The Effect of Sense of Agency on Self-Efficacy Beliefs

A Virtual Reality Paradigm

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ABSTRACT

A sense of control over the environment can stem from mere motor control to overarching belief systems of control. Sense of agency is defined as perceiving oneself as the cause of an action or its effects. It can be conceptualized as the low-level experience of online motor control over one's actions. Self-efficacy is the high-level belief in one's ability to achieve intended goals. Both constructs have been frequently studied on their own, but this is the first study that empirically investigates a possible link between the two. To this end, we conducted a virtual reality (VR) experiment in which participants had to trace shapes while experiencing both movement and feedback distortions. The experiment used a 2x2 design with the first factor being the translation of the participant's movements into VR (accurate vs distorted) and the second factor being feedback upon task completion (real vs hyper-positive). We found that these two factors manipulated the sense of agency and, in turn, influenced self-efficacy, and see this as a first step in the investigation of a possible causal link between the two constructs. Thus, the constructs of agency and self-efficacy appear more closely linked than previous research suggests. Future research targeting the sense of agency as a bottom-up influence on self-efficacy beliefs holds promising implications for both clinical and positive psychological interventions as well as motor rehabilitation.

CCS CONCEPTS

• **Human-centered computing** → *Virtual reality*.

KEYWORDS

sense of agency, agency, self-efficacy, motor control , virtual reality, Baeysian analysis, psychology

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1 INTRODUCTION

Most humans experience themselves as agents acting on their local environment. For familiar routine tasks, this feeling of agency can be very much taken for granted [Braun et al. 2018]. However, many studies show how this first-hand sense of agency (SoA) is frequently altered in psychopathologies and neurological disorders [Blakemore et al. 2002; Braun et al. 2018; Jeannerod 2009]. Notably, schizophrenic patients often feel like they are not in control and that their thoughts and actions are being controlled by outside forces.

A number of studies have been successful in manipulating the SoA and testing the extent of its malleability [Braun et al. 2018]. The degree to which SoA varies depends on an array of factors such as temporal proximity between action and effect [Haggard and Tsakiris 2009], feedback and affective states (e.g., an increase in SoA for positive action outcomes [Kaiser et al. 2021]), task difficulty, and social context (e.g., coercion and taking orders are shown to decrease the SoA [Haggard 2017]).

We use the term "SoA" to refer to the sense of control on a motor level of action. Another control construct that can be understood as an abstracted higher-level extension of SoA, is self-efficacy (SE) [Bandura 1977]. Bandura [1977] defines SE as the belief in one's own ability to achieve a specific task successfully. SE was intensively studied in the context of psychotherapy as an active target for interventions to promote remission through behaviour change [Gallagher 2012]. Therefore, SoA and SE can be understood as "I did this" and "I believe I can do this", respectively. In light of this, it has been proposed that SE can evolve as a result of repeated positive SoA experiences for a particular task [Braun et al. 2018]. It can also be understood as a positive evaluation of one's own SoA to achieve a task.

SoA can extend beyond the physical body, encompassing virtual bodies in immersive environments, along with related constructs such as body ownership (sense of ownership towards one's own body) and self-location (first-person perspective), contributing to the comprehensive phenomenon of embodiment [Gonzalez-Franco and Peck 2018; Kilteni et al. 2012]. While these constructs often co-occur, virtual reality enables the dissociation and flexible exploration of embodiment [Kilteni et al. 2012] and its potential interaction with overarching constructs of self-perception, such as SE beliefs. Here, we report the results of a VR experiment that probes the aforementioned relationship between SoA and SE.

After reviewing the theory behind SoA and SE, we describe the experimental setup and the data evaluation models and report our main finding: SoA manipulation implies SE changes. We discuss the possible practical implications of this result and outline future research directions.

2 THEORY

2.1 Sense of agency

The SoA can be defined as the subjective experience of online motor control over one's own actions and their sensory consequences.

Bayesian cue integration theory (BCIT) [Moore and Fletcher 2012; Moore et al. 2009; van Dam et al. 2014] provides a mathematical formalism for explaining SoA. According to BCIT, the brain assigns weights to different agency cues (incl. predicted sensory outcomes) proportional to their uncertainty. It then integrates all the relevant weighted agency cues as a maximum likelihood estimate, along with prior expectations of agency, and decides on the most likely cause of action. Thereby, the overall resulting agency estimate updates prior agency expectations in light of new incoming agency cues in a Bayes-optimal fashion. Furthermore, BCIT also accounts for cues such as the efferent copy, which is a copy of a movement signal that is eventually compared to action outcome [Braun et al. 2018].

In view of such theories, this study follows the BCIT account as an impetus for a SoA that is bound to motor control while also accounting for subjective judgments of contextual cues.

2.2 Self-efficacy

One of the factors that can increase one's SE is mastery experiences of specific actions. For instance, having written multiple good papers increases my SE to gather the needed resources for future papers without referring to the motor act of typing. These experiences might necessitate action through motor control. However, they expand beyond the immediate body with a higher-level goal orientation. SE theory illustrates that having relatively high SE beliefs are important for action initiation in the first place [Schwarzer 2015]. For example, people who believe they can quit smoking are more likely to attempt quitting than those who don't. SE theory is supported by a plethora of studies in the context of clinical interventions as a key predictor of adaptive behaviour and is frequently targeted as a mediator of behaviour change [Gallagher 2012; Maddux 1995].

Therefore, SE is a dynamic context-dependent belief in one's ability to employ cognitive and action-course resources necessary to successfully achieve a task; although SE might stem from mere motor control, it does not directly refer to it. Hence, SE is a highly influenceable state construct.

2.3 Research Question

This study's objective is to bridge a gap in the literature that separates SE, the high-level belief of control towards an intended goal, and SoA, the low-level perception of motor control. Thereby linking two distinguishable control constructs frequently but separately studied in the fields of social psychology and cognitive science. Since SE can arise from motor action, it is not the online sense of control over the motor act itself but rather a higher-level belief that extends to longer-term goal achievements and does not only pertain to immediate outcomes of movement. On the other hand, SoA is exactly that low-level sense of voluntary online motor control. Therefore, these two control constructs share a causal attribution of control to the self. Nevertheless, they do so on distinct levels of abstraction.

