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Full Length Article

Am I in control? The dynamics of sensory information, performance feedback, and personality in shaping the sense of control

Maren Giersiepen [a,b,*], Nils Wendel Heinrich [c], Annika Österdiekhoff [d], Stefan Kopp [d], Nele Russwinkel [c], Simone Schütz-Bosbach [a], Jakob Kaiser [e]

[a] LMU Munich, Department of Psychology, Leopoldstr. 13, D-80802 Munich, Germany
[b] LMU Munich, Graduate School of Systemic Neurosciences (GSN), Großhaderner Str. 2, D-82152 Planegg, Germany
[c] Universität zu Lübeck, Institute of Information Systems, Department of Computer Science and Engineering, Ratzeburger Allee 160, D-23562 Lübeck, Germany
[d] Bielefeld University, Social Cognitive Systems, Faculty of Technology, Inspiration 1, D-33619 Bielefeld, Germany
[e] Nuremberg Institute for Market Decisions, Steinstrasse 21, D-90419 Nuremberg, Germany

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ABSTRACT

Sense of control (SoC) over our actions is crucial for regulating our behavior. SoC arises from low-level processes, such as immediate sensory feedback, and high-level processes, such as performance evaluation. Studies using simple action-effect tasks suggest that people rely more on low-level sensory than on high-level cues of control. Yet, it remains unclear how these cues interact to shape the SoC in complex, goal-directed environments that require continuous behavioral adaptation. To investigate this, 50 participants performed a challenging motor control task akin to a video game, steering a spaceship along a continuously changing path. Sensorimotor control was manipulated by varying task difficulty via input noise across experimental blocks. After each trial, participants received negative, neutral, or positive feedback, followed by rating of their SoC. Linear mixed model analyses revealed that both sensory and evaluative feedback influenced the SoC. SoC decreased with increasing task difficulty. Furthermore, independent of difficulty, negative feedback reduced the SoC whereas positive feedback enhanced it, with a stronger effect for negative feedback. Notably, the effects of task difficulty and negative feedback were influenced by participants' depressive symptoms and their external locus of control, suggesting that generalized control beliefs modulate task-specific control experience. These findings indicate that SoC is informed by both low-level sensorimotor cues and high-level affective feedback, suggesting an integration of multiple types of information to assess control in dynamic task contexts where action-effect contingencies are extended over time. Crucially, these effects depend on trait-like control beliefs, highlighting the need to account for individual differences when investigating situated control experience.

* Corresponding author at: LMU Munich, Department of Psychology, Leopoldstr. 13, D-80802 Munich, Germany.
E-mail addresses: m.giersiepen@psy.lmu.de (M. Giersiepen), nils.heinrich@uni-luebeck.de (N.W. Heinrich), aoesterdiekhoff@techfak.uni-bielefeld.de (A. Österdiekhoff), skopp@techfak.uni-bielefeld.de (S. Kopp), nele.russwinkel@uni-luebeck.de (N. Russwinkel), s.schuetz-bosbach@lmu.de (S. Schütz-Bosbach), Jakob.Kaiser@nim.org (J. Kaiser).

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1. Introduction

Sense of control (SoC), the subjective feeling of control over a specific action (Pacherie, 2007), contributes to agency experience and a coherent sense of self. It allows us to assess our ability to bring about change in our environment, form intentions, and ultimately act upon them (Gentsch & Schütz-Bosbach, 2015; Kaiser et al., 2021; Luo et al., 2022). In well-practiced tasks, the SoC typically operates unconsciously and only reaches awareness when disrupted. For example, when riding our bicycle, we can directly relate our manipulations of the handlebar to the bicycles' movements. Yet, when a strong wind hits the bicycle from the side, control experience is disrupted, affording corrective actions to regain control.

Recent theories propose that SoC is influenced by different levels of processing, namely a lower sensorimotor level and a higher cognitive level (see Badre & Nee, 2018; Heinrich et al., 2024; Kahl et al., 2022). The sensorimotor level relies on real-time, proprioceptive and visual feedback to maintain control, while the cognitive level integrates external information, such as social or contextual cues, to evaluate performance and guide future actions. For instance, in the example of steering a bicycle, changes in driving conditions may lead to discrepancies between our manipulation of the handlebar and the bicycles' movement, diminishing our experience of control at the sensorimotor level. Furthermore, other cyclists or honking cars may provide external feedback, warning us when we deviate from the designated bike lane, thereby reducing our experience of control at the cognitive level. To reestablish perceived control, we may consequently increase our attention and focused effort to realign the bicycles' trajectory on the road.

Accordingly, various studies indicate that both low-level and higher-level manipulations influence self-reported SoC (Desantis et al., 2011; Giersiepen et al., 2024; Metcalfe et al., 2012; Österdiekhoff et al., 2024). At the sensorimotor level, changes in visual or proprioceptive feedback, such as spatially offsetting visual action effects, have been found to significantly reduce the SoC (Österdiekhoff et al., 2024). Beyond these sensorimotor influences, SoC is shaped by high-level feedback, which provides external information about performance. This type of feedback is typically categorized as positive (e.g., rewards or reinforcement), negative (e.g., error signals or penalties), or neutral. Self-reports indicate that action-congruent and positive feedback, such as rewards for executed actions, are associated with higher control compared to action-incongruent and negative feedback, demonstrating an influence of outcome valence on the cognitive layer of perceived control (Barlas et al., 2017; Barlas & Kopp, 2018; Gentsch et al., 2015; Oishi et al., 2018). Notably, most studies have examined the influence of low- and high-level cues of control in isolation, leaving their interaction in shaping the SoC unresolved.

Some theoretical and empirical work suggests a greater reliance on sensorimotor than higher-level or external cues when control can be reliably inferred from the former (Gentsch et al., 2012; Moore et al., 2009; Synofzik et al., 2013). For instance, Moore and colleagues (2009) showed that implicit measures of control were more strongly modulated by outcome primes when participants performed involuntary movements (i.e., internal predictive signals were absent) compared to voluntary ones (i.e., internal predictive signals were present). Importantly, though, the vast majority of studies investigated control experience in highly simplified task contexts, where, for example, trial-wise feedback was related to a single button press. This contrasts with real-life tasks, where high-level evaluative feedback typically occurs only after completing multi-step actions in a continuous environment, in which sensorimotor cues are arising all the time. Thus, it remains unclear how low-level and high-level cues interact to shape the SoC in dynamic, goal-directed tasks involving continuous change (Heinrich et al., 2024). Dynamic task environments require sustained action monitoring, providing a continuous stream of sensorimotor information that can be used to estimate one's SoC. At the same time, positive and negative feedback serve as salient external cues for evaluating task performance, potentially outweighing sensorimotor signals in shaping control judgments during goal-directed tasks.

Studies employing dynamic task environments present a mixed picture of the influence of sensorimotor cues and evaluative feedback on the SoC. While a recent study found that performance feedback in a dynamic visuomotor task influenced SoC more strongly when it was valid, reflecting actual performance (Dewey, 2023), other studies suggest that task instructions and performance feedback shape the SoC even when not reliably reflecting actual control over the action or its outcome (Oishi et al., 2018; Wen et al., 2015). Furthermore, their results suggest that the impact of evaluative feedback on SoC judgments increases with task difficulty. Thus, our understanding of how sensorimotor control and evaluative feedback interact to shape the SoC may be advanced by varying task difficulty during continuous, goal-directed tasks. Additionally, using rating items that precisely distinguish between participants' perceived motor control and their ability to successfully complete the task can help disentangle how distinct aspects of an action influence their SoC.

