsequent step we analyzed whether participants (i) adapted the number of steps (see Fig. 4-5A and Fig. 4-5B) and (ii) the foot placement (location and orientation, see Fig. Fig. 4-5C and Fig. 4-5D) of the step into the zone (Rebula et al., 2017) when the rewards were displayed early. Additional model specifications and other estimations not related to the stepping strategy are presented in the SI (see Appendix Table 8-3 and Table 8-4).

4.2.4. Participants adapted their stepping behavior when rewards were displayed early

As illustrated in Fig. 4-5A, participants indeed adapted the number of steps more frequently the earlier the rewards were presented (χ^2 (2) = 27.19, p < 0.001). This was true for the difference between the second step and the first step (Z = -4.12, p < 0.001, OR = 0.33, 95 % CI [0.20, 0.56] as well as the third step and the second step (Z = -2.69, p = 0.007, OR = 0.40, 95 % CI [0.21, 0.78]).

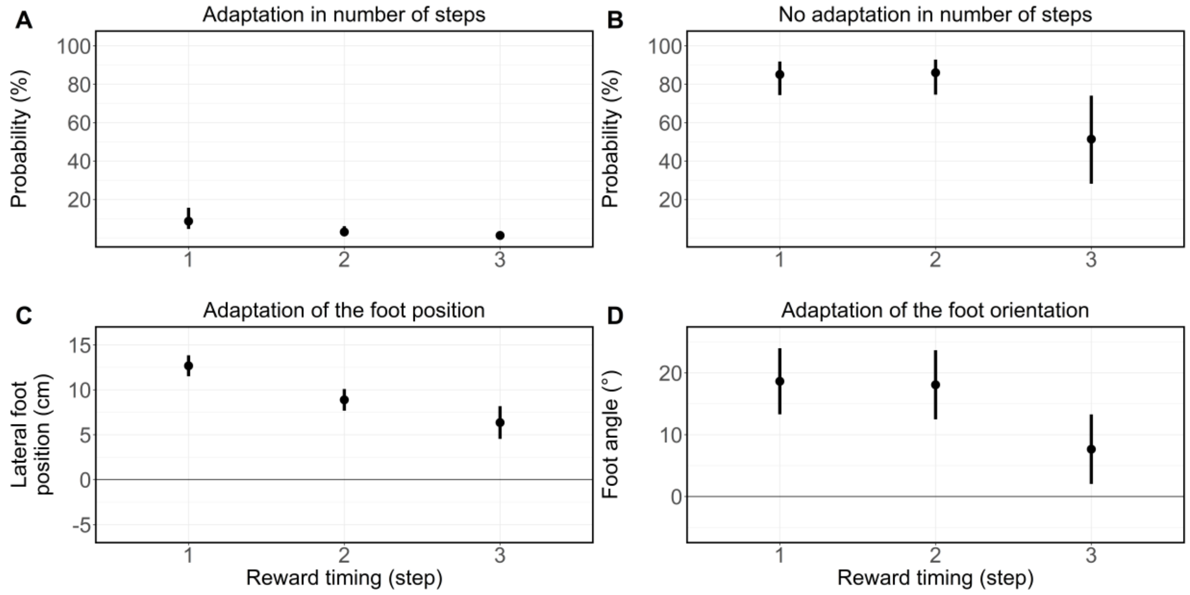

Fig. 4-5. Adaptation of stepping behavior for different timings of the reward presentation. Illustrated are only trials in which participants received higher rewards and – to achieve those – the regular four steps would have led to a cross-over step. Displayed are the estimates and 95 % CI for individual (generalized) linear mixed models. A. Probability that participants adapted the number of steps (three or five steps instead of four) to change the step into the zone and enable a lateral stepping strategy when walking towards the side with a higher reward. The probability of adaptation decreased the later the rewards were shown. B. Probability for cross-over steps to walk towards the side with higher rewards. The frequency of cross-over steps decreased particularly between the reward presentation at the second and third steps. The probability of cross-over steps was notably higher compared to the probability of adaption of the number of steps to enable a lateral step (see Fig. 4-5A). C. Side independent lateral foot position (marker at the lateral malleolus) for the step into the designated zone. Only trials where the final step into the zone required a cross-over step were included (see Fig. 4-5B). Positive values indicate a foot positioning towards the side participants finally walked to. D. Side independent foot orientation for the step into the designated zone. Only trials where the final step into the zone required a cross-over step were included (see 5B). Positive values indicate orientations towards the side participants finally walked to.

However, given that participants seemingly preferred to not adapt the number of steps when going for the higher reward by maintaining a cross-over step (see Fig. 4-5B), we further analyzed whether foot placement adaptations when stepping in the designated zone facilitated this stepping strategy. Participants indeed placed the foot further to the side they decided to walk to the earlier the rewards were presented (χ^2 (2) = 47.88, $p < 0.001$, first step vs. second step: t = -9.86, p < 0.001, estimated difference = -3.79 cm, 95 % CI [-4.55 cm to -3.04 cm], second step vs. third step: t = -3.11, p = 0.002, estimated difference = -2.53 cm, 95 % CI [-4.12 cm to -0.93 cm], see Fig. 4-5C). Additionally, they oriented (i.e. pointed) the foot further towards the side they decided to walk to when rewards were presented earlier than the latest time point, (χ^2 (2) = 14.98, $p < 0.001$, first step vs. second step: t = -0.40, p = 0.69, estimated difference = -0.57°, 95 % CI [-3.32° to 2.18°], second step vs. third step: t = -4.23, p < 0.001, estimated difference = -10.43°, 95 % CI [-15.26° to -5.60°], see Fig. 4-5D). Together, these results indicate that participants sometimes adapted the number of steps and far more often – when they did not adapt the number of steps – changed the foot placement (location and orientation) of the step into the zone when the rewards were displayed early.

To conclude, with earlier reward presentations participants adapted their stepping behavior to receive higher rewards. This provides additional (and perhaps more fine-grained) evidence for an effect of the anticipated body state on decision-making, thereby supporting the idea that dynamic action costs affect the value-based decisions (Cisek, 2007; Lepora & Pezzulo, 2015; Wispinski et al., 2020; Wunderlich et al., 2009).

4.3. Discussion

The embodied choice framework (Lepora & Pezzulo, 2015) and action-based models (Cisek, 2007; Wispinski et al., 2020; Wunderlich et al., 2009) predict that action dynamics of concurrent movement are part of the decision process. To test this prediction, we first examined whether the action dynamics of walking, a complex whole-body motor behavior, affect value-based decision-making. In a second step, we scrutinized the time course of action cost integration.

Prior to addressing the first aim, we developed and validated our experimental paradigm by elucidating the preference for stepping strategies within sequential decisions (Exp. 1). In line with previous findings, we predicted a preference for the lateral rather than the cross-over stepping strategy (Moraes et al., 2007; Moraes & Patla, 2006; Patla et al., 1991). Results confirmed this prediction, thereby indicating that cross-over steps are indeed costlier than lateral steps in our setup.

To address the first aim, Exp. 2 was then designed to investigate the integration of the immediate body state and associated action dynamics into the decision process by presenting the reward information so late that the immediate body state would necessarily dictate the subsequent lateral or a more costly cross-over step. Indeed, the immediate body state influenced the value-based decision: That is, participants walked more frequently towards the side which enabled a lateral step and avoided the side of a costlier cross-over step even at the expense of receiving less reward. In keeping with research on reaching (Bakker et al., 2017), this finding seems to confirm that the dynamic action costs of the immediate body state are part of the decision process, thereby substantiating predictions of action-based models (Wispinski et al., 2020) and the embodied choice framework (Lepora & Pezzulo, 2015).

Subsequently, in Exp. 3 we replicated Exp. 2 and further aimed at scrutinizing the time course of action cost integration in value-based decisions by systematically manipulating the time points of displaying the reward information during walking. This manipulation allowed us to disentangle the influence of the immediate vs. anticipated body states on decision-making. Results showed that, in contrast to research with passive movement on reaching (Bakker et al., 2017), the anticipated body state influenced decision-making: first, participants less frequently walked towards the side with higher rewards when a cross-over step was required by the final (anticipated) step into the zone independent of the time point of reward presentation. Second, in the case of walking towards the side with higher rewards, participants tended to adapt their action dynamics based on the (anticipated) body state that would finally facilitate this decision. This adaptation effect showed the earlier the rewards were presented.

Our findings provide first evidence that whole-body action dynamics affect value-based decisions, thereby on the one hand extending research on sequential decision-making in which cost and reward information are available before an action is initiated (Cos et al., 2011; Hagura et al., 2017; Hartmann et al., 2013; Klein-Flugge et al., 2015; Solomon, 1948). On the other hand, our findings also extend previous research that examined the effect of action dynamics on decision-making in (manual) reaching or finger tracking tasks (Bakker et al., 2017; Burk et al., 2014; Michalski et al., 2020), by showing that the impact of dynamic action cost on value-based decision-making translates to whole-body motor behaviors such as walking.

While we were able to show that action dynamics and their associated costs affect value-based decisions, future research needs to identify and further specify the nature of action costs. We deem it likely that biomechanical costs (Moraes & Patla, 2006) as well as stability costs (Moraes et al., 2007) associated with walking play a major role in action dynamic integration in decision-making, it is also conceivable that other costs such as cognitive costs, including switching motor plans (Jax & Rosenbaum, 2007; Kool et al., 2010), temporal discounting (Green et al., 1997) or weighting risks (Mishra, 2014). See information about the time to finish and task success in the Appendix Chapter 8.1.

Finally, Exp. 3 revealed that participants integrated the anticipated body state into their concurrent action planning and execution, thereby possibly reducing their action costs. More adaptation of action dynamics was observed the more time there was (i.e., the earlier the rewards were displayed) to implement the decision. The observed adaptation rules out that participants delayed their decision to the last step, thereby specifying the time course of action cost integration.

Next to revealing that adaptation was dependent on the time of reward presentation, Exp. 3 also showed that the effect of the anticipated body state on the decision trended to be dependent on the time of reward presentation. In other words, and as illustrated in Fig. 4-4C, this effect of the anticipated body state on decision-making diminished the earlier the reward information was presented, and hence the more time was given to adapt. We speculate that participants continuously update the anticipated body state and consequently have the opportunity to more effectively reduce the associated action costs the earlier the reward information is provided. There are some limitations that need to be addressed in future research. In our study, the effect of body state showed relatively large variations between participants for unequal rewards (see standard deviation of the required stepping strategy in the Appendix Table 8-1 and Table 8-3 and Appendix Fig. 8-1B and Fig. 8-1C). We speculate that perhaps different levels of physical activity and/or motivational factors might explain part of the variance. In addition, it is noteworthy that some participants even demonstrated ceiling effects for unequal rewards, especially in Exp. 2 and with early reward presentations in Exp 3. That is, some participants always walked towards the side with higher reward, and some participants almost exclusively walked towards the side with lower reward when a cross-over step was required. This generates no effect for participants with a ceiling effect and comparatively high odds ratios for the latter kind of participants. As we used a mixed model with participants as a random effect, this led to high shrinkage of the estimates for participants with comparatively high odds ratios towards the population estimate, thereby resulting in values close to 100 % (see Fig. 4-3A and Fig. 4-3B). We suggest that the ceiling effects could arise because of our fixed level of difficulty between participants. To avoid ceiling effects in future studies, the difficulty of the task or cost difference of the body state could be individualized (e.g., varying time constraints for individuals, scaling the setup based on participants' height, physical activity, or constraining the required step placement when making a directional change).

Finally, in our experiments, rewards were presented by means of points, and the motor behavior was constrained by stepping into a designated zone before bypassing the obstacle. It follows that future studies may look into different kinds of rewards and choices (e.g., monetary reward, subjective preferences for goods, performance-related choices in sports, perceptual decisions) and do so while putting less constraints on participants' motor behavior. Likewise, there are a plethora of other factors that may moderate the subjective value of choices in daily behavior, such as the cultural embedding (de Mooij & Hofstede, 2011), emotional states (Lerner et al., 2015), and age (Fischhoff & Broomell, 2020). Therefore, we recommend examining these and other potentially moderating factors to test whether our results prove robust and generalizable to other commonplace real-life situations.

To conclude, here we provide initial evidence that whole-body action dynamics during ongoing movement affect value-based decision-making. This finding may generalize to many daily situations including when walking down the aisle in the candy section and deciding which snack to go for.

4.4. Methods

4.4.1. Participants

Participants were recruited via a mailing list of the psychology department, and billboard postings at the sports science department at the Friedrich Schiller University Jena. Participants were compensated with payment (10,00 €/ hour) independent of their overall performance. Each participant attended only one experiment. We based our sample size on prior studies with decision-making as a binary outcome variable (Bakker et al., 2017; Burk et al., 2014; Hartmann et al., 2013; Michalski et al., 2020). Participants provided written informed consent before experimentation. The study was carried out following institutional guidelines. All experiments were approved by the ethics committee of the Faculty of Social and Behavioral Sciences of the Friedrich Schiller University Jena. Table 4-1 provides demographic information about the sample used in Exp. 1 to Exp. 3.

Table 4-1. Demographic information. We used the Edinburgh Inventory (Oldfield, 1971) to classify participants' handedness and the Lateral Preference Inventory (Coren, 1993) for footedness. Additional analyses (available in the public depository online) indicated that neither footedness nor handedness shifted (i.e., affected) participants' overall side preference or effect of the body state in Exp. 2 and Exp. *3.* f = female, m = male, r = right, le = left, n = no preference, md = missing data.

	Exp. 1	*Exp. 2*	*Exp. 3*
Sex	16 f, 20 m	15 f, 22 m	19 f, 16 m
Age (mean ± SD)	21.8 ± 2.4 years	22.6 ± 2.5 years	22.5 ± 3.0 years
Handedness	31 r, 4 le, 1 n	32 r, 1 le, 0 n, 4 md	31 r, 0 n, 4 le
Footedness	31 r, 2 le, 3 n.	30 r, 2 le, 4 n, 1 md	27 r, 2 le, 6 n

Experiment 1

Thirty-six healthy adults were recruited. All participants were included in the final data analysis.

Experiment 2

Forty-one subjects were recruited. Overall, four participants had to be excluded from further analyses. For two participants the reward signal was displayed too late in most trials because of a long stride. One participant was removed because the instruction was not properly understood. Another participant was removed because the same foot stepped in the designated zone in every trial, making a comparison between left and right impossible. The remaining thirty-seven participants were analyzed.

Experiment 3

Fifty-four participants attended Exp. 3. In contrast to the second experiment (see data analysis), participants more frequently changed the number of steps in the neutral reward condition when the rewards were presented one step before the designated zone (19/54 participants). As it is not possible to predict the step into the designated zone when the number of steps varies in this chosen *baseline* condition, this subgroup was excluded from further analyses. Thirty-five participants remained.

4.4.2. Apparatus and Stimulus

Fig. 4-1 displays the general setup and dimensions of the experiments. Dimensions from the start to the obstacle and targeted desks were derived from van der Wel and Rosenbaum (2007). On each desk (height = 0.73 m) a 22’’ screen (Asus VW222U) was positioned for the visual display of reward and feedback after the trial. Each screen displayed numerical points in the center with a white font on a black background. In Exp. 1, rewards were displayed immediately after a trial was initiated, and before participants started walking. In Exp. 2 and Exp. 3, both monitors first alerted the participants to prepare for the upcoming trial by displaying the German word for ready ("Bereit"). Additionally, the displays indicated the starting position for the feet via two shifted zeros (i.e., a higher zero on the left indicated that the left foot had to be in front of the right foot before starting a trial and vice versa). After the trial was initiated, both monitors displayed a go signal in the form of a "+" in the center of the screen. The go signal was replaced by the point combination while participants were walking towards the obstacle. After completion of a trial, the temporal feedback of the trial was displayed below the reward feedback (i.e., awarded points).

A black protective grating was used as an obstacle (HWC-B34, height = 1.03 m). Black tape was used as a mark on the floor and on the desk to provide orientation for the start area, the designated zone in front of the obstacle, and the position of the hand to finish a trial (see Fig. 4-1). Gait behavior was recorded by a 3D infrared system (Prime 17W, Optitrack, Corvallis, US) with eleven cameras (120 Hz). Participants wore self-brought non-reflective running shoes during the experiment and a tight-fitting top for the placement of the reflective marker on the body.

4.4.3. Procedure

After providing informed consent and demographic information, nine reflective markers (12 mm) were placed on the lateral malleolus, heel, between the first and second metatarsal head and dorsum of the hand on both body sides as well as the fifth lumbar vertebrae. Subsequently, participants were given instructions.

Experiment 1

Before a trial began both feet had to stand in parallel at the starting line (see Fig. 4-1). Participants initiated a trial by bringing their hands close together (i.e., clapping) and subsequently rewards were displayed for both sides. Participants were instructed to collect rewards and to pick a side before starting to walk towards the obstacle. They were further instructed that they had to step into the designated zone in front of the obstacle and bypass it to get to the desk on which the chosen reward was displayed. A trial was completed by touching a mark on the desk. If the participant had at least one foot in the designated zone during the trial, the chosen reward was displayed in green, otherwise in red. After the trial participants walked back to the starting line and began with the next trial. For the reward, nine different reward combinations (i.e., point combinations) could be displayed (left/right: 20/80, 30/70, 40/60, 45/55, 50/50, 55/45, 60/40, 70/30, 80/20). Both rewards always summed to 100, so that the reward on the left side could be inferred based on the reward on the right side and vice versa. Each participant began the experiment with five familiarization trials followed by 135 trials (9 reward conditions, each condition containing 15 trials). All trials were randomized within participants. Unintentionally, the randomization seed was not altered in the first experiment for most participants (31/36 participants), which means that the order of trials was random within but mostly the same between participants. The experiment lasted approximately 50-60 minutes.

Experiment 2

The procedure was similar compared to the first experiment, but at the start of the trial, the starting position was predetermined and instructed, a time constraint to finish the task was added, and the reward was displayed when participants were already close to the obstacle. Participants were instructed to get into the indicated starting position (left or right leg in front) before self-initiating a trial. At this time point, the timing of the trial started, and the go signal appeared. Participants were asked to walk towards the obstacle and were told that the reward combination would appear during their way to the designated zone in front of the obstacle. The goal was again to collect the reward by touching the mark on one of the desks within a time constraint (4 s or 6 s). The time conditions of 4 s and 6 s were based on the speed preferences observed in Exp. 1 (m = 4.9, sd = 0.6 s). 6 s was easily achievable for all subjects, while 4 s was faster compared to the preferred time in Exp. 1, thereby inducing time pressure. At the end of the trial, the reward changed color, and time feedback was displayed on the chosen side. If the time constraint was not met, the color was displayed red, and participants received no reward for this trial. If the foot at the touch-down (see data analysis for the definition of touch-down) was not completely positioned in the designated zone, the reward color was yellow and participants received the reward, but they were encouraged to make sure to fully step into the designated zone in future trials. If both conditions were met, the reward color was green, and points were awarded. After the feedback participants walked back to the starting position and began the next trial. The different reward combinations with a higher reward on one side had similar effects on the lateral decision in Exp. 1. Therefore, in Exp. 2 only five different reward combinations were displayed (left/right: 20/80, 60/40, 50/50, 60/40, 80/20). The experiment was divided into two blocks for the time conditions (4s or 6 s to finish the task). The order of the blocks for the time conditions was counterbalanced across participants. Before each block 20 familiarization trials were performed, 10 without time evaluation and 10 with time evaluation. Each block consisted of 100 trials (5 reward combinations x 2 starting positions x 10 trials per condition). Overall, 240 trials were completed in one session of about 80-90 minutes. After the first block, participants had a one-minute break. Reward combinations and starting positions were randomized between trials.

Experiment 3

The procedure was almost the same as in Exp. 2. All trials were performed in the 4 seconds time constraint condition. The timing of the reward display was either after the first, second, or third touch-down (i.e., step making ground contact). Different reward combinations with a higher reward on one side had similar effects on the lateral decision in Exp. 2. Therefore, in Exp. 3 only three different reward combinations were displayed (left/right: 40/60, 50/50, 60/40). After the instruction, participants started with 18 familiarization trials, 9 without timing evaluation, and 9 with timing evaluation. The experimental session consisted of 180 trials (3 reward combinations x 3 timings of the reward x 2 starting positions x 10 trials per condition) and lasted around 60 minutes. After 90 trials participants had a one-minute break. All conditions were randomized between trials.

4.4.4. Real-Time analysis

To identify the start, the success of stepping in the designated zone, and the completion of a trial in real-time, the position of the tracked marker was streamed from Motive 2.1.1 (Optitrack software interface) with the NatNet SDK to a self-written written MATLAB 2018a script (The Mathworks, Inc., Natick, MA, USA). A trial started, when the distance between two markers in the expected hand area was below 15 cm. Additionally, in Exp. 2 and Exp. 3, the malleolus marker of the correct foot had to be 20 cm in front of the other foot. To prevent an early launch, the displacement of the calcaneus marker between two consecutive frames had to be below 2 mm when the trial was started by bringing the hands together.

The assignment of marker positions to body parts was achieved by utilizing the standardized starting position at the start of the trial. The positioning of hand markers was assumed to be in front of the L5 marker, the toe markers were in front of the heel marker, left body parts were more to the left, and so forth. The body-specific marker ID given by the Motive software was used for the assignment of markers for the rest of the trial. In rare cases, this ID changed because of the occlusion of a marker. When a relevant marker was missing because of a wrong assignment before reward feedback was displayed, the trial was repeated. To check if participants stepped into the designated zone and for the timing of the reward presentation in Exp. 2 and Exp. 3, the touch-down of every step was calculated as the maximal horizontal displacement of the heel marker of the swing foot and the malleolus marker of the stance limb (Banks et al., 2015). To ensure only one maximum and touch down per step, after each maximum further analysis was skipped for 20 frames (0.167s). In Exp. 2 we aimed to present the rewards one step before stepping into the designated zone. To do so, rewards were presented when the malleolus marker exceeded the 1.84 m distance from the starting line at touch-down. In Exp. 1, a step exceeding 1.84 m was in 97 % the last step before stepping into the zone. In Exp. 3, we aimed to present rewards one step, two steps, or three steps before stepping into the zone. In Exp. 2 participants mainly made four steps with a 4 s time constraint. Therefore, rewards were displayed at the touch-down of the first, second, or third step in Exp. 3.

To test if the participant stepped into the designated zone, the position of the foot markers at every touch-down was compared with the area of the designated zone. All foot markers of the corresponding foot had to be in the designated zone. The trial was completed when a hand marker exceeded the horizontal position of the table marker at the beginning of the table and the hand marker was below 10 cm over the vertical height of the desk. The time between the start and end of the trial was used as time feedback after the trial.

We analyzed the lag of display for three pilot sessions. The frame of the touch-down was compared with the frame the display switched towards the reward stimulus with a synchronized reference camera. The lag between TD and display of the reward was consistent within one frame across trials and sessions (63 ± 7 ms, n = 32).

4.4.5. Data Analysis

Data preparation of kinematic data was accomplished using a self-written MATLAB 2018a code. The touch-down of every step was recalculated after the kinematic data were filtered at 12 Hz with a bidirectional fourth-order low-pass Butterworth filter. The foot stepping in the designated zone was identified as the first touch-down of a lateral malleolus marker into the designated zone (0.6 m in front of the marker at the obstacle, 0.3 cm towards both sides). The number of steps towards the obstacle was evaluated as the number of touch-downs until the step in the designated zone occurred. All touch-downs were double-checked by a second algorithm which was based on the relative velocity of both feet. As walking has a double stance phase with both feet on the floor, a step onto the ground should also be found by a minimum of the relative velocity of both malleoli markers. If there was an incongruence between both touch-down algorithms, the number of steps and step into the zone was visually checked and the algorithm with the correct values was picked. The positioning of the L5-marker in the y-axis at the end of the trial was used for assigning the lateral decision. Statistical analyses were performed with R (R Core Team, 2019). All conditions were repeated measures over subjects. For the analyses of the dichotomous outcome of the lateral choice in each Experiment, a generalized linear mixed model (GLMM) was fitted with the glmer function of the lme4 package (Bates et al., 2015). To account for the non-independence of repeated measurements, random intercepts and slopes for participants were entered as random effects. At first, the full random effect structure was fitted (random intercept, slope main effects, and all interactions). Because of convergence problems the full model was not acceptable for further analyses in most cases. If the model did not converge, we reduced the random effect structure by excluding random slopes each at a time, which were not relevant for our hypothesis, until the model converged (Barr, 2013; Barr et al., 2013; Brauer & Curtin, 2018). Inference for the fixed effects was based on likelihood ratio tests between the model with and without the predictor variable. For the confidence intervals of the estimations, the Wald intervals were used. All tests were two-sided.

Experiment 1

The influence of the predictor "Lateral decision" (factor with 2 levels: left, right, simple contrast) on the outcome "Foot in the designated zone" (binary outcome: left, right) was analyzed by fitting a GLMM.

Experiment 2

Trials were omitted if the 1.84 m boundary for the reward display was not reached before stepping into the designated zone (overstepping, rewards were displayed too late). Two participants did this regularly (> 90 % of trials) and were excluded from further analyses. Five individual trials were excluded because of problems with marker identification in the real-time analyses. After exclusion of trials and participants, a total of 7148 out of 8200 trials (i.e., 87.2 %) entered statistical analyses.

In Exp. 2 five reward combinations were displayed. To reduce model complexity, we reduced the number of reward combinations to two levels, that is unequal reward combinations (e.g., 60/40 for the left/right side) and equal reward combination with no reward difference (50/50 for the left/right side). The unequal reward combinations were merged by mirroring the decision (left = right, right = left) and step into the zone (left = right, right = left) for reward combinations with more reward on the left side (80/20 and 60/40). After mirroring, the meaning of the "Decision" and "Step in the zone" variable changed (decision: right = side with higher reward, left = side with lower reward; step in the zone: left = lateral stepping required to get towards the side with higher rewards, right = cross-over step required to get to the side with lower rewards).

For the statistical analysis of unequal rewards, the influence of the "Required stepping strategy" (factor with 2 levels: lateral or crossover step, simple contrast) and "Time constraint" (factor with 2 levels: 6 s and 4 s, simple contrast) and their interaction on the decision (binary outcome: higher reward, lower reward) was analyzed by fitting a GLMM. The requirement of a lateral step was defined as the step into the zone being incongruent to the side with higher reward (e.g., a left step into the zone and higher reward for the right target). The requirement of a cross-over step was defined as the step into the zone being congruent to the side with higher reward (e.g., a left step into the zone and higher reward for the left target).

For the statistical analysis of equal rewards, the influence of “Time constraint” (factor with 2 levels: 6 s and 4 s, simple contrast) on the decision to walk towards the side requiring a lateral step (binary outcome: yes, no) was analyzed by fitting a GLMM. For equal rewards requirement of a lateral step was defined as the step into the zone being incongruent to the side of the decision (e.g., a left step into the zone and walking towards the right target). The requirement of a cross-over step was defined as the step into the zone being congruent to the side of the decision (e.g., a left step into the zone and walking towards the left target).

Experiment 3

In Exp. 2, 31 out of 37 participants predominantly made four steps before stepping into the designated zone (mean = 98.8 %, sd = 0.02 %). In Exp 3, the reward stimulus was supposed to be presented three steps, two steps, or one step before entering the designated zone. Therefore, we decided a priori to exclusively analyze participants who predominantly used four steps in the equal reward condition when the reward would be presented with the third step, like in Exp. 2. This criterion resulted in an unexpected exclusion of 19 out of 54 participants (based on k-means clustering with two clusters), who often did not use predominantly four steps before stepping into the designated zone (below 80 % of the trials).

In Exp. 3 only three reward combinations were displayed. Like in Exp. 2, unequal reward combinations were merged. For the statistical analysis of unequal rewards, the influence of the “Required stepping strategy” (factor with 2 levels: lateral or crossover step, simple contrast), “Timing of reward presentation” (factor with 3 levels: 1. Step, 2. Step, 3. Step, sliding difference contrast) and their interaction on the decision (binary outcome: higher reward, lower reward) was analyzed by fitting a GLMM.

For the statistical analysis of equal rewards, the influence of “Timing of reward presentation” (factor with 3 levels: 1. Step, 2. Step, 3. Step, sliding difference contrast) on the decision to walk towards the side requiring a lateral step (binary outcome: yes, no) was analyzed by fitting a GLMM. The definition of the required stepping strategies was the same as in Exp. 2.

Additionally, we analyzed adaptation strategies when participants starting position was in an unfavored body state (predicted cross-over step if participants would make the regular four steps) for getting towards the side the higher reward. First, participants could adapt their number of steps to change the body state when stepping into the designated zone, meaning that the step into the zone is not equal to the predicted step into the zone based on the starting position to make a lateral step towards the side with a higher reward. The influence of the “Timing of the reward presentation” (factor with 3 levels: 1. Step, 2. Step, 3. Step, sliding difference contrast on the binary outcome “Adaptation of the number of steps” (yes/no) was analyzed by a GLMM.

Second, they could make a crossover step and not adapt their stepping behavior to get to the side with a higher reward. For trials in which participants did a cross-over step the lateral positioning and orientation of the foot stepping into the zone were analyzed. For the lateral position, the malleolus marker of the foot stepping into the zone was used. The orientation was defined as the angle between the line of the global y-direction (in walking direction) and the vector spanning between the heel marker and the toe marker in the x-y-plane (lateral direction, walking direction). Foot position and orientation were analyzed with individual linear mixed models with the procedure used for GLMMs. Side-specific effects (left/right) were neutralized by merging over cross-over steps towards the left and right side and taking the negative for cross-oversteps towards the right side. The outcome position and angle (continuous scale) were predicted by the factor “Timing of reward presentation” (factor with 3 levels: 1. Step, 2. Step, 3. Step, sliding difference contrast).

Chapter 5

Embodied decisions during walking

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Abstract

Research on embodied decision-making only recently started to examine whether and how concurrent actions influence value-based decisions. For instance, during walking humans preferably make decisions that align with a turn toward the side of their current swing leg, sometimes resulting in unfavorable choices (e.g., less reward). It is suggested that concurrent movements influence decision-making by coincidental changes in motor costs. If this is true, systematic manipulations of motor costs should bias decisions.

To test this, participants had to accumulate rewards (i.e., points) by walking and turning toward left and right targets displaying rewards across three experiments. In experiments 1a and 1b, we manipulated the turning cost based on the cur-rent swing leg by applying different symmetric turning magnitudes (i.e., same angles for left and right targets). In experiment 2, we manipulated the turning cost by administering asymmetric turning magnitudes (i.e., different angles for left and right targets). Finally, in experiment 3, we increased the cost of walking by adding ankle weights.

Altogether, the experiments support the claim that differences in motor costs influenced participants' decisions: experiments 1a and 1b revealed that the swing leg effect and stepping behavior were moderated by turning magnitude. In experiment 2, participants showed a preference for less costly, smaller turning magnitudes. Experiment 3replicated the swing leg effect when motor costs were increased by means of ankle weights.

In conclusion, these findings provide further evidence that value-based decisions during ongoing actions seem to be influenced by dynamically changing motor costs, thereby supporting the concept of "embodied decision-making".

New & Noteworthy Motor processes of concurrent movements have been shown to influence embodied decision-making. Itis hypothesized that this is driven by coincidental

changes in motor costs. We tested this claim by systematically manipulating motor costs of choice options during walking. In three experiments we show how variations in motor cost (e.g., turning angle or stepping constraints) bias decision-making, thereby supporting the concept of “embodied decision-making”.

