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We examined whether and how embodied decision biases—related to motor costs (MC) as well as cognitive crosstalk (CC) due to the body state—are influenced by extended deliberation time. Participants performed a tracking task while concurrently making reward-based decisions, with rewards being presented with varying preview time. In Experiment 1 ($N = 58$), we observed a reduced CC bias with extended preview time. Partially, this was due to participants slightly adapting tracking to serialize it in relation to decision making. However, the influence of MC was only marginal and not subject to anticipatory state adjustments. In Experiment 2 ($N = 67$), we examined whether participants integrated the immediate state at reward presentation or anticipated state when a decision could be implemented when adapting their tracking and decision behavior. Results were most compatible with the anticipated state being integrated. We conclude that humans anticipate the body state when a decision must be implemented and consider the corresponding motor and cognitive demands when adapting their decision behavior. However, anticipatory state adaptations targeting the influence of MC with extended preview time were absent, suggesting that anticipatory adaptations are starkly limited in low-practice tasks compared to more overlearned behavior like walking.

Public Significance Statement
In various situations, such as playing soccer or shopping, we make decisions while moving. In doing so, our body's position changes relative to the environment. Hence, over time, some choices become easier or harder to reach, for example, when the distance and concomitant energetic efforts change. Past research has demonstrated humans' ability to anticipatorily adapt movements to reach better choices with less effort. We explored whether humans anticipatorily consider both energetic as well as cognitive costs—which are difficult to disentangle in routine actions—when making decisions. Our results indicate that humans consider both energetic and cognitive costs. However, the ability to actively adjust movements and, thus, alter energetic and cognitive costs is limited in novel tasks compared to routine actions like walking. These findings support theories of embodied decision making and emphasize the anticipatory aspect of decision making during movement.

Keywords: multitasking, decision making, cognitive–motor interference, motor control

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In daily life, humans are routinely confronted with various decision situations. When crossing the street, which path should one choose to evade other pedestrians and get to the other side of the street quickly? When playing soccer, is it more beneficial to bypass a defender to the right or left side? In such situations, the choice options are composed of action values (i.e., time cost, distance to

goal), requiring value-based decisions for achieving higher-level goals (i.e., arrive at destination quickly, score a goal, etc.; e.g., Pezzulo & Cisek, 2016; Pierrieau et al., 2021; Rangel & Hare, 2010). A second commonality between these daily situations is that the decider moves while choosing between choice options. Notably, this contrasts with the rather static settings in the majority of (psychological) experiments studying decisions (Gordon et al., 2021). Research interest in such embodied decisions has substantially increased in the recent years (e.g., Cos et al., 2021; Grießbach et al., 2021, 2022; Kurtzer et al., 2020; Michalski et al., 2020; Raßbach et al., 2021; Yoo et al., 2021). The central premise of this line of research is that the decisions for which the cognitive system evolved are highly dynamic and that concurrent movement substantially influences decisions (Cisek, 2007, 2012; Lepora & Pezzulo, 2015). This implies that actions are not trivial means to an end for decisions made by prior (cognitive) processes. Rather, actions—and associated states—provide continuous feedback for deliberation and, thus, are a central part of decision making.

In this article, we contrast two mechanisms that could account for embodied decision biases (i.e., biases that can be attributed to the body state during decision making). To this end, we address whether extended deliberation and preparation time is used to overcome certain embodied decision biases, and whether the immediate state (when deliberation starts) or anticipated state (when a decision must be implemented) is considered when deciding while moving. In the following, we first discuss how the body state affects the motor costs (MC) for choice options and how extended preview for choice options could affect the MC bias. Second, we will discuss why the body state may encompass cognitive states influencing decision making, and how deciders might adjust the decision-making process to mitigate such a cognitive bias.

The Body State Biases Decisions by Determining the MC for Choices

Humans typically prefer lower MC (Cos et al., 2014; Hagura et al., 2017; Kurtzer et al., 2020; Morel et al., 2017), even if the corresponding option yields objectively lower reward (Cos et al., 2021; Grießbach et al., 2021, 2022; Hartmann et al., 2013; Raßbach et al., 2021). This implies that decision making consists of weighting the value and costs for each choice option, with this process likely being resolved by a distributed consensus selecting one of multiple, parallelly represented actions (affordance competition hypothesis; Cisek, 2007, 2012; Cisek & Kalaska, 2010; Pezzulo & Cisek, 2016; Wispinski et al., 2020).

When deciding while moving, MC are seldom determined a priori and can vary dynamically with concurrent movement. For example, when a soccer player[1] dribbles the ball, the right and left legs are alternatingly used as the swing leg (Grießbach et al., 2021, 2022). These movement dynamics create varying MC for steps to the left or right, depending on the momentary swing leg (see also He et al., 2018; Moraes et al., 2007; Taylor et al., 2005). That is, if the right leg is the currently moved swing leg, making a lateral step to the right affords relatively lower MC and is generally preferred to a more costly crossover step to the left, and this can be ascribed to biomechanical and stability-related factors (Grießbach et al., 2021). While, in this situation, primarily kinetic factors determine the MC, kinematic factors of movement also contribute to the MC and influence choices accordingly (e.g., Cos et al., 2014; Kurtzer et al., 2020; Michalski et al., 2020; Morel et al., 2017).

While MC are a central factor influencing motor and value-based decisions, the fact that they vary dynamically with the body state suggests that they also can be actively altered by movement adaptations. This should particularly be the case for situations in which the context grants a certain degree of choice preview. In such situations, it would be advantageous to adapt the body state so that a high-value decision can be implemented with lower motor effort (Herbort & Butz, 2012; Loffing & Cañal-Bruland, 2017; Pezzulo & Cisek, 2016; Pezzulo et al., 2008). Indeed, such anticipatory adjustments of the body state have been observed in laboratory deciding-while-moving tasks. Grießbach et al. (Experiment 3; 2021) observed that their participants changed the number of steps while approaching an obstacle that divided two lateral rewards presented during walking. By modifying the step count, participants optimized their leg movement as they reached the decision point, making it easier to choose the higher reward with a lateral step (i.e., lower MC). Essentially, when given more time to preview, participants anticipated the motor demands on their body for high-value choices and adjusted their movements accordingly.

However, the impact of MC on decisions might increase with longer preview time given novel task constraints. For example, Cos et al. (2014) found that participants integrated MC into reaching decisions after just 200 ms of target preview while stationary. As preview time increased, participants increasingly favored closer targets. Similar findings were reported by Kurtzer et al. (2020) using a deciding-while-moving task in which targets could split during movement. Relatedly, Michalski et al. (2020) noted that in their deciding-while-moving task, participants did partially ignore biomechanical MC. They argued that computational constraints in integrating MC while in motion might be responsible for this, as MC estimation and online motor control engage the same cerebellar circuits.

Taken together, kinetic and kinematic MC typically influence motor and reward-based decisions. However, whether this influence is attenuated (due to anticipatory state adjustments) or whether it might even increase with longer preview time (due to computational bottlenecks for MC estimation with concurrent movement) when deciding while moving is empirically less clear-cut. Arguably, the latter possibility might be especially relevant for deciding-while-moving tasks with novel task demands and constraints.

MC Are Often Confounded With Spatial Features of Movement

What further complicates the analysis of MC biases in embodied decisions is a confound which arises from the fact that other spatial movement features often overlap with the MC gradient between choice options (Raßbach et al., 2021). When swinging the right leg forward, a soccer player might decide to bypass another player to the right due to the lower-cost lateral step. However, the mental processes involved in controlling the movement of the right limb to a rightward location in space could also leak into the decision process, consequently biasing the choice toward a right option. That is, cognitive crosstalk (CC) from motor control processes might bias decision making, for example, depending on spatial compatibility (SC).

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[1] Note that we focus on motor costs here. There certainly exist further variables influencing the decision of the soccer player (e.g., their preferred leg, positioning of their team mates, etc.).

A recent study tried to disentangle such spatial features of movement from the typically confounded MC for choices. In a so-called multilane tracking task (MLTT; Raßbach et al., 2021), participants controlled a virtual bird cursor moving across one of three horizontal lanes on a computer screen (Figure 1). While the bird automatically moved right it was perturbed either upward or downward on the lanes. To prevent the bird from drifting too far from the currently tracked lane, participants had to continuously perform scrolling movements forward (moving bird back up) or backward (moving bird back down). While performing these movements, obstacles and point rewards on the upper and lower lane appeared. Participants were instructed to accumulate as many points as possible by switching to the upper or lower lane, which they did by moving the computer mouse either forward (switch upward) or backward (switch

Figure 1

General Trial Procedure for the MLTT in Experiment 1
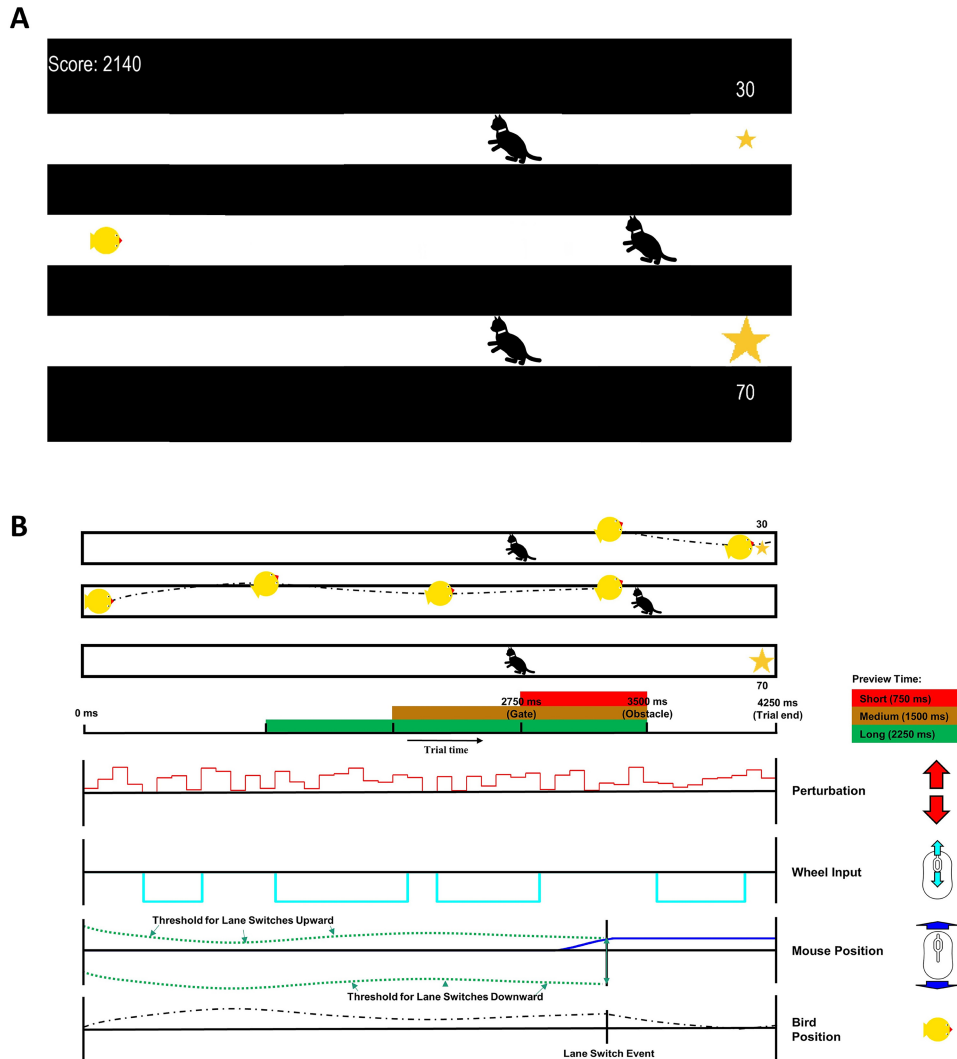
Note. Panel A: Several screenshots from the visual display concatenated to give an impression of what participants saw on their screens (a video showcase can be found in the online repository of this study via https://osf.io/v3w6m). Note that only the starting position of the bird is displayed here. Panel B: Abstracted version of the visual display. In this exemplary trial, the perturbation pushed the bird upward, requiring a scrolling movement backward to track the bird on the lane. Rewards were presented either with long (2,250 ms), medium (1,500 ms), or short (750 ms) preview time. After passing the gate, a lane switch could be performed. In this trial, the decision resulted in a lane switch to the upper lane, executed by moving the mouse forward. A switch to the upper lane also required a shorter amplitude movement (see green/light gray threshold lines in the mouse position plot), as the bird was located on the upper half of the middle lane shortly before the lane switch (due to the perturbation upward) and because the motor cost mapping corresponded to the proximity advantage mapping. The rotation of the bird served as a visual cue indicating the switch direction associated with a smaller movement amplitude. MLTT = multilane tracking task. See the online article for the color version of this figure.

downward). Essentially, an experimental manipulation determined whether proximity between the bird and a lane resulted in lower or higher MC (i.e., manual movement amplitude) to switch to that lane. First, this experimental manipulation meant that the tracking and the decision task were interdependent. Second, as the perturbation tended to push the bird closer to the lower or upper lane, the same scrolling movement and bird state could result in higher or lower MC to switch to the closer lane—thereby disentangling the MC gradient from spatial movement features.

In the abovementioned study (Raßbach et al., 2021), participants preferred lane switches which could be performed with a spatially compatible mouse movement in relation to scrolling (e.g., moving the mouse forward while scrolling forward) compared to dimensionally incompatible mouse movements, above and beyond a small preference for lane switches associated with lower MC. This suggests that reward-based decisions can indeed be biased by CC, possibly due to the activation of action representations (e.g., Greenwald, 1970; Hommel et al., 2001; James, 1890; Prinz, 1997) leaking from motor control into decision processes (see also Pezzulo & Cisek, 2016). Most importantly, the fact that both MC and CC can bias embodied decisions—and that they typically result from identical states—necessitates that both should be orthogonally manipulated when assessing the impact of a further variable on decision making, for example, preview time.