To better understand how evaluative feedback influences the SoC during continuous action, it is further necessary to examine the role of feedback valence more closely. Studies employing affective (i.e., positive and negative) feedback typically report a higher SoC for positive compared to negative feedback (see Gentsch & Synofzik, 2014). However, since most studies in this field do not employ a neutral feedback condition for comparison, it is unclear whether this effect reflects a positive-related increase or a negative-related decrease in perceived control. On the one hand, participants may exhibit a self-serving bias, wherein positive outcomes are weighted more strongly than negative ones (see Chambon et al., 2020; Villa et al., 2022). On the other hand, feedback-related changes in self-reported SoC may primarily be driven by negative feedback, as this feedback provides salient cues for behavioral adaptations in continuous task environments.

A previous study examined the relative influence of positive and negative feedback on perceived control in a task setting where participants made single key presses, each resulting in a positive (e.g., amusement), neutral (i.e., pure tones), or negative (e.g., disgust) auditory outcome (Yoshie & Haggard, 2013). The authors found that negative feedback had a stronger impact on the SoC than positive feedback, suggesting that the difference in SoC between feedback types is primarily driven by a decrease in control experience in response to negative feedback rather than an increase in perceived control in response to positive feedback. This asymmetry aligns with models of loss aversion and predictive coding (Friston, 2010; Kahneman & Tversky, 1979) which suggest that the brain prioritizes unexpected or threatening information over confirming positive signals. Negative feedback generates a prediction error, signaling a mismatch between intended and actual outcomes, which likely results in stronger adjustments in perceived control. However, it is important to note that their task did not involve continuous or goal-directed actions. Specifically, negative, neutral, and positive feedback were presented in separate blocks following single button presses, making the feedback primarily sensory in nature. Thus, it remains unclear whether positive and negative feedback are weighted equally in shaping participants' SoC in goal-directed dynamic environments (Kaiser et al., 2021).

Finally, it should be noted that long-term individual differences in the experience of control exist, shaped by dispositional traits and life experiences (Carstensen, 2024; Dewez et al., 2019). These differences manifest in various ways, such as trait-like locus of control (LoC), chronic stress exposure, and learned helplessness, which can influence how individuals perceive and respond to control-related situations. For example, individuals with a high internal LoC tend to attribute outcomes to their own actions and exhibit greater resilience in the face of negative feedback, whereas those with high external LoC may feel more dependent on external factors, leading to reduced SoC in unpredictable environments. Additionally, long-term exposure to uncontrollable negative events such as early life adversity, can lead to diminished agency perceptions and an increasing risk of developing depressive symptoms (Maier & Seligman, 2016). Conversely, individuals who have repeatedly experienced high contingency between actions and outcomes may develop an inflated SoC which has been linked to risk-taking behaviors such as problem gambling (Carstensen, 2024; Orgaz et al., 2013). These long-term differences suggest that SoC is not only influenced by immediate task conditions but is also shaped by broader personality and life history factors that may determine how individuals integrate feedback into their control judgements (see Dewey, 2023). However, the extent to which these dispositional factors interact with task-specific aspects in shaping the SoC remains poorly understood.

The goal of the current experiment was to investigate how sensorimotor cues of control interact with evaluative feedback and generalized, personality-specific control assumptions in shaping the SoC in a dynamic task environment. To this end, we utilized a modified version of the Dodge Asteroids task (Abalakin et al., 2024; Heinrich et al., 2024; Österdiekhoff et al., 2024), a visuospatial motor control task. In this task, participants steered a spaceship along a predefined path in a continuously changing environment using a computer keyboard. Control over the spaceship's movement was manipulated by two levels of input noise, amplifying movement distortion in response to keyboard inputs. After each trial, participants received either negative, positive, or neutral feedback. Unbeknown to participants, feedback type was counterbalanced, with an equal number of trials for all types of feedback within each block. Following feedback presentation, participants rated their SoC, assessing their experienced control over the spaceship steering during the preceding trial.

We hypothesized a reduction in SoC ratings (H1) in high compared to low input noise blocks (Oishi et al., 2018; Österdiekhoff et al., 2024). Additionally, we expected highest SoC ratings for positive feedback, followed by neutral, and then negative feedback (H2; Gentsch et al., 2015; Yoshie & Haggard, 2013). By directly comparing positive and negative feedback with neutral feedback, we aimed to determine whether the influence of feedback valence on SoC is primarily driven by an increase in SoC following positive feedback or a decrease in response to negative feedback. We further predicted that participants' SoC ratings would increase as their error rates decrease (H3; Oishi et al., 2018; Österdiekhoff et al., 2024). Crucially, we anticipated that feedback valence would have a stronger impact on SoC ratings in high input noise trials compared to low input noise trials, reflecting a stronger reliance on high-level affective feedback when sensorimotor noise increases (H4; see also framework of optimal cue integration, Synofzik et al., 2013). Following a reviewer's suggestion, we additionally examined whether the influence of evaluative feedback changed over the course of the experiment.

To investigate whether the effects of input noise, error rates, and outcome value on SoC are moderated by between-subject differences in control experience, we further examined the influence of participant's depression scores, as measured by the Center for Epidemiologic Studies Depression Scale Revised (CESD-R; Eaton et al., 2004; Van Dam & Earleywine, 2011), as well as their locus of control (LoC), as assessed by the Internal-External Locus of Control Short Scale (IE-4; Kovaleva et al., 2014; Nießen et al., 2022), on trial-wise SoC ratings. By including these trait measures, we could directly test whether task-specific variations in SoC were general phenomena or depended on the personalities of the participants. As previous research has associated depression with diminished control experience (Disner et al., 2011; Yu & Fan, 2016), we expected that participants with higher CESD-R scores would report a decreased SoC (H5). Additionally, as the LoC is an established measure of an individual's general tendency to attribute events to internal factors (i.e., assuming personal control) or external ones (i.e., assuming events are influenced by fate, chance, or other factors outside of one's personal control), we anticipated a reduced reliance on feedback to inform SoC ratings for participants with higher internal LoC scores (H6). Conversely, those with higher external LoC scores were expected to show an increased reliance on evaluative feedback to inform their SoC ratings (H7). Finally, in response to a reviewer's suggestion and recent findings that highlight the role of individual differences in weighting immediate sensorimotor information versus high-level feedback (Chang & Wen, 2025), we additionally explored whether participants' questionnaire scores modulated the effects of input noise on SoC ratings.

To summarize, while previous studies often focused on the influence of individual aspects on the SoC in simple task contexts, the current study examined the interaction of both low-level (i.e., sensorimotor) and high-level (i.e., affective feedback and trait-like beliefs) cues on SoC in a complex, goal-directed task environment.