5. Embodied decisions during walking

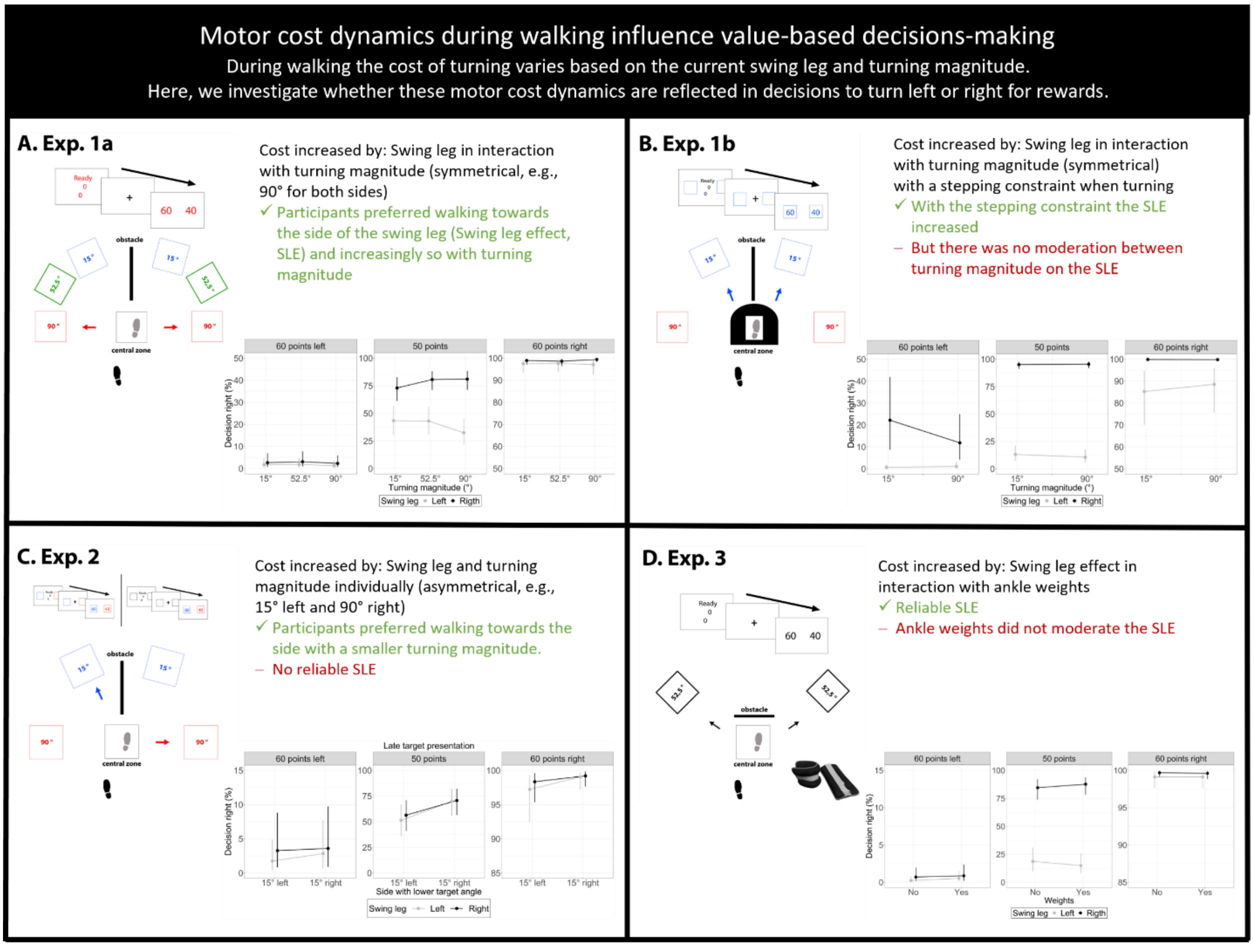

Fig. 5-1 . Graphical abstract

5.1. Introduction

Imagine being on a soccer field. You dribble the ball while approaching a defender. What will you do next? Should you try to get past the defender on the left or the right, or should you even pass the ball to one of your teammates?

As emphasized by embodied decision accounts, the decision is not merely driven, for instance, by the question of how big the expected values of rewards are (e.g., whether passing the defender on the left or right gets you in a better position to score) but also by the motor costs it takes to turn left or right (Cos et al., 2014; Hartmann et al., 2013). Obviously, if the defender is positioned further to the left, you may not choose to turn to the left side but turn toward the right side. However, while approaching the defender your position in regard to the defender constantly changes. Accordingly, if the angle to turn to one side increases/decreases, so do the motor costs (McNarry et al., 2017; Wilson et al., 2013), which may further discourage/encourage the choice to turn to that particular side. This example aims to illustrate that the decision to achieve a goal may be influenced by concurrent movements and concomitant changes in motor costs, a corollary put forth by advocates of embodied decision models (Cisek, 2007; Lepora & Pezzulo, 2015).

More specifically, action-based models of embodied decisions, like the embodied choice framework (Lepora & Pezzulo, 2015) or the affordance competition hypothesis (Cisek, 2007), argue that action and decision-making can mutually influence each other, hence not only allowing decision-making processes to command certain actions but also allowing action requirements that change as a function of time (action dynamics) to modulate decision-making processes. In contrast to classical decision-making models, which assume independent and sequential processing stages of decision-making and action (i.e., decisions are formulated as an abstract value comparison process that is independent of action, and action only starts after a decision has been made; see Refs. Newell & Simon, 1972; Wispinski et al., 2020), embodied decision models assume that actions influence decisions by parallel state-dependent feedback (Lepora & Pezzulo, 2015; Todorov & Jordan, 2002; Wispinski et al., 2020) or more directly that the decision process itself takes place as a biased competition between action representations (Cisek, 2007; Wispinski et al., 2020). Especially the latter case blurs the line between decision-making and action.

5. Embodied decisions during walking

From an empirical perspective, embodied decisions during ongoing movement have only recently started to be put under experimental scrutiny (Gordon et al., 2021; Yoo et al., 2021). The few existing studies have thus far mainly focused on the dynamic motor cost in decision-making (Grießbach et al., 2021; Marti-Marca et al., 2020; Nashed et al., 2014; Raßbach et al., 2021). For example, Nashed et al. (2014) asked participants to reach toward one of multiple lateral targets in their experiment 1b. While participants were reaching toward a chosen target, a noticeable lateral force was applied to the hand, displacing it from the reaching direction. Dependent on the strength of the displacement, participants rerouted their hand movement toward a now more suitable target. That is, a dynamic change of the body state, which affected the motor costs associated with each target, determined the selected target.

This finding provided initial evidence for the influence of action dynamics on motor decisions. However, it remained to be determined whether action dynamics influence decisions involving reward differences (e.g., the expected value of decisions in soccer, see introductory example; see also Rangel & Hare, 2010). To address this issue, Grießbach et al. (2021) aimed to analyze the influence of the dynamic motor costs during walking on reward-based decisions (for reaching, see also Cos et al., 2021; Marti-Marca et al., 2020). More specifically, during walking the alternating swing leg influences the motor cost of turning (He et al., 2018; Moraes et al., 2007; Taylor et al., 2005). A turn toward the side of the swing leg enables the participant to place the next step lateral to the side of the stance leg (e.g., left swing leg and a leftward turn, hereafter referred to as “lateral step”; see Fig. 5-2B).

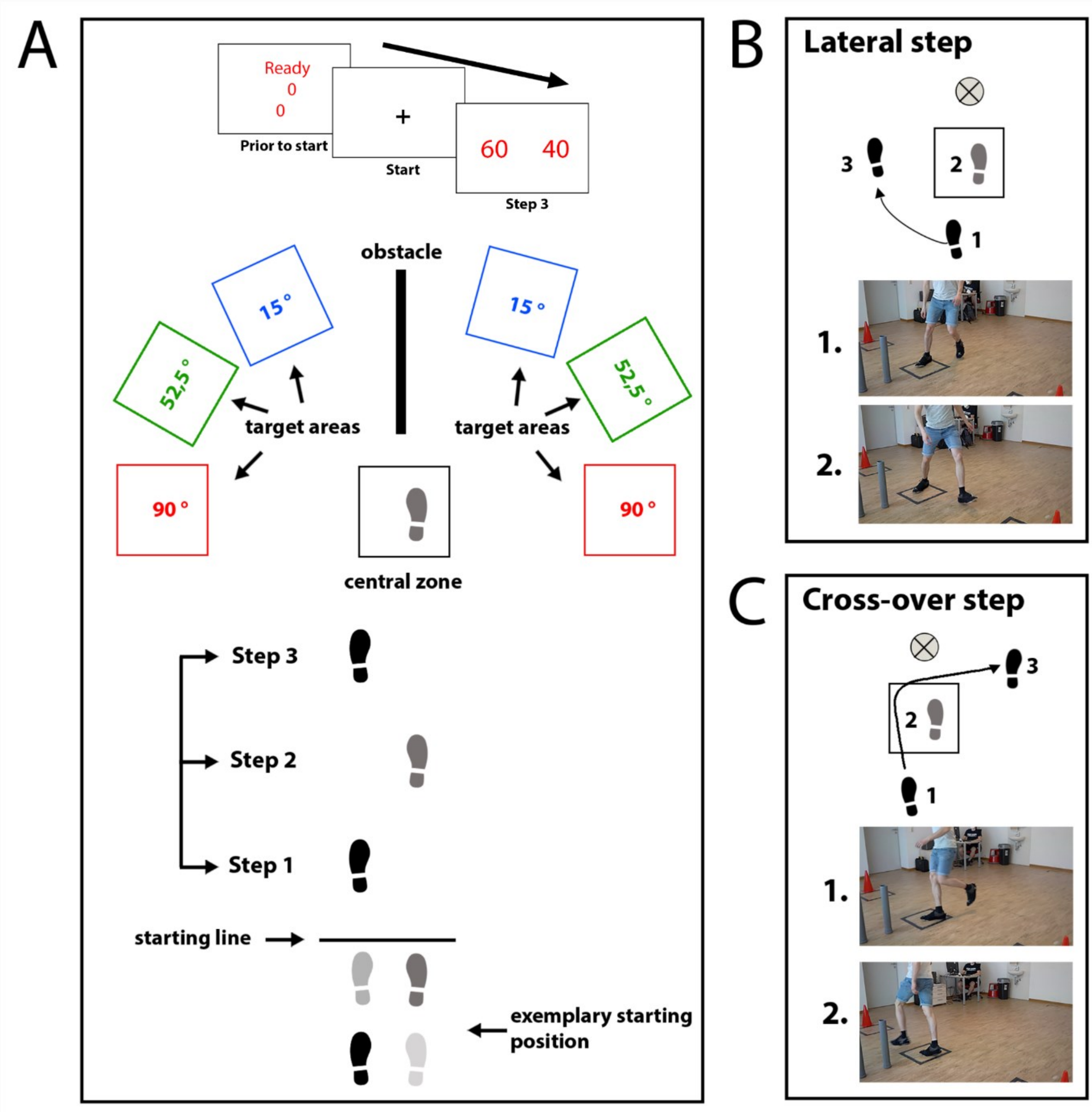

Fig. 5-2. Experimental setup of experiment 1a. A: Participants started by positioning their feet in the required starting position. The projection at the top shows the time course of cues. The starting position was displayed with a projector on the opposite side of the room (see top). The font color represented available lateral targets to finish a trial (here red, representing 90° targets). The German word "Bereit" was used in the experiment instead of "Ready" displayed here. After participants took the required starting position a "+" appeared as the Go signal and they walked toward the central zone. After the third step rewards appeared on the left and right sides of the screen. Participants had to step into the central zone and walk towards a target area to finish a trial and receive rewards. B: Example of a lateral step. Given that the right foot stepped into the zone and participants chose to walk to the left side, a lateral step can be taken. C: Example of a cross-over stepping strategy. Given that the right foot stepped into the zone, we assumed participants to make a cross-over step towards the right side.

A change opposite to the swing leg requires crossing the stance leg (e.g., left swing leg and rightward turn, hereafter referred to as "crossover step"; see Fig. 5-2C). People generally prefer to turn toward the side enabling a lateral step (Akram et al., 2010; Patla et al., 1991). To investigate whether and when the concurrent movement of walking influences reward-based decisions (Grießbach et al., 2021), participants were instructed to walk toward a central obstacle and then bypass it to collect rewards at a left or right target (for a similar setup, see Fig. 5-2A). Before turning toward the left or right target, they had to step into a central zone in front of the obstacle. Rewards were displayed at various time points during walking. Results showed that participants preferred walking toward the side enabling a lateral step based on the current swing leg (hereafter referred to as “swing leg effect”). Independent of when the rewards were displayed (early vs. late), there was a preference to walk toward the side enabling a lateral step, even to the degree that fewer rewards were obtained. The preference for the lateral step indicated that the anticipated dynamic motor costs for whole body movements like walking influence value-based decisions.

Although Grießbach et al. (2021) as well as others (Marti-Marca et al., 2020; Nashed et al., 2014) argue that concurrent movement influences decision-making by coincidental changes in motor costs, more recent findings (Raßbach et al., 2021) indicate that concurrent movement could influence decision-making also by means of shared cognitive representations (e.g., spatial representations such as left, right, top, and down) causing cognitive cross talk, and not necessarily by the motor costs alone. This idea originates from findings of multitasking research where an action in one of two independent tasks can bias responses in the second task if both tasks dimensionally overlap (Hommel, 1998; Janczyk et al., 2014). Thus far, however, cognitive cross talk and motor cost dynamics have not, with very few exceptions (Aczel et al., 2018; Michalski et al., 2020; Raßbach et al., 2021), been differentiated experimentally in embodied decisions. Notably, it cannot be ruled out that the swing leg effect found in Grießbach et al. (2021) may have been driven by shared representations (i.e., cognitive cross talk resulting from the overlap between the mental representation of the swing leg and decision-making on the left-right dimension) rather than by action cost dynamics. Therefore, the present study aimed to examine the influence of cost dynamics independent of cognitive cross talk on decision-making by manipulating action costs of embodied decisions during walking. To this end, we extended the walking paradigm of Grießbach et al. (2021) by holding the concurrent movement (i.e., the swing leg) during decision-making constant and systematically manipulating the motor costs associated with each reward option. If the cost dynamics while walking influence participants' decisions, systematic manipulations of motor costs should be reflected in more or less biased decisions (see Fig. 5-3).

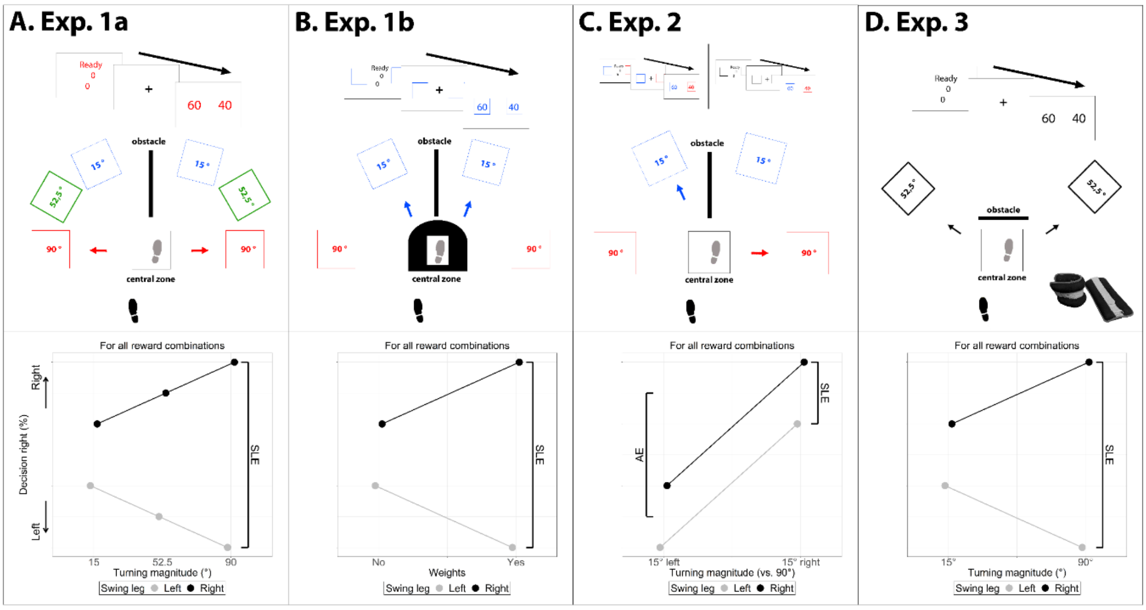

Fig. 5-3. Experimental setup and hypothesis plots for all experiments. A: experiment 1a displays the basic design used for the rest of the experiments. Bottom: the hypothesis of experiment 1a: we expected the swing leg effect (SLE) to increase with turning magnitude. B: based on the results of experiment 1a, in experiment 1b a stepping constraint was placed with carpet on the central zone. Additionally, only the 15_ and 90_ target angles were included and the cue for targets changed to rectangles on the sides (here blue for 15_ turning magnitude). For experiment 1b we had the same hypothesis as in experiment 1a, pictured at bottom. C: in experiment 2 the target angle could be asymmetric (here left 15_ in blue and right 90_ in red). The target angles were displayed either before participants started walking (top left, control condition) or with rewards in the third step (top right). Bottom: the hypothesis of experiment 2: we expected for both the early and more importantly the late target timing a preference to walk toward the side with a smaller turning magnitude (angle effect, AE), in addition to the SLE. D: In experiment 3 participants walked with and without ankle weights. Additionally, only 52.5_ turning magnitude and the same obstacle as in a prior study (14) were used instead of the cones. Bottom: the hypothesis of experiment 3: we expected the weights to increase the SLE.

One factor influencing costs while walking concerns the turning magnitude. First, for symmetric differences between left and right turns (e.g., 15° left and 15° right vs. 90° left and 90° right), the cost difference between a lateral step and a crossover step increases with turning magnitude (Taylor et al., 2005). Hence, we expected the swing leg effect to be moderated by symmetrically increased turning magnitudes (see experiment 1a and experiment 1b). Second, as smaller turns are less costly (McNarry et al., 2017; Wilson et al., 2013), we expected participants to prefer smaller turns while walking toward an asymmetric intersection (e.g., 15° left and 90° right; see experiment 2). Third, we manipulated the motor costs by administering ankle weights, expecting the swing leg effect to increase (see experiment 3).

5.2. Methods

5.2.1. Experiment 1a: Is the Swing Leg Effect Moderated by Turning Magnitude?

The crossover step is less stable and requires more muscular demands compared to a lateral step. One reason for the higher motor costs for crossover steps is that the center of mass must be placed outside the base of support of the foot for a short time (Moraes et al., 2007; Taylor et al., 2005). The displacement of the step outside the base of support increases with turning magnitudes for the crossover step, which is not the case for the lateral step. Indeed, the crossover step shows increasing motor demands for a 90° turn compared to straight walking, whereas the lateral step does not (Taylor et al., 2005). With the assumption that a crossover step approaches the energetic demands of straight walking when the turning magnitude decreases, it should become less difficult to make a turn with a crossover step versus a lateral step for smaller turning magnitudes.

Therefore, in experiment 1a we focused on the moderation of the swing leg effect by the required turning magnitude. We manipulated the angle between the left and right lateral targets symmetrically between trials (15°/52.5°/90° left and 15°/52.5°/90° right). The required turning magnitude was displayed before starting a trial. We hypothesized that participants would be biased to walk toward the side of the swing leg to avoid the crossover step. Additionally, if motor costs are responsible for the swing leg effect, we would expect an increasingly stronger swing leg effect with increasing turning magnitudes, 15°, 52.5°, and 90°, respectively.

5.2.1.1 Participants

Based on previous studies (Grießbach et al., 2021; Raßbach et al., 2022), we aimed for a sample size of 36 participants in the final analysis. For Exp 1a, we recruited 45 participants from local universities. To ensure a predictable timing of rewards and swing leg when changing direction, the experiment required to take four steps before stepping into the zone unbeknownst to our participants. Note that we chose not to explicitly prescribe four steps because such a prescription might have caused participants to change their spontaneous (i.e., natural/usual) walking behavior which in turn would diminish the ecological validity of our experiment. Five participants were excluded because they frequently violated the criterion to make four steps (> 59 %). This resulted in a final sample size of n = 40 (mean age 24.6, SD = 3.4, 23 females, 17 males, 38 right-handed, 2 missing data for handedness, 34 right-footed, 3 no preference, 2 left-footed). Participants were compensated 10,00 € after the experiment, independent of performance. All participants gave informed consent before starting the experiment. All experiments in the study were part of a research program that was approved by the ethics committee of the Faculty of Social and Behavioral Sciences of the Friedrich Schiller University Jena (FSV 19/04).

5.2.1.2 Apparatus and stimuli.

The experiment took place in a 5.90-m-long room (Fig. 5-2). The maximal distance from the starting line to the center of the central zone was 3.41 m. Black tape was used to mark the starting line, the central zone, and the lateral targets. All targets were 0.5 m x 0.5 m and in an arc with a 1.5-m distance from the central zone (from center to center). Colored cones (red, green, and blue) behind the lateral targets were used to mark the target areas and required turning magnitude for a given trial (15°, 52.5°, or 90°). To prevent participants from switching sides after the central zone, three pipes (radius = 3.7 cm, height = 55 cm) were placed as obstacles separating the left and right sides after the central zone (60 behind the center of the central zone and with 30 cm distance between obstacles). Stimuli were presented with a digital projector (NEC Corp., Tokyo, Japan; model M353WS, WXGA resolution, 60-Hz frame rate) placed on the ceiling over the central zone, projecting on a large screen facing the participant (2.92 m width x 1.83 m height). The screen was 1.80 m behind the center of the central zone. Stimuli were presented on a white background and could be either green, blue, or red, respectively (see Fig. 5-2). All stimuli were presented with a self-written script in MATLAB in real time based on the kinematic measurements (see Data analysis). Gait behavior was recorded by a three-dimensional (3-D) infrared system (Prime 17 W; OptiTrack, Corvallis, OR) with 12 cameras (120 Hz) and passive reflective markers (12 mm) placed on the lateral malleolus and heel and between the second and third metatarsal head of both feet. Starting position and the time constraint were scaled individually for each participant (Supplemental Material; see Appendix). Participants received auditory feedback indicating whether they finished in time after each trial. Auditory feedback was a beep (750 Hz for 0.8 s) or a double beep (750 Hz, 2 times for 0.3 s with 0.2-s pause between) with the integrated speaker of the projector and a sampling rate of 48,000 Hz. The meaning of the beep and double beep (in time or too late) was counterbalanced between participants.

5.2.1.3 Procedure.

After participants provided informed consent and filled out a demographic data questionnaire, the instructor attached reflective markers on the lower extremities. The experiment started with five calibration trials. Next, participants watched a narrated presentation of the instruction. Their task was to collect rewards by walking toward one of two lateral targets displayed by the color of the projected stimuli. Participants were prompted to position their feet into the predetermined starting position (left or right foot in front at the starting line) to start a trial. When the feet maintained the position for 1.5 s the prompt for the starting position was replaced with a central "+" as the Go signal. At the third

step, rewards for left and right targets were displayed (participants had not been informed about the exact timing). As rewards, one of three point combinations could be displayed (left/right: 40/60, 50/50, or 60/40). Before walking toward a lateral target, participants had to step into the central zone. To finish a trial, participants had to change direction to step with both feet into one of the two relevant lateral targets. After the trial, a sound signaled whether participants were in time. If participants were in time (see Appendix Chapter 8.2. for the determination of the time constraint), they got the reward for the side of the target they finished. If participants were not in time, they received the lower reward (40 points if 60/40, 50 points if 50/50). After finishing a trial, participants walked back to the starting line and positioned their feet to start the next trial. Each participant completed a total of 18 familiarization trials and 168 experimental trials. The experimental phase included 2 (starting position: left/right foot at starting line) x 3 (turning magnitude left/right: 15°/15°, 52.5°/52.5°, 90°/90°) x 3 (point combination left/right: 40/60, 50/50, 60/40) x 14 trials for the equal rewards (50/50) and x 7 trials each for unequal rewards (60/40 and 40/60) so that equal and unequal rewards were presented in the same number of trials. Trials were presented in random order. The experiment lasted ~70 min.

5.2.1.4 Data analysis.

Online analysis: Stimuli were presented in real time based on participants' kinematics of the tracked marker. The 3-D positions of markers were streamed with the NatNet SDK from Motive v2.1.1 (OptiTrack software interface) to a self-written MATLAB 2018a script (The MathWorks, Inc., Natick, MA). We determined the start of a trial, the timing of reward presentation at the third step, the step in the central zone, and the end of a trial based on the positioning of the foot markers (see Appendix Chapter 8.2.).

Offline analysis: For further analysis and validation of real-time data of experimental trials, kinematic data were filtered at 12 Hz with a bidirectional fourth-order low-pass Butterworth filter. We interpolated missing values up to 25 frames (0.21 s, cubic spline interpolation). We checked individual kinematic data of suspicious trials visually (see Appendix Chapter 8.2. for detection methods). After visual inspection of these trials, 6,443/7,560 trials (87.9%) were included in the statistical analysis. The remaining 12.1% of trials were predominantly excluded because participants made three or five steps instead of four (1,034 trials) and some trials because of various problems with the instruction or measurement (83 trials, see Appendix Chapter 8.2. for specifics).

For statistical analysis, we used R (R Core Team, 2019). To investigate the influence of swing leg (left or right), reward combination (60/40, 50/50, and 40/60 for the left/right side), and turning magnitude (15°/15°, 52.5°/52.5°, 90°/90° left/right) on participants' decisions (left/right side) we used the Bayes version of a generalized linear mixed model (Brauer & Curtin, 2018). We assumed a Bernoulli distribution for the outcome variable decisions (left or right) and used a logit link function. Model fitting was done with the brms package (Bürkner, 2017). We followed the guidelines of Kruschke (2021). Our scripts can be found at https://doi.org/10.17605/OSF.IO/C8MUS. We used a priori-specified contrasts based on our hypothesis (Schad et al., 2020). The factor reward was included as a Helmert contrast to investigate a side difference when the reward combination was unequal (40 points right vs. 60 points right) and to compare the effects of unequal rewards with the equal reward combination (mean of 40 points right and 60 points right vs. 50 points right). For the turning magnitude, we used a sliding difference contrast to investigate effect differences from 15° versus 52.5° and 52.5° versus 90°. For the swing leg, we used a centered sum contrast to compare the effect of the right swing leg (- 0.5) versus the left swing leg (+ 0.5). We did include a random intercept and all random slopes as random effects for subjects (Barr, 2013), but we excluded correlation parameters between random effects as they do not influence estimations of fixed effects but increase model complexity and the resulting computation time (Oberauer, 2022). The priors are specified in the Appendix Chapter 8.2. The formula for the model in the R script reads:

$$\mathrm{logit}(p_{Side}) \sim \mathrm{Points\_R} * \mathrm{Swing\_Leg} * \mathrm{Turning\_Magnitude} + (\mathrm{Points\_R} * \mathrm{Swing\_Leg} * \mathrm{Turning\_Magnitude}||\mathrm{Subject})$$

For each parameter, the Bayesian model provides a posterior distribution. The posterior distribution is a probabilistic representation of parameter values given the priors, the likelihood of the data, and the model. To summarize the posterior distribution, we provide the exponentiated estimated mean [exp(b), odds ratio (OR)], the corresponding 95% credible intervals (CrI, equal-tailed intervals), and the probability for samples below or over a certain value. The 95% credible interval defines the range within which the parameter value falls with a probability of 95%. We highlight parameters that are highly probable to be greater or smaller than a null effect (>95%) below in the text. If not otherwise specified, this was the approach for all other Bernoulli-distributed Bayesian mixed models.

5.2.2. Experiment 1b: Replication of Experiment 1a with a Stepping Constraint

To prevent the transition step in experiment 1b, we shrank the central zone to provide only enough space for a single foot and surrounded it with a no-step zone (marked by a carpet). Additionally, we used only the 15° and 90° turning magnitudes. Again, we hypothesized that the spatial constraint would increase the number of crossover steps when walking toward the opposite side of the swing leg and thereby increase the moderation of the swing leg effect by turning magnitude, resulting in a small and a large effect for the 15° and 90° conditions, respectively.

5.2.2.1. Participants.

Forty-three participants were recruited, five of whom were excluded because of the four-step criterion (>51.0%). This resulted in a sample size of n = 38 (mean age 23.9 yr, SD = 3.2; 21 females, 17 males; 34 right-handed, 3 left-handed). All participants received a performance-independent compensation of €10.00 and gave informed consent before starting the experiment.

5.2.2.2. Apparatus and stimuli.

The setup of experiment 1b was almost identical to that of experiment 1a. In contrast to experiment 1a, we only used 15° and 90° targets, displayed by red or blue cones. Additionally, we aimed to constrain the transition step by reducing the size of the central zone and putting a black semicircular carpet around the zone based on the positioning of transition steps in experiment 1a (see Fig. 5-5D, central zone: length = 0.35 m, width = 0.2

m, carpet: 0.5 m radius, 0.15 m distance before central zone, see Supplemental Video in the online material).

5.2.2.3. Procedure

The procedure was almost identical to experiment 1a. If participants stepped onto the carpet, the instructor repeated the instruction to not step onto the carpet. Each participant completed a total of 12 familiarization trials and 96 experimental trials. Experimental trials included 2 (starting position: left/right foot at starting line) x 2 (turning magnitude left/right: 15°/15°, 90°/90°) x 3 (point combination left/right: 40/60, 50/50, 60/40) x 12 trials for the equal rewards (50/50) and x 6 trials each for unequal rewards (60/40 and 40/60) so that equal and unequal rewards were presented in the same number of trials. The trial order was randomized. The experiment lasted ~50 min.

5.2.2.4. Data Analysis

We used the same online and offline analysis as in experiment 1a. After visual inspection, 3,332/4,128 trials (80.7%) were included in the statistical analysis. The remaining 19.3% of trials were predominantly excluded because participants made three or five steps instead of four (742 trials) and some trials because of various problems with the instruction or measurement (54 trials; see Appendix Chapter 8.2. for specifics). We used almost the identical statistical modeling approach as for experiment 1a. However, as there were only two levels for the turning magnitude, the angle was now coded as a centered sum contrast (
-0.5 for 15° and +0.5 for 90°).

5.2.3. Experiment 2: Turning Magnitude Influences Decision-Making

In experiment 2, we manipulated the motor cost differences for left and right turns by administering asymmetric turning magnitudes (i.e., different angles for left and right targets) because the turning magnitude relates to the energetic demands of walking independent of the swing leg (McNarry et al., 2017; Wilson et al., 2013). In short, a 15° turn is energetically less costly compared to a 90° turn. Additionally, angle influences motor decisions concurrent to actions in reaching tasks (Hesse et al., 2020; Michalski et al., 2020). For example, target selection while reaching is biased to targets that are aligned to the concurrent reaching movement (e.g., 30°) compared to less aligned targets (e.g., 90°, see Michalski et al., 2020). To investigate whether cost differences by means of the turning magnitude are part of the decision process, turning magnitudes were asymmetrically presented between both choice options in experiment 2 (e.g., 15° left and 90° right). To test whether motor costs resulting from the target angle could also be considered during action execution, the required turning magnitudes were presented while participants were walking. As a control condition, we provided information about the turning magnitude before participants started walking. 1) If the required motor costs of turning influence decision-making, we expected participants to preferably walk toward targets with a smaller turning magnitude (15° target) compared to a larger turning magnitude (90° target) for both presentation timings of the turning magnitude. 2) Additionally, as the motor costs change for both the turning magnitude and the swing leg, we also expected the decision to be influenced by both individually.