To the best of our knowledge, this study is the first empirical investigation of a causal link between SoA and SE. Of most relevance is Nataraj et al. [2020], who investigated the effects of predetermined positive and negative feedback on SoA and performance. The authors found that an enhanced SoA might be induced in a VR paradigm due to increased underlying SE expectations for a reaching-movement task. These interpretations were, however, not explicitly investigated. Thereby, the potential interplay between SoA and SE remains an open question. Hence, this study examines whether the low-level SoA influences the high-level SE in a bottom-up manner.

Empirical investigations of SoA via VR have gained traction in recent years [Aoyagi et al. 2021; Constant et al. 2022; Jeunet et al. 2018; Nataraj et al. 2020]. Many of these studies demonstrate the practicality of using VR, especially in inducing variations in SoA levels.

In our experiment, participants tried to achieve high performance in a motor task using a virtual arm. One group had shorter virtual arms that shifted at discrete intervals, disrupting their movements to reduce the SoA over the virtual arm. The other group had virtual arms synced with their real arms without shifts. Additionally, a predetermined hyper-positive feedback manipulation was used to enhance the SoA inside VR. The feedback consisted of either fixed hyper-positive or real task performance feedback. This resulted in a 2x2 design, with *hand position* ("shift" vs "no-shift") as the between-subjects factor and *feedback* ("real" vs "fixed") as the within-subjects factor.

2.4 Hypotheses

The aforementioned malleability of the SoA and the assumed link between SE and the SoA lead us to expect that the following hypotheses will hold:

- **H1** The main effect of hand position manipulation is negative (i.e. shift decreases SoA).
- **H2** The main effect of feedback manipulation is positive (i.e., fixed feedback increases SoA).
- **H3** An interaction effect between hand position and feedback manipulations is positive (i.e., shift decreases SoA despite fixed feedback).
- **H4** SoA has a positive effect on SE (also when that task is completed successfully).

H4 relates SE to the SoA. Thereby, the experimental manipulations are designed to mainly target the SoA to see whether the induced changes in SoA lead to corresponding changes in SE. (see directed acyclic graph in fig. 4 in the appendix).

3 METHODS

3.1 Task and Design

Participants were asked to trace the shape of a 3D figure in VR using a gender-congruent virtual arm. They were instructed to complete the task to the best of their ability without straying outside the figure's boundaries (similar to colouring a 2D figure, see fig. 1). There

Table 1: Overview of the design. The following abbreviations are used: within: within subjects, between: between subjects. real: real feedback, fixed: fixed feedback. The cells indicate how many percent of the trials had real or fixed feedback.

		within	
		real	**fixed**
between	**no-shift**	80% real, 20% fixed	20% real, 80% fixed
	shift	80% real, 20% fixed	20% real, 80% fixed

were 6 experimental blocks, 4 containing 25 trials and 2 15 trials. We used a 2x2 design. The first factor, *hand position*, was varied between-subjects and comprised of a no-shift and a shift condition. The hand position was translated without modifications into VR in the no-shift condition, while the shift condition introduced a spatial offset. Assignment to the shift or no-shift condition was based on random sampling (equal probability for assignment).

The second factor, *feedback*, was varied within-subjects and comprised of a real and a fixed feedback condition. So per participant, a block could contain realistic feedback in most trials or feedback fixed at a hyper-positive level in most trials. Hence, there are two long and one short block for each condition. We chose feedback as the within-subject factor to ensure an equal amount of real and fixed feedback trials in the overall experiment. Otherwise, participants in the fixed feedback condition would probably have lost trust in the feedback's veracity when noticing that their feedback stayed constant irrespective of performance in the majority of trials. For a succinct overview of the design see table 1.

3.1.1 factor 1: hand position. In the no-shift condition, the movements of the participant were translated into VR without modifications.

In the shift condition, we distorted the participant's movement by shifting it 10 cm on the horizontal axis as well as the depth axis in random directions (left/right, or backwards/forwards) at several random points during the trial. Horizontal shifts were twice as likely due to the wide spread of the shapes. The diameter of the hollow 3D shape was 2 cm wide. Thus, the salience of the 10 cm distortion of the drawing finger movement was ensured as a result of the confined motor range in which participants intended to draw. The goal was to cause a discrepancy between the intended and actual outcome of the movement, thereby reducing the SoA. The random directions and intervals between the shifts were intended to reduce predictability and prevent learning of shift patterns that would have counteracted the decrease in SoA. Based on piloting, a disproportionally shorter arm was used in the shift condition in order to further distort the intended hand positioning.

3.1.2 factor 2: feedback. After each trial, participants were presented with a score indicating their level of performance. In the real feedback condition, 80% of trials contained realistic feedback, while 20% of trials contained feedback fixed to an overly positive level. In the fixed feedback condition, these percentages were reversed. The ordering of the real feedback and fixed feedback trials within a single block was randomized. The feedback score calculation was designed to a) encourage participants to stay inside the hollow figure as long as possible and b) hit as many of the interconnected parts of the figure as possible (see fig. 1).

The participants were never informed about the numeric value of their scores. Instead, it was presented as categorical feedback in the real feedback trials. The categories comprised "poor", "good" and "excellent" and their presentation was conditional on surpassing increasingly higher thresholds of the numeric score. Additionally, the trace turned red for poor feedback and into distinguishably different shades of green for the other two positive categories.

In fixed feedback trials, the score was always "Outstanding!" and was displayed independently of the participant's performance. This manipulation was implemented with the intention to increase the SoA, as many studies show that positive feedback (even if decoupled from performance) should increase a post-hoc judgement of the SoA indicating a self-serving bias [Herman and Tsakiris 2020; Kaiser et al. 2021; Nataraj et al. 2020; Oishi et al. 2018].