2. Methods

2.1. Participants

Fifty healthy adult participants with a mean age of 24.14 years ($SD = 3.46$) participated in this study. All participants had normal or corrected to normal vision without color vision deficiencies. Due to above average error rates (see 2.4 Data analysis), two datasets were excluded during preprocessing. The final sample thus comprised 48 participants ($n_{\text{female}} = 32$, $n_{\text{male}} = 16$ indicated via self-report about their identified gender; $n_{\text{righhanded}} = 43$) with a mean age of 25.08 years ($SD = 3.44$). A power analysis in G*Power (Faul et al., 2007), following the procedure of Österdiekhoff et al. (2024), who examined how different cues affect the SoC in a dynamic multitasking environment, indicated that a sample of 23 participants would be large enough to detect medium-sized within-subject main effects with a power of 0.95 and an alpha level of 0.05. This estimate aligns with previous studies examining within-subject effects during continuous action (e.g., Heinrich et al., 2024; Oishi et al., 2018). Because detecting within-subject interactions and between-subject effects requires larger samples (Brysbaert & Stevens, 2018), we complemented our power analysis with and increased the sample size based on a literature review (Carstensen, 2024; Dewey, 2023). Participants could choose to be compensated with course credit or 9 Euro/hour. In addition, all participants received 2.10 Euro bonus they earned during the task at the end of the experiment. All participants provided written informed consent and were informed that the data of this study would be anonymized and processed confidentially. The study was approved by the ethical board of the Department of Psychology at the LMU Munich (date of approval: 29.03.2021) and was conducted in accordance with the Declaration of Helsinki.

2.2. Experimental design

To examine the influence of low- and high-level cues on participants' SoC, we used a modified version of the Dodge Asteroids spaceship-steering task (Heinrich et al., 2024; Österdiekhoff et al., 2024). In this computer-based task, participants navigate a spaceship through a dynamically changing environment using a standard computer keyboard. Task difficulty was varied across blocks by introducing either low or high sensorimotor noise to participants' keyboard input. Each trial was followed by high-level feedback that was either negative, neutral, or positive, with feedback type counterbalanced within blocks. After receiving feedback, participants rated their SoC for the current trial. The CESD-R and IE-4 questionnaires were administered at the end of the experimental session. A schematic task overview is presented in Fig. 1.

2.3. Procedure

We implemented the experiment in Python (Version 3.10; Rossum, 1995) using PyCharm, an integrated development environment (JetBrains Community Edition; Version 2019.3.5). Participants were seated approximately 70 cm from a 24-inch monitor (1920 x 1080 px; FPS: 60) on which the experimental task was presented on a black background.

Each trial started with the presentation of a white fixation cross (1° visual angle) on the screen center for 1.5 s. After the fixation cross disappeared, participants navigated a spaceship, an inverted, blue-colored triangle (1° visual angle), along a navigation path (with a thickness of 1° visual angle) that required dynamically adjusting its trajectory using button presses throughout each trial. Line trajectories were randomly generated while fulfilling the following conditions: First, every line contained vertical segments adding up to a total of 602 pixels. Second, 1330 pixels were dedicated to creating left and right turns in the path. Turns were constrained to have a size of 70 to 140 pixels to the left or right side, respectively. These settings guaranteed that each path was wide enough for effective

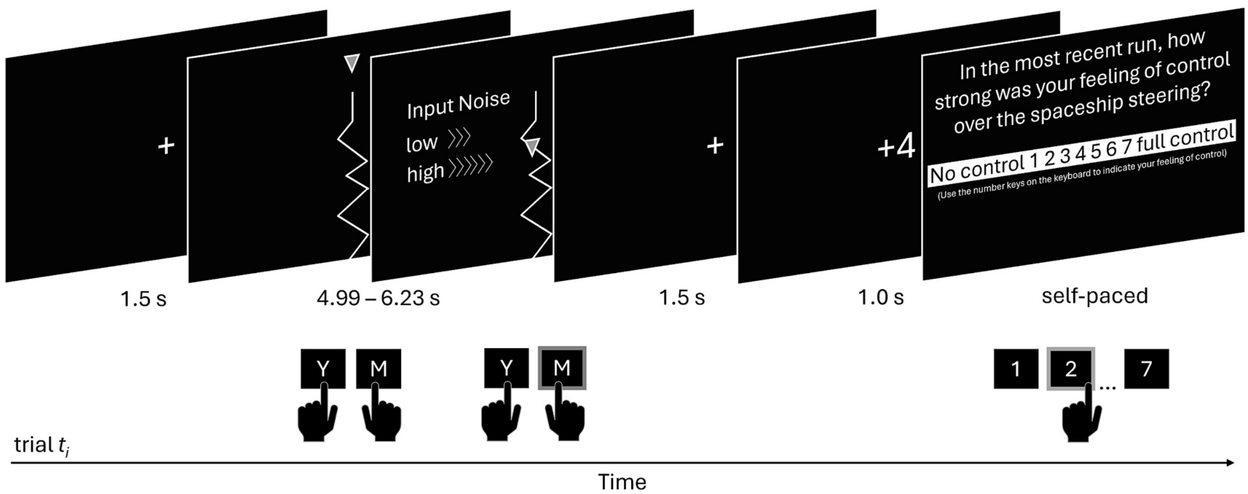

Fig. 1. Schematic task overview. Trials started with a fixation cross presented in the screen center. The spaceship, an inverted blue rectangle, entered the screen from the top at the start of the navigation task. Using the Y- and M−keys, participants steered the continuously moving spaceship along the white path as accurately as possible. Task difficulty was varied by changing input noise (low/high; condition not visible to participants) across blocks. The navigation task was followed by a white fixation cross at the screen center and the presentation of either positive (+4), neutral (*grey circle*), or negative (−2) evaluative feedback. Participants indicated their SoC over the spaceship steering at the end of each trial, using keys from '1′ (no control) to '7′ (full control). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

spaceship maneuvering while still requiring frequent adjustments to maintain optimal steering, keeping the task dynamic. To allow participants to prepare for navigation, the spaceship entered the screen 100 pixels below the top edge center and descended to the screen center (pixel 520). Participants could begin with steering as soon as the spaceship reached the center (i.e., 124 pixels prior to reaching the start of the navigation path at pixel 644).

Participants' goal was to steer the spaceship as accurately as possible along the paths' trajectory by pressing the Y-key (left) and M−Key (right) on the computers' keyboard using their left- and right-hand index finger, respectively. We opted for the Y- and M−key to avoid giving an advantage to right-handers, who might find it easier to use the arrow keys traditionally placed on the right side of a standard keyboard (see Österdiekhoff et al., 2024). Response keys registered inputs of sequential and continuous button presses. Once the spaceship reached the screen center, its position remained fixed. A dynamic task environment was created by continuously introducing new path segments at the bottom of the screen and moving the existing segments upward until they exit the screen at its top edge. Each navigation trial took between 4.99 and 6.23 s ($M = 5.12$, $SD = 0.07$) to complete.

Crucially, participants were instructed that the ease of spaceship navigation may vary across blocks of trials. In both 'low input noise' and 'high input noise' blocks, keyboard input was distorted by adding noise to participants' key presses, thereby introducing sensorimotor disturbance to spaceship navigation. The distortion followed a normal distribution, with a mean of 0 (i.e., no distortion) and a standard deviation of 0.5 for low input noise blocks and a standard deviation of 2.0 for high input noise blocks. As a result, high input noise blocks were expected to make accurate performance more difficult compared to low input noise blocks.

After navigation, negative (i.e., monetary loss of 2 cents), neutral (i.e. a grey circle), or positive (i.e., monetary gain of 4 cents) feedback was centrally presented for 1 s (1° visual angle). Gains were set to be twice as large as losses, as individuals typically perceive losses to be approximately twice as impactful as equivalent gains (Tversky & Kahneman, 1992). This also ensured that participants would end the experiment with a net gain rather than a net-zero outcome (Proudfit, 2015). At the end of each trial, participants indicated their perceived control over the spaceship, answering the question 'In the most recent run, how strong was your feeling of control over the spaceship steering?' in a self-paced manner on a seven-point Likert-scale, ranging from '1' (i.e., no control) to '7' (i.e., full control).