5.2.3.1. Participants.

Forty-three participants from local universities were recruited, four of whom were excluded for violating the four-step criterion. This resulted in a sample size of n = 39 (mean age 23.6 yr, SD = 3.8; 24 females, 15 males; 34 right-handed, 3 no hand preference, 2 left-handed). All participants received €15.00 compensation and gave informed consent before starting the experiment.

5.2.3.2. Apparatus and stimuli.

The same apparatus and stimuli were used as in experiment 1a. Identical to experiment 1b, we only used 15° and 90° targets. Again, the color on the screen represented the target option in each trial. The display of the targets changed compared to experiment 1. The targets were now displayed by rectangles on the left and right sides of the screen and could have the same or different colors, meaning that the required turning magnitude for the left and right sides could be the same or different. For example, for asymmetric angles, the left rectangle could be blue and the right one red, indicating that participants had to finish at the 15° left target or at the 90° right target (see Fig. 5-2). The colors for the turning magnitude were displayed before the trial or with the third touchdown when displaying the reward combinations.

5.2.3.3. Procedure

The procedure was almost identical to experiment 1a. One difference was that participants were instructed that asymmetric and symmetric angle combinations could occur and that turning magnitude was presented before starting a trial (early target presentation) or concurrent with walking toward the obstacle (late target presentation). The presentation timing for turning magnitudes was manipulated blockwise. Each participant completed a total of 12 familiarization trials and 96 trials per timing block, in sum 24 familiarization trials and 192 experimental trials. Per presentation timing block, experimental trials included 2 (starting position: left/ right foot at starting line) x 4 (target combination left/right: 15°/15°, 90°/90°, 15°/90°, 90°/15°) x 3 (point combination left/right: 40/60, 50/50, 60/40) with 2–8 trials dependent on the condition. The number of trials was not balanced, with fewer trials in the symmetric turning magnitude condition (2 trials for unequal rewards and 4 trials for equal rewards vs. 4 trials for unequal rewards and 8 trials for equal rewards). The trial order was randomized. The order of experimental block (timing of lateral targets) was counterbalanced between participants. Between blocks, participants had a 2-min pause to rest in a chair. The experiment lasted ~75 min.

5.2.3.4. Data analysis

We used the same online and offline analysis as in experiment 1b. After visual inspection, 6,768/8,256 trials (82.0%) were included in the statistical analysis. The remaining 18.0%of trials were predominantly excluded because participants made three or five steps instead of four (1,347 trials) and some trials because of various problems with the instruction or measurement (141 trials; see Appendix Chapter 8.2. for specifics). To reduce the complexity of the model, we focused our main analysis on the comparison of asymmetric turning magnitudes and decided to exclude trials with symmetric turning magnitudes. The respective model included starting position (left and right), reward combination (40/60, 50/50, and 60/40), target combination (15°/90° and 90°/15°), and timing of target presentation (early and late) as independent variables and participants' decisions (left/right) as the dependent variable. Contrasts and priors were identical to experiment 1b. Additionally, target timing was included as a centered sum contrast. We included all random effects terms (slopes and intercept) without correlations between the random effects. The formula for the model in the R script reads

logit(pSide) ~ Target_Timing * Points_R * Swing_Leg * Turning_Magnitude +
(Target_Timing * Points_R * Swing_Leg * Turning_Magnitude||Subject)

5.2.4. Experiment 3: Swing Leg on Decision-Making with Ankle Weights

Increasing the weights of the legs increases the energetic demands and generally decreases the stability of walking, presumably independent of the current swing leg (Graves et al., 1988; Russell et al., 2016; Skinner & Barrack, 1990). The association between motor costs and decision-making is found to be nonlinear in sequential decision-making: There is a parabolic relationship between motor effort and participants' decisions (Hartmann et al., 2013), and for stability there exists a boundary of how much perturbation is tolerable before falling or not falling (Werth et al., 2021). This nonlinear relationship results from the maximum force the muscles can generate and a buffer to tolerate perturbation before falling, making more extreme values even less preferable. Given that the crossover step is less stable and more demanding compared to the lateral step, a general increase in the requirements to walk could result in the crossover step being closer to the ceiling of stability, energy, and time requirements for the motor apparatus. Hence, we expected the effect of the swing leg on decisions to be stronger with ankle weights as compared to no additional weights (Fig. 5-3D).

5.2.4.1. Participants.

Forty-five participants from local universities were recruited, three of whom were excluded for violating the four-step criterion (>85.5%). This results in a sample size of n = 42 (mean age 21.8 yr, SD = 2.8; 24 females, 18males; 40 right-handed, 2 with no data). All participants received e15.00 compensation and gave informed consent before starting the experiment. Apparatus and stimuli. The same apparatus and stimuli were used as in experiment 1a. However, we only included the 52.5° targets, which allowed us to increase the maximal distance from the starting line to the zone to 3.71 m. We replaced the obstacle of our previous experiments with a more prominent black protective grating (HWC-B34; height = 1.03 m, width = 0.5 m). To increase the weight of the legs, we strapped 2.5-kg ankle weights around each ankle.

5.2.4.2. Procedure.

The procedure was almost identical to experiment 2. However, instead of manipulating turning magnitudes and preview time, there were two blocks of walking with and without ankle weights. Ankle weights were applied or removed before the start of the respective block. Calibration of the starting line and time constraint was based on walking without ankle weights. Each participant completed a total of 6 familiarization trials and 84 experimental trials. Experimental trials included 2 (starting position: left/ right foot at starting line) x 3 (point combination left/ right: 40/60, 50/50, 60/40) with 7 trials for each unequal reward combination and 14 trials for the equal reward combination. Starting position and point combination were randomized between trials. The order of the blocks (weights or no weights) was counterbalanced between participants. Between blocks, participants had a 2-min pause to rest in a chair. The experiment lasted ~75 min.

5.2.4.3. Data analysis.

We used the same offline and online analysis as in experiment 1a. After visual inspection, 4,347/5,040 (86.3%) trials were included in the statistical analysis. The remaining 13.7% of trials were predominantly excluded because participants made three or five steps instead of four (614 trials) and some trials because of various problems with the instruction or measurement (79 trials; see Appendix Chapter 8.2. for specifics). For the model, we used the same priors, contrasts, and random effects as in experiment 1b, with turning magnitude being replaced by the factor weight (yes or no) as a centered sum contrast (-0.5 for no weights and +0.5 for weights). The formula for the model in the R script reads:

$$\text{logit}(p_{\text{Side}}) \sim \text{Points\_R} * \text{Swing\_Leg} * \text{Weights} + (\text{Points\_R} * \text{Swing\_Leg} * \text{Weights}||\text{Subject})$$

5.3. Results

5.3.1. Experiment 1a: Is the Swing Leg Effect Moderated by Turning Magnitude?

Table 5-1 and Table 5-2 summarize the posterior distributions of experiments 1a and 1b, respectively. Fig. 5-4 displays the probability scales. Individual data for decision-making and the swing leg effect are displayed in the Appendix Fig. 8-3 and Fig. 8-4. Odds ratios below 1 correspond to a higher likelihood of walking toward the left side and odds ratios greater than 1 to the right side. With regard to unequal reward combinations, participants almost always walked toward the side with higher rewards in experiment 1a (2.37% toward the right side when 60 points were on the left side, 98.53% toward the right side when 60 points were on the right side) and experiment 1b (3.68% toward the right side when 60 points were on the left side, 98.71% toward the right side when 60 points were on the right side). This indicates that the rewards were considered by the participants.

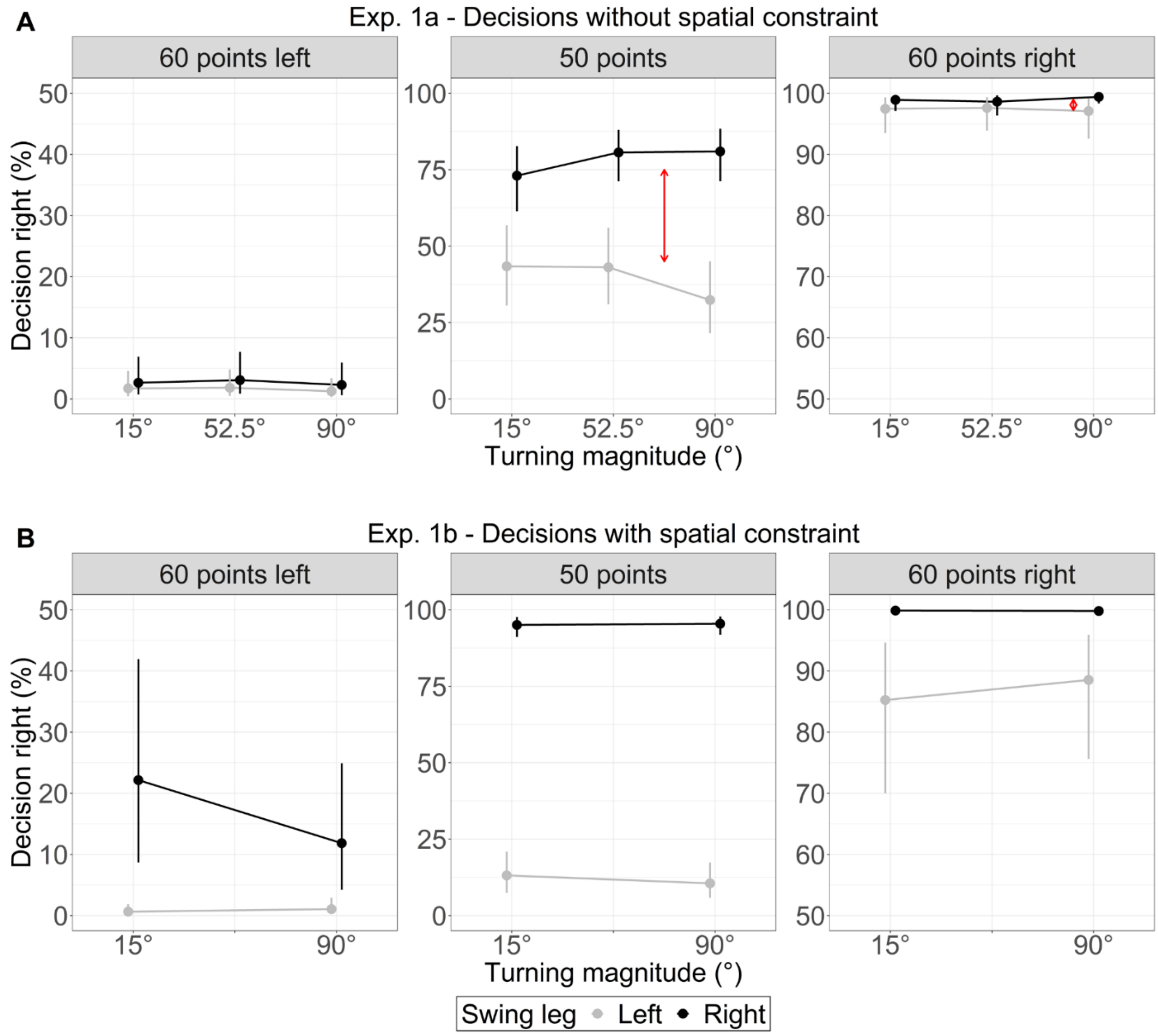

Fig. 5-4. Effect of the swing leg in decision- making for different turning magnitudes and reward combinations. A: results for experiment 1a. The swing leg effect (SLE) was reliable for all reward combinations. Additionally, the SLE increased when comparing 52.5° to 90° for the equal reward combination (center, marked by red arrow) and in the 60 points right condition (right, marked by red arrow) but not reliable for the other conditions. B: results for experiment 1b. There was a generally stronger SLE compared to experiment 1a. However, there is reliable evidence that the SLE increased with turning magnitude. The y-axis displays the probability of walking toward the rightward side. 0% would mean that participants always went toward the left side; 100% means that participants always went toward the right side. Shown are the model estimates of the mean and 95% credible interval (CrI) for each condition. Note that the y-axis scale differs between equal (center) and unequal (left and right) reward conditions.

5.3.1.1. The swing leg effect was partially moderated by turning magnitude.

Participants' decisions were biased by the swing leg after stepping into the central zone. Participants preferred walking toward the side enabling a lateral step, i.e., participants were less likely to walk toward the right target with a left swing leg compared to with a right swing leg [OR = 0.33, 95% CrI = 0.17 to 0.66, P(OR < 1) = 0.999]. The swing leg effect was greater for equal rewards (50/50) compared to unequal rewards [60/40 and 40/60; OR = 0.73, 95% CrI = 0.60 to 0.87, P(OR < 1) > 0.999]. Post hoc analysis indicated that even for unequal reward combinations, participants preferred walking toward the side enabling a lateral step [OR = 0.45, 95% CrI = 0.24 to 0.84, P(OR < 1) = 0.981]. However, because of the ceiling effects for unequal rewards, this swing leg effect is small on a probability scale (mean difference = 2.00%, 95% CrI = 0.40% to 5.37%).

Table 5-1 .Parameter summary of the fixed effects in experiment 1a. Each parameter is summarized as the mean odds ratio, the 95% credible interval, and the probability that the posterior is smaller than one. Parameters with a high probability of being smaller or greater than 1 are highlighted with a bold font (< 0.05 or > 0.95). For contrasts see methods. Model formula: logit(p_{Side}) ~ Points_R * Swing_Leg * Turning_Magnitude + (Points_R * Swing_Leg * Turning_Magnitude||Subject).

Effect	OR	95% CrI	P(OR) < 1
Intercept	1.27	[0.93 to 1.77]	0.063
Unequal rewards	**64.71**	**[25.15 to 168.55]**	**0.000**
Equal rewards	1.10	[0.98 to 1.26]	0.056
Swing leg	**0.33**	**[0.17 to 0.66]**	**0.999**
52.5° to 15°	1.08	[0.80 to 1.46]	0.310
90° to 52.5°	0.93	[0.72 to 1.20]	0.714
Unequal rewards : Swing leg	0.77	[0.55 to 1.10]	0.928
Equal rewards : Swing leg	**0.73**	**[0.60 to 0.87]**	**1.000**
Unequal rewards : 52.5° to 15°	0.89	[0.62 to 1.30]	0.731
Equal rewards : 52.5° to 15°	1.07	[0.92 to 1.26]	0.200
Unequal rewards : 90° to 52.5°	**1.42**	**[0.98 to 2.07]**	**0.031**
Equal rewards : 90° to 52.5°	0.93	[0.80 to 1.08]	0.830
Swing Leg : 52.5° to 15°	0.94	[0.58 to 1.49]	0.610
Swing Leg : 90° to 52.5°	**0.57**	**[0.33 to 0.98]**	**0.981**
Unequal rewards : Swing leg : 52.5° to 15°	1.22	[0.67 to 2.20]	0.254
Equal rewards : Swing leg : 52.5° to 15°	0.83	[0.62 to 1.10]	0.907
Unequal rewards : Swing leg : 90° to 52.5°	0.60	[0.33 to 1.13]	0.945
Equal rewards : Swing leg : 90° to 52.5°	1.03	[0.78 to 1.38]	0.407

The swing leg effect partially increased for larger turning magnitudes. The swing leg effect did not increase between the 15° and 52.5° targets [OR = 0.94, 95% CrI = 0.58 to 1.49, P(OR < 1) = 0.610]. However, the effect of the swing leg increased from 52.5° targets to 90° targets [OR = 0.57, 95% CrI = 0.33 to 0.98, P(OR < 1) = 0.981]. There was a tendency that reward combinations moderated the interaction between swing leg and angle for the latter angle comparison. The increase of the effect of the swing leg between 52.5° and 90° was slightly stronger in the 60/40 reward condition compared to the 40/60 reward condition [OR = 0.60, 95% CrI = 0.33 to 1.13, P(OR < 1) = 0.945], and the increase of the effect of the swing leg between 52.5° and 90° target angles was slightly stronger for the equal reward combination compared to the unequal reward combinations [OR = 0.83, 95% CrI = 0.62 to

1.10, P(OR < 1) = 0.907]. Because of this tendency, we ran post hoc comparisons for the interaction effect of swing leg and turning magnitude for all point combinations. For the 40/60 reward combination, there was no increase in the swing leg effect from 52.5° to 90° [OR = 0.91, 95% CrI = 0.45 to 2.83, P(OR < 1) = 0.572]. For the 60/40 reward combination, there was an increase of the swing leg effect between 52.5° and 90° [OR = 0.33, 95% CrI = 0.13 to 0.87, P(OR < 1) = 0.987], resulting possibly from a ceiling effect for 90° and a right swing leg, where participants only walked in very few trials toward the left side (see the 90° condition on right of plots in Fig. 5-4). For the equal reward combination, there was an increase of the swing leg effect between 52.5° and 90° [OR = 0.61, 95% CrI = 0.35 to 1.08 P(OR < 1) = 0.957].

In summary, the swing leg influenced participants' choices. Participants preferred to walk toward the side enabling a lateral step, even when receiving less reward. Additionally, there was partial evidence for an increased swing leg effect for larger turning magnitudes.

5.3.1.2. Participants increasingly adapted their stepping strategy for larger turning magnitudes.

We originally assumed that a crossover step would be the predominantly observed stepping strategy when walking to the opposite side of the swing leg. To check this assumption, we analyzed the location of the step after reaching the zone (see Fig. 5-5; for additional methodological information, see the Appendix Chapter 8.2.). A crossover step is marked by a position of the swing leg that crosses the stance leg. To our surprise, we observed that participants frequently avoided a crossover step but instead made a transition step (see Fig. 5-5A). That is, they placed both feet in the zone to enable a lateral step walking on.

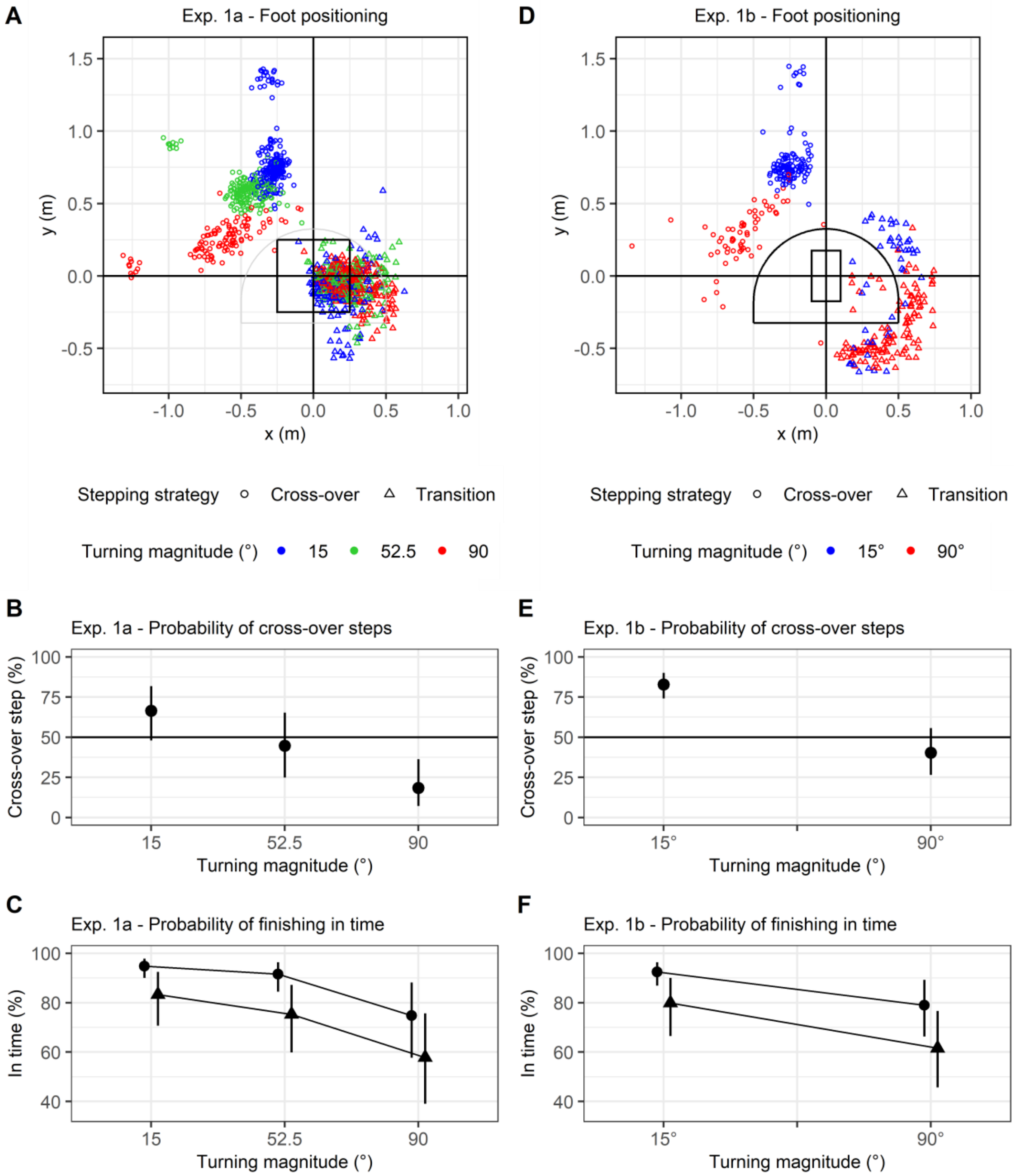

Fig. 5-5. Characteristics of the step after reaching the zone and stepping strategies with varying turning magnitude. Only trials with decisions to walk towards the opposite side of the swing leg were analyzed (and presumably a cross-over step was needed). A. Position of the step after reaching the zone from the step in the zone in Exp. 1a. Participants did not always cross the stance leg (circle-shape, cross-over steps) but stepped with the foot in the zone next to the stance leg (triangle shape, transition steps). The black rectangle represents the central zone. The gray semicircle represents the constraint area for the step after reaching the zone in Exp. 1b. For brevity reasons, the figure shows only trials in which participants walked towards the left side with a right swing leg (hence blue). When walking towards the right side, the foot positioning was similar but reflected. B. Probability of a cross-over step vs. a transition step for different turning magnitudes. Displayed are the mean estimate and 95 % CrI on the response scale. Trials for both walking directions were analyzed. C. Probability of finishing a trial in time for both stepping strategies. Trials with a transition step and larger turning magnitudes were more often too late compared to trials with a cross-over step and smaller turning magnitudes. D. Same as 3A, but for Exp. 1b. Again, participants did not always perform cross-over steps (circle-shaped) but still used transition steps (triangle shape). However, compared to Exp. 1a, the transition step was now mostly outside the constraining carpet. E. Same as 3B, but for Exp. 1b. Compared to Exp 1a,

participants more often made cross-over steps. But the frequency of cross-over steps still decreased with the turning magnitude. F. Same as 3C, but for Exp. 1b. Again, trials with transition steps and larger turning magnitudes were slower.

The frequencies of crossover steps decreased for larger turning magnitudes, from 15° to 52.5° [OR = 0.40, 95% CrI = 0.27 to 0.59, P(OR < 1) > 0.999] and from 52.5° to 90° [OR = 0.26, 95% CrI = 0.15 to 0.44, P(OR < 1) > 0.999], or, in other words, the frequency of transition steps increased with turning magnitude. Participants infrequently made crossover steps for 90° targets (18.48%, 95% CrI = 7.11% to 36.23%; see Fig. 5-5B) and accordingly, they made predominantly a transition step. The transition step takes an additional step to turn, and after seeing the results on stepping strategies, we hypothesized that the additional step could lead to a time cost. Consequently, we additionally analyzed whether the participants finished a trial within the required time constraint to receive the 60 points (see Fig. 5-5C). Indeed, trials with a transition step were slower compared to trials with a crossover step, leading to a higher probability of missing the time constraint and receiving the lower reward in experiment 1a [OR = 0.32, 95% CrI = 0.18 to 0.58, P(OR < 1) > 0.999]. Additionally, participants were slower and had a higher chance of missing the time constraint the larger the turning magnitude, from 15° to 52.5° [OR = 0.60, 95% CrI = 0.40 to 0.92, P(OR < 1) = 0.989] and from 52.5° to 90° [OR = 0.34, 95% CrI = 0.24 to 0.51, P(OR < 1) > 0.999]. Both effects additively lead to the lowest probability of being in time when making transition steps toward a 90° target (57.82%, 95% CrI = 39.07% to 75.70%). This suggests that participants made transition steps despite the cost of being too late and receiving less reward. In sum, participants frequently avoided the crossover step and more so for larger turning magnitudes. Instead, they made a transition step, which could help to stabilize the turn but prolonged the turn duration. Albeit less efficient than a lateral step, the transition step likely absorbs some of the cost difference based on the current swing leg we aimed to manipulate in experiment 1a. To experimentally control the transition step, we constrained the foot placement in experiment 1b.

5.3.1.3. Repetition effect for stepping strategies for the equal reward combination.

For the equal reward combination, one could ask why participants made more costly crossover steps in the first place, given that there was no incentive to do so. One reason could be a repetition effect from the trial before often observed for task switching. To attend to possible repetition effects responsible for crossover steps in the equal reward condition, we additionally analyzed the influence of the side and the stepping strategy (crossing with a transition or a crossover step vs. lateral step) in the previous trial (trial n - 1) on the probability of crossing with a transition step or crossover step in the equal reward conditions of trial n in experiment 1a (see Appendix Chapter 8.2., in particular Fig. 8-6, for details). Repetition of the side only unreliably affected the frequency of crossing [OR = 1.13, 95% CrI = 0.95 to 1.36, P(OR < 1) = 0.088]. Additionally, there is a small but reliable effect of repeating the stepping strategy from the trial before [OR = 1.34, 95% CrI = 1.09 to 1.69, P(OR < 1) = 0.004]. That is, if participants made a crossover or transition step in the trial before, they were more likely to make a crossover or transition step in the trial afterward. There was no interaction with side repetition, suggesting that the repetition of the stepping strategy was independent of repeating the side. If true, this suggests carryover effects of a generalized action level (crossover/transition steps make crossover/transition steps more likely independent of the direction) on decision- making, providing further evidence that decision-making and action processes are directly intertwined. Note, however, that participants still did make crossover or transition steps for equal rewards even if they did not repeat walking toward the previous side or made a lateral step previously (22.93%, 95% CrI = 16.35% to 30.36%). This means that other factors influence the occurrence of crossing behavior for equal rewards (e.g., attention or noise), which could be analyzed in future studies.

5.3.2. Experiment 1b: Replication of Experiment 1a with a Stepping Constraint

Table 5-2summarizes the posterior distribution, and B displays the model predictions on the probability scale. Individual data for decision-making and the swing leg effect are displayed in Fig. 8-3 and Fig. 8-4. Odds ratios < 1 correspond to a higher likelihood of walking toward the left side and odds ratios > 1 to the right side. With regard to unequal reward combinations, again participants almost always walked toward the side with higher rewards (3.68%toward the right side when 60 points were on the left side, 98.71% toward the right side when 60 points were on the right side). This indicates that the rewards were relevant for the participants.

Table 5-2. Parameter summary of the fixed effects in experiment 1b. Each parameter is summarized as the mean odds ratio (OR), the 95% CrI, and the probability that the posterior is <1. Parameters with a high probability >1 or <1 are highlighted with a bold font (< 0.05 or > 0.95). For contrasts, see METHODS. Model formula: logit(pSide) ~ Points_R * Swing_Leg * Turning_Magnitude + (Points_R* Swing_Leg * Turning_Magnitude||Subject)

Effect	OR	95% CrI	P(OR) < 1
Intercept	**1.71**	**[1.26 to 2.35]**	**0.001**
Unequal rewards	**50.04**	**[21.61 to 119.05]**	**0.000**
Equal rewards	0.99	[0.82 to 1.18]	0.561
Swing leg	**0.01**	**[0.01 to 0.03]**	**1.000**
90° to 15°	0.91	[0.58 to 1.42]	0.666
Unequal rewards : Swing leg	**0.44**	**[0.21 to 0.88]**	**0.991**
Equal rewards : Swing leg	**0.72**	**[0.50 to 1.01]**	**0.970**
Unequal rewards : 90° to 15°	1.03	[0.53 to 2.01]	0.467
Equal rewards : 90° to 15°	1.01	[0.77 to 1.32]	0.482
Swing Leg : 90° to 15°	1.76	[0.69 to 4.56]	0.120
Unequal rewards : Swing leg : 90° to 15°	0.76	[0.24 to 2.40]	0.678
Equal rewards : Swing leg : 90° to 15°	**0.63**	**[0.38 to 1.05]**	**0.960**

Turning magnitude did not moderate the swing leg effect. Participants again went less often toward the right target with a left swing leg compared to with a right swing leg [OR = 0.01, 95% CrI = 0.01 to 0.03, P(OR < 1) > 0.999]. Note that the effect of the swing leg was far stronger compared to experiment 1a (OR = 0.33). The effect of the swing leg again was greater for equal rewards (50/50) compared to unequal rewards [60/40 and 40/60; OR = 0.72, 95% CrI = 0.50 to 1.01, P(OR < 1) = 0.970]. There were also differences in the swing leg effect between unequal rewards. The swing leg effect increased for the left side (60 points left) compared to the right side (60 points right). This result suggests a higher preference for lateral steps when walking toward the left side. Post hoc analysis indicates that even for the weakest condition (60 points left) there was an effect of the swing leg [OR = 0.19, 95% CrI = 0.06 to 0.43, P(OR < 1) > 0.999]. On a probability scale, the difference for decision-making based on swing leg for unequal rewards was also greater in experiment 1b (mean difference = 14.1%, 95% CrI = 5.9% to 26.5%) compared to 2.00% in experiment 1a. With regard to the interaction between swing leg in the zone and turning magnitude, the effect of the swing leg did not increase between the 15° and 90° targets [OR = 1.76, 95% CrI = 0.69 to 4.56, P(OR < 1) = 0.120]. The effect difference of the swing leg between 15° and 90° targets was greater for equal rewards compared to unequal rewards [OR = 0.63, 95% CrI = 0.38 to 1.05, P(OR < 1) = 0.960]. Post hoc analysis did not reveal a difference in the swing leg effect for the equal reward combination [OR = 0.71, 95% CrI = 0.26 to 1.84, P(OR < 1) = 0.761] or for the unequal reward combinations [OR = 2.78, 95% CrI = 0.79 to 10.11, P(OR < 1) = 0.060]. In summary, in both experiments, the swing leg influenced participants' choices. Participants preferred to walk toward the side enabling a lateral step, even when receiving less reward. In experiment 1a, there was partial evidence for an increased swing leg effect for larger turning magnitudes. In experiment 1b, the size of the swing leg effect generally increased. However, no interaction was found between the swing leg effect and turning magnitude.