3.2 Materials and Software

For the VR experience, we used the HTC VIVE Pro head-mounted display (HMD), two VIVE Pro controllers, and four VIVE Pro cameras. The HMD has a resolution of 2880 x 1600 pixels (1440 x 1600 pixels per eye), 110 degrees field of view and a 90 Hz refresh rate. The virtual room used for this study was an exact replica of our real-world VR lab. The real VR lab setup had a table positioned in front of the participant, and a similar-looking virtual table was placed in the virtual room in the same position.

The software used to code the entire VR experimental procedure was Vizard version 7.4 by WorldViz. The code was written in the programming language Python, version 3.8.10. The VR hardware system (HMD, controllers, and cameras) was connected to the VR software (Vizard) via SteamVR software.

Prototypes of the figures the participants had to trace were based on one of the author's movement trajectories and were later refined. Five shapes were selected for the experiment based on pilots' reported difficulty and the author's own experience working with them. We aimed to include shapes in the experiment whose tracing was at a similar level of moderate difficulty in order to increase the chance of varied performance (and thereby feedback) of participants.

3.3 Measurements

SoA and SE were measured inside of VR after each block of trials on a 10-point scale. A row of cubes appeared before the participants, each corresponding to one rank on the scale (see supplementary video: https://youtu.be/xAIU1L_QcDI). Participants submitted their ratings by intersecting their virtual index finger with the cube corresponding to their chosen rating and pressing a button on the controller. The question for SoA was "To which extent did you feel you had control over the 3D hand throughout the previous block of trials?" (modelled after [Constant et al. 2022]) with 1 = "no control" and 10 = "complete control". The question for SE was "To which extent are you certain that you can conduct this task successfully?", with 1 = "not sure" and 10 = "very sure" (based on the recommendations from [Bandura and Schunk 1981; Wang and Richarde 1988]).

Figure 1: Experimental setup. The screen in the foreground shows the view of the participant's HMD. The green line represents the participant's drawn trace inside the magenta 3D figure.

Additionally, gender, age (along with handedness and previous VR and gaming experience), locus of control (LoC, for questionnaire see [Levenson 1981] as cited, for example, in the appendix in [Brosschot et al. 1994]) and body ownership (question 5–8 in [Ma et al. 2021]) were measured. The Levenson LoC questionnaire contains 24 items, which are evenly divided into three subscales: "internality" ($\mathrm{LoC_I}$), "powerful others" ($\mathrm{LoC_P}$) and "chance" ($\mathrm{LoC_C}$). LoC is defined as a person's tendency to believe that their life events are either internally controlled by them ($\mathrm{LoC_I}$), externally by powerful others ($\mathrm{LoC_P}$) or externally by chance ($\mathrm{LoC_C}$). Body ownership (BOw) is defined as the feeling of an object (e.g. a virtual avatar) belonging to one's body. For a detailed statistical analysis of these variables, see Alsaleh [2023]. All questionnaires were provided in English and German and allocated according to the participant's preferred language. Positional data from the controller's motion capture was recorded at 100 Hz, but not analysed.

3.4 Procedure

The experiment took place in the VR lab at the psychology department of the Philipps University of Marburg, Germany. Before the VR task, gender, age, handedness, and previous VR and gaming experience were documented. Participants performed a t-pose to adjust the virtual arms' length to the participant's real arms only in the no-shift condition. For the VR portion of the experiment, all participants put on the VR equipment and were seated at a table. They held a controller in each hand but were instructed only to use their dominant arm; the other rested on the table.

Participants filled out the locus of control questionnaire using the method described in section 3.3. Following this, they completed a training phase using simplified shapes. In the training phase, participants only received real feedback in order to familiarize them with the realistic feedback categories (see https://youtu.be/xAIU1L_QcDI as a supplementary video).

After training, the experiment's main VR task commenced. Within one block, each shape was presented an equal number of times. Participants were instructed to stay inside the boundaries of the figure and move their virtual index finger in a continuous drawing motion. Each trial had a time constraint of 10 seconds, after which the trial terminated automatically. Participants heard a ticking clock sound, indicating the passage of time, but could not see the time left. Participants were instructed to put their dominant arm back on the table between trials to standardise a trial's beginning. At the end of each block, participants filled out the SoA and SE item inside VR. An optional two-minute break was offered after the second and the fourth block to minimise participants' burden. After completing all blocks, participants filled out the body ownership questionnaire in VR. The whole VR experiment took one hour to complete; the experimenter was present during all sessions.

3.5 Participants

Recruitment was carried out mainly through the psychology department's local participant recruitment system, Sona Systems. Participants were granted course credit or monetary compensation. The exclusion criteria were upper body motor disabilities, colour blindness, significant mobility impairments, active nausea, epilepsy, and diagnosed mental illnesses. Participants gave written informed consent before the experiment.

A total sample contained 40 participants (female = 26), ages ranging from 11 to 51 (M = 24.4, SD = 7.8). Data from one participant was excluded because they followed the instructions incorrectly during the arm-length adjustment. Participants were mostly native German speakers and carried out the experiment in German (the rest in English).

3.6 Statistical Model

To inferentially test our hypotheses (see section 2.4), we employed a Bayesian regression model equivalent to a classical analysis of variance (ANOVA). Bayesian models assign probability distributions to parameters, reflecting their inherent uncertainty before (prior) and after (posterior) data observation. The first statistical model accounts for the effect of the two binary manipulations on SoA, feedback and hand position. We used the following regression equation:

$$\mu_{\mathrm{soa}_k} = \mu_{\mathrm{soa}} + \alpha_i + \beta_j + \gamma_{ij} \tag{1}$$

where μ_{soa_k} is the expected mean of SoA for the kth block, μ_{soa} is the intercept, α_i is the main effect of the hand manipulation factor, β_j is the main effect of the feedback factor and γ_{ij} is the interaction between the two factors. We used zero/one coding for the two levels of the factors, where 0 represented the control condition and 1 the manipulation. For the hand manipulation factor $i = 0$ stands for no-shift and $i = 1$ for shift, while for the feedback factor $j = 0$ stands for real feedback and $j = 1$ for fixed feedback. When all indices are zero, the only term left in (1) is the unindexed term μ_{soa}. The intercept μ_{soa} represents the expected value of SoA when all predictor parameters are zero, i.e. the control condition (no manipulation).