Unbeknown to participants, post-navigation feedback was not performance dependent but counterbalanced within blocks. Thus, participants received an equal number of negative, neural, and positive feedback in each block of trials. To create the impression that feedback reflected performance, participants were told that accurate steering of the spaceship would result in positive feedback, while substantial deviations from the target path would lead to negative feedback. They were also informed that, on some trials, no performance feedback would be given and that a grey colored circle would appear as feedback in the screen center. Finally, participants were told that they would receive a bonus based on the net gain from their best blocks at each difficulty level. Presenting neutral as well as performance-independent feedback allowed us to examine the influence of task difficulty and feedback valence on participants' SoC. Importantly, our study design allowed us to examine a) whether positive feedback is associated with higher perceived control than negative feedback and b) whether this difference is differentially driven by a decrease in control experience for negative feedback, an increase in the SoC for positive feedback, or whether both types of feedback equally influence participants control ratings. Furthermore, by manipulating both sensorimotor noise and evaluative feedback, this task setup allowed us to test how low-level and high-level information interact in shaping the SoC.

Participants started with four practice trials, followed by 8 blocks consisting of 30 trials each (240 trials in total, 40 trials for each input-noise-feedback condition). Participants were informed about their block-wise gains at the end of each block. To prevent participants from recognizing that payout was pre-determined to add up to 20 cents per block, their block-wise balance was randomly adjusted to a margin of 20 %, resulting in five different possible outcome values (16 ct, 18 ct, 20 ct, 22 ct, 24 ct).

To explore whether individual differences in perceived control influence state-dependent SoC ratings, participants completed the IE-4 (Kovaleva et al., 2014; Nießen et al., 2022) and CESD-R (Eaton et al., 2004; Radloff, 1977) on SoSci Survey (Leiner, 2024) at the end of the experiment. The IE-4 scale assumes that internality and externality comprise two dimensions of control, each measured with two items. For each item, participants were asked to indicate the extent to which they think it applies to them personally on a five-point Likert scale, ranging from '1' (i.e., does not apply at all) to '5' (i.e., applies completely). The scale has been validated and is recommended as a self-report tool for research purposes (Nießen et al., 2022). The CESD-R contains 20 items that assess symptoms of a major depressive episode as defined by the American Psychiatric Association and the Diagnostic and Statistical Manual of Mental Disorders, Fifth Edition, including an assessment of depressed mood, feelings of guilt or worthlessness, fatigue, sleep disturbances, changes in appetite, and difficulty concentrating. For each item, participants were asked to indicate how often they have felt this way recently on a five-point Likert-Scale (0 = 'not at all or less than 1 day last week', 1 = '1–2 days last week', 2 = '3–4 days last week', 3 = '5–7 days last week', 4 = 'nearly every day for 2 weeks'). The CESD-R is recommended to assess depressive symptomatology in the general population (Van Dam & Earleywine, 2011).

2.4. Data analysis

RStudio 2023.06.1 was used for preprocessing and statistical analyses of the experimental data. We examined the average trial-wise distance (in pixels) between spaceship and the navigation path to evaluate participants' task performance. Due to above-average error rates (i.e., spaceship deviations exceeding three times the interquartile range from the mean) two participants were excluded from the data during preprocessing (André, 2022).

Questionnaire scores were calculated based on the standard recommendations of the corresponding scoring instructions. To examine between-subject differences in control experience, subscale scores for internal and external LoC (IE-4) were calculated for each participant using the unweighted mean of both subscale items, resulting in a range of possible scores from 1 to 5 for both the internal and the external subscale. Depression scores were calculated as the sum of response values to all items of the CESD-R. Consequently, CESD-R scores could vary between 0 and 60, with higher scores indicating more severe depressive symptoms.

Multilevel mixed modelling was used to analyze the data, with the goal to build mathematical models that reflect the influence and interplay of low-level and high-level cues on participants' error rates (Model 1) and SoC (Model 2). Both models were estimated using the *lme4* package (Bates et al., 2014) and fitted using the Maximum Likelihood method, which estimates both fixed effects and their variance.

In both models, Participant was included as a random intercept to account for the repeated-measures structure of the data. This approach allows for the estimation of both within- and between- participant effects while preserving trial-level variability and avoiding the loss of information associated with averaging responses per condition (Meteyard & Davies, 2020). Likelihood ratio tests were used to determine the fixed effects structure of the model. Finally, we explored the models' maximal random effects structure, the most comprehensive set of random effects that could be included in the models while maintaining model stability and improving model fit, as indicated by the Bayesian Information Criterion (Barr et al., 2013; Chakrabarti & Ghosh, 2011). Including random slopes allows the model to account for individual differences in the size of within-subject effects by estimating participant-specific deviations from the average effect (Bates et al., 2015). This approach helps avoid underestimating the variability of fixed effects and reduces the risk of misattributing subject-level variance to fixed effects.

To investigate potential transformations of the predicted variables, error rates and SoC, we conducted Box-Cox distributional analyses, which yield a lambda value indicating the most appropriate power transformation (no transformation: $\lambda = 1$, logarithmic transformation: $\lambda = 0$, square root transformation: $0 < \lambda < 1$; Box & Cox, 1964). The suggested transformations result in an approximation of a normal distribution for the predicted variables and their residuals, thereby allowing for more reliable estimates of fixed and random effects than would be obtained without applying the indicated transformations.

Model 1 examined whether high input noise increased task difficulty compared to low input noise and whether error rates decreased with task practice. The final model predicting participants' Error Rates (line deviation in pixel) is displayed in Eq. (1) and included the fixed effects Input Noise (β_1; low/high) and Block Number (β_2; 1–8), as well as their interaction (β_3). The final model also featured a random slope for Input Noise ($\mu_{1,j[i]}$) within the random intercept for Participant ($\mu_{0,j[i]}$). ϵ_i denotes the residual error term. The Box-Cox distributional analysis implied a logarithmic transformation of participants' error rates ($\lambda = 0.10$; Box & Cox, 1964).

$$\log(ErrorRates_i) = \beta_0 + \beta_1 InputNoise_i + \beta_2 BlockNumber_i + \beta_3 (InputNoise_i * BlockNumber_i) + \mu_{0,j[i]} + \mu_{1,j[i]} * InputNoise_i + \epsilon_i \tag{1}$$

Model 2 examined how sensorimotor information, and higher-level feedback interact in shaping participants' SoC. The final model is displayed in Eq. (2). Model selection indicated the inclusion of the fixed effects Input Noise (β_1; low/high; H1), Feedback (β_2; negative/neutral/positive; H2), Error Rate (β_3; line deviation in pixel; H3), Block Number (β_4, 1–8), CESD-R scores (β_5; 0–60), and External LoC scores (β_6; 1–5) for a model predicting trial-wise SoC ratings. In addition, the model included an interaction of Feedback and CESD-R scores (β_7), Input Noise and CESD-R scores (β_8), Input Noise and External LoC (β_9), Feedback and Block Number (β_{10}), as well as of Input Noise and Block Number (β_{11}). It further featured a random slope effect for Input Noise ($\mu_{1,j[i]}$) within the random intercept for Participant ($\mu_{0,j[i]}$). ϵ_i denotes the residual error term. The Box-Cox distributional analysis implied a square root transformation of SoC ratings ($\lambda = 0.71$; Box & Cox, 1964). Post-hoc t-tests (two-sided) were performed to compare the relative influence of positive and negative feedback as well as sensorimotor (i.e., input noise) and high-level (i.e., evaluative feedback) control cues on the SoC.