5.3.2.1. Participants more frequently made crossover steps but still adapted their stepping strategy.

The frequency of crossover steps increased for both turning magnitudes compared to experiment 1a [OR = 2.56, 95% CrI = 0.98 to 6.71, P(OR < 1) = 0.028; see Fig. 5-5B], with no interaction between them [OR = 0.95, 95% CrI = 0.42 to 2.11, P(OR < 1) = 0.557]. However, even with the step constraint on the floor participants still made transition steps (see Fig. 5-5B). For 90 targets, the probability of crossover steps versus transition steps was roughly even (mean estimated probability of crossover steps = 38.10%, 95% CrI = 20.31% to 58.45%). The transition steps were mostly placed outside the stepping constraint on the floor. Only in a few trials did participants step on the carpet area (46/786 trials). We did not remove these trials, as it would bias the estimations of the applied stepping strategies toward crossover steps. The transition step was again slower compared to trials with a crossover step, leading to a higher chance of missing the time constraint and receiving the lower reward [OR = 0.37, 95% CrI = 0.21 to 0.64, P(OR < 1) > 0.999]. Participants were also slower and had a higher probability of missing the time constraint the larger the turning magnitude, from15° to 90° [OR = 0.34, 95% CrI = 0.21 to 0.58, P(OR < 1) > 0.999]. Both effects additively led to the lowest probability of being in time when making transition steps toward a 90° target (61.58%, 95% CrI = 45.74% to 76.65%). Again, this suggests that participants made transition steps despite the cost of being too late and receiving less reward. In sum, participants frequently avoided the crossover step and more so for larger turning magnitudes. Instead, they made a transition step, which could help to stabilize the turn but prolonged the turn duration. The effect of the swing leg became stronger with the spatial constraint on the floor in experiment 1b. But even though participants made crossover steps more frequently, participants' preference for turning toward the side enabling a lateral step was not influenced by the turning magnitude.

5.3.3. Experiment 2: Turning Magnitude Influences Decision-Making

5.3.3.1. Angle preference.

Table 5-3 summarizes the posterior distribution. Fig. 5-6 displays the results on a probability scale. Individual data for decision-making and the swing leg effect are displayed in Fig. 8-3 and Fig. 8-4 in the Appendix. Odds ratios < 1 correspond to a higher likelihood of walking toward the left side and odds ratios > 1 to the right side. Participants generally walked more frequently toward the 15° target compared to the 90° target [OR = 2.67, 95% CrI = 1.69 to 4.19, P(OR < 1) < 0.001]. The preference for the 15° targets was reduced when targets were presented late while participants were walking instead of early before the trial start [OR = 0.52, 95% CrI = 0.29 to 0.97, P(OR < 1) = 0.980]. Because the effect of the turning magnitude differed for reward combinations and for the timing of displaying the turning magnitudes, we made post hoc comparisons between turning magnitudes (15° left vs. 15° right) for the target timings individually. Participants preferred 15° targets when targets were presented early [OR = 3.69, 95% CrI = 2.14 to 6.32, P(OR < 1) < 0.001] but also when targets were presented late [OR = 1.92, 95% CrI = 1.12 to 3.35, P(OR < 1) = 0.009]. As in experiment 1a, participants almost always walked toward the side with higher rewards, and the effect of the turning magnitude is small on a probability scale for unequal reward combinations, especially for the late target presentation condition (mean difference = 1.2%, 95% CrI = 0.3% to 3.5%).

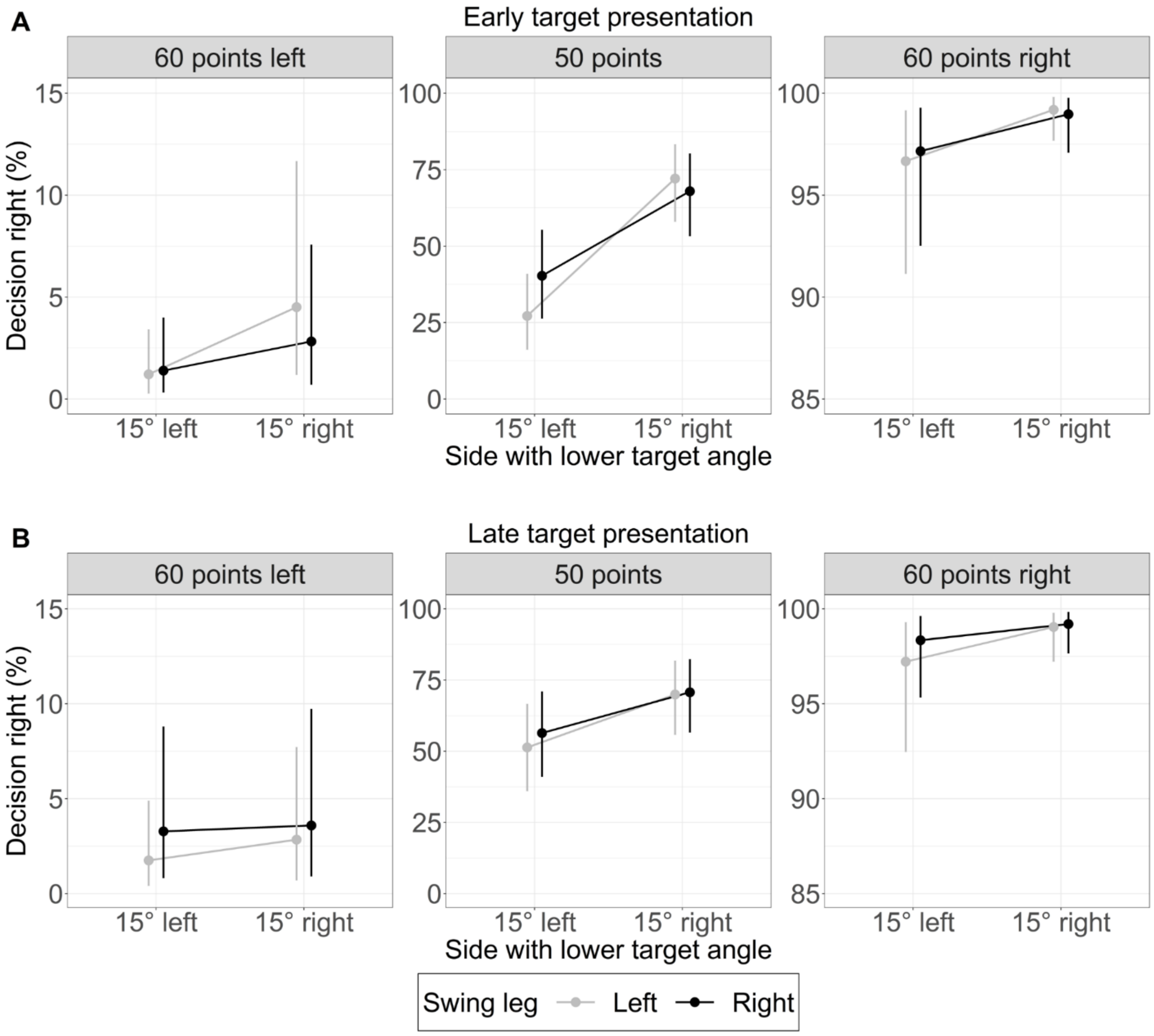

Fig. 5-6. Effect of the turning magnitude and swing leg on decisions for different presentation timings of the targets and reward combinations in experiment 2. A: results when turning magnitudes were displayed before a trial started. B: results when turning magnitudes were displayed with reward while participants were walking. Only asymmetric angle combinations are included, meaning that 15° left indicates that the right turning magnitude was 90°. 0% means that participants always went toward the left side; 100% means that participants always went toward the right side. Lateral steps are realizable in the direction of the swing leg; hence, a swing leg effect would mean that participants went more often leftward given a left swing leg vs. a right swing leg (gray below black). A preference to walk toward the side with a smaller turning magnitude (15°) would be displayed by a positive slope between points. There was a reliable effect of turning magnitude: participants preferred to walk toward the side with a smaller turning magnitude. However, there was no reliable evidence for the swing leg effect (SLE) anymore. Displayed are the model estimates (probability scale) of the mean and 95% credible interval (CrI) for each condition. Note that the y-axis scale differs between equal (center) and unequal (left and right) reward conditions.

Table 5-3. Parameter summary of the fixed effects in experiment 2. Each parameter is summarized as the mean odds ratio (OR), the 95% credible interval (CrI), and the probability that the posterior is <1. Parameters with a high probability of being <1 or >1 are in bold (<0.05 or >0.95). For contrasts, see Methods. Model formula: logit(pSide) ~ Target_Timing * Points_R * Swing_Leg * Turning_Magnitude + (Target_Timing * Points_R * Swing_Leg * Turning_Magnitude||Subject)

Effect	OR	95% CrI	P(OR) < 1
Intercept	1.31	[0.87 to 1.98]	0.095
Target Timing	1.36	[0.94 to 1.97]	0.052
Unequal rewards	**61.80**	**[25.45 to 147.54]**	**0.000**
Equal rewards	1.02	[0.92 to 1.13]	0.368
Swing leg	0.86	[0.51 to 1.43]	0.725
15° preference	**2.67**	**[1.69 to 4.19]**	**0.000**
Unequal rewards : Target timing	0.98	[0.53 to 1.78]	0.526
Equal rewards : Target timing	1.07	[0.90 to 1.27]	0.226
Swing leg : Target timing	0.73	[0.37 to 1.41]	0.833
Unequal rewards : Swing leg	0.99	[0.66 to 1.49]	0.532
Equal rewards : Swing leg	1.00	[0.83 to 1.21]	0.522
15° preference : Target timing	**0.52**	**[0.29 to 0.97]**	**0.980**
Unequal rewards : 15° preference	1.23	[0.82 to 1.84]	0.146
Equal rewards : 15° preference	1.09	[0.90 to 1.33]	0.194
Swing leg : 15° preference	**1.60**	**[0.97 to 2.65]**	**0.034**
Unequal rewards : Swing leg : Target timing	1.12	[0.58 to 2.14]	0.366
Equal rewards : Swing leg : Target timing	1.22	[0.90 to 1.66]	0.099
Unequal rewards : 15° preference: Target timing	1.24	[0.64 to 2.40]	0.259
Equal rewards : 15° preference: Target timing	0.90	[0.63 to 1.31]	0.710
Unequal rewards : Swing leg : 15° preference	0.74	[0.36 to 1.50]	0.797
Equal rewards : Swing leg : 15° preference	0.93	[0.50 to 1.74]	0.592
Swing leg : Asymmetrical angle : Target timing	1.01	[0.76 to 1.35]	0.470
Unequal rewards : Swing leg : 15° preference: Target Timing	1.09	[0.47 to 2.50]	0.414
Equal rewards : Swing leg : 15° preference: Target Timing	0.85	[0.53 to 1.35]	0.758

5.3.3.2. No swing leg effect for asymmetric turning magnitudes.

Although the focus was on comparing turning magnitudes in this study, we also analyzed the swing leg effect as in the previous study. It is noteworthy that an effect of the swing leg was unlikely in the model with only asymmetric turning magnitudes [OR = 0.86, 95% CrI = 0.51 to 1.43, P (OR < 1) = 0.725]. To follow up on this finding, we fitted another model that included the symmetric turning magnitudes to compare the effect of the swing leg between symmetric and asymmetric turning magnitudes. The effect of the swing leg indeed differed between asymmetric turning magnitudes and symmetric turning magnitudes [OR = 1.38, 95% CrI = 1.12 to 1.72, P(OR < 1) = 0.001]. As in experiments 1a and

1b, participants preferred walking toward the side enabling a lateral step for symmetric turning magnitudes [OR = 0.65, 95% CrI = 0.47 to 0.90, P(OR < 1) = 0.995].

5.3.4. Experiment 3. Swing Leg on Decision-Making with Ankle Weights

We analyzed the step into the zone for different reward combinations and ankle weights. Model estimations are displayed in Table 5-4, and a visual presentation of model estimates is displayed in Fig. 5-7. Individual data for decision-making and the swing leg effect are displayed in Fig. 8-3 and Fig. 8-4 in the Appendix.

Table 5-4 . Parameter summary of the fixed effects in experiment 3. Each parameter is summarized as the mean odds ratio (OR), the 95% credible interval (CrI), and the probability that the posterior is <1. Parameters with a high probability of being <1 or >1 are in bold (<0.05 or >0.95). For contrasts, see METHODS. Model formula: logit(pSide) ~ Points_R * Swing_Leg * Weights + (Points_R * Swing_Leg * Weights||Subject)

Effect	OR	95% CrI	P(beta) < 1
Intercept	1.01	[0.65 to 1.56]	0.475
Unequal rewards	**231.90**	**[94.57 to 587.35]**	**0.000**
Equal rewards	1.05	[0.87 to 1.25]	0.275
Swing leg	**0.17**	**[0.08 to 0.37]**	**1.000**
Weights	1.15	[0.76 to 1.72]	0.250
Unequal rewards : Swing leg	0.94	[0.52 to 1.71]	0.577
Equal rewards : Swing leg	**0.42**	**[0.27 to 0.65]**	**1.000**
Unequal rewards : Weights	0.74	[0.42 to 1.29]	0.862
Equal rewards : Weights	0.93	[0.74 to 1.17]	0.729
Swing Leg : Weights	1.10	[0.54 to 2.18]	0.392
Unequal rewards : Swing leg : Weights	0.84	[0.38 to 1.86]	0.674
Equal rewards : Swing leg : Weights	0.73	[0.47 to 1.13]	0.922

5.3.4.1. Swing leg influenced decisions independent of ankle weights.

In regard to participants' choices, participants went less often toward the left target with a right swing leg in the zone compared to a left swing leg [OR = 0.17, 95% CrI = 0.08 to 0.37, P(OR < 1) > 0.999]. The effect of the swing leg lies in between experiment 1a (OR = 0.33) and experiment 1b (OR = 0.01). The effect of the swing leg was again greater for equal rewards (50/50) compared to unequal rewards [60/40 and 40/60; OR = 0.42, 95% CrI = 0.27 to 0.65, P(OR < 1) > 0.999]. Post hoc analysis showed a swing leg effect even for unequal rewards [OR = 0.40, 95% CrI = 0.15 to 1.08, P(OR < 1) > 0.965]. On a probability scale, the difference for decision-making based on swing leg was small as in experiment 1 (mean difference = 1.0%, 95% CrI = 0.2% to 2.6%). The effect of the swing leg did not increase when participants wore ankle weights [OR = 1.10, 95% CrI = 0.54 to 2.18, P(OR < 1) = 0.392]. There was only a tendency that weights differently affected the swing leg effect for equal and unequal rewards. The effect of weights on the swing leg effect was tendentially stronger with equal rewards [OR = 0.73, 95% CrI = 0.47 to 1.13, P(OR < 1) =0.922]. For equal rewards, there was a tendency that weights increased the swing leg effect [OR = 0.58, 95% CrI = 0.26 to 1.32, P(OR < 1) =0.901].

We ran an additional analysis for the potential time cost of weights. The ankle weights increased the time needed to finish a trial independent of the swing leg (β = 0.10 s, 95% CrI = 0.06 s to 0.14 s, P(β < 0) < 0.001). An unpreferred swing leg requiring a crossover step had a similar effect on the time needed to finish the trial (β = 0.11 s, 95% CrI = 0.07 s to 0.15 s, P(β < 0) < 0.001).

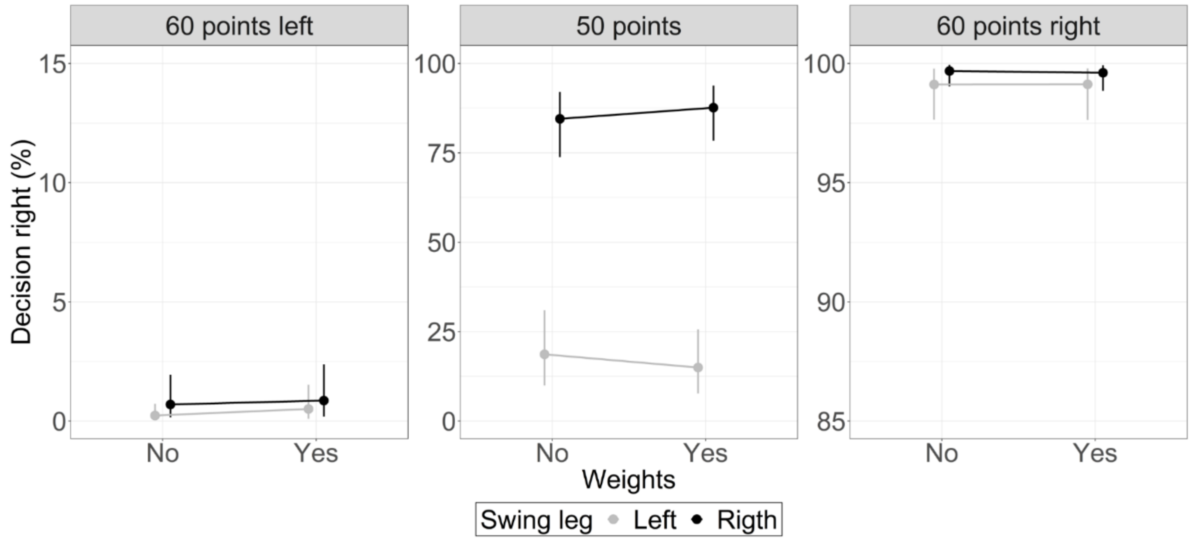

Fig. 5-7. Effect of the swing leg on decision-making with and without ankle weights and for different reward combinations in experiment 3. The x-axis displays the probability of walking toward the rightward side. 0% would mean that participants always went toward the left side; 100% means that participants always went toward the right side. Lateral steps are realizable in the direction of the swing leg; hence, a swing leg effect would mean that participants more often went leftward given a left swing leg vs. a right swing leg (gray below black). The slope of the line between points indicates the influence of weights on the swing leg effect. A stronger swing leg effect with weights would be indicated by a divergence between both lines. There was no reliable evidence that the swing leg effect increased when participants wore ankle weights. Shown are the model mean estimates and 95% credible interval (CrI) for each condition. Note that the y-axis differs between (center) and unequal (left and right) reward conditions.

In summary, we replicated the effect of the swing leg. Ankle weights decreased the time margin to finish a trial independent of the swing leg, i.e., required stepping strategy. But ankle weights did not robustly influence the effect of the swing leg.

5.4. Discussion

5.4.1. Experiment 1a and Experiment 1b

We argued that the motor cost of turning depends on the current swing leg and that this cost difference is moderated by turning magnitude. If action cost influences participants' decisions, the preference for lateral steps should also be moderated by turning magnitude. In both experiments participants indeed preferred walking toward the side enabling a lateral step, that is, they showed a swing leg effect. In experiment 1a, the swing leg effect was largest for the highest turning magnitude. When the stepping behavior was further constrained in experiment 1b, the swing leg effect generally increased; however, it no longer depended on the turning magnitude. Additionally, in experiment 1b participants tended less frequently to substitute crossover steps with transition steps. Overall, the finding that participants preferred walking toward the side enabling a lateral step replicated the findings of our previous study (Grießbach et al., 2021), thereby providing further support for the impact of concurrent movement on decision-making (Burk et al., 2014; Marti-Marca et al., 2020; Raßbach et al., 2021). Going beyond this replication, we predicted that concurrent actions influence decision-making by the emerging cost dynamics and not (only) by cognitive cross talk (Raßbach et al., 2021). Our results support this hypothesis, as changes in motor costs were reflected in decision-making. Specifically, this is evidenced by, first, an increased swing leg effect for larger turning requirements in experiment 1a and, second, a larger swing leg effect in experiment 1b compared to experiment 1a. The larger swing leg effect in experiment 1b could be a result of the additional foot placement and orientation constraints given the smaller central zone (see Appendix Chapter 8.2.). Foot placement and orientation are important for the adaptation of mediolateral stability of walking (Rebula et al., 2017; van Leeuwen et al., 2020). Hence, crossover steps could have become generally more costly with the spatial constraint, thereby indicating that the swing leg effect is moderated by action costs. However, not all variations in motor costs were reflected in decision-making. For instance, there was no interaction between turning magnitude and swing leg in experiment 1b. One explanation for this lack of an interaction could be the additional task constraint. In research on reaching, for example, it has been suggested that with more task constraints it is increasingly difficult to meet all the requirements of a given task and succeed in it while still attending to motor costs. Consequently, it has been argued that the influence of more subtle motor cost differences on decision-making decreases (Michalski et al., 2020). Another second explanation for the missing interaction could reside in the transition step. The transition step affords a “neutral” body state, in which the more stable lateral step can be made in either direction. Hence the motor cost differences between the turning directions would be reduced. Accordingly, the increased number of transition steps for larger turning magnitudes could indicate that crossover steps indeed became more costly and were therefore replaced with transition steps. If this is true, then, instead of compromising reward-based decisions, motor cost differences were counteracted by adapting the stepping behavior. When analyzing why participants crossed for equal reward combinations, we additionally observed repetition of the stepping strategy (crossing with a transition step or crossover step vs. lateral step) independent of a side repetition for the equal reward combination in experiment 1a. If true, this suggests carryover effects of an abstract action-level representation on decision-making, providing further evidence that decision-making and action processes are intertwined. From the perspective that decision-making includes competition between action representations in fronto-parietal areas (Cisek, 2012), it could suggest that these abstract action features have a higher baseline activation for a short time after the trial, leading to the increased likelihood of activation and therefore a decision to repeat the motor behavior. These repetition effects could open a window to scrutinize elements of decision-making on different hierarchical levels of the decision process and provide an opportunity for future research. Together, the larger swing leg effect in experiment 1b compared to experiment 1a and the increased swing leg effect for larger turning magnitudes in experiment 1a provide additional evidence that motor costs influence decisions with concurrent movement. Furthermore, it seems that motor cost differences can be overcome by adapting concurrent movement.

5.4.2. Experiment 2: Turning Magnitude Influences Decision- Making

Concerning the turning magnitude, participants preferred targets with a smaller angle compared to targets with a larger turning magnitude, even at the expense of receiving less reward. The effect of turning magnitude was observable when turning magnitudes were presented late while participants were walking, although weaker. As the energetic demands increase with turning magnitude (McNarry et al., 2017; Wilson et al., 2013), this could suggest that participants integrate the cost differences between asymmetric turn decisions while walking. A similar preference to move toward targets with a smaller angle was observed in some dynamic reaching experiments (Hesse et al., 2020; Michalski et al., 2020). Our results extend these findings to walking. Regarding the swing leg effect, participants again preferred walking toward the side enabling a lateral step for symmetric turning magnitudes, as in experiment 1a and experiment 1b. However, we did not find evidence for a swing leg effect with asymmetric turning magnitudes (e.g., 15° left vs. 90° right). Possible reasons for the absence of the swing leg effect with asymmetric turning magnitudes are discussed in the General Discussion. This experiment was the first in which motor costs were influenced by an environmental manipulation independent of the body state. In contrast to the body state, the cost differences from the environment were random and not predictable when presented late while participants were walking. Even for late presentations, the influence of turning magnitude suggests that environmental cost differences can be integrated on the fly without long-term anticipation (Cos et al., 2014). Additionally, the preference for 15° targets was stronger when turning magnitudes were presented before the trial, indicating that participants utilized the early target presentation to weigh options based on their costs. One mechanism behind this result could be competition on the level of action representations, which increases dynamically with time of presentation (Cisek, 2007), leading to a stronger activation and bias for the 15° target even before reward options are displayed.

5.4.3. Experiment 3: Swing Leg on Decision-Making with Ankle Weights

When adding ankle weights, we observed that the time to finish increased independent of the required stepping strategy. Even with the increase in time, the swing leg effect remained and was unaffected by the presence of the ankle weights, replicating the finding of the previous experiments and extending it to when the body state is manipulated by additional ankle weights.

5.5. General Discussion

Embodied decision accounts argue that the dynamic changes in the motor costs of behavioral options influence decision-making. Indeed, this claim has received empirical support (Cos et al., 2021; Grießbach et al., 2021; Nashed et al., 2014; Raßbach et al., 2021). However, it is unclear to what extent this truly reflects the impact of dynamic motor costs

(Raßbach et al., 2021). Here, we addressed this question by systematically manipulating the motor costs of choices during concurrent movement. To briefly summarize our main findings, in experiment 1a and experiment 1b we manipulated the motor costs of crossover steps compared to lateral steps during walking by symmetrically increasing the required turning magnitude. Participants generally preferred walking toward the side enabling a lateral step, thereby showing what we refer to as the swing leg effect. In experiment 1a, the swing leg effect was larger for higher turning magnitudes. When the stepping behavior was additionally constrained in experiment 1b, the swing leg effect further increased, albeit no longer being modulated by the turning magnitude. Additionally, when we investigated participants' stepping behavior, participants less frequently substituted crossover steps with transition steps. In experiment 2, we manipulated motor costs on top of the required stepping strategy by increasing the required turning magnitude asymmetrically. When choices required asymmetric turns, the swing leg effect disappeared. Instead, only the turning magnitude itself influenced participants' decisions. The participants preferred walking toward targets requiring smaller turning angles. Finally, in experiment 3, we manipulated the motor costs of crossover steps compared to lateral steps by adding weights to the ankles. Results revealed that participants showed a swing leg effect independent of weights. Together, the emergence of the swing leg effect under almost all conditions and across the three experiments replicates and supports the earlier studies showing that concurrent movement can influence decision-making (Grießbach et al., 2021; Marti-Marca et al., 2020; Raßbach et al., 2021). These findings generally support claims of action-based models for which action execution is an integral part of the decision process (Wispinski et al., 2020). Next to replicating the influence of concurrent movement on decision-making, the finding that changes in motor costs were reflected in decision-making supports the claim that concurrent actions influence decision-making by the emerging cost dynamics and not (only) by specific crosstalk (Raßbach et al., 2021). This concerns the increased swing leg effect for larger turning requirements in experiment 1a, the larger swing leg effect in experiment 1b compared to experiment 1a, and the influence of turning magnitude when displayed concurrently with movement execution in experiment 2. These findings add to the influence of motor costs on decision-making choices without concurrent action (Cos et al., 2014; Hagura et al., 2017; Pierrieau et al., 2021). For such sequential decisions, time and force have been identified as cost dimensions (Morel et al., 2017). When walking, relevant cost dimensions include motor variables like stability, forward progression, muscle torque, time, or energetic considerations (Minetti et al., 1994; Moraes et al., 2007; Morel et al., 2017). A challenge for future studies could be to disentangle these cost dimensions and their influence on decision-making while moving. Besides the influence of motor costs on reward-based decisions, the increased rate of transition steps for larger turning magnitudes in experiment 1a and experiment 1b also suggests that the motor costs led to adaptations in concurrent motor control. The adaptation of motor control may in turn allow overcoming cost differences between choices. This close interaction between “continuous motor decisions” and “discrete reward-based decisions” (Yoo et al., 2021) also highlights the reciprocal influence between these processes as proposed by action-based models (Cisek & Kalaska, 2010; Lepora & Pezzulo, 2015; Wispinski et al., 2020). However, some variations in motor costs were not reflected in decision-making. This concerns the missing interaction between turning magnitude and swing leg in experiment 1b, the missing swing leg effect in experiment 2, and the missing moderation of the swing leg effect by ankle weights in experiment 3. In this regard, experiment 2 is especially interesting, as asymmetric targets provided an additional cost dimension besides the swing leg. That is, the side of the lateral step was independent of the side with the smaller turning magnitude over trials, and, consequently, both should influence decision-making. One reason why variations in motor costs are not reflected in decision-making could be limitations in fully integrating motor costs during movement execution. Such missing or suboptimal integration of motor costs has been reported in other dynamic decision tasks with concurrent movement (Bakker et al., 2017; Michalski et al., 2020). It is further conceivable that temporal restrictions and the dynamic nature of costs impose limits on estimating motor costs concurrent with movement (Gordon et al., 2021; Yoo et al., 2021). If this is true, future studies could focus on the integration of action costs from multiple sources, with different time constraints, or in comparison with sequential decisions. In conclusion, the decision of whether you should dribble and pass to your opponent to the left or the right depends on the motor cost dynamics while approaching the opponent. In such dynamic situations, motor costs appear to influence both the level of decision-making and the level of motor control, highlighting the reciprocal relationship between motor cost dynamics and decision-making as suggested by models of embodied decision-making (Cisek & Kalaska, 2010; Lepora & Pezzulo, 2015; Wispinski et al., 2020).

Chapter 6:

Embodied decisions biases – stable across different tasks?

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Abstract

In everyday life, action and decision-making often run in parallel. Action-based models argue that action and decision-making strongly interact and, more specifically, that action can bias decision-making. This embodied decision bias is thought to originate from changes in motor costs and/or specific crosstalk. Recent research confirmed embodied decision biases for different tasks including walking and manual movements. Yet, whether such biases generalize within individuals across different tasks remains to be determined. To test this, we used two different decision-making tasks that have independently been shown to reliably produce embodied decision biases. In a within-participant design, participants performed two tasks in a counterbalanced fashion: i) a walking paradigm for which it is known that the motor costs systematically influence reward decisions, and ii) a manual movement task in which motor costs and specific crosstalk were manipulated to test their impact on reward decisions. In both tasks, we successfully replicated the predicted embodied decision biases. However, there was no evidence that the strength of the biases correlated between tasks. Hence, our findings do not confirm that embodied decision biases transfer between tasks. Future research is needed to examine whether this lack of transfer may be due to different causes underlying the impact of motor cost on decisions and the impact of specific crosstalk or task-specific differences.

Keywords: Interindividual differences, Decision-making, Motor control, Motor cost, Specific crosstalk, Embodied decisions, Bias

[3] One change was made to fit the wording of the overall dissertation. This modification involved renaming *cognitive crosstalk* to *specific crosstalk*.

6.1. Introduction

In everyday life, we often make decisions during actions. For instance, while driving the car we decide to change the lane, when playing soccer, we decide to play the ball to a left or right-positioned teammate, or when walking through the shoe store we decide for which pair of shoes to stop. A commonality between these decision-making examples is that, first, actions are required to implement a decision and that, second, these actions are continuously changing over time, thereby qualifying these decisions as "embodied decisions" (Gordon et al., 2021). For example, while walking through the shoe store, your position in relation to the pair of shoes and accordingly the actions necessary to approach the shoes are constantly changing.

To account for embodied decisions, action-based models like the affordance competition hypothesis (Cisek, 2007) and the embodied choice framework (Lepora & Pezzulo, 2015) argue in favor of a bidirectional relationship between action and decision-making. That is, decisions not only influence subsequent actions in a hierarchical, top-down fashion (Cooper & Shallice, 2000; Newell & Simon, 1972), but actions also bias decision-making. In support of action-based models, a number of recent studies provide empirical evidence for various types of actions such as manual movements, like reaching (Bakker et al., 2017; Cos et al., 2021; Michalski et al., 2020; Pierrieau et al., 2021) or mouse tracking (Raßbach et al., 2021), and walking (Grießbach et al., 2021; Grießbach et al., 2022). Results from the latter three recent studies suggest that for both tasks, that is, walking and manual movements, the magnitude of the embodied decision biases strongly varies between participants (Grießbach et al., 2021; Grießbach et al., 2022; Raßbach et al., 2021). While some participants show no or only a small influence of concurrent action on decision-making, others are highly influenced by their concurrent actions[4]. The observed interindividual differences prompt the question of whether embodied decision biases may generalize across tasks and hence be stable (i.e., trait-like) within individuals or whether embodied decision biases are task-specific.