Similarly and driven by **H4**, we expect SE, the response variable of the second statistical model, to explicitly depend on SoA and implicitly on the experimental manipulations of SoA. To that end, we implemented the following simple regression equation:

$$\mu_{se_k} = \mu_{\mathrm{se}} + \delta X_{soa_k} \tag{2}$$

where μ_{se_k} is the expected mean of SE after the kth block, μ_{se} is the intercept and δ the main effect of the predictor variable X_{soa_k}.

The likelihood equation (i.e. the probability of the data conditional on the corresponding model parameters) for both models is of the form:

$$y_{\text{soa}_k} \sim \text{OrderedProbit}(\mu_{\text{soa}_k}, \text{cutpoints}_{\text{soa}}, \sigma_{\text{soa}}) \quad (3)$$
$$y_{\text{se}_k} \sim \text{OrderedProbit}(\mu_{\text{se}_k}, \text{cutpoints}_{\text{se}}, \sigma_{\text{se}}) \quad (4)$$

where $\sim$ means *distributed as*, and y_{soa_k} and y_{se_k} denote the values of the response variables SoA or SE after block k. An ordered probit model was found to be suitable here to account for the ordinal rating data of SoA and SE. It assumes a normally distributed latent variable underlying the observed ordinal data. This continuous latent variable is mapped onto the ordinal scale of the observed data through thresholding cutpoint values (i.e., cutpoints cut the latent variable into ordinal categories) [Kruschke 2014]. The model does not assume equidistance between the ordered categories. Instead, it allows for arbitrary spacing between categories, using cutpoints to define boundaries between categories and predict untransformed SoA and SE ratings. A sensitivity analysis of different prior distributions, varying from weakly to moderately informative, showed no relevant impact on the posterior. Therefore, prior distributions of all parameters of both statistical models were chosen to be weakly informative [Lemoine 2019], i.e. have a relatively wide variance. From eq. (1) and eq. (2), μ_{soa}, α_i, β_j, γ_{ij}, μ_{se}, δ) are $\sim$ Normal($\mu = 1, \sigma = 10$).

Prior likelihood variances $\sigma \sim$ Gamma(shape=0.1, rate=2) and cutpoints $\sim$ Normal($\mu = [0, 1, 2, 3, 4, 5, 6, 7, 8, 9], \sigma = 1$) a priori. Bayesian analysis is conducted using PyMC version 5.2.0 to approximate the posteriors using MCMC sampling. Both equations were included in a single PyMC model. Using NUTS MCMC sampling algorithm, the model was run on 10 000 iterations and 2 chains that converged with few (2) divergences. This was solved (0 divergences) by adjusting the target acceptance rate (proportion of proposed samples accepted by the algorithm) to 0.92.

4 RESULTS

4.1 Descriptive analysis

The final sample size of $N = 234$ experimental units (6 observations per participant; total participants = 39, 20 were assigned to the no-shift subsample and 19 to the shift subsample) were included in the data analysis. The distribution of the SoA ratings (M = 6.75, SD = 2.59) was rather skewed to the left, indicating that participants show an overall bias towards higher SoA ratings inside VR. A comparable trend could also be seen in the SE ratings (M = 7, SD = 2.03). The mean scores for the other questionnaires were as follows (± indicates the standard deviation): BOw = 16.18 ± 5.22 (maximal score = 28), LoC_I = 33.64 ± 4.5 (maximal score = 48), LoC_P = 22.15 ± 3.54 (maximal score = 48), and LoC_C = 23.74 ± 3.76 (maximal score = 48).

4.2 Model Results

4.2.1 Basic Model. The following results are derived from the basic model defined in eq. (1) and eq. (2), respectively. Table 2 shows summary statistics of the posterior distributions of the parameters. Note that the SoA model results are only shown for α_1, β_1, and γ_{11} and these correspond only to the manipulated conditions. This is due to the former discussed zero/one coding of the experimental conditions. This leads to parameters indexed by zero (no-shift, real feedback) being equal to 0. To understand the interpretation of the parameters, consider α_1 as the shift manipulation effect on the SoA. According to **H1** the probability mass after observing the data should be largely assigned to values $\alpha_1 < 0$ (negative values), which would indicate that the shift manipulation of hand position has a decreasing effect on the SoA. According to table 2, we are nearly certain (a-posteriori probability $p(\theta > 0) \approx 0$) that **H1** holds.

Table 2: Summary statistics for the posterior of the basic model (see section 3.6 for a description of the model). For each parameter, the table gives the mean, the standard deviation (SD), lower and upper boundary of the 95% high density interval (HDI) and the probability of a given parameter θ being positive, $p(\theta > 0)$. All numbers are rounded to the second digit after the decimal point.

Parameter	Mean	SD	$\text{HDI}_{2.5\%}$	$\text{HDI}_{97.5\%}$	$p(\theta > 0)$
SoA					
μ_{soa}	9.92	0.64	8.67	11.16	1.00
α_1	−5.83	0.77	−7.36	−4.37	0.00
β_1	1.10	0.68	−0.19	2.47	0.95
γ_{11}	0.15	0.96	−1.77	1.98	0.57
σ_{soa}	3.56	0.29	2.99	4.13	1.00
SE					
μ_{se}	1.54	0.62	0.33	2.76	0.99
δ	0.92	0.09	0.75	1.09	1.00
σ_{se}	2.44	0.21	2.04	2.86	1.00

With the same reasoning, we can check if our hypothesized effects are observed a posteriori. μ_{soa} is the only parameter accounting for SoA values in the control condition (no-shift and real feedback). Given $\mu_{\text{soa}} = 9.92$ with a probability $p(\mu_{\text{soa}} > 0) = 1.00$ (see table 2), reflecting a non-disrupted SoA in the control condition.