$$\begin{aligned}\sqrt{SoC_i} = {} & \beta_0 + \beta_1 InputNoise_i + \beta_2 Feedback_i + \beta_3 ErrorRate_i + \beta_4 BlockNumber_i + \beta_5 CESDR_i + \beta_6 ExternalLoC_i \\ & + \beta_7 (Feedback_i * CESDR_i) + \beta_8 (InputNoise_i * CESDR_i) + \beta_9 (InputNoise_i * ExternalLoC_i) + \beta_{10} (Feedback_i * BlockNumber_i) \\ & + \beta_{11} (InputNoise_i * BlockNumber_i) + \mu_{0,j[i]} + \mu_{1,j[i]} * InputNoise_i + \epsilon_i\end{aligned} \tag{2}$$

For each of the fixed effects, we report β-estimates, standard errors, and *p*-values. Significance was evaluated against $\alpha = 0.05$. In addition, we report 95 % confidence intervals (CIs) as effect size indicators. CIs were obtained by a parametric bootstrap with 10,000 iterations. To precisely recover the results, we used a random seed (36).

3. Results

3.1. IE-4 scores

Participants reported a mean internal LoC of 3.68 ($SD = 0.82$, range: 1.5–5) and a mean external LoC of 2.11 ($SD = 0.75$, range = 1–5). Similar to the German reference sample (males and females aged 18 to 29 years; $N = 105$, Nießen et al., 2022), internal LoC scores were slightly negatively skewed (skewness = −0.73) and external LoC scores displayed a positive skewness (skewness = 1.42). Both internal and external LoC scores were lower in the current sample than in the reference sample (internal: $M = 4.13$, $SD = 0.69$; external: $M = 2.57$, $SD = 0.93$). No extreme outliers could be detected (i.e., questionnaire scores deviating more than three times the interquartile range from the mean).

3.2. CESD-R scores

Average depression scores in the current study were positively skewed (skewness = 1.28) and ranged from 0 to 44, with a mean score of 11.90 ($SD = 9.46$). Ten (20.83 %) participants exhibited critical depression scores (i.e., scores > 15). All other participants (N

= 38) scored lower, indicating no clinical significance of depressive symptomatology. No extreme outliers could be detected.

3.3. Model estimates

3.3.1. Error rates

The null model predicting error rates indicated an average trial-wise error, measured as distance between spaceship and target path, of 32.56 pixels ($\sigma = 1.03$, $p < 0.001$). Participant-specific individual differences explained 14.38 % of total variance observed in the data.

The model revealed significantly higher error rates in the high compared to the low input noise condition, confirming that spaceship steering became more difficult as input noise increased, $\beta = 1.79$, $\sigma = 1.03$, 95 % CI [1.70, 1.89], $p < 0.001$. Furthermore, a significant effect of Block Number revealed a reduction in error rates with block progression, indicating improved performance with task practice, $\beta = -1.02$, $\sigma = 1.00$, 95 % CI [−1.024, −1.018], $p < 0.001$ (Fig. 2A). Finally, a significant interaction indicated that the effect of Block Number differed for high and low input noise blocks, with the reduction in error rates being more pronounced in the low input noise condition compared to the high input noise condition, $\beta = 1.01$, $\sigma = 1.00$, 95 % CI [1.01, 1.02], $p < 0.001$ (Fig. 2B).

3.3.2. Trial-Wise SoC

The null model predicting SoC ratings indicated an average control of 3.75 ($\sigma < 0.01$, $p < 0.001$). Participant-specific individual differences explained 16.53 % of the total variance observed in the data. Distribution plots of all main effects are displayed in Fig. 3A.

Participants reported a decreased SoC when input noise changed from low to high, $\beta = -0.13$, $\sigma = 0.01$, 95 % CI [−0.35, −0.01], $p = 0.005$ (H1). While self-reported SoC in the low input noise condition increased with task practice ($\beta = 4.78*10^{-5}$, $\sigma = 2.61*10^{-6}$, 95 % CI [$1.44*10^{-5}$, $1.01*10^{-4}$], $p < 0.001$), a significant negative interaction of Input Noise and Block Number indicated that high input noise blocks were associated with a gradual decrease in SoC, $\beta = -3.71*10^{-4}$, $\sigma = 5.11*10^{-6}$, 95 % CI [$-5.62*10^{-4}$, $-2.23*10^{-4}$], $p < 0.001$ (Fig. 3B). Furthermore, error rates were negatively associated with SoC ratings, indicating that participants' SoC changed with actual efficiency in motor control, $\beta = -8.03*10^{-5}$, $\sigma = 5.14*10^{-8}$, 95 % CI [$-8.85*10^{-5}$, $-7.27*10^{-5}$], $p < 0.001$ (H3).

In contrast to neutral feedback, negative feedback significantly decreased SoC ratings, $\beta = -8.44*10^{-3}$, $\sigma = 2.23*10^{-4}$, 95 % CI [-0.01, $-3.90*10^{-3}$], $p < 0.001$. Conversely, in contrast to neutral feedback, positive feedback significantly increased SoC ratings, $\beta = 7.84*10^{-3}$, $\sigma = 2.23*10^{-4}$, 95 % CI [$3.44*10^{-3}$, 0.01], $p < 0.001$ (H2). The final model also featured a significant interaction of Feedback and Block Number, indicating that the influence of positive feedback on SoC ratings decreased over time, $\beta = -1.14*10^{-4}$, σ

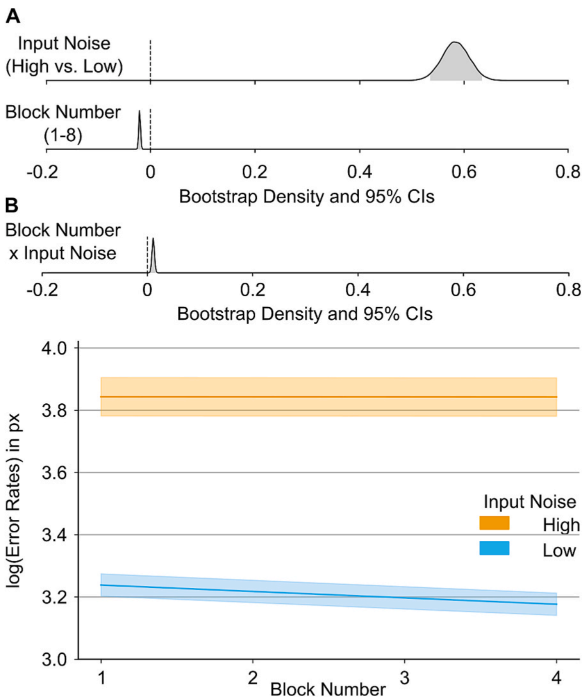

Fig. 2. Model results predicting participants' Error Rates (log transformed average distance to the line in pixels). **A)** Distribution of significant main effects, obtained through a parametric bootstrap. The data was bootstrapped 10,000 times, with model refitting for each iteration. The distributions represent the resulting model parameters, and the grey-shaded areas indicate the 95 % CIs. Increasing input noise significantly increased participants' error rates, whereas advancing block number significantly decreased them. **B)** Bootstrapped distribution of the interaction between Input Noise (low/high) and Block Number (1–4 for each the high and the low input noise condition), characterized by a stronger decrease in error rates for blocks with low compared to high input noise. The colored areas around the estimated mean values in the graph indicate standard errors.