On the one hand, there is initial evidence in favor of the generalization hypothesis. First, previously studied tasks such as manual movements and walking share certain

[4] For instance, with respect to manual movements see the variance (random effects) in Table 1 in Raßbach et al. (2021), or for walking see Table 8-1 and Table 8-3.

properties including the selection of the speed of movement which tends to correlate within participants. For instance, it has been shown that people who reach faster also tend to walk faster (Labaune et al., 2020). Labaune et al. explain this relationship with a common control process for the selection of speed. Second, deciding while walking is essentially multitasking (Raßbach et al., 2021). In multitasking, the execution of two or more tasks is known to affect each other and the strength of these influences generalizes between tasks. This generalization is argued to reflect a trait-like multitasking ability (e.g., Morgan et al., 2013; Watson & Strayer, 2010) or a stable individual preference for strategic task coordination (e.g., Bruning et al., 2021). Similarly, if the embodied decision bias was stable across tasks, it would point either to individually stable strategic preferences or a common higher-order control process. Furthermore, if embodied decision biases transfer between tasks, this might be practically useful to predict behavior, for instance, from a computerized task to behavior under more ecological conditions (like turning left or right while walking, driving a car, etc.). This may be particularly relevant in rehabilitation contexts (Marinho et al., 2019; Rowe & Siebner, 2012), for the diagnoses of psychological disorders (Cohen & Verghese, 2019), or for optimizing task performance (Anguera et al., 2013).

On the other hand, some findings speak in favor of the task-specificity of embodied decision biases. From a neurophysiological perspective, decisions and actions do not have a clear boundary. Decision-relevant information like the value of choice options blends together in effector-specific networks in the brain (Cisek & Kalaska, 2010). That is, the neuronal activation for decisions effectuated with reaching movements is separately represented compared to eye movements or leg movements. If blending between action and decision plays a role in embodied decision biases, it is conceivable that such biases are effector-specific and hence variable between tasks.

To investigate whether embodied decision biases generalize across different tasks within individuals, we asked participants to perform a manual movement task and a walking task (see Fig. 6-1). Both tasks have revealed embodied decision biases reliably (Grießbach et al., 2021; Grießbach et al., 2022; Raßbach et al., 2021). As illustrated in Fig. 6-1, in both paradigms, participants continuously move towards an obstacle that they have to pass by. Passing by the obstacle on one side or the other, however, yields different rewards. While in the walking paradigm (from now on referred to as TWWT, Turning-While-

Walking-Task) participants walk toward the obstacle, in the manual movement task (from now on referred to as the MLTT, multilane tracking task) participants track a lane by controlling a cursor with the computer mouse. Applying these two tasks in a within-participant design, we tested the following general hypotheses: If embodied decision biases transfer between tasks, then the strength of the biases should correlate. If embodied decision biases are task-specific, then the strength of the biases should not correlate between tasks. In the following section, first, we further specify the tasks and provide more detail on how embodied decision biases are operationalized within the two tasks. We then translate the general hypotheses into specific, experimental hypotheses.

6.1.1. The walking task (TWWT)

Action-based models argue that action information feeds back into the decision process (Lepora & Pezzulo, 2015). Hence, it is possible to track action-related variables such as motor costs and weigh decision-making in real-time (Wispinski et al., 2020), an assumption that has been backed up by various experimental studies (Brenner & Smeets, 2015; Cos et al., 2021; Marti-Marca et al., 2020). In the walking task, we focused on the embodied decision bias based on changes in motor costs (Grießbach et al., 2021; Grießbach et al., 2022). While walking, the motor cost to turn varies with the current swing leg. Turning towards the side of the current swing leg enables an easier lateral step. Turning the opposite of the current swing leg requires a more effortful cross-over step (Moraes et al., 2007; Patla et al., 1991; Taylor et al., 2005). To investigate the potential impact of motor costs on decision-making, the cost to turn in front an obstacle was manipulated by predetermining the starting position (e.g., left foot in front of the right foot) and thereby the side of the swing leg when turning. An embodied decision bias by means of motor costs would be reflected in a preference to choose the side enabling an easier lateral step. Indeed, the swing leg influenced decision-making, indicating an embodied decision bias due to changes in motor costs. Alternatively, the swing leg effect could also be based on representational overlap between decision-making and concurrent motor control (e.g., a shared representation between the left swing leg and left decisions), often observed in multitasking research (Hommel, 1998; Janczyk et al., 2012; Janczyk et al., 2014). Using a computerized version of the walking task requiring manual movements, we aimed to disentangle this “specific crosstalk” and the bias by motor cost in a subsequent study.

6.1.2. The manual movement task (MLTT)

In the MLTT, instead of walking participants had to track a horizontal lane with a virtual bird avatar (Raßbach et al., 2021). A constant downward or upward perturbation of the avatar required scrolling the mouse wheel up or down. Concurrently, a central obstacle moved toward the avatar and participants had to decide to switch to a parallel upper or lower lane offering different rewards. Instead of turning while walking, participants decided for a lane switch by moving the mouse forward or backward in the horizontal plane. Specific crosstalk varied based on the required scrolling direction to stabilize the avatar. The motor cost for a lane switch was manipulated by reversing the mapping between avatar position (and, thus, scrolling direction) and the necessary movement magnitude for a lane switch in different blocks.

Indeed, results showed that participants' decisions were not only influenced by the required movement magnitude but additionally by the concurrent scrolling action to stabilize the avatar on the lane. That is, participants switched more often to the upper lane when scrolling upwards (moving the avatar upward) compared to downwards (moving the avatar downward). These results hence confirmed an embodied decision bias based on motor costs and additionally suggest specific crosstalk between action and decision-making.

6.1.3. Experimental hypotheses

In sum, both in the walking task and in the manual movement task we found evidence for embodied decision biases. In the present study, we aimed at testing whether such biases generalize within individuals across different tasks. If these biases generalize across tasks, we expected a positive correlation between the swing leg effect (SLE) in the TWWT and the scrolling effect and/or cost effect in the MLTT. If these biases are task-specific, there should be no correlation between the SLE and the scrolling effect. Additionally, if the SLE in the walking task correlates with the scrolling effect, it would suggest that the SLE is partly driven by specific crosstalk, and not exclusively by motor costs.

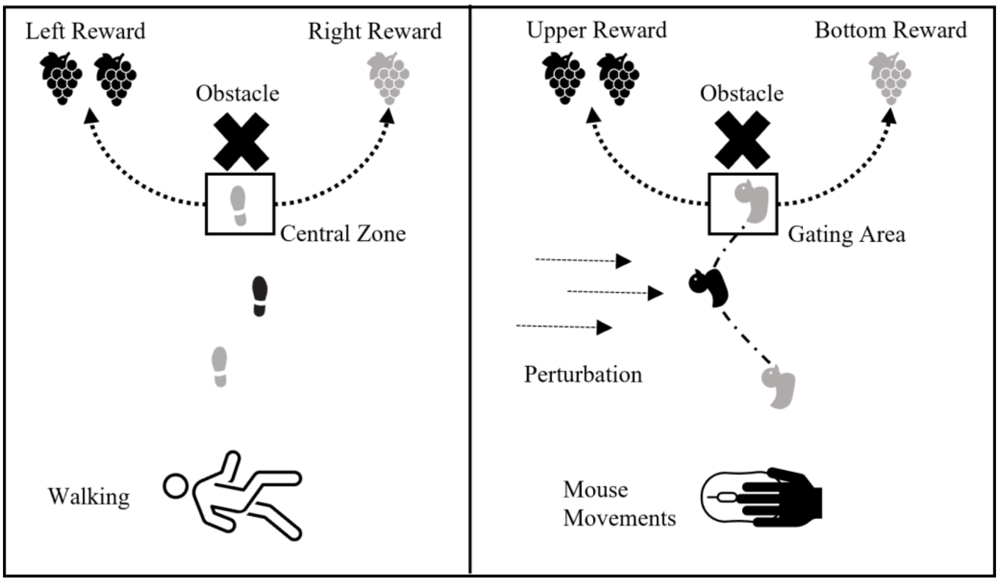

Fig. 6-1. Conceptual representation of the experimental design of the walking task and the manual movement task. Lower action costs towards either choice option are exemplified by the same color coding between the current body state, i.e., swing leg in the walking task, vertical position of the bird in the manual movement task, and reward. A. Walking task. B. Manual movement task. Note that the display of the manual movement task is rotated 90° for clarity reasons. A more detailed presentation of both experiments is displayed in the Appendix (see Fig. 8-7 and Fig. 8-8).

6.2. Methods

6.2.1. Participants

We planned to do our power analysis by calculating Bayes factors (BF) and stop when $BF_{10} > 10$ or $BF_{10} < 10$ for both hypothesis-relevant correlation terms or when hitting 100 participants. We had to stop after 89 participants because of moving the lab to a new location. For eight participants there was a problem with saving the data for the MLTT and no data was available. They had to be excluded from the final analysis. Two participants always stepped with the same foot into the central zone, which meant that they would not contribute to the estimate of the SLE in the walking experiment. Therefore, they were also excluded from the analysis. After exclusion, the final sample size was n = 79 (mean age 22.7 years, SD = 3.5 years, 44 females, 35 males, 76 right-handed, 1 missing data for handedness, 66 right-footed, 8 no preference, 5 left-footed). Participants were compensated 15,00 € after the experiment, independent of performance. All participants gave informed consent before starting the experiment. Both experiments in the study were part of a research program that was approved by the ethics committee of the Faculty of Social and Behavioral Sciences of the Friedrich Schiller University Jena (FSV 19/04) and the ethics committee of the Department of Psychology of the University of Würzburg (GZEK 2019-33).

6.2.2. Turning-While-Walking-Task (TWWT)

6.2.2.1. Apparatus and Stimuli

The maximal distance from the starting line to the center of the central zone was 3.56 m (see Fig. 8-7). The left and the right target was at a 52.5° angle at a 1.5 m distance from the central zone. The targets and the zone were 0.5 m x 0.5 m in size. To enforce a decision after reaching the central zone, three pipes (r = 3.7 cm, height = 55 cm) served as obstacles dividing the left and right sides after the central zone (60 cm behind the center of the central zone and with a 30 cm distance between obstacles). Black tape was used for the starting line, the central zone, and the lateral targets.

A digital projector displayed all stimuli (NEC Corp., Tokyo, Japan; Model M353WS, WXGA resolution, 60 Hz frame rate) on a large screen facing the participant (2.92 m width x 1.83 m height) at 1.80 m behind the center of the central zone. Black stimuli were presented on a white background. All stimuli were presented with a self-written script in MATLAB in real time based on the kinematic measurements (see data analysis). A 3D infrared system (12 cameras, Prime 17W, Optitrack, Corvallis, US) recorded Gait behavior (120 Hz) with passive reflective markers (12 mm) placed on the lateral malleolus, heel, and between the second and third metatarsal head of both feet.

Participants received auditory feedback indicating whether they finished in time after each trial. For auditory feedback served a beep (750 Hz for 0.8 s) or a double beep (750 Hz, two times 0.3 s with 0.2 s pause in between) with the integrated speaker of the projector and a sampling rate of 48000 Hz. The meaning of the beep and double beep (in time or too late) was counterbalanced between participants. Individual time constraints and starting positions were determined by baseline walking behavior before the experiment (see Appendix Chapter 8.3.).

Stimuli were presented in real time based on the position of the marker. To do this, the 3D positions of markers were streamed with the NatNet SDK from Motive v2.1.1 (Optitrack software interface) to a self-written MATLAB 2018a script (The Mathworks, Inc., Natick, MA, USA). Important events included the start of a trial, the timing of reward presentation at the third step (Banks et al., 2015), the step in the central zone, and the end of a trial based (see Appendix Chapter 8.3. for further information about detection of these events).

6.2.2.2. Procedure

The order of experiments was counterbalanced. Participants either started with the TWWT or the MLTT. Concerning the TWWT, participants started by providing informed consent and demographic data. Next, the instructor attached reflective markers on the feet. The experiment started with five baseline trials to determine the starting position and the time constraint (see Appendix Chapter 8.3.). Afterward, participants watched a narrated presentation of the instruction.

The instruction prompted them to collect rewards by walking toward one of two lateral targets. To start a trial, they had to position their feet into the predetermined starting position (left or right foot in front at the starting line) displayed on the screen. After 1.5 s, a central "+" appeared as the Go-Signal. After three steps one of three reward (point) combinations for the left and right targets appeared on the screen (left/right: 40/60, 50/50, or 60/40; participants have not been informed about the exact timing). Participants had to step into the central zone before walking towards a lateral target. To receive either, participants had to stand in the left or right target with both feet. Afterward, auditory feedback signaled the time information. If they were in time, they received the reward of the chosen side. If they were too late, they received the lower reward (40 points if 60/40, 50 points if 50/50). After the trial, participants could start the next trial on their own.

Each participant completed a total of 12 familiarization trials and 60 experimental trials. The experimental phase included 2 (starting position: left/right foot at starting line) x 3 (point combination left/right: 40/60, 50/50, 60/40) x 10 trials. Trials were presented in random order. The task lasted about 30 minutes.

6.2.3. Multilane-Tracking-Task (MLTT)

6.2.3.1. Apparatus and Stimuli

The MLTT was conducted in a separate room. Participants were seated 60 cm in front of a LED monitor (ASUS TUF Gaming VG259QM) with a screen diagonal of 24.5 inches, a screen resolution of 1920 by 1080 pixels, and a refresh rate of 120 Hz. The main input device for the experiment was a Fujitsu M530 computer mouse (1200 dpi) connected via USB to the lab PC. The experiment was realized with a self-written Python script (version 3.7), mainly using the Python module *pygame* (Shinners, 2011). The basic visual scenery of the MLTT consisted of three horizontal white lanes on a black background spanning the entire display (visual angle per lane: 3.63°). The bird avatar (height and width in degree visual angle: 2.42) was displayed as a schematic yellow bird (see Fig. 8-8). Two obstacles (depictions of cats) were positioned on the upper and lower lane and represented a gate (height and width in degree visual angle per obstacle: 3.63°; horizontal position: 1.13 x 1920 px). One similar obstacle was positioned on the middle lane and represented the obstacle participants had to evade, comparable to the pipes in the TWWT (horizontal position: 0.92 x 1920 px). Rewards were displayed as yellow stars on the upper and lower lane (height and width in degree visual angle: 3.02°; horizontal position: 1.35 x 1920 px) as well as numerals in white text (Arial, font size 31 pts [1.04 ° visual angle]) to the right above and below the bird for the upper and lower star, respectively (see Fig. 8-8). Importantly, only the numerals were informative about the points associated with the stars. The reward objects always had the same size and only signaled the end of a trial.

Movement of the visual scenery was realized by shifting the obstacles (cats) and rewards (stars) stimuli to the left of the screen with an average movement speed of about 5 pixels per frame update. A frame update was performed every 10 ms and the current state of a trial was recorded after each update (i.e., the sampling rate was 100 Hz). Frame rate and program logic were decoupled so that frame time deviances did not profoundly impact temporal stimulus events such as collisions or reward presentation. The horizontal position of the bird was fixed while its vertical position was determined by a unidirectional perturbation upward or downward, uniformly randomized between roughly 8.59 and 14.31 pixels, applied every 100 ms.

The motor cost manipulation, explained in more detail in the following Procedure (MLTT) section, was implemented by varying the mouse movement threshold for a lane switch as a linear function of the bird's position on the middle lane (see Appendix Chapter 8.3.). A visual cue (bird rotating and pointing in the direction of lower motor costs, see Fig. 8-8) was implemented to facilitate motor cost integration.

6.2.3.2. Procedure

Participants first received written instructions about the MLTT on the computer screen. They were informed that they would control a small yellow bird moving from left to right across one of three horizontal lanes. The instructions also noted that the bird would be vertically perturbed by gusts of wind (i.e., the perturbation), pushing the bird either upward or downward within a trial. To prevent the bird from drifting too far from the lane, participants had to scroll downwards or upwards with the mouse wheel to move the bird back to the center of the lane. Participants were also informed that several objects (obstacles and rewards) would appear within a trial. They were told to evade the central obstacle by performing mouse movements to switch lane (forward to the upper lane and backward to the lower lane). The instructions also noted that the necessary movement magnitude for lane switches would vary as a function of the bird's position on the middle lane in the different experimental blocks and that the rotation of the bird avatar would indicate the direction of higher/lower action costs. Most importantly, participants were instructed to accumulate as many points as possible by collecting stars.

After the general instructions, participants were instructed and could practice the MLTT in one block of 30 trials in the *congruent* and *incongruent* motor cost condition (60 trials in total). In the *congruent* condition, if the bird was perturbed upward and was thus, on average, positioned on the upper half of the middle lane, switches to the upper lane required a shorter mouse movement but a longer movement in the *incongruent* position dependence condition (see Fig. 8-8). Conversely, if the cursor was perturbed downward and was positioned on the lower half of the middle lane, switches to the upper lane required a shorter mouse movement in the *incongruent* but a larger magnitude mouse movement in the *congruent* condition.

After the practice trials, the experimental trials followed. Each trial started with a 1000 ms long display of the stationary visual scene including the lanes and the bird. Participants were instructed to use this time interval to reset the computer mouse position from the preceding trial to a neutral starting position for the next trial. Afterward, the (partially invisible) scene shifted to the left and the perturbation started to push the bird either upward or downward. If participants did not counteract the perturbation and consequently drifted too far from the currently tracked lane (i.e., the center of the bird outside the bounds of 425 and 655 pixels on the vertical axis of the screen), a corresponding error message was displayed ("Der Vogel wurde von der Bahn geweht!", which is German for "The bird was blown off the track!"). After 3250 ms of performing the motor control task, the obstacles and rewards were displayed. Participants then had 750 ms to perform a mouse movement forward or backward to switch to the upper or lower lane, respectively.

If participants failed to perform a mouse movement of sufficient magnitude for either lane switch direction within the 750 ms interval, they collided with the central obstacle, and an error message was displayed ("Oh nein, die Katze auf der mittleren Bahn hat Dich gefressen!", which is German for "Oh no, the cat on the middle lane has eaten you!"). In case of a successful lane switch, the cursor instantaneously moved to the respective lane and participants still had to counteract the perturbation until the bird reached the reward object (star). Then, the next trial started. Each trial had a duration of 5000 ms, with error trials having a duration of 6000 ms.

Participants worked on 2 (position dependence of motor costs: *congruent*, *incongruent*) x 2 (perturbation: *upward*, *downward*) x 3 (point combination upper/lower lane: 40/60, 50/50, 60/40) x 20 (repetitions) experimental trials (240 trials in total). Position dependence of motor costs was manipulated blockwise with block order being randomized for each participant separately. All other factors were manipulated trial wise with trial order being randomized for each block and participant separately. The MLTT part of the experiment lasted about 40 minutes.

6.2.4. Data analysis

In the TWWT, kinematic data were filtered at 12 Hz with a bidirectional fourth-order low-pass Butterworth filter. We interpolated missing values up to 25 frames (0.21 s, cubic spline interpolation). 5100/5265 trials (97 %) were included in the statistical analysis. Trials were excluded because participants made only three steps until reaching the zone and hence rewards were displayed too late (68 trials) or because of problems with the measurement (97 trials, losing a marker while walking, or tracking problems).

In the MLTT, 19700/20336 (97 %) trials were included in the final analysis. 636 trials were excluded because participants did not perform a clear lane switch movement with the mouse in between the gating zone. We defined a lane switch movement as movements during the trial exceeding 50 pixels which was roughly the cut-off for differences in the distribution for movement lengths around zero compared to peaks below or above zero as observed in a histogram.

For statistical analysis, we used R (R Core Team, 2019). To calculate the correlation between the SLE for the TWWT and the scrolling effect and cost effect in the MLTT we used a Bayesian version of a multivariate generalized linear mixed model. We assumed a Binomial distribution for the outcome variable “decision” for both experiments and hence used a logit link function on the outcome variable. For the decision in the TWWT, we included the *swing leg* as a predictor. For the decision in the MLTT, we used *position dependence*, the *perturbation direction*, and their interaction as predictors. We included all random effects (intercepts, slopes, and correlations) in the model. In prior studies, embodied decision biases were observed for all reward combinations, even though partially in different magnitudes (Grießbach et al., 2021; Raßbach et al., 2021). Hence, we decided not to include reward combination as a predictor as the number of estimates for the model would increase drastically (Brauer & Curtin, 2018). Model fitting was done with the brms package (Bürkner, 2017). We followed the guidelines of (Kruschke, 2021). Our scripts are publicly available at https://osf.io/8gxqe/?view_only=5cd1d6bf48e84e30a3096f36354ffc0d.

We used a priori specified contrasts based on our hypothesis (Schad et al., 2020). For the swing leg, position dependence, and scrolling direction, we used a centered sum contrast to compare the effect of the right swing leg/congruent/downwards (-0.5) vs. the left swing leg/incongruent/upwards (+0.5). The priors are specified in the SI.

For each parameter, the Bayesian model provides a posterior distribution. The posterior distribution is a probabilistic representation of parameter values given the priors, the likelihood of the data, and the model. To summarize the posterior distribution, we provided the estimated mean ($\hat{\beta}$), the equal-tailed 95% credible interval (CrI), and the probability for samples below or over a certain value. The 95% CrI defines the range within which the parameter value falls with a probability of 95 %. We highlight parameters for which over 95 % of the posterior distribution (values) are positive/negative compared to negative/positive below in the text.

We also provide Bayes Factors as a measure of whether data shifted the likelihood towards or away from the null model ($\beta = 0$) compared to the prior likelihood, suggesting the change in evidence for or against the null model. As our hypotheses are directional, we expect a positive correlation. We also tested the evidence ratio of the effect being positive compared to a negative correlation.

6.3. Results

6.3.1. Reward influenced decision-making

Before examining the influence of action on decision-making, we validated whether participants followed the instruction by fitting a model only with rewards as a predictor for target decisions. Reward influenced participants' decisions in both tasks. For the TWWT, participants went more often to the right side given that 60 points were displayed on the right side versus 60 points on the left side (OR = 38.07, 95% CrI = 21.94 to 70.35, p(OR > 1) > 0.999, BF_{01} < 0.001). The same was true for the MLTT (OR = 1.66, 95% CrI = 1.39 to 2.00, p(OR > 1) = 0.999) > 0.99, BF_{01} < 0.001).

The influence of reward on decision-making correlated between experiments (r = 0.37, 95% CrI = 0.12 to 0.60, p(r = 0) = 0.05, BF_{01} = 0.06, p(r > 0) > 0.999, RE_{+} = 340.23). That is participants who accumulated more rewards in the MLTT also accumulated more rewards in the TWWT.

6.3.2. Concurrent action influenced decision-making

Table 6-1 summarizes the posterior distributions of the correlation model. Fig. 6-2 displays the probability scales of the individual effects. Odds ratios below 1 correspond to a higher likelihood for a leftwards (TWWT)/downwards (MLTT) choice and odds ratios greater than 1 for a rightwards (TWWT)/upwards (MLTT) choice. As displayed in Table 6-1, embodied decision biases were present in both tasks. In the TWWT, participants preferred walking towards the right side given a right swing leg compared to a left swing leg (SLE, Fig. 6-2A). In the MLTT, participants preferred to switch upwards given that they had to compensate for a downwards perturbation by scrolling upward (Scrolling main effect, Table 6-1 and Fig. 6-2B). Additionally, the scrolling effect interacted with the position dependence (cost effect, Table 6-1 and Fig. 6-2B).

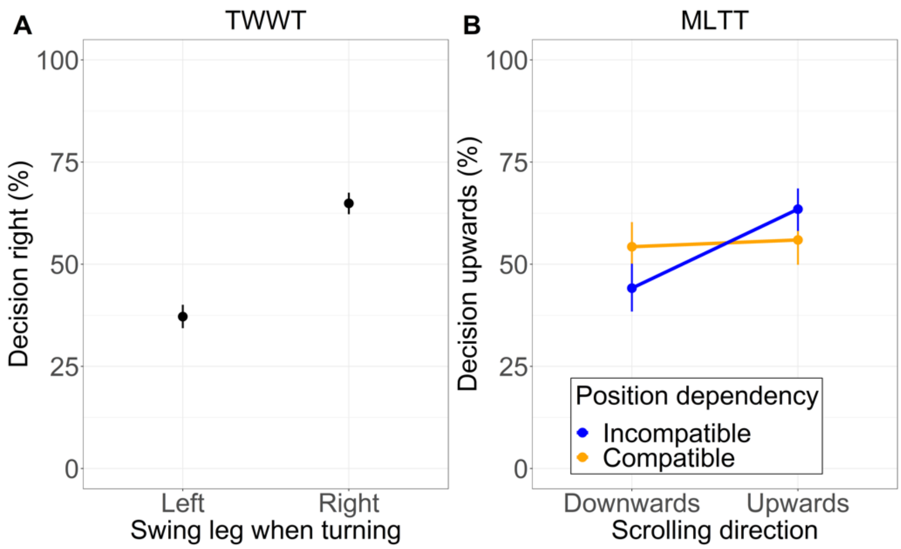

Fig. 6-2. Swing leg effect in the TWWT, scrolling effect, and cost effect in the MLTT. Estimates are marginalized over reward feedback. The SLE is defined by the preference to turn towards the side of the swing leg (left side when turning with a left swing leg and vice versa). The scrolling effect is the preference to jump toward the direction of scrolling with the mouse wheel. The cost effect is based on the interaction of the scrolling direction and the position dependence condition.

Table 6-1. Parameter summary of the fixed effects. Each parameter is summarized as the mean odds ratio, the 95% credible interval, and the probability that the posterior is smaller than one. The hypothesis-relevant parameter a marked in bold. For contrasts see methods.

Effect	OR	95% CrI	P(OR) < 1	BF_{01}
TWWT: Intercept	1.05	[0.98 to 1.12]	0.10	-
MLTT: Intercept	1.20	[1.02 to 1.41]	0.01	-
TWWT: SLE (Left:Right)	**3.13**	**[2.57 to 3.80]**	**<0.001**	**<0.01**
MLTT: Dependency (Comp:Incomp)	0.95	[0.88 to 1.03]	0.89	6.18
MLTT: Scrolling effect (Downwards:Upwards)	**1.53**	**[1.20 to 1.95]**	**<0.001**	**0.01**
MLTT: Cost effect (Dependency:Scrolling effect)	**2.06**	**[1.26 to 3.34]**	**0.002**	**0.03**

6.3.3. No correlation of embodied decision biases between tasks

Next, we focused on the correlation term between the random slopes for the TWWT and the MLTT (see Fig. 6-3).

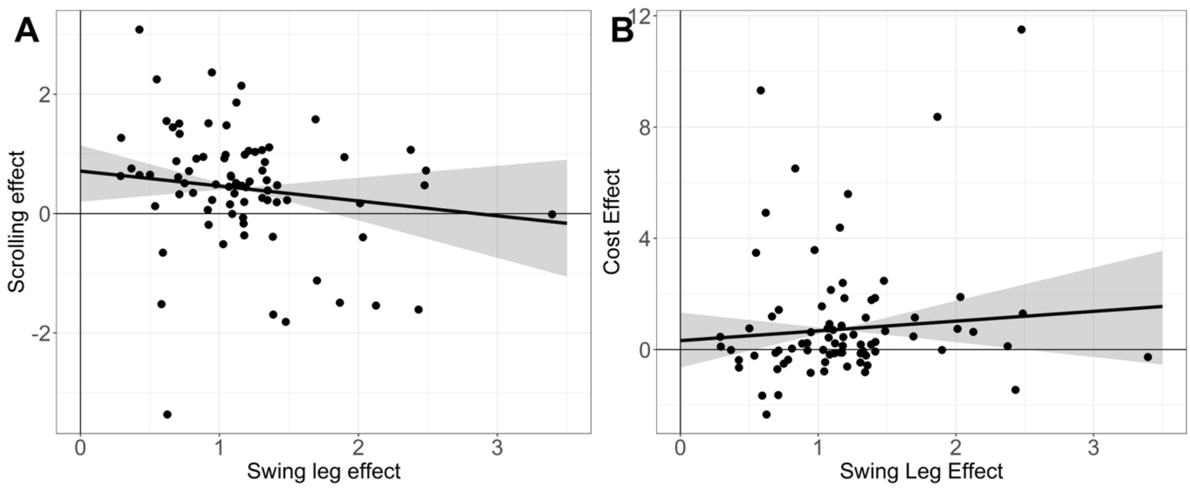

Fig. 6-3. Correlation between the effects of both tasks. A. Correlation between the scroll effect and the SLE. **B.** Correlation between the SLE and the cost effect. Displayed are the estimates of random effects of individual participants (note that these are shrinked towards the mean, a property of mixed models) as individual points, the mean correlation line (note that the correlation line is not based on the individual estimates per se) and 95 % CrI. The 95 % CrI is 0 at the means of both effect because only variation in the slope is plotted and not variation in the intercept (mean was taken). Data is displayed as log odds ratios.

The SLE and the scrolling effect were not positively correlated, but the correlation was negative or near zero, $\rho = -0.16$ (95% CrI = -0.42 to 0.11, $BF_{01} = 1.13$, $p(\rho = 0) = 0.53$). More specifically, the Bayes Factor near 1 indicated that it is inconclusive whether the null hypothesis ($\rho = 0$) or the alternative hypothesis is preferred ($\rho \neq 0$). However, our hypothesis explicitly states a positive correlation between the SLE and the scrolling effect. Hence, we additionally calculated the evidence ratio of the slope being positive rather than negative ($ER_+ = 0.13$, $p(\rho > 0) = 0.12$). The Evidence Ratio below 1 indicates moderate evidence that the correlation between the SLE and the scrolling effect is negative.

Concerning the SLE and the motor cost effect in the MLTT, if there was a positive correlation between both effects, it would be weak at most. More specifically, the correlation between the SLE in the TWWT and the motor cost effect in the MLTT is estimated to be $\rho = 0.10$ (95% CrI = -0.16 to 0.36, $BF_{01} = 1.74$, $p(\rho = 0) = 0.63$). Again, the Bayes Factor near 1 indicates that it is inconclusive whether the null hypothesis ($\rho = 0$) or the alternative hypothesis is preferred ($\rho \neq 0$). However, our hypothesis explicitly states a positive correlation between the SLE and the motor cost effect. Hence, we additionally calculated the evidence ratio of the slope which was positive rather than negative ($ER_+ = 3.54$, $p(\rho > 0) = 0.78$), indicating moderate evidence that the correlation between the SLE and the scrolling effect is positive. However, even if there would be a positive relationship, this relationship is likely to be small (e.g., for $\rho > 0.32$: $ER_{>0.32} = 0.05$, $p(\rho > 0.32) = 0.05$). Additionally, this effect is highly dependent on one participant (see Fig. 6-3B). After exclusion of this participant, the correlation decreased and averaged into a negative value ($\rho = -0.04$, 95% CrI = -0.27 to 0.19, $ER_{+} = 0.63$, $p(\rho > 0) = 0.39$).

In conclusion, the correlations between the embodied decision biases observed in each task are negative, or close to zero. Hence these results do not indicate that these biases are strongly positively correlated between tasks.

6.3.4. Reliability of measures

To test whether the embodied decision biases are stable measures and suited for the analysis of individual differences we tested the reliability of the measure with a split-half analysis. That is, we assigned every second trial to one of two levels to compare whether the effect correlates between these trials (Schuch et al., 2021). The split-half correlation for the SLE in the TWWT was $r = 0.74$ (95% CI = 0.39 to 0.95, $BF_{01} < 0.01$, $p(\beta = 0) < 0.001$), and the split-half correlation for the scrolling effect in the MLTT was $r = 0.93$ (95% CI = 0.85 to 0.98, $BF_{01} < 0.01$, $p(\beta = 0) < 0.001$). For the cost effect in the MLTT, the split-half correlation was $r = 0.95$ (95% CI = 0.90 to 0.89, $BF_{01} < 0.01$, $p(\beta = 0) < 0.001$). Hence, the reliability of all three effects was high and hence the embodied decision biases are suitable for the analysis of interindividual correlations.