In **H3** it was hypothesized that $\gamma_{11} > 0$ because we expect a decreasing effect of the shift manipulation on the SoA during fixed feedback. Posterior results show $p(\gamma_{11} > 0) = 0.566$, i.e. the probability of γ_{11} being above 0 is only marginally above chance. Thereby, the results offer neither support for nor against **H3**.

Finally, **H2** predicted that $\beta_1 > 0$ (positive effect of fixed feedback on SoA). We consider the posterior probability of β_1 being positive ($p(\beta_1 > 0) = 0.95$) as high and thus overall in favour of **H2**, although admittedly the 95% high density interval (HDI) does not completely exclude 0 ($\text{HID}_{2.5\%} = -0.19$).

Taken together the results for **H1** and **H2** indicate that the manipulation of SoA was successful, while the existence of an interaction term (**H3**) remains uncertain. This paves the way for the assumption posed in **H4**. The main research question of this experiment was whether SoA influences SE. To answer this question, **H4** assumes that if variations in SoA is induced, SE will follow. The statistical model of eq. (2) allows for testing this hypothesis on a correlational level only. **H4** predicts $\delta > 0$ (from eq. (2)) and the posterior results show that on average $\delta = 0.92$ with a probability $p(\delta > 0) = 1$, see also fig. 2. Hence, a posteriori we are highly certain that the induced variations in SoA are also reflected on SE. Further models

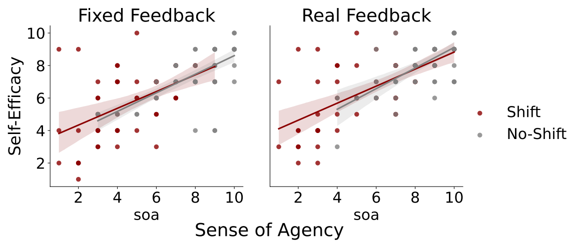

Figure 2: Regression lines between SoA and SE for each condition. The points indicate data values after each block. The lines show an implicit correspondence between SoA and SE given the different conditions as hypothesized.

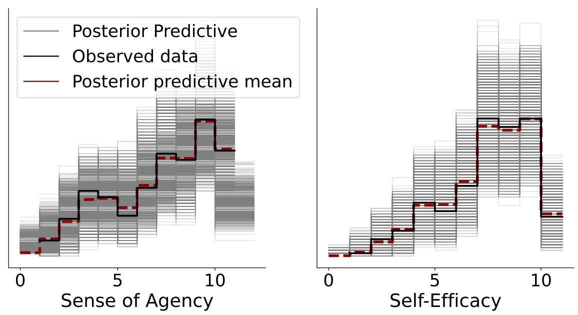

Figure 3: Posterior predictive distribution of the basic model. The figure shows that on average the basic models are capable of reproducing potential future data similarly distributed as the observed data. Out-of- range values for SoA are due to technical issues with the PyMC implementation.

that explicitly assume a dependence of SE also on the conditions are included in later model comparisons.

To inspect the same assumptions only for participants who conducted the task successfully, restricting the data to observations with an average score above 0.7 per block of trials (threshold for "Good" performance) is necessary. Although such results are not directly comparable to the previous ones of the full $N = 234$, the same conclusions were reached for this subset of the data ($N_{\text{success}} = 193$, see fig. 5 in the appendix). Because we were dealing with ordinal and skewed data, we chose the Spearman correlation coefficient ρ to quantify the relationship between the SoA and SE. ρ was 0.7 with a p-value of < 0.001, indicating a high correlation [Cohen 1988]. ρ values per condition show the highest correlation of 0.68 in the control condition and a lowest value of 0.52 in the shift and real feedback condition, and a ρ of 0.61 in the two fixed feedback conditions (p-values < 0.001 for each condition). A posterior predictive check was used to check the goodness of fit of the ordered probit model to the observed data (see fig. 3). Spearman's ρ_{ppc} between the posterior predictive mean sampled data for both response variables SoA and SE against the raw data was also calculated, with $\rho_{soa_{ppc}} = 0.58$ and $\rho_{se_{ppc}} = 0.69$ with p-values < 0.001. Finally, leaving-one-out (LOO) cross-validation was used to evaluate the model's predictive performance by predicting the outcome for one data point based on all remaining data points for each observation in turn. Results suggest the model fits the data well and there is no overfitting.

4.2.2 Model Expansion. The models illustrated so far can be expanded by introducing control variables such as body ownership (BOw) and locus of control (LoC), along with basic demographics such as gender and age (all control variables were standardized and their effects should be interpreted accordingly). Denoting the control variable of interest as f_{cont_k}, both basic models with potential interactions can be expanded as follows:

$$\mu_{soa_k} = \mu_{\text{soa}} + \alpha_i + \beta_j + \gamma_{ij} + \zeta f_{cont_k} + \nu_{ij} f_{cont_k} \tag{5}$$

$$\mu_{se_k} = \mu_s e + \delta X_{soa_k} + \omega f_{cont_k} \tag{6}$$

where ζ is the main effect of the control variable on SoA and ν_{ij} is the interaction between the factor hand position, the factor feedback, and the control variable. ω is the main effect of the control variable on SE. Fitting these models as before leads to the same results for the previously analysed parameters.

LOO cross-validation with Pareto-smoothed importance sampling was used to select best-fitting models with highest ELPD (expected log pointwise predictive density, see [Gelman et al. 2014]). Furthermore, a BIC (Bayesian Information Criterion) was also calculated to penalize unnecessarily complex models (high number of parameters).