CC when deciding while moving appears analogous to task compatibility effects reported in the multitasking literature (e.g., Hommel, 1998; Huestegge & Koch, 2009; Janczyk et al., 2012, 2014; Koch & Prinz, 2002). In this context, deciding while moving can be seen as a specific form of multitasking that involves a motor control task nested within a higher-level decision-making context (Botvinick, 2008; Haruno et al., 2003; Pezzulo & Cisek, 2016; Raßbach et al., 2021; Uithol et al., 2012). Hence, findings from the multitasking literature elucidating how extended preview for task stimuli affects dual-task performance might lend themselves to formulate expectations on how CC is affected by extended preview of rewards.

First and foremost, the occurrence of crosstalk between motor control and decision making implies that the respective task sets cannot be fully shielded from each other, suggesting a parallel mode of task processing (e.g., Fischer & Plessow, 2015; Fischer et al., 2014). To reduce crosstalk when performing two tasks simultaneously, the cognitive system must switch to a more serial processing mode via the engagement of executive control mechanisms (Botvinick et al., 2001; Logan & Gordon, 2001). Such mechanisms could determine a specific task schedule that allocates cognitive resources primarily (or exclusively) to one task in specific time periods during dual-task performance (Kahneman, 1973; Meyer & Kieras, 1997a, 1997b; Tombu & Jolicoeur, 2003). For example, a soccer player might plan when to increase their dribbling speed (resource allocation mainly to motor control) and when to slow down to decide which pass to play or move to make (resource allocation mainly to decision making) while approaching the defending line on a counterattack.[2]

While a more serial processing mode could reduce the risk for CC, the additional executive control steps involved in task scheduling and task switching are likely to be more time consuming (Meyer & Kieras, 1997a, 1997b). This is also suggested by commonly observed patterns in task switching studies: A switch from Task A to an upcoming Task B is typically associated with switching costs, that is, increases in reaction times and error rates for the upcoming task

(Kiesel et al., 2010; Koch et al., 2018; Vandierendonck et al., 2010). However, when the preparation time for the upcoming task is increased (e.g., by presenting a task cue prior to the task stimulus), switch costs can be substantially reduced. This is commonly interpreted as evidence that executive control mechanisms can switch task sets (i.e., which stimuli to attend, which responses to prepare, how to link stimuli with responses, etc.) in advance—at least to a certain degree, as residual switch costs often remain (Longman et al., 2014; Meiran, 1996; Monsell & Mizon, 2006). In conclusion, the multitasking literature suggests that task processing when deciding while moving might shift from a more crosstalk-susceptible parallel processing mode with shorter preview times to a more crosstalk-resistant serial mode with extended preview.

The Present Studies

Besides replicating prior studies on CC during embodied decisions (Grießbach et al., 2023; Raßbach et al., 2021), the central goal of this study was to test whether humans adapt embodied decision making with extended preview of rewards to attenuate MC (Grießbach et al., 2021) and/or to reduce the risk for CC (Raßbach et al., 2021). In Experiment 1 (online study), we examined whether the previously observed modulation of the MC bias with increasing preview time (Cos et al., 2014; Grießbach et al., 2021) could be—at least partially—a hidden modulation of CC or whether these biases are differentially modulated by preview time. To subsequently scrutinize whether the immediate state at reward presentation (Bakker et al., 2017) or the anticipated state when a reward-based decision can be implemented (Grießbach et al., 2021) is integrated into decisions and state adaptations, Experiment 2 (lab study) introduced a design with dynamically altering states to disentangle the immediate from the anticipated state. In all experiments, we applied the MLTT procedure (Grießbach et al., 2023; Raßbach et al., 2021).

We define the term MC bias as the preference for choice options that require less physical effort due to lower kinematic demands (Cos et al., 2014; Kurtzer et al., 2020). If participants used extended preview to (anticipatorily) adapt to the motor demands, we expected a decreasing MC bias with increasing preview time. This would align with previous research using a similar paradigm (Grießbach et al., 2021). Conversely, if participants could not fully integrate the MC with short preview time and did not anticipate the motor demands for choices (Cos et al., 2014; Kurtzer et al., 2020; Michalski et al., 2020), the MC bias was expected to increase with preview time.

We further define the term CC bias as the tendency to choose a reward depending on spatial features of the concurrently performed movement (e.g., due to overlapping representations, attentional processes, etc.).[3] We expected a decreasing CC bias with increasing preview time. This would correspond to findings and modelling frameworks from the multitasking literature, specifically that extended

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[2] Note that whether slowing down the dribbling speed requires less processing resources might heavily depend on the skill level of the player. We will further discuss the role of practice in deciding-while-moving tasks in the General Discussion section.

[3] We intentionally use the term cognitive crosstalk instead of response crosstalk. While it is entirely possible that response crosstalk contributes to or is the main cause for the effect observed in this and prior studies, we argue that the term response crosstalk might prematurely limit the range of other possible mechanisms (e.g., visual attention; see also the General Discussion section).

preview allows for a more serial (i.e., crosstalk-resistant) task schedule and associated preparatory task set reconfigurations (Meiran, 1996; Meyer & Kieras, 1997a, 1997b; Monsell & Mizon, 2006).

Experiment 1

In Experiment 1 we examined whether the preview time for rewards modulated the MC and/or CC bias when making reward-based decisions while moving. Furthermore, we analyzed how participants adjusted their movement (i.e., tracking) behavior depending on the (experimentally induced) MC and/or the SC between concurrent movement and decision making. Experiment 1 was conducted online (see Homogenizing the Experimental Context in Online Experiments section in the online supplemental materials for further details).

Method

We report how we determined our sample sizes, all data exclusions, all manipulations, and all measures. All data, code (analyses and experiment scripts), and video demonstrations of the experiment are available at https://osf.io/ewth4/. The experiments and their analyses were not preregistered. All experiments were approved by the ethics committee of the Department of Psychology of the University of Würzburg (GZEK 2019-33) and conformed to the Declaration of Helsinki.

Participants

We intended to collect a sample of at least 50 participants, based on previous deciding-while-moving studies (Grießbach et al., 2021; Raßbach et al., 2021) and the restrictions we had for data collection (for further details, the reader is referred to the Sample Size Determination and Post-hoc Sensitivity section in the in the online supplemental materials). Ultimately, 69 participants (median age: 25 years, range = [19 years, 38 years]; 50 female, 18 male, one nonbinary; 62 right-handed, seven left-handed) were recruited via the participant-acquisition website (Sona Systems, n.d.) of the Department of Psychology at the University of Würzburg in summer of 2021. Prior to experimentation, all participants gave their informed consent. Participants received course credit or performance independent financial compensation (15€).

Stimuli and Experimental Setup

We used the same stimuli and general experimental setup as described in Raßbach et al. (2021); further technical details are included in Section 3. Experiment 1 in the online supplemental materials. The experiment was written in Python 3.7 using the module *pygame* (Shinners, 2011). During the experiment, participants controlled an emblematic bird. The bird moved across one of three horizontal white lanes on a black background (Figure 1; we highly encourage readers to view the video demonstrations at https://osf.io/v3w6m). Bird tracking was performed by scrolling with the mouse wheel forward (moving it up) or backward (moving it down). Lane switches were performed by manual movements with the whole computer mouse forward (switch to upper lane) or backward (switch to lower lane). Rewards were displayed as yellow stars, with larger stars representing higher rewards (the respective point scores were also displayed above the upper and below the lower star). A gate (two obstacles on the upper and lower lane) signaled when a lane switch could be performed. An obstacle on the middle lane indicated the latest time point at which a lane switch could be performed. Gate, central obstacles, and stars appeared at the same time, depending on the preview time condition. The (accumulated) score in the current block was displayed in the upper left screen corner.

Trial Procedure

The bird always started on the middle lane (Figure 1). After 1,000 ms (inter-trial interval), the *x*-coordinates of most objects in the scene, except the bird, were reduced, creating the illusion that the bird shifted to the right (see Section 3.1. Scene Velocity in the online supplemental materials for technical details). The bird's *y*-coordinate was affected by a perturbation upward or downward (see Figure 1 or Section 3.2. Perturbation in the online supplemental materials for technical details). Participants had to counteract this perturbation to prevent the bird from drifting too far from the lane (e.g., when the bird was perturbed upward in a trial, they had to repeatedly scroll backward to track the bird). If the bird drifted completely from the lane, participants lost 50 points and received an error message ("Der Vogel wurde von der Bahn geweht!" which is German for "The bird was blown off the track!") and the trial counted as a tracking error.

After a period of tracking, rewards and obstacles appeared. Reward distributions ranged from 10/90 to 90/10 (points upper/lower lane) in steps of +10/−10. The time interval between reward stimuli onset and potential collision with the central obstacle depended on the preview time condition (long = 2,250 ms, medium = 1,500 ms, short = 750 ms). After passing the gate, participants had 750 ms to perform a manual movement to switch lanes. They did so by moving the whole computer mouse either forward (=switch to upper lane) or backward (=switch to lower lane). Essentially, the necessary movement amplitude for lane switches was dependent on the position of the bird and the MC mapping. In the proximity advantage condition, a lane switch to the closer lane relative to the bird required a smaller movement amplitude. In the proximity disadvantage condition, a lane switch to the farther lane relative to the bird required a smaller movement amplitude. If participants moved the computer mouse before the gate, an error message was displayed ("Du hast die Maus zu früh bewegt!" which is German for "You moved the computer mouse too early!") and the trial was counted as a premature movement error.

If participants moved the (invisible) computer mouse cursor beyond an internally computed threshold for a switch in either direction, the bird instantaneously moved to the corresponding lane. If participants did not perform a lane switch in time, the bird collided with the central obstacle. In this case, participants lost 50 points and a corresponding 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!"), with the trial being recorded as a collision error.

After a lane switch, participants still had to counteract the perturbation. The reward was collected automatically after a total trial time of 4,250 ms. In error trials, the error message was shown until 6,000 ms after the start of the trial.

Disentangling MC From the Spatial State

To disentangle the body/bird state from the MC for lane switches, we established a criterion that determined how far from the midline

of the screen participants had to move the (invisible) mouse cursor to switch lanes in either direction. Specifically, the movement amplitude threshold (MAT in the following) for a lane switch upward or downward was a linear function of the bird position (BP) and the MC mapping (MCM) given by Formula 1 as:

$$\text{MAT}\,[\text{px}] = 280\,[\text{px}] \pm 2.17 \times \text{MCM} \times \text{BP}\,[\text{px}]. \qquad (1)$$

Here, BP represents the bird offset from the center of the middle lane on the y axis (negative if below the midpoint, positive if above). MCM represents an indicator variable ($1 = proximity\ advantage$, $-1 = proximity\ disadvantage$). The scaled bird position was added to the base threshold of 280 pixels for switching to the lower lane and subtracted from it for switching to the upper lane. In essence, the MC for switching lanes depended on both the bird's position (affected by the perturbation and scrolling) and the prevalent MC mapping.

Given a screen resolution of 1,920 by 1,080 pixels and a standard computer mouse, switching in either direction required a manual movement of approximately 2.84 cm when the bird was precisely in the middle of the lane (see Section 3.3. Converting the MAT Threshold to the Metric Scale in the online supplemental materials for technical details). With the bird in between the central position and maximal offset, the higher-cost lane switch required a manual movement of about 4.11 cm, while the lower-cost lane-switch required a movement of about 1.58 cm. In the proximity advantage condition, switching to the closer lane relative to the bird corresponded to the lower-cost choice, while in the proximity disadvantage condition, switching to the farther lane relative to the bird corresponded to the lower-cost choice (Figure 2). This manipulation allowed us to orthogonally control MC and the bird (and body) state.

Design

Participants completed 108 practice trials (54 for each MC mapping condition) in the beginning of each session. They then moved on to two experimental blocks, each corresponding to one MC mapping condition. Each experimental block was further divided into three subblocks of 56 trials, with the first two trials being randomly drawn warmup trials. The experiment comprised 9 (reward on upper/lower lane: 10/90, 20/80, 30/70, 40/60, 50/50, 40/60, 30/70, 20/80, 10/90) by 2 (perturbation: upward, downward) by 2 (MC mapping: proximity advantage, proximity disadvantage) by 3 (preview time: long, medium, short) conditions repeated 3 times per session, resulting in up to 648 experimental trials in total. Only MC mapping was manipulated block-wise. Block order was pseudorandomized for each session and participant, and trial order was pseudorandomized for each subblock separately. All factors were manipulated within subjects.

General Procedure and Instructions

Participants received an executable file and instructions via an online repository (importantly, they could only participate if they used Windows 10 and a computer mouse with a scroll wheel). The experiment comprised two sessions, each lasting approximately 50 min. In the first session, participants first provided their age, gender, and (self-reported) handedness. They were then given instructions with screenshots explaining the experimental procedure, including the general trial procedure. The instructions emphasized that the bird's position on the middle lane affected the manual movement amplitude required for switching lanes, with the lower-cost lane switch indicated by a bird rotation toward the upper/lower lane (Figure 2). Participants were instructed to accumulate as many points as possible, maintain an upright posture about 60 cm from the display, and wear visual aid if needed.

The practice trials provided a more detailed introduction to the MC mapping and its interaction with the bird position. Before each practice block, instructions and screenshots depicting the MC gradient for an exemplary trial were displayed (the videos in the online repository of this study showcase this in more detail, https://osf.io/v3w6m). After the practice blocks, the experimental trials began. Following each experimental subblock, participants received a performance summary detailing accumulated points and errors. Participants proceeded at their own pace after each subblock. At the end of the first session, participants were prompted to send back their data set and advised to take a break of at least 4 hr before the second session, to be completed within 48 hr. The second session followed the same procedure and ended with a questionnaire primarily asking for technical issues. Participants were then thanked and asked to submit their second data set.

Data Recording, Outlier Exclusion, and Data Reduction

The trial state was recorded after every frame update, with the maximum sampling rate being 100 Hz. Data were processed in R Version 4.1.1 (R Core Team, 2021), mainly using the packages *tidyverse* and *ggplot* (Wickham, 2009; Wickham et al., 2019).