6.4. Discussion

In this study, we aimed to examine whether embodied decision biases generalize across tasks such as walking and manual movements (Bruning et al., 2021; Harter & Leahy, 1999; Labaune et al., 2020; Morgan et al., 2013) or whether they are task-specific (Cisek & Kalaska, 2010). To this end, participants performed two tasks that reliably produced embodied decision biases in previous studies but differed in the concurrent task requirements, namely, a walking task (Grießbach et al., 2021), and a computerized version of the walking task requiring manual movements (Raßbach et al., 2021). We predicted that if embodied decision biases transfer between tasks, then the size of the biases in the walking and the manual movement task should correlate. By contrast, if embodied decision biases are task-specific, then the size of the bias should not correlate between tasks. Results showed that both tasks separately produced the predicted embodied decision biases, thereby replicating the findings of previous studies (Grießbach et al., 2021; Grießbach et al., 2022; Raßbach et al., 2021). However, concerning the main research question, results did not reveal a positive correlation between embodied decision biases of the two distinct tasks. Yet, the impact of reward was correlated between tasks, that is, participants who received more rewards in the TWWT also received more rewards in the MLTT. Each of these findings will be discussed in detail in the remainder of the discussion.

6.4.1. Embodied decision biases in the TWWT and the MLTT

We were able to replicate embodied decision biases in both tasks. In the TWWT, participants' decision to turn while walking was influenced by the side of the alternating swing leg when turning. As the motor cost changes based on the current swing leg (Patla et al., 1991; Taylor et al., 2005) the SLE suggests that action influences decision-making by dynamic changes in motor cost (Grießbach et al., 2021; Grießbach et al., 2022). Alternatively, the SLE could also be based on specific crosstalk (e.g., a shared representation between the <u>left</u> swing leg and <u>left</u> decisions), often observed in multitasking research (Hommel, 1998; Janczyk et al., 2012; Janczyk et al., 2014).

The MLTT was designed to disentangle whether the embodied decision bias is driven by motor cost and specific crosstalk. In the MLTT, participants' decisions to switch to the upper or lower lane were influenced by the concurrent scrolling movements with the mouse wheel to counteract a perturbation of the bird avatar (indicating specific crosstalk) as well as by the mapping between avatar position (as predominantly determined by the perturbation) and the required movement magnitude for lane switches in either direction (indicating motor cost bias). Hence, the results from both tasks corroborate the claim from action-based models that the decision process and action are heavily intertwined (Cisek, 2007; Cisek & Kalaska, 2010; Gordon et al., 2021; Lepora & Pezzulo, 2015), and further add to the growing evidence showing that concurrent action influences the decision process (Cos et al., 2021; Grießbach et al., 2021; Pierrieau et al., 2021; Raßbach et al., 2021).

6.4.2. Embodied decision biases did not transfer between tasks

Although we replicated embodied decision biases in both tasks, however, there was no evidence that these biases were positively correlated between tasks, neither for the SLE and the scrolling effect nor for the SLE and the cost effect in the MLTT. If anything, there were tendencies for a negative correlation between the SLE and the scrolling effect. There are several potential explanations for the non-existent (positive) correlation of embodied decision biases between tasks.

First, the lack of a correlation could be interpreted to indicate that the biases are rather task-specific and hence not stable across tasks within individuals. If true, this would mean, on the one hand, that embodied decision biases are not a result of a general multitasking ability (Morgan et al., 2013; Watson & Strayer, 2010), stable individual preferences for task coordination (Bruning et al., 2021), or a common motor control process as reported for vigor (Labaune et al., 2020). On the other hand, it would raise the question what the task-specific features are that account for the differences in embodied decision biases within individuals across tasks. There are several candidates, that is, notable differences between the tasks which could make the crosstalk task specific. First, because decision-relevant variables are reflected in effector-specific networks in the brain (Cisek & Kalaska, 2010) and the effectors to implement the tasks differ, it follows that this difference in effectors may account for whether crosstalk generalizes between tasks or not. In other words, the neural activations for reaching movements, eye movements, and leg movements are each separately represented. It is hence conceivable that embodied decision biases in a manual movement task such as the MLTT may only generalize to tasks that rely on arm movements, but not to walking tasks such as the TWWT. It may even be the case that embodied decision biases are not only effector-specific, but even movement- or action-specific. To further disentangle these possibilities, future studies are needed that manipulate the similarity of effectors and/or movements when studying interindividual differences of embodied decision biases between tasks.

Second, concerning specific crosstalk, the direction of movement was different between the tasks (i.e., left and right for the TWWT and upwards and downwards for the MLTT). If specific crosstalk is based on abstract representations of action (effects) like spatial similarity (Simon et al., 1970), it might be useful to compare tasks with spatially similar representations in future studies (e.g., left and right in both tasks). Importantly, while specific crosstalk may (at least partially) explain embodied decision biases in both the TWWT and the MLTT, it was only experimentally tested in the MLTT. Whether specific crosstalk also accounts for embodied decision biases in the TWWT remains to be determined.

Concerning the task-specificity of embodied decision bias driven by motor costs such as in the SLE, a relevant factor could be the actual and/or perceived motor cost varying between individuals. Motor costs of movements are reduced with familiarity and learning (Huang et al., 2012). If true, participants who are more skilled in making crossover steps in the TWWT (e.g., due to experience with such movements like from playing soccer) may have a lower cost of making the cross-over step independently of the energetic cost of jump movements in the MLTT. Individual differences in the weight distribution could also become important for objectively different costs between both tasks. Hence, the cost itself becomes task specific. Based on this argument, future studies would be well-advised to measure the motor cost more objectively and make them comparable between tasks. This could be done for example by measuring the absolute metabolic cost (Huang et al., 2012; McNarry et al., 2017) or relative force requirement (Morel et al., 2017) of movements.

Alternatively, it could be that the correlation between the effects of both tasks is rather small and is not reliably detectable with a sample size of n = 79 (Cohen, 1992; Schönbrodt & Perugini, 2013)[5]. This is especially true if the SLE, scrolling effect, or cost effect is unreliable, making a correlation harder to detect (Schuch et al., 2021). When testing for reliability with the split-half method, however, we observed that the SLE (r = 0.80), the cost effect (r = 0.96), and the specific crosstalk effect (r = 0.92) are relatively stable. Hence, a correlational approach between the effects of both tasks is justifiable. Nonetheless, split-half methods have their limitations, and reliability would be better solved by measuring the embodied decision biases across multiple sessions and analyzing whether the strength of these biases remains stable within participants between sessions (Schuch et al., 2021).

Finally, our results showed that the impact of reward was positively correlated between tasks. Participants receiving more rewards in the TWWT also received more rewards in the MLTT. It suggests a common mechanism for the influence of reward between both tasks that is worth to be studied in more in-depth in future research. For instance, an overarching motivational component like a subjective sensitivity for rewards (e.g., Crane et al., 2018) might explain the stable, but inter-individually different impact of reward.

[5] E.g., from a frequentist perspective n = 85 would be needed to find a correlation of 0.3 with 80 % power.

6. Embodied decision bias – individually stable across tasks

To conclude, we successfully replicated embodied decision biases in a walking task and a manual movement task. However, these biases did not generalize across tasks within individuals, suggesting that embodied decision biases are rather task specific.

Chapter 7

General Discussion

For a long time, psychological research focused on the idea that cognition follows a sequential and modular process (Fodor, 1983; Newell & Simon, 1972), resulting in a neglect of action in study designs (Rosenbaum, 2005). However, this perspective might be particularly precarious when it comes to decision-making, as lower-level motor control processes often occur simultaneously with higher-level decision processes, (see Chapter 2). Research on multitasking (Koch et al., 2018), embodiment (Janczyk et al., 2014) and specifically embodied choices (Lepora & Pezzulo, 2015) suggest that action influences decision-making by crosstalk between both processes and parallel feedback of cost dynamics – thereby severely questioning the sequentiality and modularity of decision-making. If true, systematic manipulation of action should bias concurrent decision-making.

In the current thesis, we tested this prediction by investigating the influence of concurrent action on decision-making in three studies (Chapters 4 - 6). Indeed, concurrent action reliably affected reward-based decision-making throughout our studies within multiple experiments. That is, the decision to walk towards a left or right target was significantly influenced by the swing leg before turning, even at the expense of receiving less reward: Participants preferred walking toward the side enabling a lateral step. Hence, our results which will be shortly summarized in the following challenge the idea that decision-making is a sequential and modular process (see Chapter 2).

In specific, Study 1 began by validating the experimental design of our new walking paradigm. Using this paradigm, we started to investigate whether action influences decision-making and the time course of this effect. The results revealed that it is not the immediate swing leg when rewards are displayed but rather the anticipated swing leg that is used before turning which influences decision-making. Additionally, the earlier the rewards were shown the more frequently participants were able to adapt their stepping behavior by means of changes in the number of steps, foot orientation, and foot location before turning. Therefore, Study 1 provided first evidence that concurrent action influences value-based decision-making during walking.

However, it remained unclear whether action influenced decision-making by parallel feedback of cost dynamics or specific crosstalk (Raßbach et al., 2021). For this reason, Study 2, aimed to investigate the hypothesis that the costs dynamics of choice options during action influence decision-making. To this end, we systematically manipulated the action costs for choice options by increasing the target angle symmetrically without (Exp. 1a) and with stepping constraint (Exp. 1b), increasing the target angle asymmetrically (Exp. 2), and adding ankle weights (Exp. 3). Study 2 predominantly confirmed that the manipulation of action costs biased participants' choices during walking. First, we observed that the SLE increased for higher target angles in Exp. 1a. Second, the SLE also increased when a stepping constraint was present (Exp. 1b) compared to the experimental setup without a stepping constraint (Exp. 1a). Third, the turning magnitude itself influenced participants' decisions, i.e., participants preferred to walk toward the side with a lower target angle (Exp. 2). Finally, the target angles in Exp. 1a and Exp. 1b influenced participants stepping strategy. That is, instead of performing a cross-over step, participants exhibited transition steps more frequently, presumably to reduce the cost requirements of the cross-over step.

While our findings clearly advocate the occurrence of embodied decision biases in a walking task, parallel work found similar results in a computerized task with manual movements (Raßbach et al., 2021). In both tasks, participants showed a wide range of effect sizes to the influence of action on decision-making, with some people being greatly affected by their actions and others showing little or no effect. In Study 3, we investigated whether the strength of the observed embodied decision biases generalize for individuals between our walking task and a computerized version requiring manual movements. As there was no significant correlation between both tasks concerning the influence of action on decision-making, our results could not confirm that embodied decision biases during walking generalize to embodied decision biases in manual movements.

Altogether, our results provide evidence that concurrent action influences decision-making, thereby impeaching the sequential and modular view of the decision process. Instead, our findings indicate that concurrent action influences the decision process by parallel feedback of action costs or specific crosstalk, which we will both be discussed in the next sections.

7.1. Action influences decisions by means of parallel feedback of action costs

The SLE which was found in all three studies and its interaction with turning magnitude in Exp 1a of Study 2 can be interpreted as a decision process receiving feedback of the costs for choice options during action (Lepora & Pezzulo, 2015). The cost dynamics during walking emerge from the alternating swing leg which impact the stepping strategy to turn toward the left or right side (see Chapter 3). Based on the inverted pendulum model of walking (Winter, 1995), the mediolateral stability of the body is determined by placing the swing leg at a location that intercepts the falling CoM. Whether the CoM will land within or outside the base of support provided by the feet can thereby be considered a measure of dynamic stability (Hof et al., 2005). To turn during walking, a lateral step can be taken toward the side of the swing leg while a cross-over step is required opposite to the side of the swing leg. In this respect, mediolateral stability is compromised for the cross-over step, as the CoM has to leave the base of support provided by the feet (Moraes et al., 2007; Taylor et al., 2005) and increasingly so for higher turning magnitudes. On the contrary, this is not the case for the lateral step where the CoM falls into the direction of the current swing leg. As a consequence, the reduction in stability for cross-over steps seems to serve as a cost to turn resulting in the preference for the lateral stepping strategy especially for higher turning magnitudes.

Next to the SLE, the main effect for turning magnitude in study 2 (Exp. 2) might also be indicative of cost dynamics feeding back into the decision process. As higher turning magnitudes are energetically more demanding (McNarry et al., 2017; Wilson et al., 2013), the decision process seems to account for the cost dynamics reflected in the preference to turn toward targets with a smaller angle.

Our manipulations of action costs did not only manifest at the level of decision-making but also at the level of lower-level stepping behavior. That is, we observed an adaptation of stepping behavior to avoid the cross-over step or presumably increase the stability of the cross-over step. For instance, participants adapted the number of steps or the foot location and orientation in Study 3 (Exp 3). The adaptation of their step behavior enabled them to make a more stable lateral step instead of a cross-over step and the adaptation of foot placement has also been shown to increase stability during gait (van Leeuwen et al., 2020). Similarly, participants avoided the cross-over step by performing transition steps instead which was increasingly observed with turning magnitude in Study 2 (Exp 1a and Exp. 1b). These transition steps bypass the stability disadvantages accompanied by the cross-over step by allowing a lateral step in either direction. Accordingly, participants seem to either have compromised rewards in favor of making a lateral step or alternatively they adapted their movements to reduce the action costs of the expected cross-over step.

Our findings for walking are generally in line with research on manual movements. For manual movements, the state of the arm (e.g., hand position or velocity) determines the costs of reaching towards different targets which in turn predict where and how to reach (Nashed et al., 2014). This is true not only for motor decision, but as more recently observed also for decisions including rewards (Cos et al., 2021; Comite et al., 2022; Marti-Marca et al., 2020).

However, compared to manual movements, the current study relied on notions like states, action, and costs from feedback control theories only conceptually for now and not computationally. This is due to the complexity of the state and action space of walking, which makes computational modeling intractable. For reaching, computational prediction from Optimal Feedback Control (OFC) already have been validated (Nashed et al., 2014; Todorov & Jordan, 2002). Additionally, recent studies began to include OFC in a hierarchical model of decision-making, as conceptually proposed in the working model in Chapter 2. This was achieved by adding a hierarchical decision layer, which evaluates choice options parallel during action and accordingly (re)selects the feedback controller which minimizes the sum of the *cost-to-go* and the negative cost of rewards parallel during action (Comite et al., 2022). Noteworthy, first computational attempts to add hierarchical layers to OFC have also been made very recently for a low dimensional model of stepping behavior during walking (Desmet et al., 2022). Future work could go a similar route with our paradigm including rewards.

In this regard it should be noted that compared to manual movements, the cost function of walking comprises additional factors. To date the best fit of action costs for manual movements is represented by the squared motor control command to create moments (Diedrichsen et al., 2010), which could be because of energetic or motor variability reasons. For walking, it is less clear, what the cost function exactly entails, as there are additional constraints like stability. Stability is a likely candidate acting as a cost during walking as falling is aversive, hinders the progress of getting toward the destination (Moraes et al., 2007), and influences the control of stepping behavior (van Leeuwen et al., 2020). However, it is also likely that the instability correlates with the integrated strength of motor commands or energetic demands (i.e., instable situations have to be more controlled and should be more demanding). There are first attempts to disentangle the cost parameters for foot placement during walking, showing that energetic requirements are not the only relevant variable (Moraes et al., 2007; Render et al., 2021).

In a similar vein to differences in the cost function between reaching and walking, the input and the representation of the state and actions are less clear for walking. If the framework holds for modeling behavior during action, questions arise like what are the inputs (e.g., visual or proprioceptive) to create a state representation of the system? What are the state representations to select and compare actions on (low-level or high-level)? What are the representations of actions? Based on the inverted pendulum model of walking, step placement and CoM seem to be likely candidates to represent and act on as it seems to play a dominant role in controlling the stability of the whole body. However, how close low-dimensional models, like the inverted pendulum model for control of the CoM (Winter, 1995), or the virtual pivot point for the control of angular momentum (Maus et al., 2010), can model more complex behavior remains an open question. In this respect, first ideas for a conceivable study design to answer the previously introduced questions in the field of walking will be presented within the last subchapter of this discussion.

In sum, our results provide evidence for parallel processing of action cost during ongoing action which influences the decision process. This parallel feedback provides evidence against the view of a serial model of information processing for decision-making (Wispinski et al., 2020). Additionally, our results underlined the appropriateness of hierarchical feedback models as a theoretical framework for embodied decision-making (Lepora & Pezzulo, 2015). Whether the same is true for other cognitive processes (Pezzulo & Cisek, 2016) remains to be determined.

7.2. Action influences decision-making by specific crosstalk

Feedback control theories propose that action influences decisions indirectly by changes in the *body state* which, in turn, influence the cost-to-go to implement a choice. Alternatively, *action* itself could directly interfere with the decision process resulting in specific crosstalk (see Chapter 2). Interestingly, a direct bidirectional relationship between action and cognition is highlighted in the broad field of embodied cognition (Shapiro, 2019). Most commonly, evidence indicates that specific crosstalk could emerge based on overlapping representations shared between cognitive and action processes (e.g., Janczyk et al., 2014; Liepelt et al., 2012).

Based on these findings decision-making and the side of the swing leg could rely on overlapping representations (e.g., *left* swing leg and *leftward* decision). Hence, specific crosstalk might provide another explanation for the SLE in our walking task. However, as the SLE in the walking task was confounded with motor costs, it has yet to be determined whether specific crosstalk emerges during walking. On the contrary, with respect to manual movements, the results of Study 3 which was designed to disentangle the influence of motor cost and specific crosstalk advocate the presence of specific crosstalk in keeping with prior work (Raßbach et al., 2021). The respective results showed that the concurrent scrolling direction to control the avatar (e.g., moving *upwards*) affected participants' reward-based decisions (e.g., jumping *upwards*) independent of motor costs. Hence, for manual movements, concurrent action influences decisions seemingly not only by action cost dynamics but also by specific crosstalk.

In accordance with our behavioral results, neurophysiological findings of decision-making tasks also suggest the occurrence specific crosstalk: If decision-making would be modular like proposed in good-based models of decision-making (Padoa-Schioppa, 2011), one would expect a separation of decision variables like value and stochastic information from action planning and execution. However, this is not the case. Instead, decision-related variables are reflected in areas of motor planning and motor execution (Cisek & Kalaska, 2010). One way to explain these findings is suggested by action-based models of decision-making, which claim that decision-making takes place not as a competition between abstract representations of choice options but directly between actions (Wispinski et al., 2020). Interestingly, if decision-making takes place on the level of actions one might also expect that concurrent action execution interferes with the decision process (Michalski et al., 2020), which I argue is similar to specific crosstalk. Additionally, it would also allow having direct information about the action cost during movement, for example, simply through weighting the activation of actions by their respective costs and hence could be a mechanism for both crosstalk and parallel feedback of action.

In sum, results from the computer task indicate specific crosstalk, which might also be (partially) responsible for the SLE. While feedback by action cost challenges a sequential processing of decisions, specific crosstalk challenges the modularity of the decision process. A more thorough elaboration on specific crosstalk has been recently presented by Raßbach et al. (2021).

7.3. Embodied decision biases are task-specific between participants

Notably, we observed embodied decision biases not only in walking but also in manual movements (see Study 3). Even though the strength of these effects were highly individual in both tasks, there was no correlation of the strength between individuals, suggesting that the embodied decision biases were task specific.

The task-specificity of embodied decision biases is not only in contrast with studies in multitasking revealing an individual proneness to interference between different tasks (Bruning et al., 2021; Morgan et al., 2013; Watson & Strayer, 2010). In fact, it also not compatible with the finding that walking and manual movements share control processes like the vigor of movement, that is, individuals who walk faster also tend to reach faster (Labaune et al., 2020).

However, multiple other lines of reasoning support task specificity, which are based mainly on the differences between the tasks which we employed. First and foremost, the tasks used different types of effectors - manual movements in a computer task and whole-body movements, with a focus on the legs, for walking. Research on action-based models (Wispinski et al., 2020) and observations of brain activity during decision-making suggests that the brain processes action and decision-making in specific areas that are related to the type of effectors being used (Cisek & Kalaska, 2010; Gold & Shadlen, 2007). For example, circuits that execute eye movements reflect decision-related variables in tasks involving eye movements, and circuits responsible for manual movements reflect decision-related variables involving manual movements (e.g., Cui & Andersen, 2011; Wunderlich et al., 2009). Consequently, if embodied decision biases emerge from these effector-based circuits, it is conceivable that walking and manual movements each exhibit their individual proneness to embodied decision biases. In this case, one might expect that embodied decision biases generalize within effectors or are specific between overlapping representations of actions (Graziano, 2016).

Second, the representations which are expected to be responsible for specific crosstalk differed between both tasks. That is, the congruency of actions and decisions was determined by the left and right direction in the walking task while it was upwards and downwards in the computer task. If true that specific crosstalk is based on overlapping representations, one might hypothesize that these representations have to be present in both tasks to generalize.

Third, it remains uncertain whether walking exhibits specific crosstalk. If there are no overlapping representations for walking and turning decisions, then the generalization between both tasks in not possible.

Fourth, the operationalization of action costs differed between both tasks. This refers particularly to stability as it represents an important parameter for walking but not for reaching. If the SLE is caused by differences in stability but the cost effect in reaching emerges from differences in the integrated motor command, the observed specificity of the biases would indicate independence between the cost parameters. I.e., the cost of stability during walking is weighted independent of the control requirements during reaching.

Altogether, the results of Study 3 indicate that the embodied decision biases observed during walking do not generalize to manual movements This task specificity might be enrooted in the systematic differences between our tasks. Possible approaches to address these differences will be presented in the next subchapter.

7.4. Suggestions for future research

7.4.1. Precise identification of the control system for walking

For the purposes of our study, we defined states and costs respectively as changes in the side of the swing leg and differences in stability to turn with a lateral step or cross-over step. Since we were able to demonstrate that the swing leg influences the decision process, our conceptual manipulation can be considered useful. However, from a control perspective, it remains unclear what exactly comprises the states, actions, and cost function for the control and choices during walking, which is arguably a complex whole-body movement.

First of all, to address the uncertainty what comprises the cost function, future studies could test stability as a variable in the decision-process more directly. If the inverted pendulum model holds and the concept of margins of stability (a measure of stability that acts as a cost during walking) is valid, then it should be possible to reduce stability by manipulating the position and orientation of the foot or by restricting ankle moments during and after turning (van Leeuwen et al., 2020). This should in turn increase the SLE. In reverse, one would predict a reduction in the SLE when the CoM is stabilized mediolaterally, e.g., as in van Leeuwen et al. 2022. Preliminary support for this claim is indicated by the adaptation of foot placement for the cross-over step in Study 1 (Exp. 3) and the increased SLE in Study 2 when providing an unspecific constraint for foot placement (Exp. 1a, compared to Exp. 2).

Secondly, as concerns the state representation during walking, manipulating the perception of state variables which are thought to be important during walking might provide insight. This could concern high-level states, like the position or velocity of the CoM or lower-level states like the angle of individual joints (see Hore & Watts, 2005 for disentangling higher-level and lower-level state estimates during throwing). Again, the perceived location of the foot placement and the high-level state of the CoM could be an appropriate candidate. There are several ways to manipulate the perceived position of the foot, even if the actual position of the foot remains unchanged. This can be done through visual illusions, such as by manipulating the appearance of the leg in a virtual reality setting (Saunders & Knill, 2003; Buhler & Lamontagne, 2018), or by altering the proprioceptive information that the body receives about the position of the foot, such as through mechanical vibrations (Hazime et al., 2012), for example, on the hip abductors (Hof & Duysens, 2013).

Following up on the more precise identification of the control system, computational models of OFC already provide a good fit for motor control and decision-making during reaching (Todorov & Jordan, 2002; Nashed et al., 2014). Although it might be a challenge to design a computational model of walking, recent work started to model a simplified controller using step placement as the basis to control (Desmet et al., 2022). This idea could be used to validate whether our findings (e.g., the SLE with its various interactions, or the adaptation of foot placement found in Study 1 and Study 2) emerge by OFC with a low-dimensional cost function including higher-level task constraints and influences like reward.

Finally, it can be difficult to analyze and predict successful performance in complex behaviors, like playing soccer, because the space of possible states and actions is large and the cost function (a measure of how good or bad an action is) is too complex. In these situations, it is not always clear which actions will lead to a reward (i.e., be optimal) and which actions will not. When it is uncertain which actions will lead to a reward, it would be helpful to use techniques that simplify the data (dimensional reduction) and statistical learning approaches on large datasets to identify the important factors (states and actions) that are related to reward (Gordon et al., 2021).

7.4.2. Disentangling specific crosstalk and feedback processes

Especially for walking, disentangling specific crosstalk from the feedback of action cost dynamics remains to be a challenge. For the computer task in study 3, this was done by reverting the relation between action costs and body state, which is not something that can easily be done in real life. I suggest an alternative approach which removes the cost differences for choice options altogether. If action influences decision-making besides changes in action costs, it indicates crosstalk. For example, imagine a task where the participant has to walk in a straight line to the other side of the room to effectuate a decision. To make the decision process more ambivalent and avoid ceiling-effects, one could replace the reward decision task with a perceptual decision task (Hagura et al., 2017). In this case, an ambivalent stimulus must be presented while walking. To indicate the choice, the participant is instructed to press a left or right button when arriving on the other side of the room. Walking is still required and congruency between decision-making (i.e., a left or right button press) and the current swing leg (i.e., left or right) during the display of the perceptual stimulus can be manipulated, without cost differences being involved. If the swing leg influences decisions by specific crosstalk, the side of the current swing leg should still influence the decision to press the left or right button.

7.4.3. Unspecific crosstalk

We did not address unspecific crosstalk in our studies. Unspecific crosstalk is thought to arise based on limited capacities to control both action and decision-making (Koch et al., 2018). To investigate unspecific crosstalk, future studies might implement manipulations of the difficulty of walking, for instance, by changing the shoes to make walking more challenging, changing the structure of the ground, or walking faster (Patel et al., 2014). However, when manipulating the speed of walking, one has to control for decision time, which could confound the results (Usher & McClelland, 2001). If there is unspecific crosstalk, participants' decisions should generally become more random, that is, independent of rewards and of the directed biases of action like specific crosstalk or feedback of cost dynamics.

7.4.4. Generalization and task specificity

Our research differs from previous cognitive psychology studies in that we wanted to make our experiment more realistic to everyday life. Other studies in this field have mostly looked at manual movements, but we focused on the whole-body movement of walking because it is a common activity in daily life. We believe that our findings will apply to various situations where turning while walking is needed, such as playing soccer or navigating around obstacles while walking on a sidewalk. In the future, it would be useful to test our findings in these real-life situations to see if they hold up.

One limitation of the generalizability of the effect size of embodied decision biases is suggested by the results of task specificity in study 3, indicating no generalization of embodied decision biases in the walking task and computer task with manual movements. But how specific could the influences of action be? Neurophysiological research indicates effector-specific crosstalk between actions and decision-making (Cisek & Kalaska, 2010). If true, it might be suitable to validate whether the biases from action generalize between effectors (e.g., left or right hand) or categories of action (e.g., pulling movements vs. pushing movements with the arm, see Graziano, 2016). Additionally, the walking task and the computer task with manual movements differed regarding their representational content from which specific crosstalk is thought to emerge. Designing a manual movement task with left/right components for motor control and making decisions would align the representational content of both tasks.

Lastly, cost variables might differ between walking and manual movement tasks because of the stability requirements during walking. Hence, investigating the generalizability between two tasks both requiring stability (e.g., walking, slacklining, or handstands) might be a fruitful route for future research.

7.4.5. Other challenges of embodied decisions

While we extended research on decision-making by investigating the influence of action on concurrent decision-making, real-life situations comprise additional challenges, some which are currently not captured by our task (Gordon et al., 2021). More specifically, this includes the identification of choice options, which are not restricted to two discrete and fixed options displaying rewards but are arguably uncountable and continuous in situations like soccer. A solution for future research would be to increase the number of choice options and investigate which choice options people attended to and why (Gordon et al., 2021; Johnson & Raab, 2003).

Further, our focus was on decision-making under certainty (rewards and how to get them were certain). In contrast, everyday decision-making often includes uncertainty in the outcome, for instance rewards are often probabilistic (e.g., whether a goal shot scores a goal for one choice is not certain). In this respect, giving stochastically distributed rewards or punishments as the implementation of such manipulations in future experiments appears to be quite intuitive. Last but not least, prior choices and actions in everyday life open the possibility for new choices but close others indicating more sequential combinatorial solutions for higher levels of decision-making. As a consequence, it might be interesting to observe how humans weigh costs and rewards under these situations (i.e., how far can they anticipate temporally and spatially? What do they focus on?) and how far specific crosstalk reaches in the cognitive-behavioral hierarchy.

7.5. Conclusion

In three studies and multiple experiments we investigated the relationship between action and decision-making. Our results revealed that these embodied decision biases emerge by parallel feedback of the action costs and specific crosstalk. Accordingly, these embodied decision biases provide evidence against a modular and sequential view on decision-making, but support models based on feedback control and a bidirectional relationship between action and decision-making.

Chapter 8

Appendix

8.1. Supplementary Information: Body Dynamics of gait influence value-based decisions

8.1.1. Individual data for decision-making

The main article provides model estimations and 95% CI of the merged reward combinations (Fig. 4-3 and Fig. 4-4) without considerations of individual data. To give a more complete overview of the distribution of individual data before merging over rewards, scatterplots are provided for decision-making of Exp. 1 to Exp. 3 in Fig. 8-1.