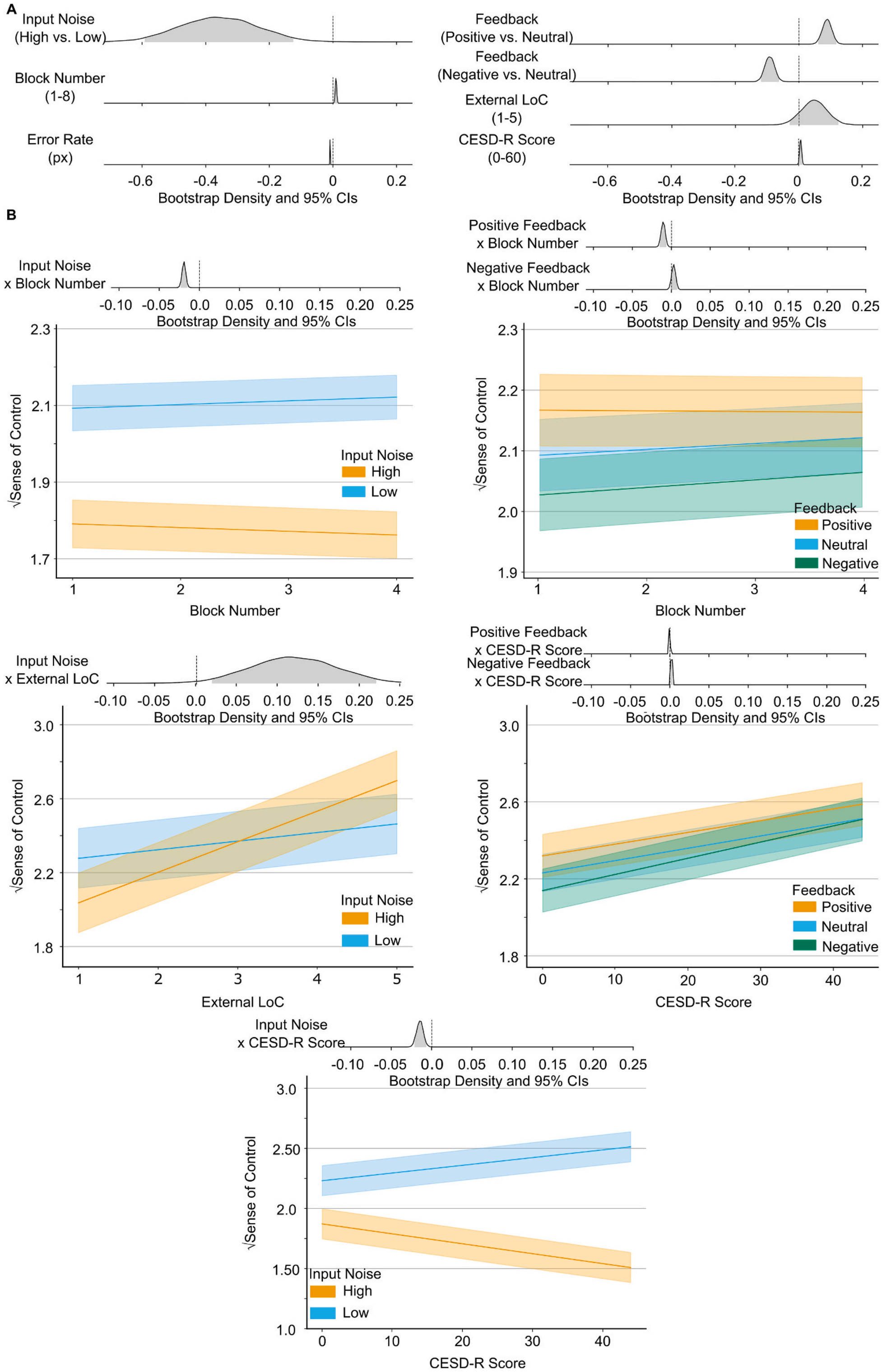

Fig. 3. Model results predicting trial-wise SoC (measured on a 7-point Likert scale; mean square root transformed). Distributions of the main effects (**A**) and interaction effects (**B**) included in the final model, derived from a parametric bootstrap. The data was bootstrapped 10,000 times, with model refitting for each iteration. The distributions represent the resulting model parameters, and the grey-shaded areas indicate 95 % CIs. The colored areas around the estimated mean values in the graph indicate standard errors.

$= 6.58*10^{-6}$, 95 % CI [$-2.46*10^{-4}$, $-3.12*10^{-5}$], $p < 0.001$ (Fig. 3B). The effect of negative feedback on SoC did not significantly change with task progression, $\beta = 7.31*10^{-6}$, $\sigma = 6.57*10^{-6}$, 95 % CI [$-5.53*10^{-6}$, $5.98*10^{-5}$], $p = 0.291$. Post-hoc t-tests (two-sided) of the bootstrapped CIs revealed a significant difference in means of positive and negative feedback, with the mean of the paired difference being significantly greater than zero, $\Delta M = 3.32*10^{-3}$, $t(9999) = 12.86$, 95 % CI [$2.28*10^{-3}$, $3.83*10^{-3}$], $p < 0.001$. Thus, while both positive and negative feedback affected SoC ratings, the impact of negative feedback was significantly stronger.

Contrasting our expectations (H4), the final model featured no interaction between Input Noise and Feedback ($p > 0.05$), indicating that low-level sensorimotor information and higher-level feedback independently contribute to the SoC during goal-directed dynamic tasks. To compare whether Input Noise or Feedback had a stronger effect on participants' SoC ratings, we computed a paired *t*-test (two-sided) on the bootstrapped β-values. The test revealed a significant difference, with the mean of the paired differences being significantly greater than zero for both negative feedback ($\Delta M = 0.27$, $t(9999) = 217.69$, 95 % CI [0.26, 0.27], $p < 0.001$) and positive feedback, $\Delta M = 0.27$, $t(9999) = 220.58$, 95 % CI [0.268, 0.272], $p < 0.001$. These results indicate that input noise had a stronger impact on self-reported SoC than post-trial affective feedback.

In addition to task-specific effects, individual differences in control experience significantly affected participants' SoC ratings. Whereas the main effect of External LoC on SoC was not significant ($\beta = 2.16*10^{-3}$, $\sigma = 1.55*10^{-3}$, 95 % CI [$-8.61*10^{-4}$, 0.02], $p = 0.244$; H7), External LoC positively interacted with Input Noise, $\beta = 0.01$, $\sigma = 2.70*10^{-3}$, 95 % CI [$3.08*10^{-4}$, 0.05], $p = 0.027$. While in the low input noise condition, SoC did not vary with external LoC, SoC ratings increased with external LoC scores in the high input noise condition (Fig. 3B).