Results show that the SoA models controlling for age and BOw (two models each, one with all possible and another with fewer interaction terms, see fig. 6 in the appendix) have the largest ELPDs ranging from -451,97 to -450,31. Because the ELPD difference between these models is within the range of 1, all four of them were selected (ELPD differences < 4 are considered small). A further BIC comparison of these four models explicitly preferred the parsimonious models controlling for age and BOw but with fewer terms. These two SoA models were selected for further analysis (of the form: eq. (5)). With this same rationale, the BOw model with all interaction terms and the gender model yielded the highest ELPDs among the SE models (see fig. 7 in the appendix). BIC results, however, preferred the gender model over the large BOw model. Therefore, the SE model controlling for gender (of the form: eq. (6)) was selected for the analysis here. Both selected SoA models correspondingly show a main effect of BOw $\zeta = 0.19$ with ($p(\zeta > 0) = 0.77$), and a main effect of age $\zeta = -1.15$ with ($p(\zeta < 0) = 1$), and an interaction of 1.86 and 0.97 ($p(\nu > 0) = 1$ and $p(\nu > 0) = 0.97$), respectively. This suggests a small increasing effect of BOw on SoA, but a larger increasing effect when it interacts with both conditions. Particularly, the descriptive analysis demonstrates a higher effect of BOw on SoA for the shift condition (see fig. 8 in the appendix). Age has a decreasing effect on SoA, indicating the older the participants the lower the SoA they report.

The selected SE model that controls for gender (male=1) shows a main effect ($\omega = 1.43$) with $p(\omega > 0) = 1$. This indicates that males exhibit higher SE beliefs towards the motor task (see fig. 9 in the appendix). Finally, when considering only successful observations, the LoC_C (chance subscale) seems to surface as a good fitting model for the SoA with a decreasing main effect of $\zeta = -0.89$ and $p(\zeta < 0) = 0.99$ and an interaction effect $\nu = 0.56$ with a $p(\zeta < 0) = 0.81$ (see fig. 10 in the appendix). This is, however, a slight decreasing effect in contrast to this model's α_1 effect of -5.87.

Overall, the results show considerable evidence for the proposed hypotheses. SoA manipulation was successful, and accordingly, there was a positive correspondence and possible dependence between SoA and SE.

5 DISCUSSION

We conceptualize SoA and SE as interconnected but distinctly dissociable experiences of control. Both contribute to the full-spectrum experience of human agentic control over the environment. SE is intensely studied in the field of social psychology as the high-level, domain-specific belief in one's capacity to act towards achieving a goal. SoA, on the other hand, is the low-level perception of control stemming from a motor action and its sensory consequences and is frequently investigated in the cognitive sciences. To the best of our knowledge, this study is the first to integratively connect the SoA and SE in one framework and examine their potential bottom-up causal relationship using a VR paradigm.

The main finding of this study is that there is a considerable association between motor-bound SoA and SE beliefs about achieving high performance in a motor task by controlling a virtual arm in VR. These results are based on a set of experimental manipulations to induce the necessary variation of the SoA. The goal was to investigate SE's association with these induced variations in VR. We disrupted the translation of motion capture into VR through discrete shifts of the virtual hand's position combined with a relatively shorter arm. This led to a substantial decrease in the sense of agency over the arm. In the corresponding control condition, the motion capture was translated synchronously into VR, which led to an intact sense of agency [Braun et al. 2018]. A further SoA-enhancing effect was induced through the presentation of predetermined hyper-positive feedback regarding task performance. When this fixed feedback was presented to participants in the no-shift condition, considerably higher SoA levels were detected. This is in line with previous research demonstrating a self-serving bias when presented with predetermined positive feedback disproportionate to actual performance [Nataraj et al. 2020]. However, a smaller decrease in the SoA was also detected in the shift condition when the fixed positive feedback was presented; these effects were subtle and hence larger sample sizes are needed to further substantiate them.

Introducing additional variables like BOw and age improved the models in terms of their ability to predict the SoA data. Interestingly, a higher sense of ownership towards the avatar arm was associated with increased SoA, mostly in the shift condition. This could mean BOw is crucial in sustaining the SoA, especially when the SoA is jeopardized by incongruent sensory feedback (like in the shift condition). Notably, a relatively high SoA was observed in the no-shift condition even for low BOw, implying a potential ceiling effect of the rating scale in capturing higher SoA that could put an upper cap on the association between BOw and SoA (see fig. 8 in the appendix).

Similar to previous research, the SoA decreased with age. A previous study shows that although older adults were less sensitive to external cues of their sense of control compared to younger adults, they showed decreased SoA levels [Cioffi et al. 2017].

Controlling for participants' gender improved the prediction of SE belief levels, particularly for males. This corroborates existing literature that generally shows males have stronger SE beliefs than their female counterparts in a wide array of different domains [Huang 2013; Vasil 1992].

Furthermore, similar results were found when only blocks of successful completions of the task were considered. For this subset of the data, the chance subscale of the LoC questionnaire improves the explanatory power of the SoA model. When participants conducted the task successfully, a slight decrease in SoA was observed, particularly when they reported a higher tendency to attribute outcomes to mere chance or luck. This means participants who believe in chance felt a decrease in their SoA despite performing well. Such findings connect a rather stable personality trait to SoA, the dynamic low-level perception of motor control. These effects have not been previously reported in the literature. Dewey and Knoblich [2014] found no correlations between the internal LoC and the SoA. However, the VR studies conducted by Jeunet et al. 2018 and Fribourg et al. [2021] showed a negative relationship between SoA and the internal scale of LoC.

5.1 Definition Issues

Social scientists use SoA to refer to a high-level sense of control, while cognitive and computational scientists use SoA to refer to a low-level sense of motor control. We argue these two terms are used for dissociable experiences. Presumably there is a discernible conceptual difference between different levels of self-causation attribution to actions and their outcomes. On the one hand, there is motor action and its immediate sensory consequences, and on the other hand, a series of composite actions that can be executed to achieve a goal. The goal can vary from specific to general. While all low-level senses of control originate from moving a body, it is highly plausible that higher levels of a sense of control can be almost exclusively psychological.