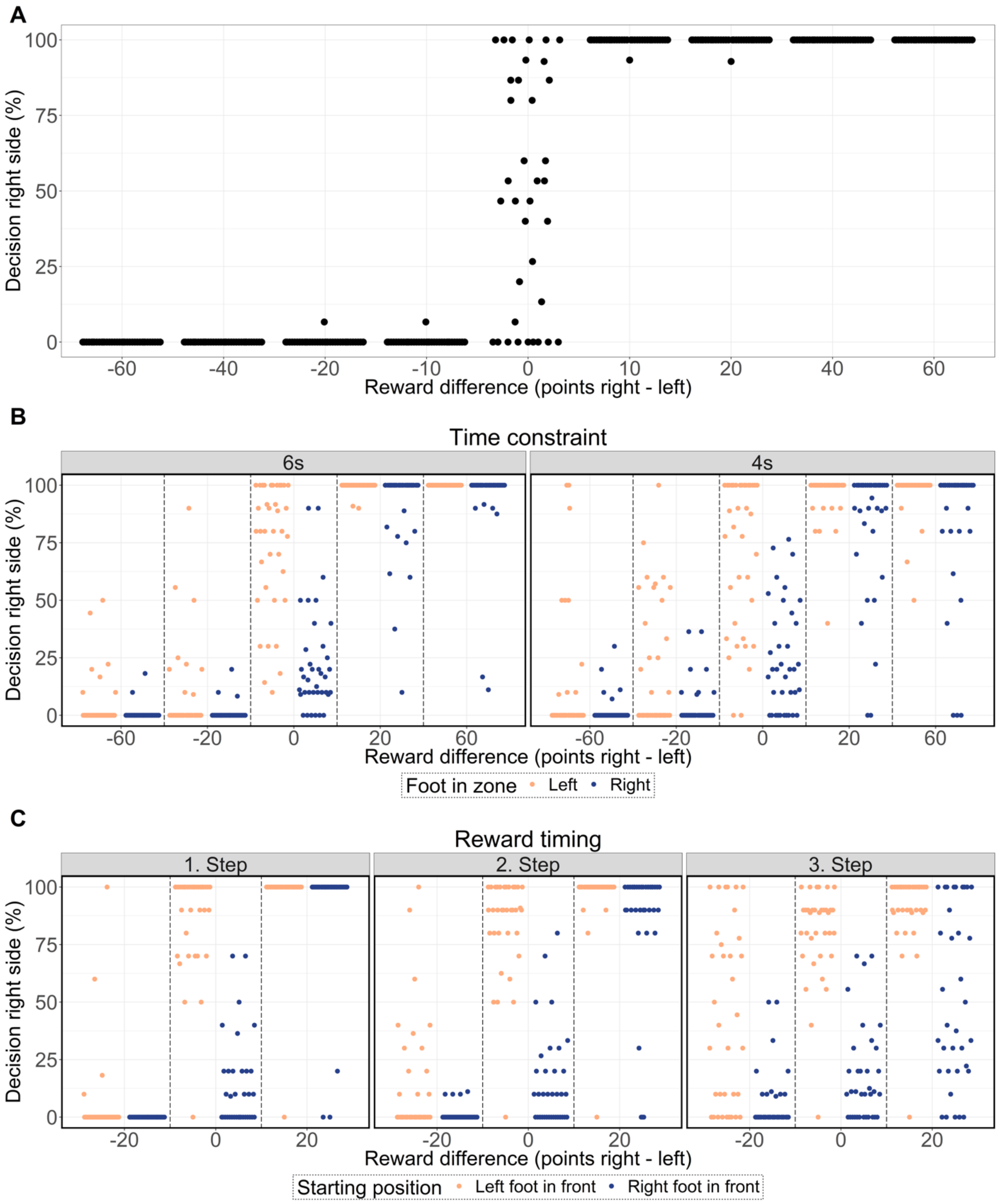

Fig. 8-1. Scatter plot of the individual data for decision-making in Exp. 1 to Exp. 3. Dots display the probabilities for individual subjects and are jittered for better visual inspection. 0 % indicates that participants always walked towards the left side. Note that in some conditions participants almost always went to the side with higher rewards, resulting in the stacking of individual means at 0 or 100 %. A. Exp. 1. B. Exp. 2. A lateral stepping strategy was required when the decision and step into the zone were incongruent (e.g., left step into the zone and walking towards the right target). A cross-over stepping strategy was required when the decision and step into the zone were congruent. C. Exp. 3. The starting position corresponds to the step into the zone for the regular four steps participants observed in Exp. 2.

8.1.2. Model specifications for decision-making in Exp. 2 and Exp. 3

8. Appendix

The main text provided model terms and likelihood ratio tests relevant to our hypothesis. Further model specifications including additional model terms and the inclusion of random effects are specified in Table 8-1 to Table 8-4. These tables only provide Wald statistics (Z), and no likelihood ratio tests for the inference of non-hypothesis relevant terms. Note that odds ratios higher than one indicate that decisions were more likely towards the side with higher rewards (Table 8-1 and Table 8-3) or the right side (Table 8-2 and Table 8-4) and vice versa for odds ratio lower than 1. The defined contrast resulted in that the first-named level (e.g., for RSS: Lat in Table 8-1 and Table 8-3) was always compared to the second-named level in the brackets (e.g., for RSS: Cross in Table 8-1 and Table 8-3).

Table 8-1. GLMM estimations for unequal rewards in Exp. 2. The decision to walk towards the side with higher rewards (yes, no) was predicted by the factor "Required stepping strategy" (lateral or cross-over step), "Time constraint" (4 s or 6 s), and the interaction between both predictors. The random effect "Participant" with intercept and slope for the "Required stepping strategy" and "Time constraint" were included with correlation terms. OR = Odds ratio, RE = Random effect, TC = Time constraint, RSS = Required stepping strategy, Lat = Lateral step, Cross = Cross-over step.

Predictors	*Log-Odds*	*OR*	*CI*	*Z*	*p*	*RE Std.*
Intercept	5.66	152.05	91.31 to 908.67	9.66	**<0.001**	2.25
TC (4 s vs. 6 s)	-2.83	0.06	0.01 to 0.43	-2.80	**0.005**	3.63
RSS (Lat vs. Cross)	-1.59	0.20	0.07 to 0.63	-2.77	**0.006**	2.09
TC (4 s vs. 6 s) : RSS (Lat vs. Cross)	0.07	1.07	0.36 to 3.17	0.12	0.906	-

Table 8-2. GLMM estimations for equal rewards in Exp. 2. The decision to walk towards the side requiring a lateral step (yes, no) was predicted by the factor "Time constraint" (4 s or 6 s). The random effect "Participant" with intercept and slope for "Time constraint" were included with correlation term. OR = Odds ratio, RE = Random Effect, TC = Time constraint.

Predictors	*Log-Odds*	*OR*	*CI*	*Z*	*p*	*RE Std*
Intercept	1.34	3.81	2.67 to 5.43	7.41	**<0.001**	0.99
TC (4 s vs. 6 s)	-0.19	0.83	0.55 to 1.24	-0.91	0.362	0.84

Table 8-3. GLMM estimations for unequal rewards in Exp. 3. The decision to walk towards the side with higher rewards (yes, no) was predicted by the factor "Required stepping strategy" (lateral or cross-over step), "Timing of reward presentation" (1. step, 2. step, 3. step) and the interaction between both predictors. The random effect "Participant" with intercept and slope for "Required stepping strategy", and the "Timing of reward presentation" were included without correlation terms. Note that in the main text for estimations and inference of the interaction term we used an additional model which included the interaction as a random effect, as suggested by(Barr, 2013). Hence the values for the interaction deviate here. OR = Odds ratio, RE = Random effect, TC = Time constraint, RSS = Required stepping strategy, Lat = Lateral step, Cross = Cross-over step.

Predictors	*Log-Odds*	*OR*	*CI*	*Z*	*p*	*RE Std.*
Intercept	4.68	107.60	40.97 to 282.61	9.50	**<0.001**	2.21
TR (2. step vs 1. step)	-2.89	0.06	0.01 to 0.25	-3.75	**<0.001**	1.76
TR (3. step vs 2. step)	-2.47	0.08	0.04 to 0.16	-7.51	**<0.001**	1.18
RSS (Lat vs. Cross)	-2.67	0.07	0.02 to 0.20	-4.92	**<0.001**	2.42
TR (2. step vs 1. step) : RSS (Lat vs Cross)	0.09	1.09	0.26 to 4.53	0.12	0.905	-
TR (3. step vs 2. step) : RSS (Lat vs Cross)	-0.70	0.50	0.21 to 1.17	-1.59	0.111	-

Table 8-4. GLMM estimations for equal rewards in Exp. 3. The decision to walk towards the side requiring a lateral step (yes, no) was predicted by the factor "Timing of reward presentation" (1. step, 2. step, 3. step. The random effect "Participant" with intercept and slope for "Timing of reward presentation" of the first level (2. step vs. 1. step) were included without correlation term. OR = Odds ratio, RE = Random Effect, TS = Timing Reward.

Predictors	*Log-Odds*	*OR*	*CI*	*Z*	*p*	*RE Std.*
Intercept	1.93	6.91	4.89 to 9.76	10.96	**<0.001**	0.93
TR (2. step vs 1. step)	-0.27	0.76	0.52 to 1.12	-1.40	0.163	0.18
TR (3. step vs 2. step)	-0.22	0.80	0.60 to 1.07	-1.49	0.137	-

8.1.3. Was decision-making in Exp. 1 sequential?

Exp. 1 served as a paradigm for sequential decision-making to determine the cost difference between the lateral step and the cross-over step. Therefore, the rewards were displayed before participants started walking. That is, cost and reward information were available before an action was initiated. However, participants were only instructed to choose before walking. If decisions were indeed sequential, we expected participants stepping behavior to reflect their decision (to implement the lateral stepping strategy observed in Fig 1) already at action initiation in the first step. Therefore, we ran additional analyses on the side of the first step and step length based on participants' choices. Results are illustrated in Fig S2 and indicate that most participants completed the decision before starting to walk.

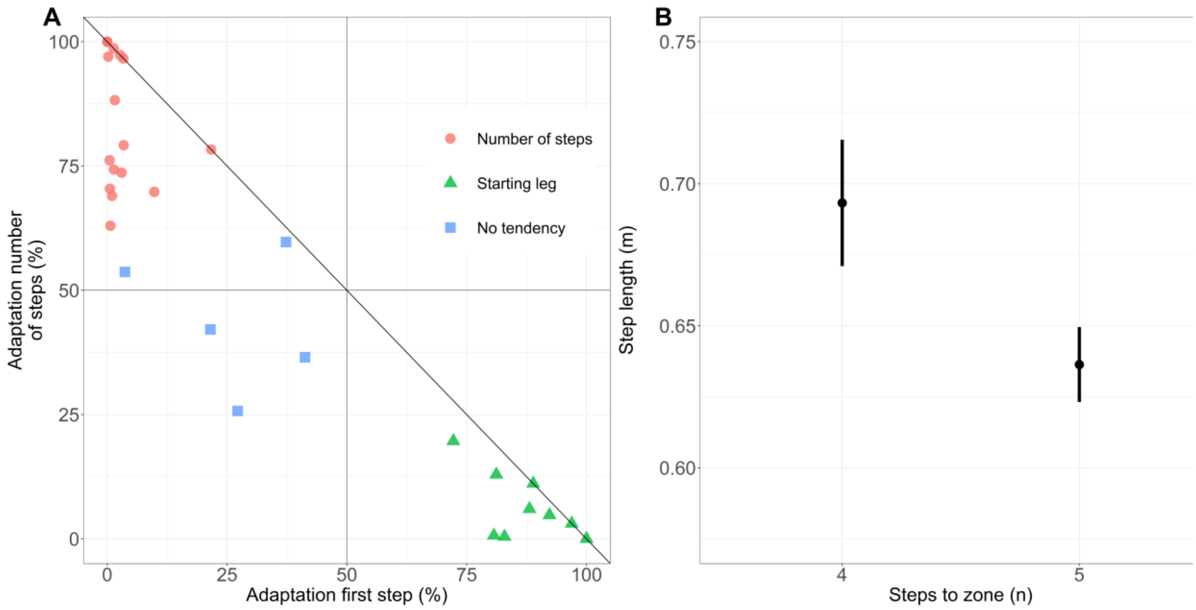

Fig. 8-2. Adaptation strategies of the first step to implement a lateral stepping strategy. A. To enable a lateral step for both sides, participants had to switch the foot with which they stepped into the designated zone. This could be done by varying the stride length and therefore the number of steps (e.g., even to odd) or the side of the first step (e.g., left to right). Displayed is the percentual change in the number of steps (even or odd) and starting leg (left or right) between walking to the left compared to the right side. Values below the diagonal line are underspecified because there is no clear preference of stepping behavior for each side (e.g., 50 % even steps and 50 % right starting leg when going to the left and right side could be interchanged and would result in no difference for both variables). Each value is the probability for individual participants. Participants were classified into applying one of three strategies based on k-means-clustering. Adaptation of the first step provides evidence that action is selected after the specification of the decision (sequential decision-making). B. Analysis of the step length of the first step for participants which had no tendency or the tendency to change the number of steps. Displayed is the mean and 95% CI (within-subject). The step length of the first step was already shortened, suggesting that these participants also selected their action after the specification of the decision (sequential decision-making).

More specifically, to switch the foot in the designated zone, a change in the starting leg or a change in the number of steps could be performed. To evaluate adaptation strategies that enable a lateral step, the difference (in %) for both the starting leg and the number of steps (odd or even) between going to the left and right sides were calculated. One participant did not adapt the stepping behavior at all and was excluded from this analysis. Because data clusters were observed (see Fig. 8-2A), the data were analyzed by k-means clustering (elbow method), to obtain the number of clusters and classify participants based on the style of adaptation. 9/35 participants already switched the side of the first step based on the decision to walk towards the left or right side, indicating that decision and action initiation was indeed sequential. For participants that did not preferably adapt the side of the first step (26/35), we further analyzed the step length of the first step as the distance of both lateral malleolus marker at touch-down (see Fig. 8-2B). One participant did not make 5 steps (but 3) and was excluded for the analyses of the step length. The step length of the first step was already shortened when adapting the number of steps from 4 to 5 steps ($t(25) = 6.35$, $p < 0.001$, dz = 1.25, 95% CI [0.045 m, 0.088 m], see also Fig. 8-2B). The early adaptation of the step length of the first step also indicates that decision and action initiation was indeed sequential.

8.1.4. Information about the time to finish and task success

Exp. 2 and Exp. 3 involved a time constraint of 6 s (Exp. 2) or 4 s (Exp. 2 and Exp. 3). Participants received no reward when they finished the task too late. The time to receive rewards(Green et al., 1997) and reward uncertainty are relevant factors of decision-making(Mishra, 2014). Therefore, the time to finish the task and task success was further analyzed.

As a manipulation check for the factor “Time constraint” in Exp. 2 we analyzed whether the time conditions influenced the time to finish the task. The average time to finish the task in the 6 s time condition was 4.40 s (sd = 0.36) and in the 4 s time condition 3.66 s (sd = 0.16). Differences in the time to finish the task were significant ($t(36) = 13.11$, $p < .001$, $d_z = 2.16$, 95 % CI = 0.62 to 0.85 s). In the 6 s time condition 0.1 % of trials were too late, in the 4 s time condition 7.2 % of trials were too late. A GLMM revealed that this difference as significant ($\chi^2(1) = 57.35$, $p < 0.001$, OR = 0.02, 95 % CI = 0.01 to 0.07). This means that like expected participants finished slower and more often within the time limit in the 6 s time constraint.

8. Appendix

Additionally, we compared the time to finish the task between the lateral stepping strategy and the cross-over stepping strategy in both time conditions with a repeated-measures ANOVA. There was a significant interaction between time conditions and stepping strategy (F = 31.82, p < 0.001, η_p^2 = 0.006). Separate dependent t-tests for both time constraints revealed that in both cases the time to finish the task was longer for cross-over steps and this difference increased in the 6 s time condition (4s: $t(35) = 4.68$, $p < 0.001$, $d_z = 0.78$, 95 % CI = -0.04 to -0.11, 6s: $t(35) = 7.28$, $p < 0.001$, $d_z = 1.21$, 95% CI = -0.11 to -0.20, p-values with Bonferroni correction). We also tested whether a cross-over step decreased the probability of getting towards the target in time and receiving the reward. In the 6 s time condition only 4/3673 trials were not in time (3 for lateral stepping behavior and 1 for the cross-over step). In the 4 s time constraint, trials with cross-over step were not significantly less frequent within the time constraint than trials with a lateral step (χ^2 (1) = 1.04, p = 0.31, OR = 0.77, 95 % CI = 0.49 to 1.21), indicating that a cross-over step slowed participants but did not decrease the chance of receiving rewards.

Similarly, we also checked whether trials with a cross-over step compared to the lateral step involved a time cost in Exp. 3. The cross-over step was 0.07 s (95 % CI = 0.04 to 0.10 s) slower than the lateral step ($t(33) = 5.45$, p < 0.001, $d_z = 0.93$). The probability of reaching the reward in time decreased when doing a cross-over step compared to a lateral step (χ^2 (2) = 8.92, p = 0.002, OR = 0.40, 95 % CI = 0.24 to 0.68), indicating that a cross-over step slowed participants and did decrease the chance of receiving rewards.

8.2. Supplementary Information: Embodied decisions during walking

8.2.1. Methods Exp. 1a

8.2.1.1. Calibration and familiarization trials

To individualize the starting position and the time constraint and hence control for task difficulty between participants, they performed calibration trials before the experiment. In calibration trials, we instructed participants to walk as fast as possible between both ends of the room for five trials before experimentation. Based on pilot data, the starting line's comfortable distance to the central obstacle's midpoint was 0.22 m smaller than the mean walking distance of the first four steps in the calibration trials. However, the maximal distance of the starting position in the experiment was partially limited by the size of the laboratory (3.41 m) if participants' step length went beyond this distance. In prior experiments we did have a fixed 4 s time constraint (Grießbach et al., 2021). When individualizing the time constraint, we aimed to preserve this mean of 4 s but individualize around it. Pilot data showed that participants need 1.9 s on average to make four steps. To get towards the mean of 4 seconds, we added 2.1 s which includes a fixed time to make the decision, turn towards one target and walk 1.5 m towards the target area. For calibration trials, we defined the trial start as the first time where one of the lateral malleoli markers exceeded a horizontal velocity of 0.1 m/s for 0.125 s consecutively, based on the difference (derivative) between the position of consecutive frames.

Regarding the familiarization trials, the required time to finish was projected on the screen for the first nine trials, and no auditory feedback was given on whether participants were too late or too early. In the following nine trials and for the rest of the experiment, there was only sound feedback indicating whether participants were in time.

8.2.1.2. Online analysis

To start a trial, the following conditions had to be met:

1. Six markers had to be in an area around the starting line (-0.3 to 2.1 m horizontal, -0.3 to 0.3 lateral, and under 0.25 m height). If six markers were in the area, these markers were identified by the assumed starting position (left foot positioned left to the right foot, toe positioned more to the front than the lateral malleolus, lateral malleolus more to the front than the heel).

2. The most forward marker had to be close to the starting line (horizontal ± 0.05 m, lateral ± 0.3 m).
3. The predetermined foot had to be in front.
4. The malleolus marker stood still, i.e., was not displaced between consecutive frames for more than 0.004 m.

If all four conditions were met for 180 frames (1.5 s), a trial started. The timing of the reward presentation at the third step was accomplished by estimating the timing of the touch-down (first contact of the foot with the ground) kinematically while walking towards the central zone. To estimate every step's touch down, the maximal horizontal distance of the heel marker of the swing leg and the lateral malleolus marker of the stance leg was calculated (Banks et al., 2015). For the maximal distance, we checked the horizontal difference of the position between two frames for an inversion (i.e., a distance increase switching to a distance decrease between consecutive frames). To ensure one maximum per touchdown, the analysis of touchdown was paused for 0.125 after finding a touchdown. To check whether participants stepped into the central zone, we compared the position of the lateral malleolus marker of all touch-downs to the area of the central zone. If the participant did not step into the central zone a warning message appeared centrally on the projected display ("Markierung beachten" in German, freely translated as "Note marking"). To end a trial, the number of markers that were identified in one of the two required targets was added. If more than four markers were in the target area (more than one foot), the trial ended. The time from trial start to the end was measured with MATLABs intern stopwatch timer ("tic", "toc") and used as comparison and feedback to check whether participants finished in time.

8.2.1.3. Offline analysis

To identify the correct foot stepping into the zone, we checked the kinematic data visually for trials in which:

1. the foot in the mark was not defined by the online analysis,
2. a second self-written velocity-based algorithm for estimating the touch-down did not agree with the distance-based algorithm from Banks et al. (2015),
3. the toe of the foot first passing the beginning of zone did not agree with the foot touch-down in the zone,

4. rewards were presented too late when the foot was already in the central zone,
5. participants switched sides rapidly (0.25 s) before a trial finished, as an indication for ignoring the obstacle.
6. a trial was not finished, or there was no kinematic data available,
7. before finishing a trial, they stepped in the wrong target with at least one marker of the foot (e.g., 15° instead of 90° target).

For the Bayesian model, we used informative priors for the effect of reward and weakly informative priors for all other parameters. To determine these priors, we used prior predictive checks on the probability scale for decisions, aiming for a roughly uniform distribution for equal rewards (50/50) and a biased distribution towards the side of higher rewards (60/40 and 40/60). We expected a bias towards higher rewards and used informative priors (a normal distribution with mean = 2 and sd = 1) based on our study with a similar setup (Grießbach et al., 2021). For the intercept we used a normal distribution (mean = 0, sd = 1). For all other regression coefficients, we used a normal distribution (mean = 0, sd = 0.5). We used an exponential distribution for the standard deviation of all random effects (lambda = 1). We did include a random intercept and all random slopes as random effects for subjects, but we excluded correlations parameter between random effects because of model complexity and the resulting computation time.

Stan uses an MCMC algorithm for sampling the posterior distribution. We sampled eight independent Markov chains with 4000 samples each. The first 2000 samples were warm-up samples, only the last 2000 samples were used to approximate the posterior distribution. To check whether samples converged, we visually inspected the chains and the Rhat statistic (all values were below 1.01). The effective sample size for all models was predominantly higher than 10000, and always above 1000 samples (see models saved in the osf repository).

8.2.1.4. Exclusion of trials

After visual inspection, eight trials were excluded because of dropped markers or missing data for a marker. Two trials were excluded because participants did not step into the mark. Five trials were excluded because participants ignored the obstacle. 46 trials were excluded because rewards were shown too late because of missing a touch-down. 15 trials were missing because of missing data or not finishing a trial. One trial was excluded because of a false start. Six trials were excluded because participants finished to the wrong target. 204 trials were excluded because participants did not take four steps.

8.2.1.5. Analysis of stepping strategies

To check whether participants made cross-over steps like expected, we also analyzed the position of the step after reaching the zone. To do that we calculated the position at touch-down (mostly velocity-based algorithm) of the center of the foot determined by half the distance between the calcaneus marker and lateral malleolus marker of the respective foot. The position of the step after reaching the zone was determined by the vector between the position of the center of the foot stepping into the zone (step n) and the center of the step afterward (step n + 1). We observed the following stepping strategies, when the swing leg was opposite to the side participants walked to (see Fig. 5-4A and Fig. 5-4D): participants crossed with the swing leg towards the side of the stance leg (cross-over step), or they positioned their foot next to the stance leg (transition step). In five trials the same leg was used for the step into the zone and the step afterward. These trials were not included in the analysis of stepping strategies. The transition step allows to switch the stance leg and make a lateral step towards either side. We classified transitions steps and cross-over steps based on their position to the foot in the zone. When the foot center of the step afterward crossed the foot center in the zone towards the ipsilateral side (greater or smaller than 0, dependent on the side), we classified the step as a cross-over step, else a transition step (see Fig. 5-4). Because of very few trials (6) which were very close to zero in the frontal plane but already strongly into the 15° target direction for the sagittal plane, we classified a transition step by a second criterium of being not outside the leading boundary of the central zone into the direction participants finished.

8.2.2. Methods Exp. 1b

8.2.2.1. Exclusion of trials

After visual inspection, ten trials were excluded because participants ignored the obstacle. Four trials were excluded because a marker dropped before reaching the central zone. One trial was excluded because the participant did not step into the central zone. Ten trials were excluded in which participants went firstly towards the wrong target. Twenty-eight trials were excluded because of problems identifying touch-downs in real-time. One trial was excluded because the participants started walking after the time constraint. 283 trials were excluded in which participants did not take four steps.

8.2.2.2. Small changes to Exp. 1a

To avoid false starts observed in Exp. 1a, the first display did not transition abruptly to the second display, but when participants stood still in the required starting position the color of the starting position changed proportionally to the number of frames in 1/180 steps from black (visible) to white (not visible). After 1.5 s, as in Exp. 1, the screen switched to displaying a “+”.

8.2.3. Methods Exp. 2

8.2.3.1. Exclusion of trials

After visual inspection, two trials were excluded because a marker dropped before reaching the zone, 20 trials were excluded because participants did not step into the zone, 14 trials were excluded because participants ignored the obstacle, 53 trials were excluded because the reward was presented too late, three trials were not finished correctly, four participants were excluded because of rarely making four steps (< 36.5 %, 768 trials), and 52 individual trials were excluded because participants went towards the wrong target. 219 trials were excluded in which participants did not take four steps.

8.2.4. Methods Exp. 3

8.2.4.1. Exclusion of trials

After visual inspection, sixteen trials were excluded because a marker dropped before reaching the zone, six trials were excluded because participants did not step into the central zone, 56 trials were excluded because rewards were presented too late, and one trial was not validly finished. 293 trials were excluded in which participants did not take four steps.

8.2.5. Results – Additional analyses

8.2.5.1. Individual data for decision-making

In the main paper, we only visualized model estimates for decision-making data for clarity reasons. Fig. 8-3 provides additional information about the raw data. Noteworthy is the high number of participants always walking towards the side with higher rewards, resulting in ceiling effects for these individuals.

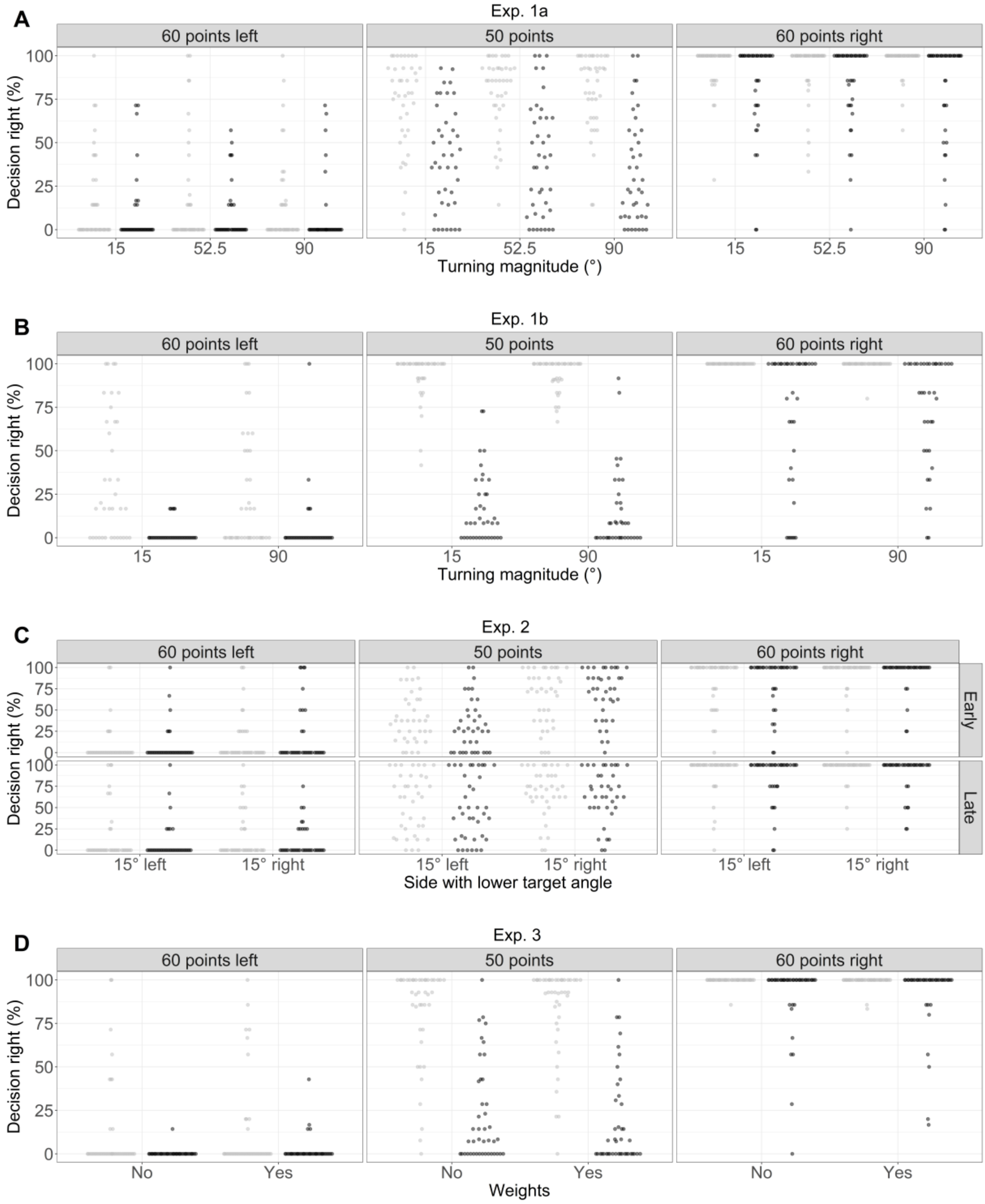

Fig. 8-3. Bee swarm plots of the individual data for decision-making. Every dot displays the percentage of an individual walking towards the left or right side**.** Dots are jittered for clarity purposes**. A.** Results for Exp. 1a. **B.** Results for Exp. 1b. **C.** Results for Exp. 2. **D.** Results for Exp. 3.

Because of the high variance of the swing leg effect between subjects, especially for unequal reward combinations, we visualized the raw data for the swing leg effect in Fig. 8-4.

Noteworthy are a few individuals with a strong swing leg effect (over 80 % of trials towards the side of the lateral stepping strategy).

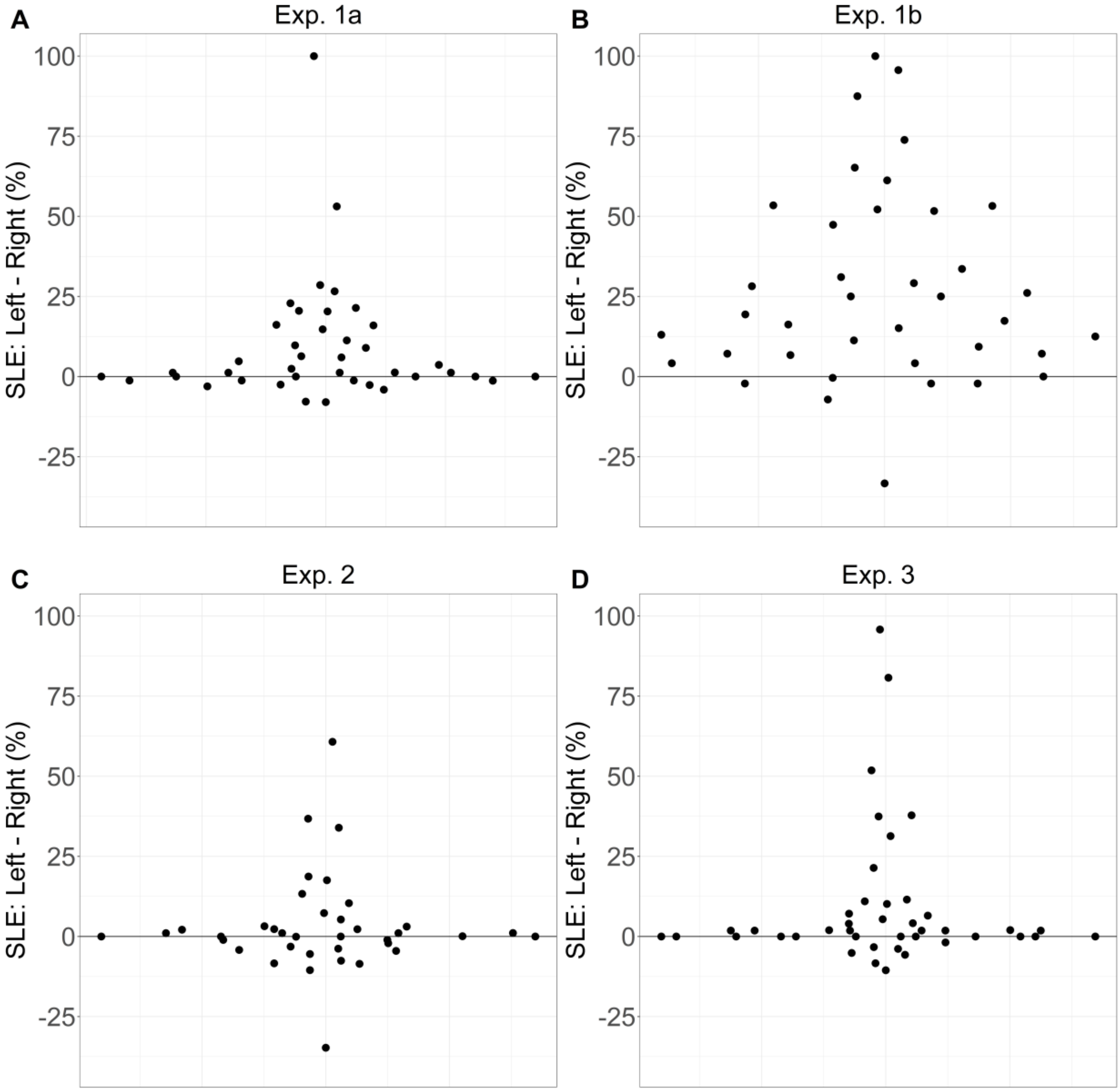

Fig. 8-4. Bee swarm plot of the swing leg effect for unequal reward combinations. The dots display the individual percentage difference of walking towards the right side given a left vs. a right swing leg. 100 % percent means that participants always walked towards the left side, given a left swing leg, and always walked towards the right side, given a right swing leg. Zero percent means, that participants went as often to the left and right side for the left and right swing leg. Dots are jittered for clarity purposes. **A.** Results for Exp. 1a. **B.** Results for Exp. 1b. **C.** Results for Exp. 2. **D.** Results for Exp. 3.