We applied an a priori determined combination of a median-based criterion and an absolute threshold of 50% to detect outliers in error rates (Wentura & Degner, 2010). Participants were marked as an outlier and excluded from the analyses (a) if they made an error in more than 50% of trials or (b) showed an error rate larger than the third quantile plus 1.5 times the interquartile range of the error rate sample distribution (Tukey, 1977). This concerned $n = 10$ participants which were excluded from all analyses. We assumed that such high error rates would either signal that the participants did not fully understand the instructions, did not invest much effort in performing the task, or had technical difficulties during the experiment.

One additional participant aborted the experiment after the first practice block and was also excluded. Consequently, the data of 58 (age: $Mdn = 25$ years, range $= [19$ years, 38 years]; 43 female, 15 male; 54 right-handed, four left-handed) participants were analyzed. Of these, three only sent back data sets for a single session. One further participant aborted the second session prematurely and had missing data for 159 trials.

We removed the first two warm-up trials for each subblock as well as trials including equal rewards on both lanes (50/50; up to 72 trials) and rebinned the remaining reward distributions into the levels lower (10/20/30/40) and higher (60/70/80/90) reward on the upper lane. Furthermore, we created two new factors and grouped trials accordingly. The first factor, MC, represented whether reaching the higher reward in a trial was associated with lower or higher MC, depending on the perturbation direction (determining the average bird position) and the MC mapping for the respective block. For example, if the higher reward was

Figure 2

Simplified Illustration of the Interaction Between the Bird Position (Which Was Influenced by the Perturbation Direction and Scrolling) and the Motor Cost Mapping (Which Determined Which Lane Switch Required Less Effort Depending on the Bird Position)
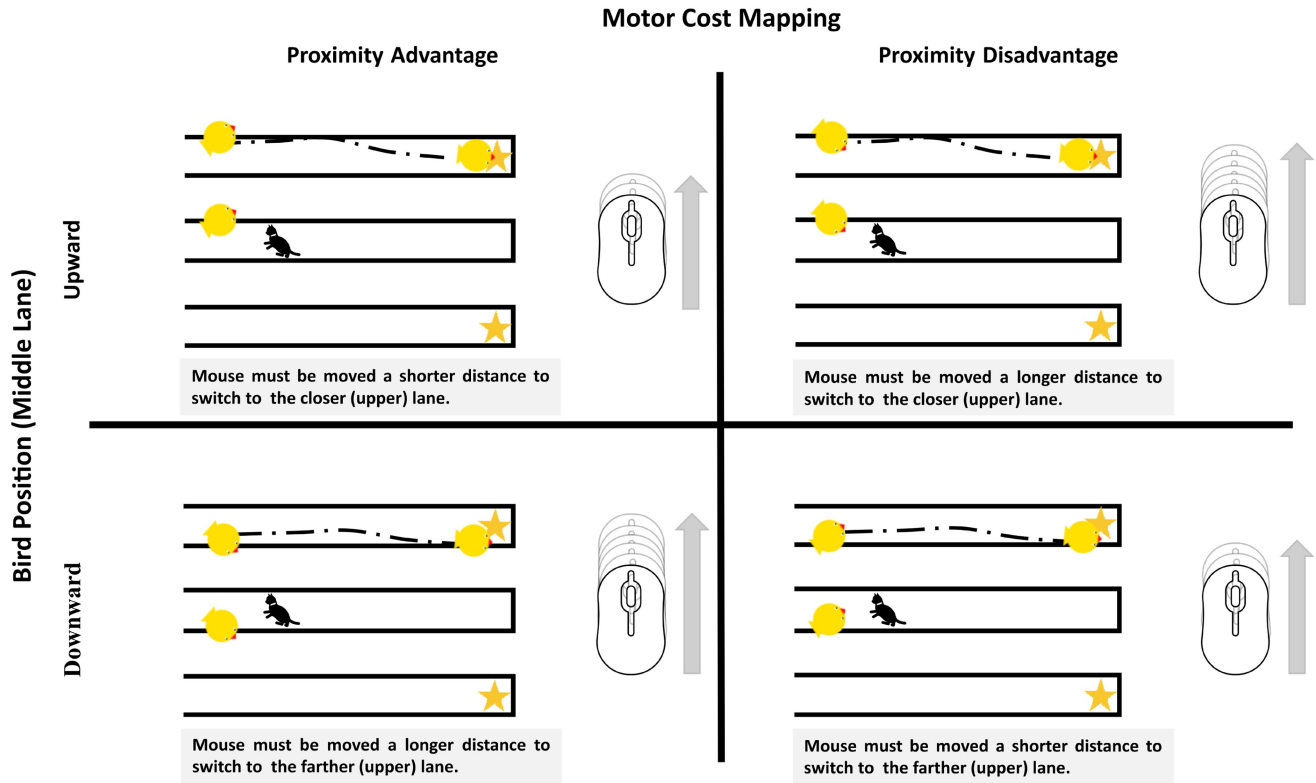
Note. The motor cost mapping allowed us to control the direction of lower motor costs independent from the bird and body state due to the perturbation. In simpler terms, we could make the same bird position (and, thus, body state due to scrolling) result in either higher or lower motor costs for a lane switch, based on the motor cost mapping. Note that this figure only shows situations where a lane switch to the upper lane was performed. Switching to the lower lane always involved inverted motor costs compared to switching to the upper lane, meaning higher effort when a switch upward required lower effort and vice versa. See the online article for the color version of this figure.

presented on the upper lane, the bird was pushed downward by the perturbation (i.e., the bird was farther from the upper than the lower lane), and the MC mapping favored proximity, then collecting the higher reward required higher MC. The second factor, SC, reflected whether switching to the higher reward could be achieved by performing a spatially compatible (e.g., movement forward while scrolling forward) or incompatible (e.g., movement backward while scrolling forward) mouse movement relative to the necessary scrolling direction for a specific trial.

Trials in which participants performed a successful lane switch but committed a tracking error afterwards were included in the analyses (877 trials). Trials in which participants committed a tracking or collision error after having passed the gate and had moved the (invisible) mouse cursor at least one third of the distance from the vertical midpoint of the screen toward either side of the visual display were coded as a corresponding decision to switch to the upper or lower lane (105 recoded tracking error trials; 1,801 recoded collision error trials). All other error trials were discarded. Consequently, the decision analysis comprised 29,955 trials (89.66% of the theoretically achievable 33,408 trials with 58 participants and 576 trials each).

Decision Analysis

For each participant and design cell, we counted the number of lane switches toward the higher reward out of the total number of trials. We then used a Bayesian generalized linear mixed model to model the logit-transformed probability of switching to the higher reward. Our model included population-level effects for MC, SC, preview time, as well as all possible interactions (see Section 3.4.1. Model Formula in the online supplemental materials). All group-level effects were modeled, but no group-level correlation parameters as these are not fundamental for inference (Oberauer, 2022). For factors with two levels (MC, SC), we applied centered sum-to-zero contrasts, so that the respective parameters represented the difference between factor levels in the dependent variable on the logit scale. For preview time—which had three levels—we used forward difference coding to estimate parameters representing the differences between long and medium as well as between medium and short preview time in the dependent variable on the logit scale.

We used the brm() function of the *brms* package to fit our model (Bürkner, 2018). We mainly used weakly informative priors for

our estimates (see Section 3.4.2. Priors in the online supplemental materials). The decision model converged without problems (see Section 3.4.3. Model Convergence in the online supplemental materials). We report the model estimates on the logit scale (for individual empirical data points, see Figure S1 in Section 3.5. Estimated Marginal Means and Empirical Data Points for Lane Switch Decisions in the online supplemental materials) as well as estimates and comparisons for the absolute MC and CC bias on the probability scale (for collecting the higher reward, HR) as a function of preview time. The MC bias was given by Formula 2 as

$$\text{Bias}_{\text{MC}} = \text{Pr}(\text{HR} \mid \text{MC} = \text{L}) - \text{Pr}(\text{HR} \mid \text{MC} = \text{H}), \quad (2)$$

with a positive MC bias indicating a preference for lower (L) compared to higher (H) MC. Accordingly, the CC bias was given by Formula 3 as

$$\text{Bias}_{\text{CC}} = \text{Pr}(\text{HR} \mid \text{SC} = \text{C}) - \text{Pr}(\text{HR} \mid \text{SC} = \text{IC}), \quad (3)$$

with a positive CC bias indicating a preference to switch to the lane associated with a spatially compatible (C) compared to an incompatible (IC) manual movement relative to scrolling (SC). Note, that the posterior samples of the fitted model were used for computing these decision bias estimates.

State Analysis

We conducted a further analysis to investigate how participants actively controlled the bird position (similar to the step/footing analysis in Grießbach et al., 2021), which could reflect state anticipation to attenuate MC and/or task serialization to prohibit CC. We focused on trials in which participants had switched (or had intended to switch in recoded error trials) to the lane with the higher reward, totaling up to 26,982 trials. We normalized the bird position relative to the lane center in pixels to a % of the vertical resolution. We then interpolated the bird position every 10 ms for each trial, session, and participant (see also Figure S2 in Section 3.6. Bird Trajectory Plots in the online supplemental materials). We multiplied the bird positions for downward perturbation trials by −1 and scaled all position values by the SD, meaning the model parameters are in SD units. Hence, we termed the dependent variable in the state analysis bird offset from the lane center, with positive values indicating that the bird was offset in the direction of the perturbation, such as toward the lower lane when perturbed downward.

The factors in the state analysis model included MC, SC, and preview time, but also the additional factor trial time. Trial time had two levels representing two time points within each trial: the bird position at gate passing and the last position before a lane switch. Figure 3 shows plots for expected results depicting different tracking adaptation patterns based on whether participants considered MC, CC, or both when adjusting the bird position with different preview times. Figure 4 depicts the relationships between the bird and body state and our independent variables.

Details on the model formula and all population-level parameters (Section 3.7.1. Model Formula and Parameter Table under Section 3.7. State Model Specification), priors (Section 3.7.2. Priors) and convergence (Section 3.7.3. Model Convergence) for the state analysis model are included in the online supplemental materials. We used the same contrast coding schemes as for the decision analysis.

Bayesian Inference

As a measure of effect existence, we report the probability of direction (*pd*; Makowski, Ben-Shachar, & Lüdecke, 2019; Makowski, Ben-Shachar, Chen, & Lüdecke, 2019). The *pd* represents the proportion of the posterior samples of a parameter which have the same sign as the median of the posterior distribution. We interpret effects with $pd > 95\%$ as being reliably positive or negative.

As a measure of effect significance, we report the Bayes factor (BF) in favor of the point null (BF_{01}), calculated as the Savage–Dickey density ratio (Bürkner, 2018; Wagenmakers et al., 2010). Given the data, a $\text{BF}_{01} > 1$ indicates that the prior probability shifted in favor of the null (i.e., it became more likely that the effect is close to 0, or at least very small), while a $\text{BF}_{01} < 1$ indicates that the prior probability shifted in favor of the alternative hypothesis.

Results

Participants Favored Higher Rewards (Decision Analysis)

Participants strongly favored higher rewards, indicated by the reliably positive intercept ($\hat{\beta}_0 = 3.40$, 95% equal-tailed credible interval [CrI] [2.96, 3.84], $pd = 100\%$; Table 1 and Figure 5). Overall, they were 29.96 times more likely to choose the higher reward over the lower one (Odds = 29.96, 95% CrI [19.30, 46.53]).

Additionally, participants more often chose the higher reward with extended preview. They were more likely to choose the higher reward with long preview time ($\log OR = 4.02$, 95% CrI [3.57, 4.49]) compared to medium preview time ($\log OR = 3.74$, 95% CrI [3.30, 4.21]; $\hat{\beta} = -0.28$, 95% CrI [−0.46, −0.12], $pd = 99.96\%$, $\text{BF}_{01} = 0.08$). Moreover, participants were more likely to choose the higher reward with medium preview time compared to short preview time ($\log OR = 2.42$, 95% CrI [1.96, 2.88]; $\hat{\beta} = -1.32$, 95% CrI [−1.61, −1.04], $pd = 100.00\%$, $\text{BF}_{01} < 0.01$).

### MC Slightly Biased Lane Switching Decisions (Decision Analysis)

Participants showed a slight preference for lane switches associated with lower MC, as indicated by the reliably negative MC effect ($\hat{\beta} = -0.21$, 95% CrI [−0.45, 0.04], $pd = 95.23\%$, $\text{BF}_{01} = 2.59$; Table 1 and Figure 5). In practical terms, when the MC for collecting the higher reward were lower rather than higher, the odds of participants choosing the higher reward were about 1.23 times larger ($OR = 1.23$, 95% CrI [0.96, 1.57]). However, the effect on the logit scale as well as the absolute MC bias on the response scale were rather small (Table 2).

The slight preference for lower MC switches was not reliably modulated by preview time (long vs. medium: $\hat{\beta} = -0.09$, 95% CrI [−0.41, 0.23], $pd = 70.97\%$, $\text{BF}_{01} = 7.30$; medium vs. short: $\hat{\beta} = 0.15$, 95% CrI [−0.10, 0.41], $pd = 87.89\%$, $\text{BF}_{01} = 5.26$). There were also no reliable differences in the MC bias between preview times on the response scale (all $pds \leq 62.26\%$, all $\text{BF}_{01} \geq 6.84$; Table 2).