Therefore, better definitions and unified categorizations of the full spectrum of partially dissociable levels and corresponding operationalization methods still need to be formally established. This study tried to experimentally bridge a construct of control typically understood as psychological (SE) and the classically motor-bound sense of control (SoA).

5.2 Limitations

While the association between SoA and SE found in this study does not speak against our hypothesis of a bottom-up causal influence of SoA on SE, the overall results need further investigation to confirm such a causal relationship. We intended for the manipulations to only influence SoA. However, it is plausible that they might have also effected SE and thus confounded the relationship between the two variables. A more basic first step would be an attempted double dissociation [Van Orden et al. 2001] of SoA and SE to ensure that the two concepts are distinct from one another.

A high-level SE belief and a motor-bound SoA seem to require better methods to capture their dissociable levels of abstraction. The use of self-reports here might be limiting because they only allow an explicit post-hoc judgement of the measured construct. Most people are not aware of their SoA in everyday life. Hence, when being asked to report it their answers can easily become contaminated with irrelevant contextual cues such as the participant's emotional state. The scale we used, "How much did you feel control over the 3-D arm...", relates to a motor-bound SoA, but is a more cognitive response than the first-hand experience of control.

Such post-hoc judgment might reflect a higher level SoA, sometimes referred to as "judgment of agency" in the literature [Synofzik et al. 2008]. Widely adapted techniques that implicitly measure SoA, such as intentional binding could potentially be more suitable here. Intentional binding [Haggard et al. 2002] refers to the phenomenon that the interval between the start of an action and its outcome is experienced as shorter for intentional actions than for unintentional ones. One way to add intentional binding to the experiment would be to ask participants to estimate the temporal length of a trial. We would expect underestimated lengths for the conditions that are supposed to enhance SoA (no-shift and fixed feedback). However, the intentional binding paradigm has been critiqued for reflecting general causal inference rather than inference about self-causation [Buehner 2012].

Other manipulation techniques, like masking the to-be-drawn figure (difficult perception of target figure), could permit investigations of prospective SoA and its implications on SE via dysfluent action selection [Sidarus and Haggard 2016]. Overall, there is still a dire need to develop better measures for the implicit feeling of motor-bound agency. Furthermore, although Bandura's guidelines were generally followed for creating the task-specific SE scale, further content and predictive validity assessments are required to determine whether the scale stringently measures what it purports to measure [Bandura 2006].

The data analysis conducted here only accounts for differences between block ratings without considering interindividual differences. Issues with the cutpoints implementation in PyMC might have attenuated the quality of the results, especially because the intercept terms tended to overshoot when assigned large prior SDs. Statistical analysis of success rates across trials for each shape could be useful for selecting shapes that better fulfil the criterion of being moderately difficult.

5.3 Practical Implications and Future directions

Most importantly, this study's results offer promising possibilities for implementing clinical and positive psychological interventions. Behaviour change is one of the most fundamental goals of psychotherapy, and various evidence-based interventions do already target SE beliefs to promote healthier behaviour. This study sheds light on percepts of motor control as an impetus behind SE beliefs, thereby inspiring a bottom-up approach in cultivating higher SE beliefs, which could be important for tackling disorders like depression [Nakamura and Tanaka 2021]. Given the growing interest in implementing psychological interventions in VR [Kim and Kim 2020], our approach might enable the flexible induction of the SoA with different techniques, including gamified feedback features as well as outcome control, in a highly immersive experience.

Stroke patients typically suffer from motor deficits that require long physical rehabilitation to relearn basic movements for daily tasks. SE beliefs are highly important for post-stroke rehabilitation outcomes [Gangwani et al. 2022; Szczepańska-Gieracha and Mazurek 2020]. Previous findings show that SoA can also be induced vicariously by observing a virtual body-double perform a particular task invoking a mental rehearsal of the action, which nudges sensorimotor preparedness for actual action [Gorisse et al. 2021]. Hence, enhancing the SoA in this way in VR can promote motor-task-specific SE beliefs of stroke patients leading to improved rehabilitation outcomes.

The reported negative association between SoA and LoC_C despite successful task performance elicits the question of whether this relates to the observed discrepancy between low SE beliefs despite experiential mastery [Huang 2013]. SE theory states that mastery experiences are the most effective sources to cultivate high SE [Gallagher 2012]. Future research on the nuanced effects of potential factors dissociating the relationship between SoA and SE is therefore needed. Moreover, modelling approaches that seek to understand prior belief update upon expectation violation [Panitz et al. 2021] might be relevant here to understand how negative or low SE expectations upgrade to higher levels upon unanticipated positive performance experiences. This is also pertinent for investigating the overarching relations of SoA and SE in the context of perceived lack of control found in depression, i.e., learned helplessness.

The gender differences found in SE beliefs towards the motor task is a common trend across various other domains of SE beliefs [Huang 2013]. The relationship between a social psychological construct of control and an instrumental cognitive sense of control could inspire positive psychological interventions for mitigating negative gender stereotypes. For instance, gender bias observed in job-application behaviour shows males are more forgiving to mismatching job requirements when applying than females, which explains a majority of the prominent discrepancies in job positions between genders. Overall, targeting SoA-SE connection can serve as a promising approach for positive behaviour change. The wide application range of VR and its practicality in intervening on the SoA can serve as an appropriate medium for such positive psychology interventions.

Research on motor-bound SoA and SE beliefs is highly established yet within separate subdisciplines. The relationship demonstrated here in VR holds promising integrative insights on constructs of control and perhaps enables a bridging point towards a more unifying framework for agentic human experience.

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A APPENDIX

This appendix contains a list of figures that further illustrates the statistical analysis results and causal relationships investigated in this paper.