A significant main effect of CESD-R further indicated that depressive symptomatology positively influenced SoC ratings, $\beta = 4.10*10^{-5}$, $\sigma = 9.77*10^{-6}$, 95 % CI [$3.31*10^{-9}$, $1.56*10^{-4}$], $p = 0.047$ (H5). Crucially, CESD-R score interacted with Negative Feedback, indicating a weaker influence of negative feedback on SoC with increasing depression scores, $\beta = 4.00*10^{-6}$, $\sigma = 3.94*10^{-7}$, 95 % CI [$6.07*10^{-7}$, $1.04*10^{-5}$], $p = 0.001$ (Fig. 3B). Follow-up correlational analyses confirmed that the reduction in perceived control for negative compared to neutral feedback (i.e., the difference in ratings between neutral and negative conditions) was less pronounced in individuals with higher depression scores, $r_{\text{pearson}} = -0.33$, $t(46) = -2.33$, 95 % CI [-0.56, -0.05], $p = 0.024$. No significant interaction of Positive Feedback and CESD-R score could be observed, $\beta = -9.14*10^{-8}$, $\sigma = 3.94*10^{-7}$, 95 % CI [$-2.29*10^{-6}$, $8.52*10^{-7}$], $p = 0.630$.

Finally, we observed a significant negative interaction of Input Noise and CESD-R scores, $\beta = -2.14*10^{-4}$, $\sigma = 1.68*10^{-5}$, 95 % CI [$-5.19*10^{-4}$, $-4.31*10^{-5}$], $p < 0.001$. This interaction revealed that individuals with higher depression scores experienced increased SoC under low input noise, but a diminished SoC under high input noise (Fig. 3B). Follow-up participant-level correlations confirmed that the difference in perceived control between low and high input noise blocks was greater among individuals with higher CESD-R scores, $r_{\text{pearson}} = 0.42$, $t(46) = 3.14$, 95 % CI [0.15, 0.63], $p = 0.003$.

To examine whether depressive symptoms more strongly affected the influence of low-level or high-level cues on perceived control, we performed follow-up t-tests (two-sided) on the bootstrapped β-values of the interaction terms of CESD-R scores with Input Noise and CESD-R scores with Feedback. The test indicated that depressive symptoms more strongly modulated the impact of low-level sensorimotor feedback than of high-level evaluative feedback on participants' SoC, $\Delta M = 0.01$, $t(9999) = 304.92$, 95 % CI [0.0125, 0.0127], $p < 0.001$.

Overall, the results showed that sensorimotor information and evaluative feedback independently influenced the SoC during a dynamic, goal-directed motor control task. Notably, negative feedback more strongly influenced SoC ratings than positive feedback, potentially reflecting a reduced influence of positive feedback on SoC over time. Furthermore, the impact of both evaluative feedback and sensorimotor information was moderated by individual differences. A higher external LoC was associated with greater perceived control under conditions of increased sensorimotor noise, while higher levels of depressive symptoms diminished the impact of negative feedback on control experience and increased the reliance on sensorimotor cues.

4. Discussion

This study aimed to investigate how low-level sensorimotor control and high-level factors, including feedback valence and trait-like differences in control experience, interact to shape the SoC in a dynamic task environment. Using a modified version of the Dodge Asteroids task (Heinrich et al., 2024; Österdiekhoff et al., 2024), we manipulated sensorimotor control through input noise and provided participants with post-trial feedback (positive, negative, or neutral) to assess their impact on trial-wise SoC. Additionally, we examined how trait-like differences in LoC (IE-4 scores) and depressive symptoms (CESD-R scores) modulated these effects.

Our results revealed that sensorimotor control strongly influences SoC, as participants reported significantly lower control in the high input noise condition than in the low input noise condition (H1). Additionally, performance improvements (i.e., decreasing error rates) were associated with increased SoC (H3). This supports the idea that motor coordination dynamically informs control perception. Notably, task practice selectively enhanced perceived control in the low input noise condition, while being associated with a gradual decrease in the high input noise condition. This suggests that sensorimotor disruptions impair the ability to establish a stable control estimate over time. By introducing a continuous manipulation of motor control during action execution, this finding extends previous research on the SoC in dynamic task environments that shows a reduction of SoC by introducing action-effect delays (Inoue et al., 2017; Oishi et al., 2018; Wen et al., 2015). Furthermore, as our post-trial questions directly assessed perceived control over spaceship steering, our inferences directly relate to participants' motor control. This distinction helps separate motor control, which lies at the core of the SoC, from the perceived ability to successfully complete the task, two aspects not consistently dissociated in previous studies (see Oishi et al., 2018).

Furthermore, in line with our expectations (H2), affective feedback modulated the SoC, with positive feedback increasing and negative feedback decreasing perceived control. The significant interaction of positive feedback and block number additionally revealed that the influence of positive feedback diminished over time. This may suggest that, while the psychological impact of negative feedback remained stable, participants gradually habituated to positive feedback, leading to a reduced effect on self-reported control experience. Crucially, negative feedback exerted a stronger influence on SoC than positive feedback, indicating a negativity bias in control judgments. This finding aligns with models of error monitoring and the utilization of prediction errors during reinforcement learning, which suggest that negative feedback is more salient and promotes behavioral adaptation more effectively than positive reinforcement (Cavanagh et al., 2010; Yoshie & Haggard, 2013).

Importantly, this result contrasts with self-serving bias theories, which posit that individuals preferentially integrate positive feedback while disregarding negative feedback (e.g., Chambon et al., 2020). Our results suggest that whether a valence-specific bias towards positive or negative feedback exists may likely depend on the task demands: In performance-driven contexts, negative feedback may be more important due to its greater corrective utility. In fact, insights from neuroscience indicate that feedback-induced theta oscillations originating from the anterior cingulate cortex likely constitute a neural mechanism translating negative, but not positive, feedback to behavioral adaptations by increasing cognitive control (Cavanagh & Frank, 2014; Cavanagh et al., 2010; Giersiepen et al., 2023, 2024). In the current experiment, participants were instructed to maximize their performance-dependent bonus. Although we did not directly assess whether participants believed that the feedback was contingent on their performance, the modulation of perceived control by feedback type suggests that participants did associate the feedback with their steering performance. In this context, negative feedback may have been more salient, serving as an instructive cue to adapt behavior on subsequent trials. Alternatively, the increased salience of negative compared to positive feedback may not have been driven by its informative value for subsequent action but rather relate to participants' surprise at receiving it (Noordewier & Breugelmans, 2013; Wurm et al., 2022). More specifically, although participants were informed that feedback was performance-dependent, we ensured an equal frequency of negative, neutral, and positive feedback to evaluate the relative impact of positive and negative feedback on self-reported SoC. Thus, while positive feedback may have reinforced participants' perceived control, negative feedback might have conflicted with their expectations, thereby more strongly diminishing their SoC over spaceship navigation.

It should be noted that, in contrast to our prediction, feedback effects on SoC were not moderated by task difficulty (i.e., input noise; H4), suggesting that low-level and high-level cues independently contribute to control perception. This hypothesis was based on studies using non-dynamic task environments, showing an increased reliance on externally provided feedback when immediate sensorimotor feedback was unreliable (Gentsch et al., 2012; Moore et al., 2009; Synofzik et al., 2013). In the current study, input noise was employed to disrupt the relation between participants' keyboard input and the spaceships' movement. Given that this distortion was enhanced in high compared to low input noise blocks, we hypothesized that participants would display an increased reliance on positive and negative feedback to infer their SoC in blocks with high input noise. In contrast to that assumption, and consistent with a recent study on self-reported control during continuous action (Dewey, 2023), our findings indicate that the influence of evaluative feedback on the SoC did not depend on the reliability of sensorimotor signals. Rather, our results suggest that dynamic, goal-directed tasks provide a continuous stream of sensorimotor information that remains influential even under high uncertainty. Our findings also contribute to the discussion on whether invalid feedback affects self-reported SoC. While some studies suggest that external feedback primarily influences participants' SoC when it reliably reflects performance (e.g., Dewey, 2023), others indicate that feedback shapes SoC ratings even when unrelated to behavior (e.g., Wen et al., 2015). Consistent with Wen et al., our results show that both positive and negative feedback significantly modulate perceived control, despite being entirely independent of actual performance.