CC Biased Lane Switching Decisions (Decision Analysis)

Participants displayed a CC bias, indicated by the reliably positive effect of SC ($\hat{\beta} = 1.13$, 95% CrI [0.73, 1.53], $pd = 100\%$, $\text{BF}_{01} < 0.01$; Table 1 and Figure 5). In practical terms, when the higher reward could be obtained with a spatially compatible mouse movement, participants were 3.10 times more likely to choose it compared to when

Figure 3
Expected Result Plots for the State Analysis
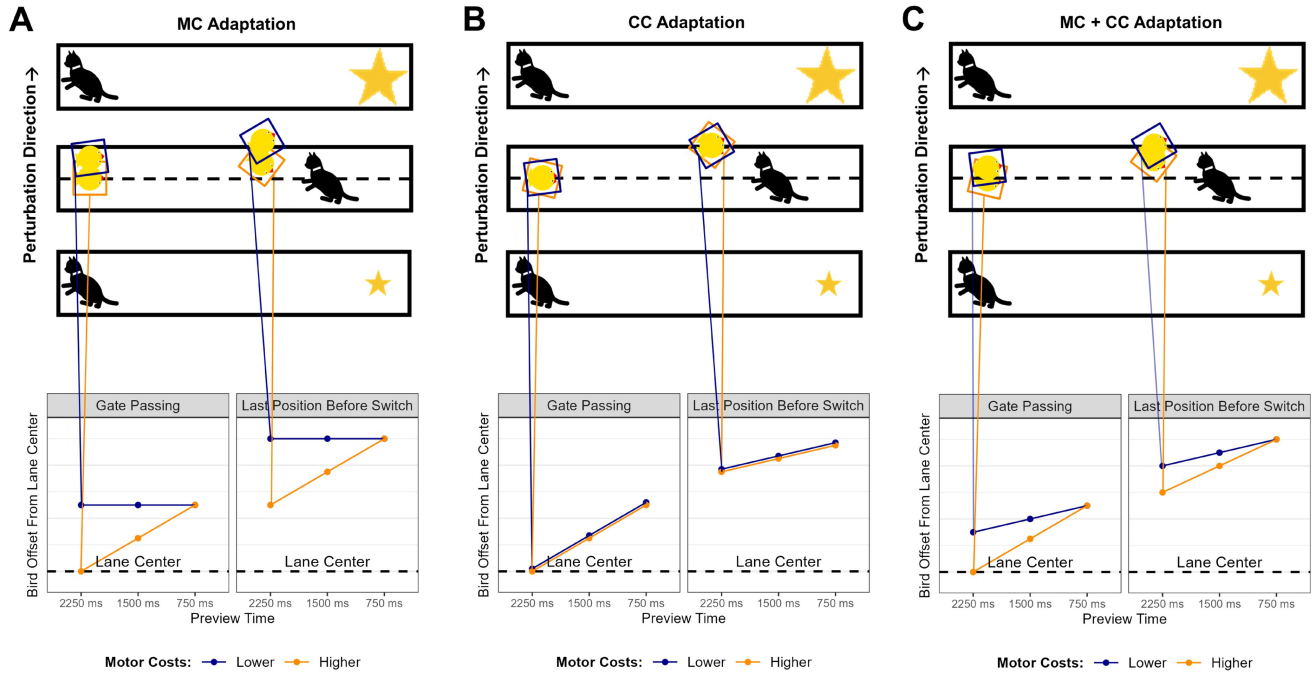
Note. Panel A: Expected state adaptations if participants considered only MC when making decisions. With extended preview, participants were expected to counteract perturbations more intensely, positioning the bird closer to the lane center (or even beyond). This should primarily concern trials in which the higher reward was associated with higher MC (orange/light gray). When MC for the higher reward were lower (blue/dark gray), participants were expected to not adapt the bird position with increasing preview, as the motor costs already favored higher-reward decisions. Panel B: Expected state adaptations if participants focused solely on prohibiting CC. Regardless of MC, participants were expected to counteract the perturbation (i.e., scroll) more intensely with extended preview, allowing them to focus less on tracking while implementing the reward-based decision—that is, they were expected to serialize tasks. Panel C: Expected bird adaptations if participants tried to attenuate the influence of motor costs as well as cognitive crosstalk with extended preview. This result pattern is basically a mixture of the result patterns from Panel A and B. Note: For the state analysis, we mirrored the bird positions for trials with downward perturbations so that positive values indicated that the bird was offset in the perturbation direction (e.g., more upward on the lane for upward perturbations), while negative values indicated the opposite (e.g., more downward on the lane for upward perturbations). MC = motor costs; CC = cognitive crosstalk. See the online article for the color version of this figure.

an incompatible movement was necessary ($OR = 3.10$, 95% CrI [2.08, 4.62]). On the response scale, the CC bias was notably larger than the MC bias and reliably positive (Table 2).

The SC effect was not modulated by preview time on the logit scale (long vs. medium: $\hat{\beta} = 0.19$, 95% CrI [−0.12, 0.51], $pd = 87.90\%$, $BF_{01} = 4.34$; medium vs. short: $\hat{\beta} = −0.08$, 95% CrI [−0.36, 0.22], $pd = 70.33\%$, $BF_{01} = 7.84$; Table 1). On the response scale, the CC bias showed a decreasing absolute influence on lane switching decisions with increasing preview time. While the CC bias was only slightly smaller with long compared to medium preview time ($Mdn_{diff} = 1.03\%$, 95% CrI [0.31%, 2.10%], $pd = 99.79\%$, $BF_{01} = 0.38$; Table 2), the CC bias was notably smaller with medium compared to short preview time ($Mdn_{diff} = 5.78\%$, 95% CrI [2.94%, 9.77%], $pd = 100\%$, $BF_{01} < 0.01$).

### General Effects Influencing the Bird Position (State Analysis)

We will turn to the state analysis next. The bird was generally offset in the direction of the perturbation, as indicated by the reliably positive intercept ($\hat{\beta}_0 = 0.27$, 95% CrI [0.19, 0.36], $pd = 100\%$; Figure 6). Overall, participants positioned the bird closer to the lane center at gate passing ($M = 0.10$, 95% CrI [0.01, 0.20]) compared to shortly

before a lane switch ($M = 0.44$, 95% CrI [0.35, 0.54]), which was indicated by the reliably positive effect of trial time ($\hat{\beta} = 0.34$, 95% CrI [0.26, 0.42], $pd = 100\%$, $BF_{01} < 0.01$). This effect was reliably modulated by SC ($\hat{\beta} = −0.44$, 95% CrI [−0.54, −0.35], $pd = 100\%$, $BF_{01} < 0.01$), indicating that the increase in the bird offset between gate passing and lane switching was more pronounced when the tracking and decision response were spatially incompatible ($M_{diff} = 0.56$, 95% CrI [0.47, 0.65]) compared to spatially compatible ($M_{diff} = 0.12$, 95% CrI [0.03, 0.21]).

Participants Did Not Anticipatorily Alter the State to Attenuate MC (State Analysis)

In anticipation of the following results, we found no evidence that participants performed anticipatory bird adjustments to reduce the MC for collecting higher rewards (Figure 6). Overall, participants did not position the bird differently as a function of MC ($\hat{\beta} = 0.01$, 95% CrI [−0.02, 0.04], $pd = 68.51\%$, $BF_{01} = 43.59$). More importantly, participants did not intensify bird adjustments with extended preview to mitigate higher MC when collecting the higher reward. Specifically, there were no reliable differences in bird adjustments depending on MC between long and medium preview time ($\hat{\beta} = 0.03$, 95% CrI [−0.02, 0.08], $pd = 84.79\%$, $BF_{01} = 17.49$) nor between

Figure 4

Factors Determining Reward-Based Decisions
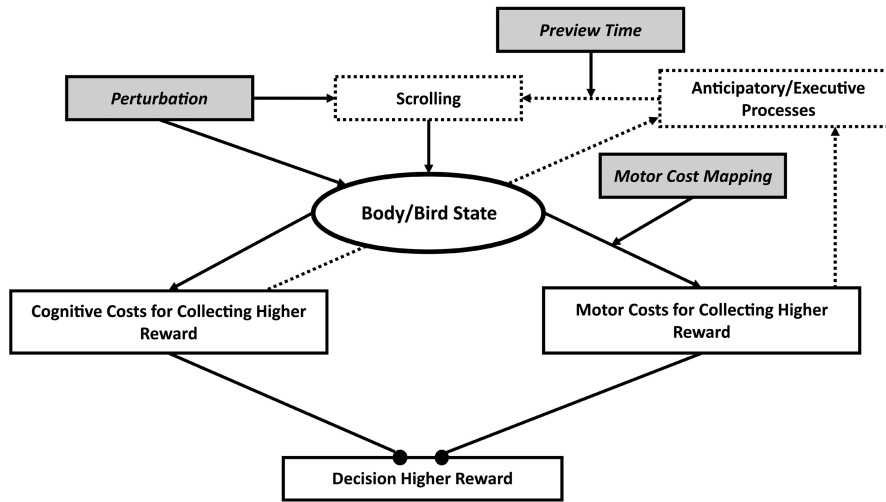
Note. Higher motor and cognitive costs (due to cognitive crosstalk) should reduce the probability of choosing the higher reward. While both types of costs were dependent on the body and bird state, motor costs were additionally dependent on the motor cost mapping. We assumed that participants might anticipate motor and/or cognitive costs during decision making and attenuate them by adapting their (scrolling) movements and, thus, the body/bird state (see also Figure 3). We expected anticipatory scrolling adaptations to increase with extended preview. As a result, participants were expected to choose the higher reward more often with extended preview, either by reductions in the influence of motor costs, cognitive crosstalk, or both. Paths and variables under subjective control are printed in and surrounded by dotted lines. Independent variables in the experiment are printed in italic within slightly greyed out boxes.

medium and short preview time ($\hat{\beta} = 0.00$, 95% CrI [−0.04, 0.04], $pd = 50.56\%$, $BF_{01} = 35.04$).

Participants Adapted the Overall Bird State With Longer Preview Time (State Analysis)

Similar to our predictions, the bird offset from the lane center was overall reliably smaller with long ($M = 0.16$, 95% CrI [0.07, 0.25]) compared to medium preview time ($M = 0.30$, 95% CrI [0.21, 0.38]; $\hat{\beta} = 0.14$, 95% CrI [0.11, 0.17], $pd = 100\%$, $BF_{01} < 0.01$). This effect

was reliably modulated by trial time ($\hat{\beta} = −0.10\%$, 95% CrI [−0.14, −0.06], $pd = 100\%$, $BF_{01} < 0.01$), indicating that the drift of the bird into the perturbation direction between gate passing and lane switching was slightly larger with long preview time ($M_{diff} = 0.37$, 95% CrI [0.29, 0.45]) compared to medium preview time ($M_{diff} = 0.28$, 95% CrI [0.20, 0.36]). Moreover, this interaction was further modulated by SC ($\hat{\beta} = 0.09$, 95% CrI [0.02, 0.16], $pd = 99.33\%$, $BF_{01} = 1.04$). The bird drifted slightly more into the perturbation direction between gate passing and lane switching with long compared to medium preview time when participants performed spatially incompatible tracking and

Table 1

Population-Level Effects (Logit Scale), 95% CrIs (Logit Scale, Equal-Tailed), pd, and BF_{01} for Experiment 1

Parameter	$\hat{\beta}$	CrI	pd (%)	BF_{01}
Intercept	**3.40**	**[2.96, 3.84]**	**100.00**	**—**
Spatial compatibility	**1.13**	**[0.73, 1.53]**	**100.00**	**<0.01**
Motor costs	**−0.21**	**[−0.45, 0.04]**	**95.23**	**2.59**
Preview time (2,250 ms vs. 1,500 ms)	**−0.28**	**[−0.46, −0.12]**	**99.96**	**0.08**
Preview time (1,500 ms vs. 750 ms)	**−1.32**	**[−1.61, −1.04]**	**100.00**	**<0.01**
Spatial compatibility : motor costs	0.06	[−0.29, 0.41]	64.00	7.14
Spatial compatibility : preview time (2,250 ms vs. 1,500 ms)	0.19	[−0.12, 0.51]	87.90	4.34
Spatial compatibility : preview time (1,500 ms vs. 750 ms)	−0.08	[−0.36, 0.22]	70.33	7.84
Motor costs : preview time (2,250 ms vs. 1,500 ms)	−0.09	[−0.41, 0.23]	70.97	7.30
Motor costs : preview time (1,500 ms vs. 750 ms)	0.15	[−0.10, 0.41]	87.89	5.26
Spatial compatibility : motor costs : preview time (2,250 ms vs. 1,500 ms)	−0.10	[−0.68, 0.48]	63.15	4.27
Spatial compatibility : motor costs : preview time (1,500 ms vs. 750 ms)	−0.03	[−0.52, 0.46]	54.95	5.35
N_{id}	58			

Note. Parameters with a high probability of being strictly positive or negative ($pd > 95\%$) are printed in bold. CrI = equal-tailed credible interval; pd = probability of direction; BF = Bayes factor.