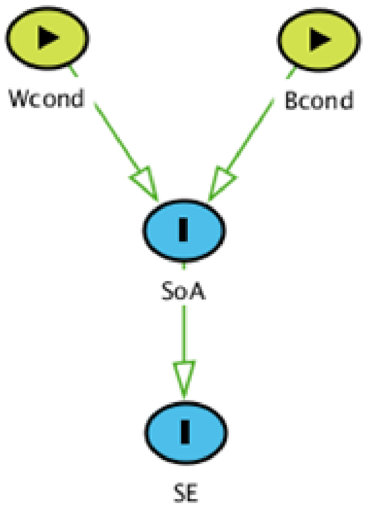

Figure 4: Directed acyclic graph for causal relations between all variables included in the basic model. "Wcond" is the within-subject factor feedback and "Bcond" is the between-subject factor hand position.

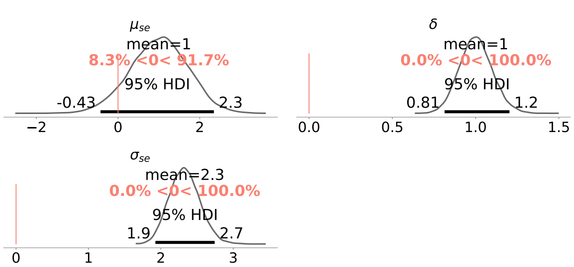

Figure 5: Posterior distributions of the basic model's parameters of the response variable SE only for successful data points. The pink line represents the 0 values as a reference for the no-effect point in relation to the 95% HDI (black horizontal line).

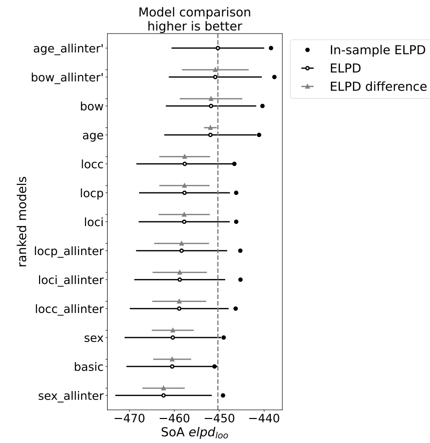

Figure 6: ELPD-based comparison between SoA models. "allinter" indicates that all possible interaction terms were included in the model. basic: basic model with no controls (see section 3.6), age: model controls for age, sex: model controls for gender, bow: model controls for body ownership, locc: model controls for chance scale of locus of control (LoC), locp: model controls for powerful others scale, loci: model controls for internal scale.

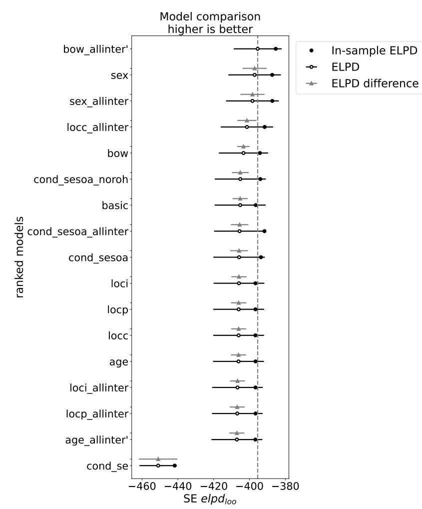

Figure 7: ELPD-based comparison between SE models. "allinter" indicates that all possible interaction terms were included in the model. basic: basic model with no controls (see section 3.6), age: model controls for age, sex: model controls for gender, bow: model controls for body ownership, locc: model controls for chance scale of locus of control (LoC), locp: model controls for powerful others scale, loci: model controls for internal scale, cond_se: model assumes that only the conditions directly influence SE, cond_sesoa: model assumes that both the conditions and SoA directly influence SE as well as an interaction term between the conditions and SoA named "roh", cond_sesoa_noroh: model has same terms as cond_sesoa model except for roh.

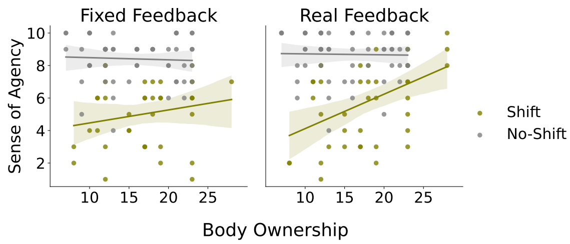

Figure 8: Regression lines between Bow and SoA. The points indicate data values that were measured at least once. A trending increase in SoA ratings as a function of BOw is only observable in the shift condition. This can be understood as BOw having an increasing effect when hand position was manipulated. This effect is slightly steeper in the fixed feedback condition. It is possible that there are ceiling effects in the no-shift condition.

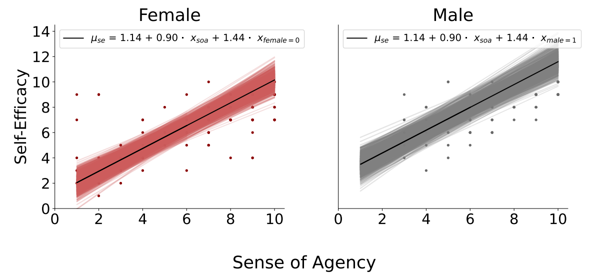

Figure 9: Posterior regression line between the SoA and SE for the female and male subsample. The points indicate data values that were measured at least once. The black line is the posterior mean, surrounded by samples from the posterior. SE ratings of males started at 3.

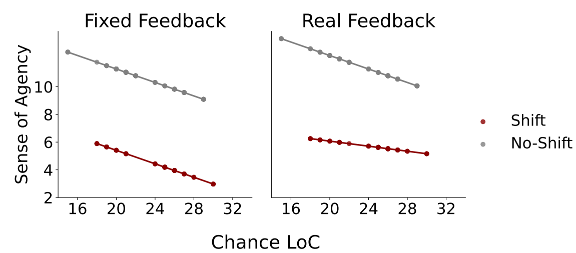

Figure 10: Posterior regression line between $\mathrm{LoC_C}$ (chance scale of locus of control) and the $\mathrm{LoC_C}$ model's expected values of SoA. The $\mathrm{LoC_C}$ data is from the experiment, while the SoA values were retrieved from posterior μ_{soa_k}. The higher the external orientation of LoC the lower the expected SoA.