Sense of Control in Dynamic Multitasking and its Impact on Voluntary Task-Switching Behavior

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Abstract

The sense of control (SoC) is the subjective feeling of being in control over an action, influenced by controllability, difficulty and feedback. However, it remains unclear how SoC is formed in multitasking scenarios. We conducted a study to analyze SoC and its impact on task-switching behavior in multitasking scenarios. Participants were required to perform two tasks in parallel while in control of one task at a time, requiring voluntary switching. We found that task-specific SoCs are influenced by the controllability and difficulty of each task. An overall SoC can be explained mainly by these task-specific SoCs. But, the overall SoC did not correlate with the frequency of task switches or the relative time spent on one task. Our analysis indicates that the SoC of a more control-demanding task has greater impact on the overall SoC and even affects the task-specific SoC of the other task, as well as task-switching behavior.

Keywords: Sense of Control; multitasking; task-switching

Introduction

Humans form a feeling of control when taking actions to achieve a goal, while possibly being disturbed by external factors. For instance, if a person is driving a car and suddenly slides due to ice on the road, they lose control. This phenomenology related to one's control over own actions is called the *sense of control (SoC)*. SoC depends on the controllability of the action in single-tasks, specifically the alignment between intentions and outcomes (Pacherie, 2007), and is affected by higher cognitive load in more difficult tasks (Dewey, 2023; Hon, Poh, & Soon, 2013) or post-hoc feedback (Metcalfe, Van Snellenberg, DeRosse, Balsam, & Malhotra, 2012). SoC is believed to influence action regulation. For instance, in the scenario described above, a low level of feeling in control would trigger a shift in the control strategy, e.g., slowing down without frantic movements to regain control (Kahl, Wiese, Russwinkel, & Kopp, 2022).

But how is a SoC formed when one has to control multiple complex tasks? Multitasking refers to the ability of an individual to coordinate multiple tasks to achieve an overall goal (MacPherson, 2018). Humans perform multitasking daily, such as office workers (González & Mark, 2004) or when changing the radio channel while driving a car in traffic (Wintersberger, Riener, Schartmüller, Frison, & Weigl, 2018). The driver will not look away from the road in a dangerous situation but will wait until it is safe to adjust the radio, corresponding to a high feeling of control over the action.

Despite several studies on SoC as well as on switching behavior in multitasking, it remains unclear how humans form a SoC in multitasking scenarios and how it may correlates with their task-switching behavior. Do they form task-specific SoCs for each subtask or only one SoC for the overall situation? Do they frequently switch tasks in scenarios where they have a low feeling of control, or do they switch less and focus on one task while ignoring the other? Moreover, lab studies on multitasking with two continuous tasks are rare.

We conjecture that, in a multitasking scenario, task-specific SoCs are formed based on one's perceived level of control over each individual task. We hypothesize that this task-specific SoC is influenced by the controllability and difficulty of the task, as well as feedback about its success or failure. Furthermore, we propose that an overall SoC related to the feeling of being in control over the whole multitasking situation develops. To explore the cognitive and sensorimotor processes underlying task-switching behavior in multitasking scenarios, a form of cognitive control is assumed to be necessary for deciding about switches. Since the SoC is a component used for regulating actions, we further hypothesize that the feeling of control correlates with task-switching behavior. To validate these hypotheses, we conducted a study measuring SoC and task-switching behavior in human multitasking. In the following sections, we first present background and related work. We then present an experimental study design, report the results of a conducted study, and end with a discussion of implications and limitations.

Background and Related Work

The *sense of control* (SoC) is a phenomenology that describes the feeling of being in control over a situated action. It is seen as a sub-component of the *sense of agency*, the sense an agent has that he or she is responsible for a given action. A SoC arises in humans at different time scales and cognitive levels depending on how their intentions align with particular outcomes. On the one hand, a small difference between intentions and outcomes produces a high SoC, i.e. feeling of control. On the other hand, a big difference between intentions and outcomes leads to the feeling of not being in control (Pacherie, 2007). Additional components affecting the SoC are cognitive load and post-hoc performance feedback: increased cognitive load decreases the SoC (Dewey, 2023; Hon et al., 2013); positive post-hoc performance feedback in-

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creases the SoC and can even give an illusion of control when the feedback is not valid (Metcalfe et al., 2012).

SoC can be measured implicitly and explicitly. An implicit measure is, for example, temporal binding, which is the perceived reduction of the time between an action and its outcomes (Haggard, Clark, & Kalogeras, 2002). However, the use of implicit measures is controversial (Dewey, 2024; Buehner, 2012) and explicit, yet subjective measures of SoC in the form of questionnaires with single-item scales (Dewey, 2023; Wen, Charles, & Haggard, 2023) and multi-item scales (Jahanian Najafabadi, Küster, Putze, & Godde, 2023) are widely used.