Figure 5

Absolute Embodied Decision Biases and Estimated Marginal Means and on the Response Scale
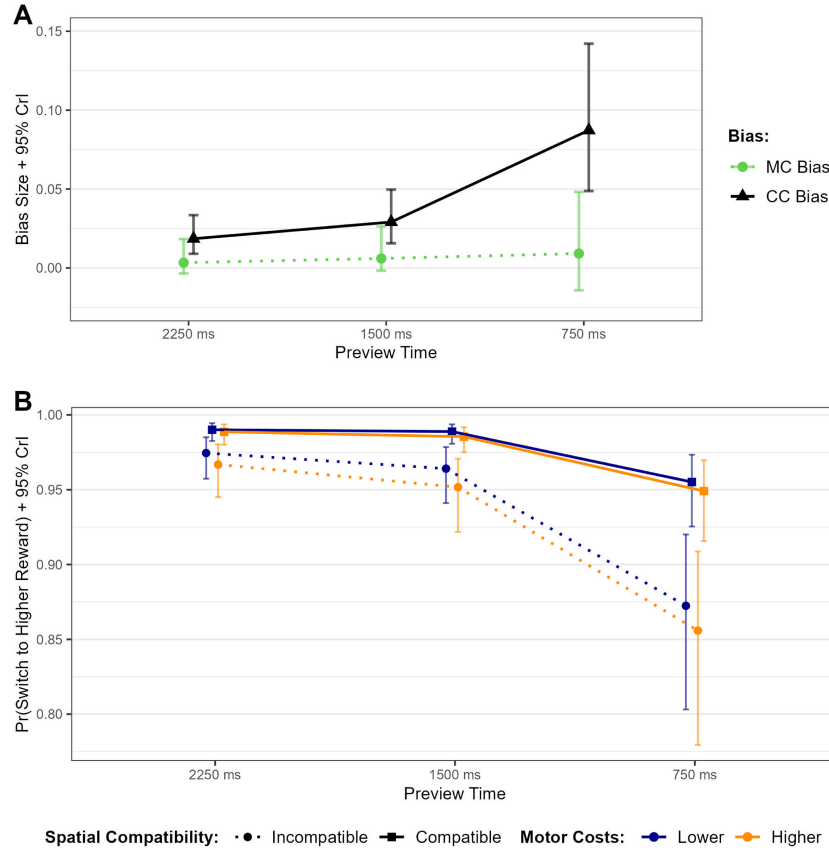
Note. Panel A: Absolute embodied decision biases (color/linetype/shape) and 95% CrIs as a function of preview time (*x* axis). A positive MC bias reflects a preference for lower motor costs. A positive CC bias indicates a preference for lane switches associated with a spatially compatible mouse movement relative to scrolling. Panel B: Estimated marginal means and 95% CrIs on the probability scale as a function of motor costs (color), spatial compatibility (linetype/shape), and preview time (*x* axis). Note, that the *y* axis does not span the whole probability range but only the interval [0.75, 1.00]. Data points are jittered along the *x* axis for better visual inspection. CrI = equal-tailed credible interval; MC bias = motor cost bias; CC bias = cognitive crosstalk bias. See the online article for the color version of this figure.

decision responses ($M_{\text{diff}} = -0.14\%$, 95% CrI [$-0.20$, -0.09]) than when they performed spatially compatible responses ($M_{\text{diff}} = -0.05$, 95% CrI [-0.11%, -0.00%]).

Lastly, the bird offset was also slightly but reliably smaller with medium ($M = 0.30$, 95% CrI [0.21, 0.38]) compared to short ($M = 0.37$, 95% CrI [0.28, 0.46]) preview time ($\hat{\beta} = 0.07$, 95% CrI [0.02, 0.11], $pd = 99.85\%$, $\text{BF}_{01} = 0.41$). This effect was reliably modulated by trial time ($\hat{\beta} = 0.10$, 95% CrI [0.05, 0.15], $pd = 99.99\%$, $\text{BF}_{01} = 0.03$), indicating that the bird drifted slightly more into the perturbation direction between gate passing and lane switching with short ($M_{\text{diff}} = 0.37$, 95% CrI [0.29, 0.45]) compared to medium preview time ($M_{\text{diff}} = 0.28$, 95% CrI [0.20, 0.36]). This interaction was not reliably modulated by SC ($\hat{\beta} = -0.06$, 95% CrI [-0.14, 0.02], $pd = 92.48\%$, $\text{BF}_{01} = 6.02$).

In summary, participants countered the perturbation more intensely with longer preview time. The bird generally drifted in the perturbation direction between gate passing and lane switching, especially when tracking and lane switching responses were incompatible. However, with longer preview time, this bird drift was apparently compensated by more pronounced positional adjustments before gate passing.

Discussion

Experiment 1 was conducted to replicate previous studies that partially attribute the effect of the body state on embodied choices to CC, to check whether participants adapt the state to mitigate effects of MC, and, relatedly, whether participants engage in task serialization to mitigate effects of CC. First and foremost, we replicated the results of previous studies (Grießbach et al., 2023; Raßbach et al., 2021), namely that reward-based decisions are influenced both by (kinematic) MC as well as CC from concurrent movement. Participants favored lane switches that required lower amplitude manual

Table 2

Embodied Decision Biases (on the Response Scale) for Each Preview Time Condition, Difference Comparisons Between Separate Preview Times, pd and BF_{01} for Each Comparison

| Bias | Preview time | Median and CrI (%) | Comparison | | | | | |
------	--------------	--------------------	Versus medium			Versus short		
			Difference (%)	pd (%)	BF_{01}	Difference (%)	pd (%)	BF_{01}
MC	Long	0.34 [−0.34, 1.83]	0.28 [−0.61, 1.64]	76.27	13.43	0.58 [−1.81, 3.68]	72.32	10.18
	Medium	0.60 [−0.17, 2.64]	—	—	—	0.29 [−2.13, 3.00]	62.26	6.84
	Short	0.91 [−1.41, 4.82]	—	—	—	—	—	—
CC	Long	1.85 [0.90, 3.35]	1.03 [0.31, 2.10]	99.79	0.38	6.84 [3.70, 11.34]	100.00	<0.01
	Medium	2.91 [1.57, 4.97]	—	—	—	5.78 [2.94, 9.77]	100.00	<0.01
	Short	8.72 [4.88, 14.21]	—	—	—	—	—	—

Note. Point estimates represent the median of the posterior distributions. CrI = equal-tailed credible interval; BF = Bayes factor; MC = motor cost bias; CC = cognitive crosstalk bias.

movements, even at the expense of receiving less reward. However, this effect was small, especially on the response scale. More strongly, participants preferred lane switches which could be performed with a manual movement spatially compatible with the concurrently performed (scrolling) movement. These results demonstrate that the body state can bias reward-based decisions not only via MC, but also via CC due to concurrent movement. However, in natural behavior like walking, both aspects of the state are confounded. Consequently, what appeared to be a MC bias in previous paradigms (Grießbach et al., 2022; Kurtzer et al., 2020; Michalski et al., 2020) might have actually been—at least partially—a CC bias (Grießbach et al., 2023; Raßbach et al., 2021; but see Grießbach et al., 2022).

Figure 6

Estimated Marginal Means and 95% CrIs of the Bird Position as a Function of Motor Costs (Color), Spatial Compatibility (First Panel Header), Preview Time (x Axis), and Trial Time (Second Panel Header)
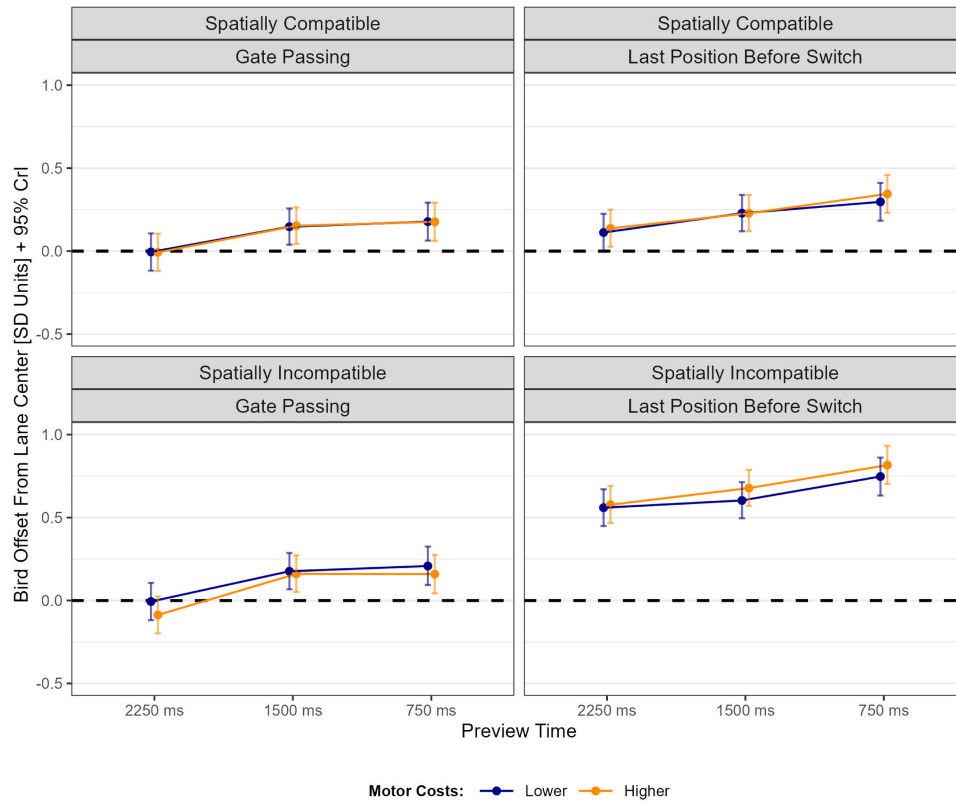
Note. y axis is zoomed in for better visual inspection. Positive values indicate that the bird was offset in the direction of the perturbation (i.e., more upwards for an upward, more downwards for a downward perturbation). CrI = equal-tailed credible interval. See the online article for the color version of this figure.

Our initial hypothesis, based on a previous study (Grießbach et al., 2021), posited that the MC bias would diminish as preview time increased. We conjectured that participants might engage in anticipatory state adjustments to attenuate the MC for obtaining higher rewards. However, if no such anticipatory adjustments occurred and the integration of MC into decision making followed the temporal patterns observed in recent manual reaching paradigms (Cos et al., 2014; Kurtzer et al., 2020; see also Michalski et al., 2020), we expected an increase in the MC bias with extended preview. Our findings did not reveal any modulation of the MC bias by preview time. Moreover, participants did not adapt the state with extended preview based on the experimentally induced MC. Most likely, the MC were too minimal to warrant anticipatory state adjustments. Notably, participants consistently maintained the bird near the lane center (see Figure S2 in Section 3.6 Bird Trajectory Plots in the online supplemental materials), effectively minimizing the MC gradient between choice options—independent of reward preview. Consequently, the adoption of more preview-specific tracking policies would have likely incurred additional control costs that would likely have outweighed the reduction of MC for collecting the higher reward (Todorov & Jordan, 2002; Yoo et al., 2021).

Moreover, we expected a reduction of the CC bias with extended preview, driven by a more serial approach to task processing (e.g., Fischer & Plessow, 2015; Logan & Gordon, 2001; Meyer & Kieras, 1997a, 1997b). The results indeed supported this hypothesis. With longer preview time, participants exhibited a reduced preference to execute lane switches that were spatially compatible with concurrent scrolling, resulting in more high-reward choices. The results from the state analysis also suggested the adoption of a more serialized task processing approach, with participants positioning the bird closer to the lane center with extended preview. This strategic positioning potentially allowed them to allocate cognitive resources away from tracking to decision making as they finalized their decision and implemented it. These findings provide evidence that implementing serial processing when deciding while moving serves as an effective means for mitigating crosstalk between motor control and decision-making processes. However, Experiment 1 could not fully exclude the possibility that participants acted upon the immediate state when rewards became visible to mitigate the risk for CC—which is why we conducted Experiment 2 to provide further evidence that participants anticipate future states and associated costs and adapt to them to make more high-value choices.

Experiment 2

In Experiment 1, the MLTT paradigm simulated deciding while moving without phasic changes in the movement state typically observed in natural behavior like walking (where the left and right leg are alternatingly used as the swing leg; Grießbach et al., 2021). Thus, the experimental setup of Experiment 1 could not disentangle whether participants based their decisions and associated state adaptations on the immediate state at reward presentation or the anticipated state when a decision could be implemented into action. Previous research has provided evidence that under (passive) body motion, the immediate body state is integrated into motor decisions, leading to suboptimal reaching trajectories (Bakker et al., 2017). This suggests that anticipation and integration of future states into decisions might be starkly limited under novel movement demands and constraints. In a different study, the anticipated body state was integrated into reward-based decisions

during walking, with corresponding step and footing adaptations aimed at attenuating the MC when a decision could be translated into action (Grießbach et al., 2021). However, this study did not orthogonally manipulate MC and spatial features of the body state. Hence, participants might have anticipated (and tried to attenuate) the motor or cognitive costs resulting from the body state—or potentially both.

In Experiment 2, we disentangled the state when rewards became visible (immediate state) from the state when a decision could be translated into a manual movement (anticipated state). If participants integrated the immediate state into their decisions, we expected the MC and/or the CC bias to reverse between long and medium, as well as between medium and short preview time (i.e., when the immediate state differed between subsequent levels of preview time). However, if participants integrated the anticipated state into decisions, we expected the MC and CC bias to be solely determined by the anticipated state (with the biases potentially shrinking with extended preview due to anticipatory state adjustments/task serialization; see Grießbach et al., 2021).

Note, that we conducted an online study prior to Experiment 2 (for a more detailed description, see Section 4. Online Pilot Experiment and Subsections in the online supplemental materials). For this online study, we increased the impact of the bird position on the MC gradient between lane switches and reduced the Windows cursor sensitivity (i.e., larger manual movements were required to move the invisible mouse cursor and reach the lane switch thresholds). This indeed led to a substantial MC bias as well as a CC bias as observed in Experiment 1. However, some aspects of the MLTT implementation in the pilot experiment hindered a clear interpretation of the results. Consequently, we improved the MLTT design for Experiment 2 to foster the validity of our results and their interpretation and conducted Experiment 2 in the lab to increase the experimental control over input and output devices.

Method

Participants

We strived for a sample of at least 64 participants. Ultimately, we collected data from 74 participants (age: $Mdn = 24$ years, range = [19 years, 37 years]; gender: 61 female, 13 male; self-reported handedness: 69 right-handed, four left-handed, one ambidextrous) to compensate for data set exclusions. Participants were again recruited via the participant-acquisition website (Sona Systems, n.d.) of the Department of Psychology at the University of Würzburg in spring/early summer of 2022 (note that 15 participants had participated in earlier experiments).[4] Prior to experimentation, all participants gave their

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[4] Analyzing the decision data with the additional factor of prior participation revealed that participants who had participated earlier collected the higher reward generally more often, showed a more pronounced increase in higher-reward-decisions with medium compared to short preview time, and exhibited a tendentially smaller motor cost bias. However, it is unlikely that this was a result of practice, as reliable improvements in dual task performance are typically observed only after multiple practice sessions (not intermitted by several weeks or months in which performance improvements are also monetarily rewarded (e.g., Liepelt et al., 2011; Strobach et al., 2012). It seems more likely that participants with prior experience in the MLTT already were among high-performing individuals in the prior experiments and, thus, had higher intrinsic motivation for participating. Most importantly, the overall result pattern was similar between participants with and without prior experience.

informed consent. Participants received a performance-independent compensation of 15€.