8.2.5.2. Foot placement in the zone for cross-over steps in Exp. 1a and Exp. 1b

In Exp. 1b, the swing leg effect was larger compared to Exp. 1a. One main difference between the experiments was the additional constraint of foot placement into the central zone in Exp. 1b (see Fig. 5-4A and Fig. 5-4D for the dimension of the zone). Foot orientation and lateral foot placement have been shown to influence mediolateral stability while walking (Rebula et al., 2017; van Leeuwen et al., 2020). Hence, if the additional constraint in Exp. 1b led to less adaptative foot placement regarding participants turning direction, this might indicate that the cost of making cross-over steps increased. This could be a reason for the stronger swing leg effect in Exp. 1b.

Hence, we analyzed participants' foot orientation and lateral positioning when stepping into the zone before turning with a cross-over step. Foot orientation was defined as the angle between the global forward axis and the lateral component of the vector between the calcaneus marker and the toe marker of the foot at touch-down when stepping into the zone. Lateral foot positioning was defined as the lateral positioning of the malleolus marker of the foot stepping into the zone at touch-down, with the origin being in the center of the central zone. We again used Bayesian mixed models for inference. Foot orientation and foot placement were modeled by a linear model with the decision (left or right, sum contrast) and turning magnitude (Exp. 1a: 15°, 52.5°, and 90°, sliding contrast, Exp. 1b: 15° and 90°, sum contrast) as independent variables. Conditional estimates of the mean and 95 % CrI of the independent variables are displayed in Fig. 8-5.

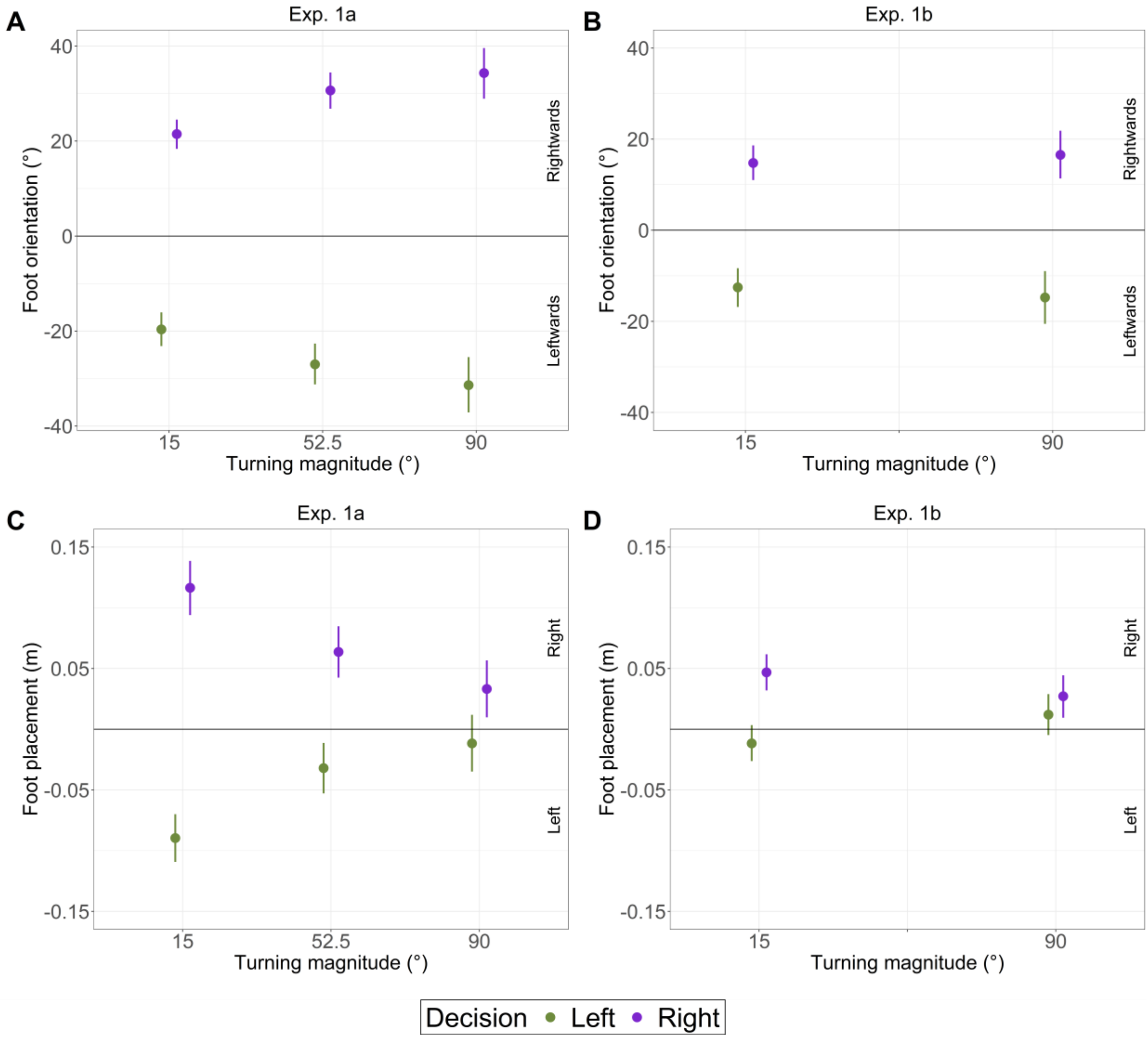

Fig. 8-5. Foot orientation and lateral foot placement for the step in the zone before turning with a cross-over step. Shown are the model estimates of the mean and 95 % CrI for each condition. **A.** The lateral foot orientation for Exp. 1a was directed towards the direction of the chosen target (left or right). The foot angle increased/decreased with turning magnitude towards the chosen target. **B.** The lateral foot orientation for Exp. 1b was less directed towards the chosen target compared to Exp. 1a, i.e., more straightforward and only marginally increased with turning magnitude. **C.** In Exp. 1a, the foot placement was directed towards the chosen target, and decreasingly with turning magnitude. **D.** In Exp. 1b, the foot placement was more central and less adapted with turning magnitude.

Concerning the foot orientation, in Exp. 1a, participants directed their foot towards their choice, i.e., leftwards if they turned left or rightward if they turned right (see Fig. 8-5A), and increasingly so with increasing target angle. More specifically when walking to the left side the foot angle decreased from -19.65° at 15° turning magnitude (95% CrI = -23.14° to -16.05°, $P(\beta < 0) > 0.99$) by -11.73° at 90° turning magnitude (95% CrI = -16.79° to -6.56°, $P(\beta < 0) > 0.99$), indicating that the foot angle was oriented more leftward. When walking to the right side the foot angle increased from 21.49° at 15° turning magnitude (95% CrI = 18.36° to 24.52°, $P(\beta < 0) < 0.01$) by 12.85° at 90° turning magnitude (95% CrI = 7.59° to 18.03°, P(β

< 0) < 0.01), indicating that the foot angle was oriented more rightward. In Exp. 1b, participants oriented their foot also towards the chosen side, but less so and additionally less dependent on turning magnitude (see Fig. 8-5B). More specifically, when walking to the left side the foot angle decreased from -12.53° at 15° turning magnitude (95% CrI = -16.85° to -8.35°, $P(\beta < 0) > 0.99$) by only - 2.24° at 90° turning magnitude (95% CrI = -7.28° to 2.78°, $P(\beta < 0) = 0.81$), indicating the foot angle was only marginally oriented more leftward. When walking to the right side the foot angle increased from 14.78° at 15° turning magnitude (95% CrI = 11.03° to 18.61°, $P(\beta < 0) < 0.01$) by only 1.77° at 90° turning magnitude (95% CrI = -2.45° to 6.01°, $P(\beta < 0) = 0.20$), again indicating that the foot angle was only marginally oriented more rightward.

Concerning the lateral foot placement, in Exp. 1a, participants stepped towards the chosen side, i.e., towards the left in the central zone when walking towards the left side and vice versa (see Fig. 8-5C). The foot placement in the direction of walking decreased with the target angle. More specifically when walking to the left side the foot placement increased from -0.09 m at 15° turning magnitude (95% CrI = -0.11 m to -0.07 m, $P(\beta < 0) > 0.99$) by 0.08 m (95% CrI = 0.06 m to 0.10 m, $P(\beta < 0) > 0.01$) at 90° turning magnitude, indicating that the foot was placed more rightward. When walking to the right side the foot placement decreased from 0.12 m at 15° turning magnitude (95% CrI = 0.09 m to 0.14, $P(\beta < 0) < 0.01$) by -0.08 m at 90° turning magnitude (95% CrI = -0.10 m to -0.07 m, $P(\beta < 0) > 0.01$), indicating that the foot was placed more leftward. In Exp. 1b, participants placed their foot close to the center of the central zone, and adaption with turning magnitude was decreased (see Fig. 8-5D). More specifically when walking to the left side the foot placement increased from -0.01 m at 15° turning magnitude (95% CrI = -0.03 m to 0.00 m, $P(\beta < 0) = 0.94$) by 0.02 m (95% CrI = 0.01 m to 0.04 m, $P(\beta < 0) < 0.01$) at 90° turning magnitude, indicating that the foot was placed more rightward. When walking to the right side the foot placement decreased from 0.05 m at 15° turning magnitude (95% CrI = 0.03 m to 0.06 m, $P(\beta < 0) < 0.01$) by -0.02 m at 90° turning magnitude (95% CrI = -0.03 m to -0.01 m, $P(\beta < 0) > 0.99$), indicating that the foot was placed more leftward.

In sum, the stepping behavior indeed differed between Exp. 1a and Exp. 1b and could be part of the explanation for the observed differences in the swing leg effect between both experiments.

8.2.5.3. Carry-over effects for crossing in the equal reward combination

For the equal reward combination, one could ask, why participants went towards the side of crossing in the first place. As we focused only on rewards and motor costs, it would be conceivable that participants would always walk towards the side enabling a lateral step. While there are a few possible explanations (motor cost dependent on more than just the side of the foot, noise in the decision process, see Findling & Wyart, 2021, or attention, i.e., looking at the left or right side, see Orquin et al., 2021) that we cannot address in the current study, one possibility we can address is whether participants had a repetition effect from the previous trial, that is, whether they showed crossing behavior for unequal reward because there was a tendency to walk towards the side of the previous trial or repeat the stepping strategy of the previous trial (lateral step or crossing).

To test for a repetition effect, we analyzed the influence of the side and the stepping strategy (crossing with a transition or a cross-over step vs. lateral step) in the previous trial (trial n-1) on the probability of crossing in the equal reward conditions of trial n (see Fig. 8-6) in Exp. 1a. We only analyzed Exp. 1a and Exp. 2, as the number of cross-over steps was higher compared to Exp. 1b and Exp. 3.

Results of Exp. 1a showed that repetition of the side only unreliably affected the frequency of crossing (OR = 1.13, 95% CrI = 0.95 to 1.36, $P(\beta < 0) = 0.09$). Additionally, there is a small but reliable effect of repeating the stepping strategy from the trial before. That is, if participants crossed in the trial before, they were more likely to cross in the trial afterwards (OR = 1.34, 95% CrI = 1.09 to 1.69, $P(\beta < 0) < 0.01$)). There was no interaction with side repetition, suggesting that the repetition of the stepping strategy was independent of repeating the side, meaning that showing crossing behavior to the left increased the likelihood to cross towards the left or right side in the next trial. If true, this suggests carry-over effects of a generalized action level on decision-making, providing further evidence that decision-making and action processes are directly intertwined. From the perspective that decision-making includes competition between actions, it could suggest that these lower-level action characteristics have a higher baseline activation for a short time after the trial leading to the increased likelihood of activation and therefore decision to repeat the motor behavior.

Note, however, that participants still crossed for in 22.93 % of trials (95% CrI = 16.35 % to 30.36 %) even if they did not repeat walking towards the previous side or crossing behavior. This means that other factors influence the occurrence of crossing behavior for equal rewards (e.g., attention or noise) which may be examined in future studies.

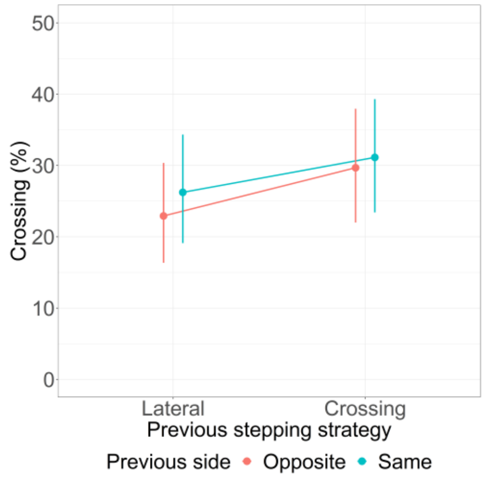

Fig. 8-6. Repetition effects of the side and stepping strategy from the previous trial for the equal reward combination. Only Data from Exp. 1a were analyzed. Lateral steps are defined as walking towards the side of the swing leg. Crossing is defined as walking opposite to the site of the swing leg, including transition steps and cross-over steps.

For Exp. 2 we also fitted a model for carryover effects between trials (side and stepping strategy) like we did for Exp. 1a, but with the interaction of target timing. There was no moderation of carry-over effects by the target timing, neither on repetition of the side of the last trial (OR = 0.86, 95% CrI = 0.64 to 1.17, P(OR < 1) = 0.83) nor on repetition of the stepping strategy trial (OR = 1.08, 95% CrI = 0.80 to 1.45, P(OR < 1) = 0.31). Like in Exp. 1a, there was no main effect of side repetition (OR = 0.94, 95% CrI = 0.80 to 1.09, P(OR < 1) = 0.80) but a weak effect of repeating the stepping strategy (OR = 1.18, 95% CrI = 0.98 to 1.41, P(OR < 1) = 0.04).

8.3. Supplementary Information: Embodied decision bias – individually stable across tasks?

8.3.1. Turning-while-walking-task (TWWT)

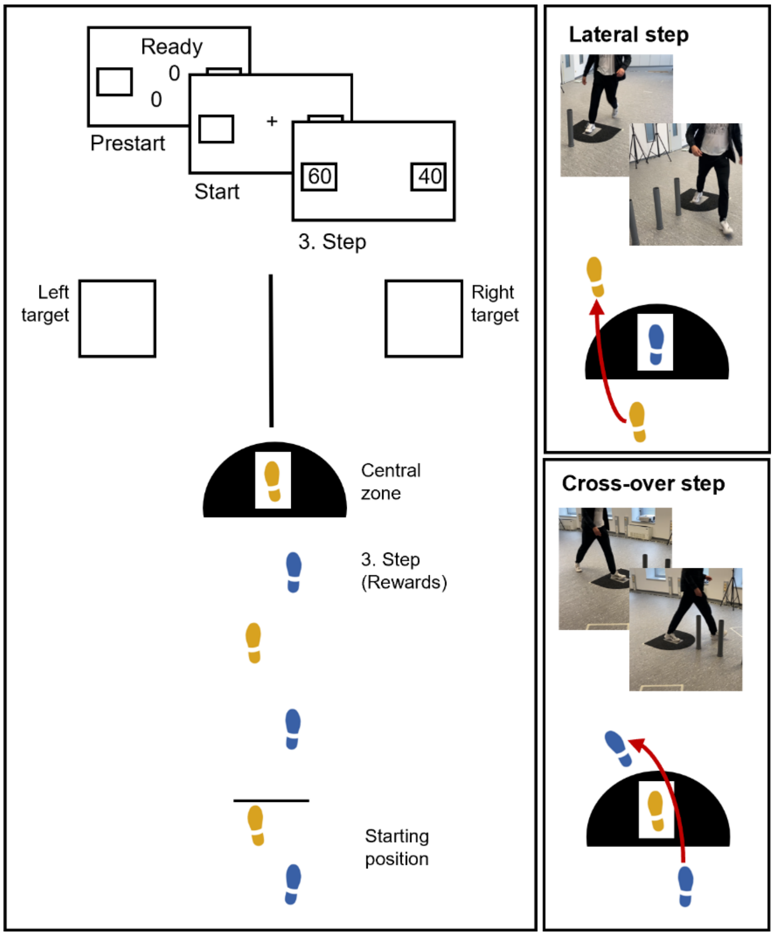

Fig. 8-7. The Turning-While-Walking Task (TWWT). Participants started by positioning their feet in the required starting position. The starting position was displayed with a projector on the opposite side of the room (see rectangles at the top). After participants took the required starting position, they walked toward the central zone. After three steps, rewards for the left and right sides were projected on the screen. Participants had to step into the central zone and walk towards a target area to finish a trial and receive rewards. Right side top: Example of a lateral step. Given that the right foot stepped into the zone and participants chose to walk to the left side, a lateral step could be taken. Right side bottom: Example of a cross-over stepping strategy. Given that the right foot stepped into the zone, we assumed participants to make a cross-over step towards the right side.

8.3.1.1. Calibration and familiarization trials

Similar to our previous study (Grießbach et al., 2022), the starting position and the time constraint, and hence control for task difficulty between participants were individualized by performing calibration trials before the experiment. In calibration trials, participants had to walk as fast as possible between both ends of the room for five trials before experimentation. To achieve an average distance of four steps before reaching the central zone, the starting line was shifted so that the distance between the starting line and the midpoint of the central zone was 0.22 m smaller than the mean walking distance of the first four steps in the calibration trials, but maximally 3.41 m because of the length of the room. The time constraint was calculated as the average time to make four steps in the calibration time plus 2.1 s (Grießbach et al., 2022). For calibration trials, we defined the trial start as the first time where one of the lateral malleoli markers exceeded a horizontal velocity of 0.1 m/s for 0.125 s consecutively, based on the difference (derivative) between the position of consecutive frames.

In the following familiarization trials, to familiarize with the time constraint the required time to finish was projected on the screen for the first six trials, and no auditory feedback was given regarding whether participants were too late or too early. In the following six trials and for the rest of the experiment, there was auditory feedback was provided to indicate whether participants were in time.

8.3.1.2. Online analysis

Identical to Grießbach et al. (2022), the following conditions had to be met for 180 frames (1.5 s) to start a trial:

1. Six markers had to be in an area around the starting line (-0.3 to 2.1 m horizontal, -0.3 to 0.3 lateral, and under 0.25 m height). If six markers were in the area, these markers were identified by the assumed starting position (left foot positioned left to the right foot, toe positioned more to the front than the lateral malleolus, lateral malleolus more to the front than the heel).
2. The most forward marker had to be close to the starting line (horizontal ± 0.05 m, lateral ± 0.3 m).
3. The predetermined foot had to be in front.
4. The malleolus marker stood still, i.e., was not displaced between consecutive frames for more than 0.004 m.

To present rewards at the third step, the touch-down (first contact of the foot with the ground) of every step was estimated kinematically (Banks et al., 2015). A touch-down was defined when the horizontal distance of the heel marker of the swing leg and the lateral malleolus marker of the stance leg reached a maximum, i.e., the horizontal difference of the position between two frames inverted from positive to negative. To ensure one maximum per touchdown, the analysis of touchdowns was paused for 0.125 after finding a touchdown. To check whether participants stepped into the central zone, we compared the position of the lateral malleolus marker of all touch-downs to the area of the central zone. If the participant did not step into the central zone a warning message appeared centrally on the projected display ("Markierung beachten" in German, freely translated as "Note marking"). A trial ended if more than four markers were in the target area (more than one foot. The time from trial start to the end was measured with MATLABs intern stopwatch timer ("tic", "toc") and used as comparison and feedback to check whether participants finished in time.

8.3.1.3. Offline analysis

To identify the correct foot stepping into the zone, we checked the kinematic data visually for trials in which:

1. the foot in the mark was not defined by the online analysis,
2. a second self-written velocity-based algorithm for estimating the touch-down did not agree with the distance-based algorithm from Banks et al. (2015),
3. the toe of the foot first passing the beginning of the zone did not agree with the foot touch-down in the zone,
4. rewards were presented too late when the foot was already in the central zone,
5. participants switched sides rapidly (0.25 s) before a trial finished, as an indication of ignoring the obstacle.
6. a trial was not finished, or there was no kinematic data available.

8.3.2. Multilane Tracking Task (MLTT)

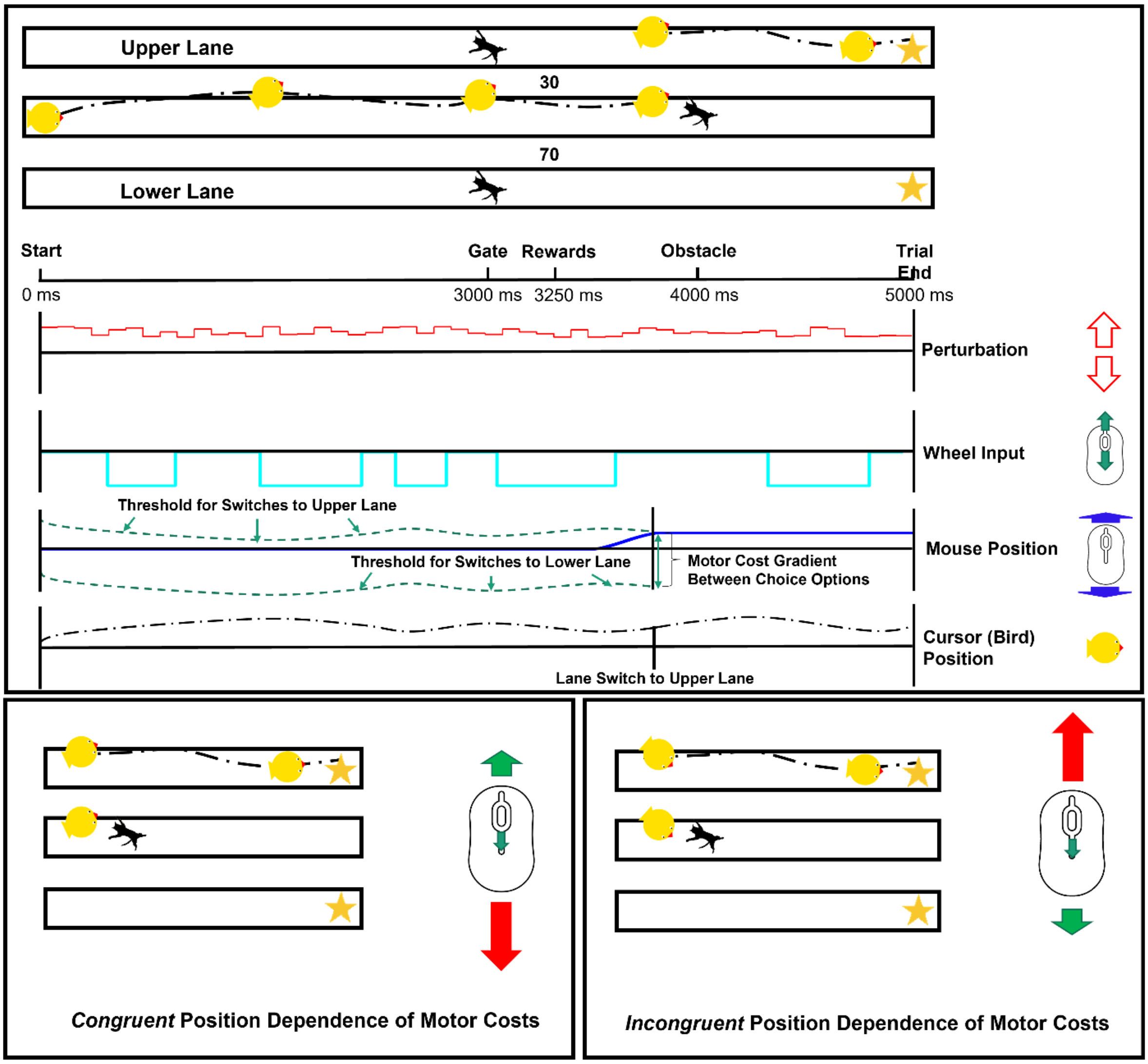

Fig. 8-8. The Multilane Tracking Task (MLTT). Each trial in the MLTT started with the bird on the middle lane. After 1000 ms, the visual scenery started to scroll leftward, giving the impression that the bird moved rightward. From then on, the perturbation shifted the y-axis position of the bird either upward or downward (upward in the depicted exemplary trial) and participants had to counteract it by scrolling with the mouse wheel either up or down. After 3000 ms of tracking, participants passed the gate after which a lane switch could be performed. Rewards and obstacles were visible after 3250 ms, with the point distribution being depicted as numerals above and below the middle lane slightly in front of the cursor. Lane switches were performed by sliding the computer mouse either forward (switch to upper lane) or backward (switch to lower lane). For this, participants had about 750 ms after reward onset until collision with the central obstacle. Depending on the position dependence of motor costs condition, the motor costs for each choice varied as a function of the bird's position (and, thus, the body (finger) state in the tracking task). In the shown trial, the congruent condition is depicted (see also lower left panel at the bottom; the incongruent condition is depicted in the lower right panel), with lane switches to the lane the bird was positioned closer to requiring a lower magnitude of mouse movement. Here, a switch to the upper lane is depicted (i.e., a lower-cost switch). This is comparable to participants choosing a lateral step in the TWWT (see Fig. 8-7). The reward on the respective lane was collected automatically. For original video footage, the reader is referred to the online repository of this study.

8.3.2.1. Determination of the movement threshold in the MLTT

Given the mouse dpi setting of 1200, a constant weight for the position of the bird avatar of 0.36, and a mouse cursor sensitivity setting of $\frac{1}{8}$ (i.e., 3 on the respective Windows cursor sensitivity scale), the necessary movement magnitude for performing a lane switch was determined via the following formula:

$$m = \frac{300\,px\ \pm\ d\ \times\ \frac{1}{0.36}}{\left(1200 \times \frac{1}{2.54}\right) \times\ \frac{1}{8}}$$

with *m* being the required movement magnitude (in cm) and *d* being the absolute distance between the center of the bird avatar and the center of the middle lane (in pixels). Note that the movement magnitude for a lane switch to the lane affording lower motor costs referred to subtracting the second term in the numerator from the first term, while a lane switch affording higher motor costs referred to adding the second term in the numerator to the first term. Consequently, if the bird was positioned exactly in the middle of the lane (d = 0), a movement of 300 pixels (m = 6.10 cm) of the mouse cursor (computer mouse) was necessary to switch to either lane. Note that the required mouse cursor movement was capped by the screen resolution and could not exceed 535 pixels in either direction to account for the screen restrictions. Thus, the lane switch affording higher motor costs (depending on the specific perturbation and congruency condition) could require a maximum movement magnitude of 9.06 cm on the horizontal plane.

8.3.3. Data Analysis

For the Bayesian model, we used weakly informative priors for all parameters. To determine these priors, we used prior predictive checks on the probability scale for decisions, aiming for a roughly uniform distribution. For the intercept we used a normal distribution (mean = 0, sd = 1). For all other regression coefficients, we used a normal distribution (mean = 0, sd = 0.5). We used an exponential distribution for the standard deviation of all random effects (lambda = 1). For the correlation parameter, we used a Lewandowski-Kurowicka-Joe distribution with η = 3.

Stan uses an MCMC algorithm for sampling the posterior distribution. We sampled twelve independent Markov chains with 8000 samples each. The first 2000 samples were warm-up samples, only the last 6000 samples were used to approximate the posterior distribution. To check whether samples converged, we visually inspected the chains and the Rhat statistic (all values were below 1.01). The effective sample size for all relevant parameters was higher than 10000.

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E.G. wrote the first draft of the manuscript. All authors wrote, revised, and edited the manuscript. R.C.B. and O.H. supervised the project.

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R.C.B., O.H. and E.G. conceptualized and designed the study. E.G. collected, visualized, and analyzed the data. E.G wrote the first draft of the manuscript. All authors wrote, revised, and edited the manuscript. R.C.B. and O.H. supervised the project.

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E.G., O.H., and R.C.-B. conceived and designed research; E.G. performed experiments; E.G. analyzed data; E.G., O.H., and R.C.-B. interpreted results of experiments; E.G. prepared figures; E.G. drafted manuscript; E.G., P.R., O.H., and R.C.-B. edited and revised manuscript; E.G., P.R., O.H., and R.C.-B. approved final version of manuscript.

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Ehrenwörtliche Erklärung

Ich bestätige, dass mir die geltende Promotionsordnung der Fakultät für Sozial- und Verhaltenswissenschaften der Friedrich-Schiller-Universität bekannt ist. Ich habe die vorliegende Dissertation selbst angefertigt, keine Textabschnitte eines Dritten oder eigener Prüfungsarbeiten ohne Kennzeichnung übernommen und alle von mir benutzten Hilfsmittel, persönlichen Mitteilungen und Quellen in meiner Arbeit angegeben. Die in dieser Arbeit inkludierten bereits veröffentlichten oder eingereichten Publikationen sind in Zusammenarbeit mit den genannten Ko-Autoren entstanden, welche an der Studienplanung, -auswertung und Erstellung der entsprechenden Manuskripte mitwirkten. Ich bestätige weiterhin, dass die Hilfe eines kommerziellen Promotionsvermittlers nicht in Anspruch genommen wurde und dass Dritte weder unmittelbar noch mittelbar geldwerte Leistungen von mir für Arbeiten erhalten haben, die im Zusammenhang mit dem Inhalt der vorgelegten Dissertation stehen. Diese Dissertation wurde nicht zuvor als Prüfungsarbeit für eine staatliche oder andere wissenschaftliche Prüfung eingereicht. Ebenfalls habe ich zuvor nicht die gleiche, eine in wesentlichen Teilen ähnliche oder eine andere Abhandlung bei einer anderen Hochschule als Dissertation eingereicht.

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Ort, Datum Unterschrift