Our results further indicate that trait-like control beliefs shape task specific SoC. First, while there was no significant main effect of external LoC on SoC ratings, a significant interaction between external LoC and input noise emerged. Specifically, individuals with a higher external LoC reported greater SoC under high input noise compared to those with a lower external LoC. This finding does not provide evidence for the assumption that individuals with a high external LoC, who attribute events to external factors such as fate or luck (Kovaleva et al., 2014; Nießen et al., 2022), would show an increased reliance on performance feedback (H7). It instead suggests that externalizing the causes of events changes how sensorimotor reliability influences perceived control during dynamic, goal-directed tasks.

Second, our results revealed that participants with higher scores on the CESD-R were less strongly affected by negative feedback than participants with lower scores, indicating a reduced negativity bias in individuals with a higher expression of depressive symptoms (H5). This unexpected finding contrasts with research on depression-related cognitive and perceptual biases, where negative information is processed more strongly than positive information (see e.g., Disner et al., 2011; Roiser et al., 2012). In the current context, participants with higher depression scores seem to have been less emotionally reactive to negative trial-wise feedback. This may reflect blunted outcome processing associated with depression, where the ability to adequately incorporate negative feedback to adjust behavior is impaired (Steele et al., 2007). Crucially, while depressive tendencies were associated with a reduced sensitivity to negative feedback, they more strongly impacted the influence of input noise on perceived control. Specifically, individuals with higher CESD-R scores showed a stronger influence of input noise on SoC ratings. This suggests that elevated depressive tendencies may enhance the sensitivity to the loss of control conveyed through low-level sensorimotor feedback.

Taken together, these findings underscore the importance of considering individual differences in how low-level and high-level feedback is processed when studying control perception. The modulation of perceived control by both depressive symptoms and external LoC partly aligns with recent work showing that individuals differ in how they weight different cues of control (Chang & Wen, 2025). Importantly, the current study identifies two trait-like factors, depressive symptoms and external LoC, that shape this integration process.

The findings of the current study align with the hierarchical framework of situated action control proposed by Kahl et al. (2022). According to this framework, input noise affects a low-level SoC by generating a mismatch between expected and observed spaceship behavior. In contrast, post-trial feedback would be predicted to directly target a high-level SoC by providing explicit information to evaluate task performance. While, according to the model, participants' SoC ratings would not explicitly differentiate between low-level and high-level information, ratings are assumed to reflect an integration of cues at both levels. Future work should test these propositions by directly scrutinizing the mechanisms underlying the emergence of SoC in dynamic tasks. To this end, studies should examine the neural and computational signatures underlying the integration of sensorimotor and affective feedback in signaling control. This approach would allow us to also directly relate the influence of positive and negative feedback on SoC ratings to neural measures of feedback processing, such as the reward positivity or midfrontal theta oscillations (see Giersiepen et al., 2024). Moreover, it has been shown that cognitive load during task execution decreases perceived control (Dewey, 2023). Future studies could therefore examine whether the weighting of low- and high-level cues shifts with task proficiency, for example, by comparing cue integration in well-practiced versus novel tasks.

Some limitations should be considered when interpreting the results of the current study. First, our sample consisted of a non-clinical population with generally low depression scores. To draw robust inferences on the influence of psychiatric disorders on the task-specific SoC, future studies should consider a more heterogeneous sample, including individuals diagnosed with a depressive disorder. Additionally, our sample size may have been insufficient to detect all within-subject interactions and between-subject differences in self-reported SoC. Specifically, our power analysis was conducted based on within-subject main effect hypotheses and did not account for higher-order effects or between-subject differences. As a result, our study may have been underpowered to detect smaller effects.

The current study focused on the effect of low-level and high-level cues on explicit, self-reported SoC. Even though SoC ratings were influenced by feedback type, we did not explicitly assess whether participants believed that the feedback was contingent on their performance. Thus, the current results do not allow us to determine whether the reduced influence of positive feedback on perceived control over time reflects a habituation to positive outcomes or growing skepticism about the feedback's validity. Furthermore, while our results suggest a stronger impact of negative compared to positive feedback on SoC, using gains twice as large as losses introduces a methodological confound that may have influenced the strength of the effects. However, the pattern of results, characterized by a stronger influence of negative compared to positive feedback, suggests that outcome magnitude alone is unlikely to account for this asymmetry. Future studies could address these limitations by directly assessing participants' belief in the performance-feedback contingency and by including a control condition that accounts for the asymmetry in outcome magnitude. Finally, further insight may be gained from assessing implicit measures of control. This is especially relevant, considering that not all aspects related to situated control may be subject to reflective, conscious experience (Pacherie, 2007).

5. Conclusion

Using a dynamic motor control task, the current study provides new insights into the interplay of low-level sensorimotor cues and high-level evaluative feedback in shaping the SoC during continuous, goal-directed action. Employing a complex task design, our results provide insight to the emergence of SoC under dynamic conditions that resemble everyday behavior, thereby extending previous work that predominantly examined the SoC in simpler task scenarios. Our findings demonstrate that sensorimotor noise and evaluative feedback independently contribute to task-specific SoC. Furthermore, affective feedback appears to be asymmetrically weighted in shaping the SoC, with negative feedback exerting a stronger influence than positive feedback. Crucially, the impact of low-level and high-level cues is modulated by depressive symptoms and individual differences in the external LoC. Future work should therefore account for individual differences when investigating the mechanisms underlying situated control experience.

Declaration of generative AI and AI-assisted technologies in the writing process

During the preparation of this work the author(s) used ChatGPT (OpenAI) in order to improve readability of individual sentences. After using this tool/service, the author(s) reviewed and edited the content as needed and take(s) full responsibility for the content of the published article.

CRediT authorship contribution statement

Maren Giersiepen: Writing – original draft, Visualization, Software, Project administration, Methodology, Formal analysis, Data curation, Conceptualization. **Nils Wendel Heinrich:** Writing – review & editing, Visualization, Software, Project administration, Methodology, Formal analysis, Conceptualization. **Annika Österdiekhoff:** Writing – review & editing, Software, Project administration, Methodology, Conceptualization. **Stefan Kopp:** Writing – review & editing, Supervision, Funding acquisition, Conceptualization. **Nele Russwinkel:** Writing – review & editing, Supervision, Funding acquisition, Conceptualization. **Simone Schütz-Bosbach:** Writing – review & editing, Supervision, Funding acquisition, Conceptualization. **Jakob Kaiser:** Writing – review & editing, Supervision, Methodology, Funding acquisition, Conceptualization.

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Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Data availability

Data and study materials are available via Open Science Framework: https://osf.io/6ujth/?view_only=c1a4bf962e5d44f9b20443470987e6da

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