Stimuli and Experimental Setup

In Experiment 2, the experimental conditions and setup closely resembled those of Experiment 1 with a few notable adjustments (see Section 5. Experiment 2 and subsections in the online supplemental materials for technical details). To provide participants with greater degrees of freedom for state adjustments, we increased the lane height from 135 to 166 pixels on the 1,920 by 1,080 pixels display. The hardware and equipment remained consistent throughout, including identical PCs equipped with the following components: Intel Core i5 6500 CPU, 8GB DDR4 RAM, and NVIDIA GeForce GTX 745 GPU. The displays used were BenQ ZOWIE XL 2411 LCDs with a 24-in. screen diagonal, operating at a refresh rate of 100 Hz and a resolution of 1,920 by 1,080 pixels. The input devices used were Fujitsu M520 computer mice with a sensitivity of 1,000 dpi. The formula computing the MATs for lane switches in either direction (given the bird position and MC mapping) was only slightly adjusted compared to the online pilot experiment in which a reliable MC bias was observed (see Section 5.1. Motor Cost Adjustments in the online supplemental materials).

Trial Procedure

Only procedural modifications will be reported in the following sections. Rewards and obstacles appeared with long (2,750 ms), medium (1,750 ms), or short (750 ms) preview time before colliding with the central obstacle (Figure 7). Participants were instructed to initiate decision making as soon as rewards became visible.

A significant change was introduced in the perturbation dynamics. Compared to Experiment 1, the perturbation direction now reversed every 1,000 ms, resulting in three changes in perturbation direction before encountering the central obstacle (a video showcase is available at https://osf.io/hzcwk). Additionally, one more change in perturbation direction occurred after passing the central obstacle on the upper or lower lane after a successful lane switch. Participants were once again tasked with countering the perturbation, alternately scrolling forward and backward, in accordance with the specific trial's perturbation pattern. These patterns followed an "upward–downward–upward–downward–upward" or "downward–upward–downward–upward–downward" sequence (the second to last perturbation direction indicates the perturbation direction when a lane switch could be executed; it was used as a basis for coding trials in the subsequent decision and state analyses). In each section, the perturbation was computed similar to Experiment 1 (see Section 3.2. Perturbation in the online supplemental materials), but the randomization involved a random draw from a uniform distribution with bounds 0.5 and 1.0 instead.

Trial time for completed trials amounted to 4,750 ms, with the next trial beginning after an inter-trial interval of 1,000 ms. In error trials, the error message was shown until 5,750 ms after trial start.

Design

Participants completed six practice blocks for each combination of MC mapping and preview time with 18 trials each (i.e., 108 practice trials in total). This was followed by 600 experimental trials, divided into four blocks of 150 trials each. The MC mapping changed between blocks, and block order was counterbalanced between participants. Each mapping block included three subblocks of 52 trials each, with the first two trials being randomly drawn warmup trials from the subblock. Preview time was manipulated between subblocks. Subblock order was pseudorandomized for each block and participant separately. Reward and perturbation were manipulated trial-wise. Trial order was pseudorandomized for each subblock separately. Consequently, the experiment comprised 3 (reward on upper/lower lane: 30/70, 50/50, 70/30) by 2 (MC mapping: proximity advantage, proximity disadvantage) by 2 (perturbation direction: upward, downward) by 3 (preview time: long, medium, short) conditions. Unequal reward distributions (30/70, 70/30) were repeated 20 times per design cell, while the equal reward distribution was only repeated 10 times per design cell.

General Procedure and Instructions

The general procedure and instructions were practically identical to Experiment 1 (for changes introduced in the online pilot experiment, see Section 4.2. General Procedure and Instructions in the online supplemental materials). After the experiment, participants were prompted to indicate the approximate proportion of trials in which they had postponed or changed their final decision although rewards were presented earlier (0%–100% in steps of 10%). The experimental session lasted about 90 min.

Data Recording, Outlier Exclusion, and Data Reduction

We applied the same outlier criterion as for Experiment 1 and excluded $n = 7$ participants from the analyses as they had very high error rates compared to the rest of the sample. Hence, the final sample consisted of 67 participants (age: $Mdn = 24$ years, range = [19 years, 37 years]; 55 female, 12 male; 62 right-handed, four left-handed, one ambidextrous).

We excluded trials with equal rewards on both lanes, resulting in 480 experimental trials per participant. We recoded some error trials as in Experiment 1, totaling 2,337 tracking error trials after lane switching, 238 tracking error trials after gate passing, and 2,332 collision error trials. Consequently, 29,674 trials were included in the decision analysis (92.27% of the achievable 32,160 trials with 67 participants contributing 480 experimental trials each).

As the factor decision time was partially modulating effects in the online pilot experiment (see Section 4.7. Results and Corresponding Subsections in the online supplemental materials), we performed a median split on participants' ratings of the proportion of trials in which they had postponed or changed their decision ($Mdn = 30\%$, range = [0%, 100%]). A model including decision time (and all interactions including this factor) did not reveal any reliable effect modulations. Consequently, we removed decision time and all corresponding interactions to reduce model complexity for both the decision and state analysis.

Decision Analysis

The procedure for the decision analysis was identical to Experiment 1. Empirical means for individual participants (Figure S8 in Section 5.2. Estimated Marginal Means and Empirical Data Points for Lane Switch Decisions in the online supplemental materials) as well as details on priors and model convergence (Section 5.3. Decision Model Specification With Subsections 5.3.1., 5.3.2., and 5.3.3. in

Figure 7

General Trial Procedure for the MLTT in Experiment 2
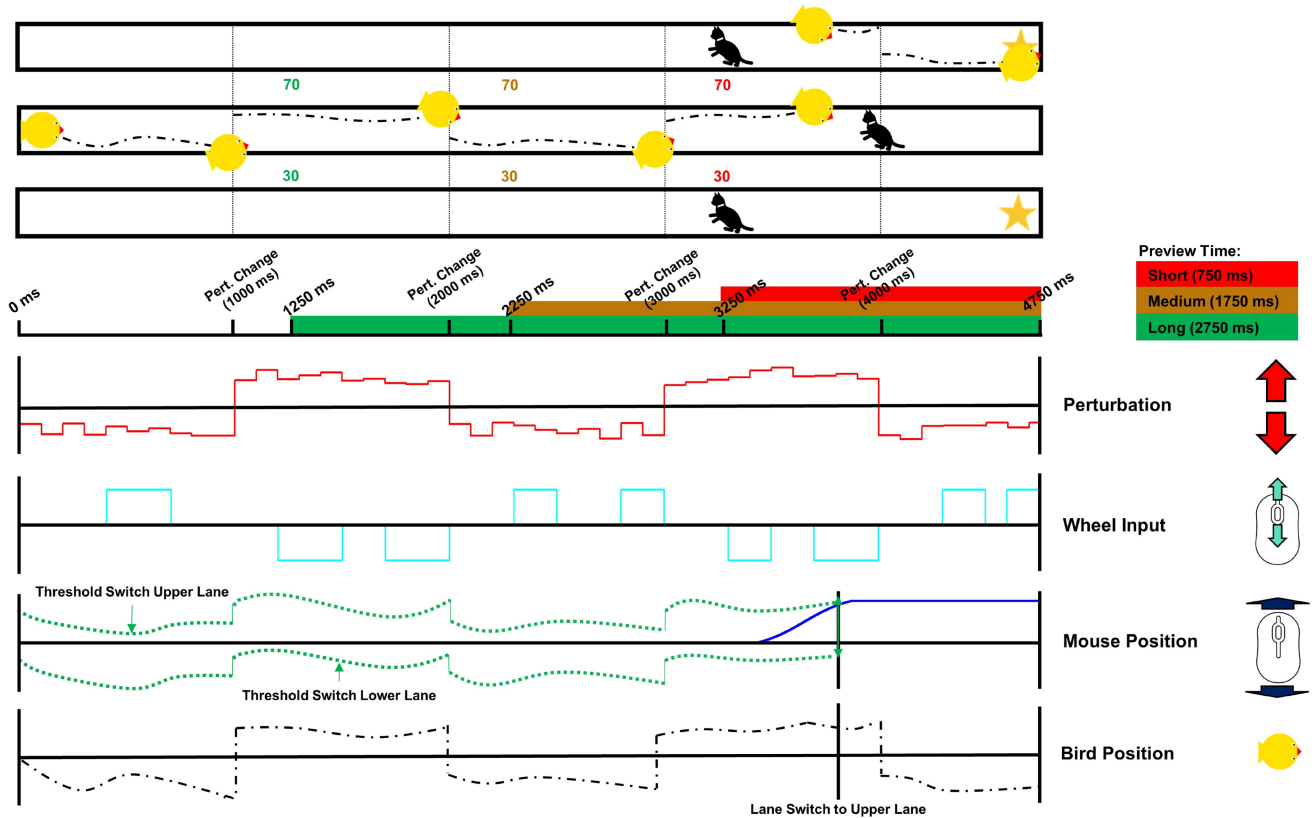
Note. This figure is an abstracted version of the actual visual display. A video demonstration of the actual experiment can be found online (https://osf.io/hzcwk). The central change in the trial procedure concerned the periodically changing perturbation direction which participants countered by alternatingly changing the scrolling direction. In combination with the different preview times, this meant that the immediate bird and body state differed between consecutive preview times, while the anticipated state in terms of the motor cost gradient and the scrolling direction necessary when a lane switch could be performed would still be comparable. The motor cost mapping in this trial corresponded to the proximity disadvantage condition. MLTT = multilane tracking task; Pert. Change = perturbation change. See the online article for the color version of this figure.

the online supplemental materials) are included in the online supplemental materials.

State Analysis

The procedure for the state analysis was identical to Experiment 1. Bird trajectory plots (Figure S9 in Section 5.4. Bird Trajectory Plots in the online supplemental materials) as well as details on priors and model convergence (Section 5.5. State Model Specification With Subsections 5.5.1., 5.5.2., and 5.5.3. in the online supplemental materials) are included in the online supplemental materials. The state analysis comprised 22,735 trials in which participants had collected the higher reward.

Results

Participants Again Favored Higher Rewards (Decision Analysis)

Participants strongly favored collecting the higher reward, as indicated by a likely positive intercept ($\hat{\beta}_0 = 2.40$, 95% CrI [2.03, 2.76],

$pd = 100\%$; Table 3). They were 11.02 times more likely to choose the higher reward over the lower one (Odds = 11.02, 95% CrI [7.61, 15.80]; Figure 8). While the preference for the higher reward did not reliably differ between long ($\log OR = 3.23$, 95% CrI [2.81, 3.65]) and medium ($\log OR = 3.31$, 95% CrI [2.90, 3.72]) preview time ($\hat{\beta} = 0.08$, 95% CrI [−0.16, 0.31], $pd = 76.39\%$, $BF_{01} = 8.75$), participants chose the higher reward reliably more often with medium compared to short ($\log OR = 0.66$, 95% CrI [0.22, 1.09]) preview time ($\hat{\beta} = -2.66$, 95% CrI [−3.07, −2.26], $pd = 100.00\%$, $BF_{01} < 0.01$).

Anticipated MC Strongly Biased Reward-Based Decisions (Decision Analysis)

Participants exhibited a strong preference for lower MC, supported by a reliably negative MC effect ($\hat{\beta} = -3.24$, 95% CrI [−4.52, −1.98], $pd = 100\%$, $BF_{01} < 0.01$; Table 3). The odds for switching to the higher reward were 25.53 times larger when the MC were lower compared to higher ($OR = 25.53$, 95% CrI [7.24, 91.84]; Figure 8). Correspondingly, the MC bias was large and reliably positive on the response scale (Table 4).

Table 3
Fixed Model Estimates (Logit Scale), 95% CrIs (Logit Scale, Equal-Tailed), pd, and BF$_{01}$ for Experiment 1

Parameter	$\hat{\beta}$	CrI	pd (%)	BF$_{01}$
Intercept	**2.40**	**[2.03, 2.76]**	**100.00**	—
Spatial compatibility	0.26	[−0.06, 0.57]	94.65	2.29
Motor costs	**−3.24**	**[−4.52, −1.98]**	**100.00**	**<0.01**
Preview time (2,750 ms vs. 1,750 ms)	0.08	[−0.16, 0.31]	76.39	8.75
Preview time (1,750 ms vs. 750 ms)	**−2.66**	**[−3.07, −2.26]**	**100.00**	**<0.01**
Spatial compatibility : motor costs	**0.46**	**[0.12, 0.80]**	**99.63**	**0.24**
Spatial compatibility : preview time (2,250 ms vs. 1,500 ms)	0.10	[−0.25, 0.48]	70.24	6.59
Spatial compatibility : preview time (1,500 ms vs. 750 ms)	−0.17	[−0.59, 0.24]	79.35	4.73
Motor costs : preview time (2,250 ms vs. 1,500 ms)	−0.08	[−0.45, 0.32]	65.56	6.35
Motor costs : preview time (1,500 ms vs. 750 ms)	**0.41**	**[−0.00, 0.82]**	**97.43**	**0.90**
Spatial compatibility : motor costs : preview time (2,250 ms vs. 1,500 ms)	−0.11	[−0.85, 0.64]	62.23	3.38
Spatial compatibility : motor costs : preview time (1,500 ms vs. 750 ms)	**−0.55**	**[−1.11, −0.01]**	**97.61**	**0.73**
N_{id}	67			

Note. Parameters with a high probability of being strictly positive or negative ($pd > 95\%$) are printed in bold. CrI = equal-tailed credible interval; pd = probability of direction; BF = Bayes factor.

On the logit scale, the effect of MC did not reliably differ between long ($\log OR = -3.33$, 95% CrI [−4.64, −2.03]) and medium ($\log OR = -3.40$, 95% CrI [−4.70, −2.12]) preview time ($\hat{\beta} = -0.08$, 95% CrI [−0.45, 0.32], $pd = 65.56\%$; BF$_{01}$ = 6.35; Table 3). However, the effect of MC was reliably larger with medium compared to short ($\log OR = -2.99$, 95% CrI [−4.28, −1.73]) preview time ($\hat{\beta} = 0.41$, 95% CrI [0.00, 0.82], $pd = 97.43\%$, BF$_{01}$ = 0.90). On the response scale, the magnitude of the MC bias was similar between long and medium preview time ($Mdn_{diff} = -0.47\%$, 95% CrI [−4.44%, 3.31%], $pd = 60.58\%$, BF$_{01}$ = 2.39; Figure 8 and Table 4). However, the MC bias was reliably smaller with medium compared to short preview time ($Mdn_{diff} = 41.88\%$, 95% CrI [26.78%, 51.36%], $pd = 100\%$, BF$_{01}$ < 0.01), indicating that MC played a significant role in lane switching decisions with short preview time, but their influence diminished (and potentially reached a plateau) with medium preview time.

CC due to the Anticipated State Marginally Biased Lane Switching Decisions (Decision Analysis)

In contrast to Experiment 1, participants showed only a marginal preference for lane switches linked to spatially compatible manual movements relative to scrolling ($\hat{\beta} = 0.26$, 95% CrI [−0.06, 0.57], $pd = 94.65\%$, BF$_{01}$ = 2.29; Table 3). The CC bias on the response scale was also rather small and partially associated with directional uncertainty (Figure 8 and Table 4).

Interestingly, the SC effect was more pronounced when the MC for collecting the higher reward were higher ($\log OR = 0.49$, 95% CrI [0.15, 0.82]) than when they were lower ($\log OR = 0.03$, 95% CrI [−0.35, 0.40]), as indicated by the reliably positive interaction effect ($\hat{\beta} = 0.46$, 95% CrI [0.12, 0.80], $pd = 99.63\%$, BF$_{01}$ = 0.24; Table 3). In trials where collecting the higher reward required a larger manual movement, the odds for choosing the higher reward were 1.63 times higher with spatially compatible compared to incompatible manual movements ($OR = 1.63$, 95% CrI [1.16, 2.27]). Conversely, when the higher reward required a shorter manual movement, the odds for choosing the higher reward were nearly identical for both SC conditions ($OR = 1.03$, 95% CrI [0.70, 1.50]).

On the logit scale, the SC effect was not modulated by preview time (long vs. medium: $pd = 70.24\%$, BF$_{01}$ = 6.59; medium vs.

short: $pd = 79.35\%$, BF$_{01}$ = 4.73; Table 3). On the response scale, the absolute CC bias also did not differ between long and medium ($pd = 56.00\%$, BF$_{01}$ = 2.97) nor medium and short ($pd = 72.70\%$, BF$_{01}$ = 1.21) preview time (Table 4).

General Effects Influencing the Bird Position (State Analysis)

As previously for Experiment 1, the state analysis revealed that the bird position was primarily influenced by the perturbation, evident from the reliably positive intercept ($\hat{\beta} = 0.67$, 95% CrI [0.55, 0.79], $pd = 100\%$; Figure 9). Furthermore, the bird offset from the lane center was again smaller at gate passing compared to shortly before a lane switch, signaled by a reliably positive trial time effect ($\hat{\beta} = 0.33$, 95% CrI [0.28, 0.38], $pd = 100\%$, BF$_{01}$ < 0.01). There was a reliable trial time by SC interaction ($\hat{\beta} = -0.44$, 95% CrI [−0.52, −0.36], $pd = 100\%$, BF$_{01}$ < 0.01). This indicated that the bird exhibited greater offset into the perturbation direction between gate passing and lane switching when participants executed spatially incompatible ($M_{diff} = 0.55$, 95% CrI [0.49, 0.62]) compared to compatible mouse movements relative to scrolling ($M_{diff} = 0.11$, 95% CrI [0.05, 0.18]).

Participants Did Not Attenuate MC by Anticipatory Bird Adjustments (State Analysis)

We found no evidence that participants intensified scrolling and, thus, bird adjustments to mitigate MC with extended preview (Figure 9). In fact, we observed a somewhat contrasting trend, in that the bird tended to be more centrally positioned with short preview time when MC were higher compared to lower. Given that this trend is more likely to reflect a certain survivor bias due to the analyzed trials, and for the sake of brevity, we refrain from interpretating the corresponding effects (see Table S4 in Section 5.5.1. Model Formula and Parameter Table in the online supplemental materials for a parameter table).

Participants Did Not Adapt the Body and Bird State to Serialize Task Processing (State Analysis)

As mentioned in the prior section, there was an unexpected partial trend for the bird being positioned closer to the lane center with

Figure 8

Absolute Embodied Decision Biases and Estimated Marginal Means on the Response Scale
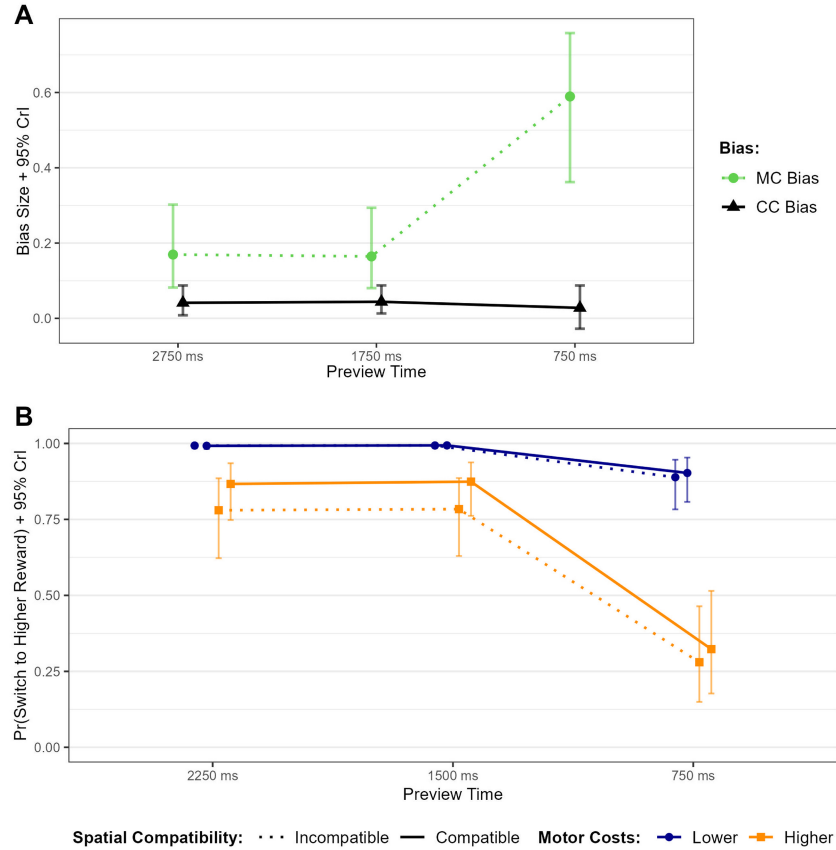
Note. Panel A: Median embodied decision biases and 95% CrIs as a function of preview time (panels). Panel B: Estimated marginal means and 95% CrIs on the response scale, as a function of motor costs (shape/color), and spatial compatibility (linetype), and preview time (*x* axis). Data is jittered along the *x* axis for better visual inspection. CrI = equal-tailed credible interval; MC bias = motor cost bias; CC bias = cognitive crosstalk bias. See the online article for the color version of this figure.

shorter preview time (Figure 9). These result patterns likely arose from a survivor bias in the analyzed trials. As for the effects involving MC, we refrain from interpreting these results as anticipatory state adaptations (see Table S4 in Section 5.5.1. Model Formula and Parameter Table in the online supplemental materials for a parameter table).

Table 4

Absolute Embodied Decision Biases for Each Preview Time Condition, Difference Comparisons Between Respective Embodied Decision Bias for Separate Preview Times, pd for the Difference, and BF$_{01}$

Bias	Preview time	Median and CrI (%)	Comparison					
			Versus medium			Versus short		
			Difference (%)	*pd* (%)	BF$_{01}$	Difference (%)	*pd* (%)	BF$_{01}$
MC	Long	16.95 [8.19, 30.23]	−0.47 [−4.44, 3.31]	60.58	2.39	41.27 [26.38, 51.11]	100.00	<0.01
	Medium	16.46 [8.03, 29.38]	—	—	—	41.88 [26.78, 51.36]	100.00	<0.01
	Short	58.95 [36.21, 75.80]	—	—	—	—	—	—
CC	Long	4.13 [0.82, 8.73]	0.23 [−2.98, 3.68]	56.00	2.97	−1.56 [−7.53, 4.95]	68.94	2.21
	Medium	4.41 [1.30, 8.75]	—	—	—	−1.84 [−7.45, 4.48]	72.70	1.21
	Short	2.79 [−2.76, 8.73]	—	—	—	—	—	—

Note. Point estimates represent the median of the posterior distributions. BF = Bayes factor; *pd* = probability of direction; MC = motor cost bias; CC = cognitive crosstalk bias; CrI = equal-tailed credible interval.

Figure 9

Estimated Marginal Means and 95% CrIs of the Bird Position as a Function of Motor Costs (Color), Spatial Compatibility (First Panel Header), Trial Time (Second Panel Header), and Preview Time (x Axis)
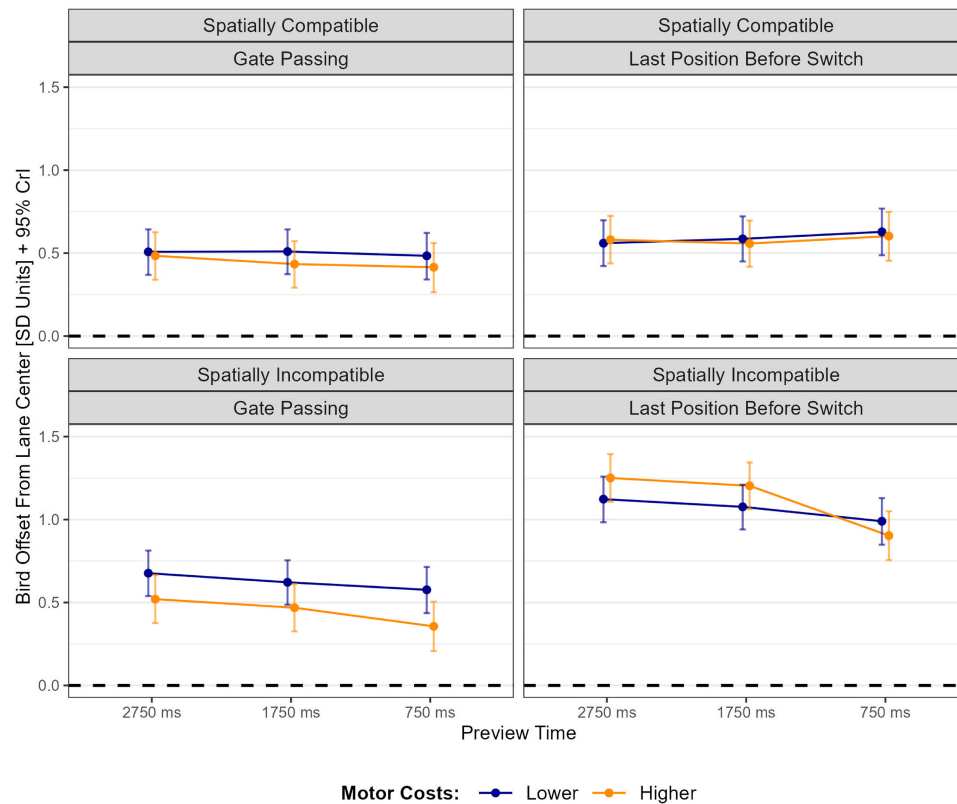
Note. Note that the *y* axis does not span the complete tracking range and was scaled for modeling purposes. Data is jittered along the *x* axis for better visual inspection. CrI = equal-tailed credible interval. See the online article for the color version of this figure.

Participants Antedated Decision Making With Extended Preview (Exploratory Analysis)

In this explorative analysis, we examined whether participants antedated decision making to meet the motor and cognitive demands of their decisions, effectively switching lanes earlier. In line with the decision analysis results, this would provide further evidence that participants integrated the anticipated state into their decisions. For this purpose, we ran an additional model estimating the time point of lane switching, using the same predictors as the decision model (model formula, priors, and convergence are described in Section 5.6. Switch Time Model Specification and Subsections in the online supplemental materials). Results revealed that participants indeed performed lane switches earlier with long compared to medium preview time ($\hat{\beta} = 0.03$, 95% CrI [0.01, 0.05], $pd = 99.97\%$, $BF_{01} = 0.35$; response scale: $\hat{\beta} = 14.70$ ms, 95% CrI [6.04 ms, 23.17 ms]), and also remarkably earlier with medium compared to short preview time ($\hat{\beta} = 0.45$, 95% CrI [0.41, 0.50], $pd = 100\%$, $BF_{01} < 0.01$; response scale: $\hat{\beta} = 208.34$ ms, 95% CrI [188.62 ms, 227.57 ms]). Hence, participants seemingly adapted temporal aspects of decision making with extended preview.

Discussion

In Experiment 2, the MC bias was strongest with short preview time, while participants favored higher rewards more strongly with medium and long preview time, effectively reducing the influence of MC on decisions. As the sign of the MC bias did not change with preview time, participants most likely integrated the anticipated state—when a decision could be translated into a manual mouse movement—into their decisions (Grießbach et al., 2021). Note, that while participants jumped more frequently to the higher reward with increasing preview time, we found that the MC effect on the logit scale was slightly smaller with short compared to medium preview time. However, when transforming the model estimates back to the response scale, the large increase in higher-reward choices likely thwarted the only slight increase in the MC effect from short to medium preview time.

CC due to spatial features of concurrent movement had a notably smaller impact on decisions in Experiment 2 compared to prior studies (Grießbach et al., 2023; Raßbach et al., 2021) as well as Experiment 1 (and the online pilot study). This was likely due to the wider tracking lanes, allowing participants to counteract the perturbation with less frequent scrolling, as evidenced by the generally

larger bird offset in the state analysis. Similar exploitations of lax task constraints were observed by Grießbach et al. (2022) in that participants performed a transition step to negate experimentally induced MC in their walking task. Critically, the CC bias result pattern did not suggest that participants integrated the immediate state into their decisions.

Moreover, participants did not exhibit overt anticipatory state adjustments with extended preview to mitigate high MC or reduce CC. Instead, there was some evidence for greater state control with shorter preview time. This could indicate some form of anticipatory state adjustment and/or serialized task processing when it was certain that the time to decide between rewards was short. However, these effects more likely reflected a survivor bias regarding the analyzed trials (i.e., participants were more likely to collect the higher reward given a randomly smaller bird offset due to variability in tracking). As this makes these results hard to interpret as anticipatory adjustments, we refrain from doing so.

Interestingly, participants performed lane switches earlier with extended preview, suggesting they antedated decision making to align with decision-related motor demands. This likely contributed to them being able to collect the higher reward more often with extended preview time, indicating that participants integrated the anticipated state and associated motor demands into their decisions.

General Discussion

We set off to examine whether and how embodied decision biases due to MC (e.g., Grießbach et al., 2021, 2022; Kurtzer et al., 2020; Michalski et al., 2020) as well as CC (Grießbach et al., 2023; Raßbach et al., 2021) are modulated by the preview time for rewards. The MLTT paradigm (Raßbach et al., 2021)—a computerized task simulating situated, embodied decisions—allowed us to disentangle MC from the cognitive state during movement. In Experiment 2, we added movement dynamics similar to real-word behavior like walking (Grießbach et al., 2021, 2022). In combination with the preview time manipulation, the movement dynamics allowed us to assess whether the immediate (i.e., when rewards became visible) or the anticipated (i.e., when a decision could be translated into action) body state was integrated into decision making and associated anticipatory adjustments.

Overall, we replicated and extended previous work (Grießbach et al., 2023; Raßbach et al., 2021). That is, what might appear as a MC bias can—at least partially—be CC in disguise. Albeit the sizes of the embodied decision biases differed between experiments, the bias directions were consistent. Our results fit well within the embodied choice framework positing bidirectional relations between decision making and action (Lepora & Pezzulo, 2015; Pezzulo & Cisek, 2016). That is, actions and associated states are not simply means to an end to implement a decision, but rather a central factor influencing which decision is ultimately made.

Anticipation of MC Led to Temporal Adjustments for Decision Making

Based on a previous study (Grießbach et al., 2021), we hypothesized that participants could compensate for high MC of high-value reward options by anticipatory state adjustments with extended preview time. Alternatively—and potentially due to computational

bottlenecks when integrating MC into decisions while moving in unfamiliar tasks (Michalski et al., 2020)—we expected an increasing MC bias with extended preview time.

We found evidence that deciders can attenuate the absolute size of the MC bias with longer preview time. However, this was not due to overt anticipatory state adaptations. Most likely, this was related to a tradeoff relationship between MC and CC under the present low-practice conditions. Adapting the bird position necessitated more intensive scrolling movements (i.e., a stricter motor control policy; Todorov & Jordan, 2002; Yoo et al., 2021), which in turn would have increased the motor and cognitive control costs due to the corresponding (finger) movements. Continuous and intense scrolling could have even resulted in more parallel task processing, increasing the risk for CC (Fischer & Plessow, 2015; Fischer et al., 2014; Logan & Gordon, 2001), which would have further reduced the benefit of attenuated MC. Thus, overcoming the MC bias by preview-specific body state adjustments was likely not beneficial or feasible in the present experiments. However, anticipatory state adjustments reducing the MC for high-value reward options have been observed in a recent study (Grießbach et al., 2021). The walking paradigm applied in that study used a highly overlearned action (i.e., walking) concurrent to decision making. For such actions, participants might be able to perform anticipatory state adjustments (e.g., by altering the number of steps) without disproportionally increasing control costs. Related to this, cadence control (i.e., adapting the number of steps) is assumed to involve lower order brain areas typically not involved in more cognitive tasks (for a review, see Al-Yahya et al., 2011). This could also explain why anticipatory cadence adjustments might be feasible without increasing control costs or CC when deciding while walking.

Instead of anticipatory state adjustments, participants in Experiment 2 performed decision actions earlier with extended preview time.[5] This suggests that deliberation and potentially motor planning processes started earlier if preview time allowed for it (Wong et al., 2015). Consequently, participants made more high-value decisions with extended preview as they could successfully perform even more effortful and costly manual movements. This necessitates that participants acknowledged the advantage of antedating deliberation, as it enabled them to perform an action associated with a higher-level goal (accumulating points) which would have been harder to attain when always postponing decision making (Pezzulo et al., 2008; Pezzulo & Cisek, 2016)—in other words, participants likely anticipated the state at decision implementation and integrated the corresponding motor demands into the decision process. This is in line with a recent study providing evidence that biomechanical costs for manual reaches bias reward-based decisions very early in the decision process, but that top-down (i.e., higher-level goal related) processes can overrule this initial bias in decisions associated with longer reaction times (Pierrieau et al., 2021).

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[5] Note that a similar result pattern regarding lane switch times emerged for Experiment 1, with earlier lane switches as preview time was extended. Thus, such temporal adjustments of decision-making seemingly also helped reduce the cognitive crosstalk bias as observed in Experiment 1. Notably, in the online pilot experiment described in the online supplemental materials, lane switches were only slightly performed earlier with extended preview time, in congruence with the finding that the embodied decision biases remained constant with extended preview.

Task Serialization Can Attenuate CC When Deciding While Moving

Regarding the modulation of the CC bias, we expected that participants switch to a more serial processing mode with extended preview. Consequently, a more serial task processing mode would have reduced the risk of crosstalk from motor control into decision processes, effectively diminishing the CC bias (Fischer & Plessow, 2015; Fischer et al., 2014; Logan & Gordon, 2001).

We found that CC indeed diminished with increasing preview time, at least in Experiment 1. Partially, this attenuation could be attributed to preparatory state adaptations, potentially allowing deciders to withdraw cognitive resources from tracking the bird or even suspend tracking temporarily when implementing their decision into action. This can be interpreted as a switch from a parallel to a more serial task processing mode, reducing crosstalk between motor control and decision processes (Fischer et al., 2014; Fischer & Plessow, 2015; Logan & Gordon, 2001).

Interestingly, these state adaptations were observable both when tracking and decision responses were spatially compatible (e.g., scrolling forward and manual movement forward) and incompatible (e.g., scrolling forward and manual movement backward). The fact that participants seemingly also serialized processing in the spatially compatible case—for which crosstalk should not be detrimental—might be related to the fact that even when tracking and decision responses were compatible, tracking performance suffered when participants implemented their decisions, albeit to a lesser degree. This could be seen as a form of mixing cost also observable in task switching studies, where task performance is generally worse when two task sets have to be prepared and maintained compared to only one task set during a block (Kiesel et al., 2010; Koch et al., 2018). Thus, task serialization might have also produced the benefit of reducing crosstalk for trials with spatially compatible responses, explaining why participants converged to this tracking policy overall. Alternatively, the allocation of visual attention when deciding on or finally implementing a lane switch might be responsible for this pattern. That is, when trying to switch lanes, participants likely focused visual attention more toward the lane and reward they intended to switch to (i.e., they monitored the future action effect of the bird switching to a lane; Pfeuffer et al., 2016)—thus, visual feedback for tracking on the middle lane was likely temporarily degraded, leading to worse tracking performance even when responses were spatially compatible.

Notably, we did not find evidence for task serialization when MC were more pronounced in Experiment 2. This was likely due to the CC bias being relatively small due to the laxer tracking requirements. This might indicate that deciders do not always consider every potential state variable in embodied decision situations, but only the ones which are associated with the highest costs—that is, they apply heuristics to optimize embodied decision making (Raab, 2017). We also cannot rule out that the movement dynamics in Experiment 2 have prevented task serialization attempts. Switching the response (i.e., scrolling direction) between perturbation sections can be seen as a "mini" task switch, which requires at least some task set parameters to be altered, for example, visual attention (Kiesel et al., 2010). Previous research has shown that even with extended preparation time spatial attention is not efficiently directed toward predictable locations of upcoming task stimuli, leading to residual task switch costs due to attentional inertia

(Longman et al., 2014)—which might have also played a role in Experiment 2.

Embodied Choices as Multitasking

In the introduction, we framed deciding while moving as dual tasking and argued that similar interference effects (i.e., task-compatibility effects due to CC) should emerge. Notably, classical multitasking paradigms employ tasks which are functionally independent from one another (e.g., Janczyk et al., 2014) while the tasks in the MLTT paradigm constitute a more nested or hierarchical structure with bidirectional influences. That is, tracking must be performed within a reward-based decision context, with tracking performance influencing motor and cognitive costs for decisions (however, other hierarchical organizations are possible; Uithol et al., 2012). However, hierarchical models of action and motor control are typically not concerned with crosstalk-like effects, but focus on computational (i.e., normative) bidirectional relationships between hierarchical levels (Haruno et al., 2003; Wolpert et al., 2003). Our results indicate that CC effects also occur in tasks with a hierarchical structure and are subject to task serialization. This suggests that findings and theoretical frameworks from the multitasking literature can be used to conceptualize the impact of actions on decision making in embodied choices.

Limitations and Future Work

Practice Might Influence the Cost–Benefit Ratio for Anticipatory State Adjustments

Interestingly, participants showed no signs of anticipatory state adjustments to attenuate or even negate the MC bias. As mentioned in previous sections, there might exist a tradeoff between CC and MC in our paradigm (which also raises further questions how deciders compared these different costs, i.e., the "apples-and-oranges" problem; e.g., Potts & Rosenbaum, 2021; Rosenbaum & Feghhi, 2019). This tradeoff might be less relevant for highly overlearned actions like walking, where online adaptations of cadence control might only slightly increase (cognitive) control costs (Al-Yahya et al., 2011; Grießbach et al., 2021).

It is possible that the tracking and decision task in the MLTT paradigm might require less processing resources after substantial practice (via automatization and/or shortening of response selection; Pashler, 1984; Ruthruff et al., 2006). Alternatively, executive processes responsible for switching between tracking and decision making might become more efficient (Liepelt et al., 2011; Steyvers et al., 2019; Strobach et al., 2012). This would mean that participants could reduce the MC for collecting higher rewards while keeping the risk of CC due to intensified tracking (e.g., due to residual activation of the tracking task set; Monsell, 2003) low. This enhanced intertask coordination ability might also improve efficient allocation of visual attention after directional movement changes, which would further facilitate tracking performance and enable anticipatory state adjustments (Longman et al., 2014).

However, prior research showed that practice and prior experience do not always facilitate anticipatory actions (Herbort & Kunde, 2019). Instead, the task representation must be adapted to the contingencies of the performed tasks, for example, by explicit instruction. Interestingly, motor inefficiencies during task performance can seemingly also trigger adjustments of such task representations

(Mathew et al., 2017). Given that the relatively high MC in Experiment 2 can be interpreted as such motor inefficiencies, it is surprising that we did not observe anticipatory state adjustments aimed at reducing these inefficiencies. Thus, it seems more likely that general tradeoff relationships between tracking and associated control costs hindered anticipatory state adjustments in the present study—which might change after substantial practice. Future studies could investigate whether changing the task representation by more explicit instructions or rather intensive practice with the MLTT facilitates anticipatory state adjustments.

What Is Behind CC in the MLTT?

The preference for spatially compatible manual movements in relation to scrolling—that is, the CC bias we observed—could be the result of overlapping action representations for the motor control and decision making task (Hommel, 1998, 2020; Hommel et al., 2001; Janczyk & Kunde, 2020). That is, while performing the tracking task, some feature codes for scrolling might become activated (e.g., "forward" or "backward"), which likely also played a role in representing the decision action. Consequently, activation of the spatially compatible decision action might reach the execution threshold more easily compared to the spatially incompatible decision action, leading to the tendency to perform the spatially compatible decision action more often (see also Ratcliff & McKoon, 2008).

However, other mechanisms could also account for CC in the current experiments. First, the perturbation of the bird might have led to inhibition-of-return (IOR; Posner, 1980; Posner & Cohen, 1984). For example, if the bird is perturbed downward, attention might be first allocated to the lower half of the screen. IOR might then prompt a shift of attention toward the upper half of the screen. As a result, the reward stimulus in the corresponding lane might receive preferential processing, thereby biasing decisions to switch toward that reward. Second, the scrolling action itself might have biased attention, resulting from everyday human–computer interactions. For instance, when searching for the login button at the top of a website, one has to scroll forward and visual attention subsequently tends to focus on the upper half of the visual display to monitor whether the button becomes visible (see Pfeuffer et al., 2016).

Ultimately, this study was not designed to disentangle these different crosstalk mechanisms. Furthermore, it could be that multiple mechanisms contribute to CC as observed in this study. Measuring the allocation of visual attention when performing the MLTT and comparing it to the allocation of visual attention in similar paradigms (e.g., Grießbach et al., 2021, 2022) might be a promising avenue for future research.

Conclusion

When deciding while moving, humans anticipate future states and associated motor and cognitive costs. However, overt anticipatory state adjustments are starkly limited in novel tasks, presumably due to tradeoff relationships between state adaptations attenuating MC and simultaneously increasing (cognitive) control costs. Given such limitations, deciders seem to anticipatorily antedate decision making to make time for demanding motor planning and execution. Moreover, CC due to concurrent movement can be reduced by serializing motor control and decision-making

processes—given that MC do not increase disproportionally with such serialization attempts. We conclude that more sophisticated anticipatory state adaptations in novel task contexts might only become feasible after intensive practice.

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