Multitasking refers to the ability of an individual to coordinate multiple tasks to achieve an overall goal. Several cognitive processes are assumed to be necessary for successful multitasking, such as planning and memory capabilities (MacPherson, 2018). Humans perform multitasking every day, although it often leads to worse performance and is more error-prone than single-task performance (Monsell, 2003; Rubinstein, Meyer, & Evans, 2001; Katidioti & Taatgen, 2014). Examples are office settings where humans check emails while in a meeting (González & Mark, 2004) or driving scenarios where humans use the mobile phone or change the radio channel while driving (Wintersberger et al., 2018).

There are different types of multitasking. First, *concurrent* multitasking, also called dual-tasking, means that several tasks are performed in parallel. Second, *serial* multitasking means that one task is performed at a time and switching between multiple tasks is necessary to achieve the overall goal (MacPherson, 2018). Another type of multitasking is *discretionary* multitasking in which the human has discretion over which tasks should be processed when considering multiple tasks (Adler & Benbunan-Fich, 2013).

Switching between tasks is believed to belong to executive control functions that are necessary to cognitively control behavior (Monsell, 2003). For analyzing task-switching behavior, previous studies caused task switches by *external triggers*. The first task-switching paradigm was conducted by Jersild (1927). In this task-switching paradigm, the task is either changed from one trial to the other or not. Hence, differences between a task-switch and no task-switch can be analyzed. Studies have shown that alternating between two tasks leads to switching costs, the additional time it takes to respond compared to repeating a task (Allport, Styles, & Hsieh, 1994; Rogers & Monsell, 1995; Rubinstein et al., 2001; Monsell, 2003) which reflect the additional cognitive load when reconfiguring the task-set for the new task (Monsell, 2003; Rogers & Monsell, 1995).

More recent research studied task-switching behavior for *internally triggered* switches, also called voluntary task switches (Arrington & Logan, 2004) or self-interruptions (Adler & Benbunan-Fich, 2013). Voluntary switching can be influenced by several cues, e.g. time passed since the last switch (Gutzwiller, Wickens, & Clegg, 2016), completion of a part of one task (subgoal completion) (Payne, Duggan, & Neth, 2007), priority or difficulty of the task (MacPherson, 2018; Wickens, Gutzwiller, & Santamaria, 2015; Gutzwiller et al., 2016). It is argued that the completion of the sub-goal releases cognitive resources and thus causes a task change (Salvucci & Taatgen, 2008; Katidioti & Taatgen, 2014; Iqbal & Bailey, 2005). Additionally, a task switch is initiated when the current task is no longer rewarding (Payne et al., 2007). Other studies showed that an internal task switch is performed when there is an imbalance between the difficulty of the task and the participant's abilities: If the task is perceived as too easy, participants switch to overcome monotony; if the task is perceived as too hard, participants switch to overcome exhaustion and satisfy the need for a break (Adler & Benbunan-Fich, 2013). Note that this was tested on tasks where no reward was given. Research also showed that voluntary switches were executed quite frequently, even if sequentially processing the tasks would result in higher performance (Payne et al., 2007; Katidioti & Taatgen, 2014).

Research Question and Hypotheses

The purpose of the present study is to investigate how the SoC is formed in multitasking scenarios and how it might correlate with task-switching behavior. Multitasking situations impose a considerable load on the cognitive system and tax its underlying resources. It is thus not clear whether and how an SoC can be formed under such conditions.

As described above, previous research has found that the SoC (in single-task situations) is influenced by one's ability to predict action outcomes (controllability) (Pacherie, 2007), cognitive load (difficulty) (Dewey, 2023; Hon et al., 2013), but also feedback received post-hoc (reward) (Metcalfe et al., 2012). Based on these highly task-specific influences, we assume that (in multitasking situations) a task-specific SoC exists and represents the feeling of being in control over actions in this very task. That is, with multiple tasks being performed simultaneously, multiple task-specific SoCs are being formed. Additionally, we hypothesize that the additional layer of cognitive control in charge of task-switching would also rest upon another, overall SoC that maps out the subjective feeling of being in control of the overall multitasking situation. We assume that this overall SoC arises from the task-specific SoCs and overall performance feedback.

At the same time, it is assumed that voluntary task-switching is influenced by task factors (degree and imbalance of difficulty, rewards) as well as by internal cognitive factors (resources, costs). However, it is unclear how exactly these various factors are taken into account in the cognitive and sensomotoric processes that underlie action regulation and dynamic task-switching. We adopt the view that multiple levels of processing and control are involved and that voluntary task-switching does not only emerge from a reactive strategy responding continuously to external factors. In addition, we assume a form of cognitive control that continuously assesses the current situation and adaptively takes decisions about when to switch tasks and how to act upon them.

Since the SoC is an important component (or result) of this subjective self-assessment and assumed to be involved in action regulation (Kahl et al., 2022), we conjecture that the SoC also plays an important role in dynamic multitasking.

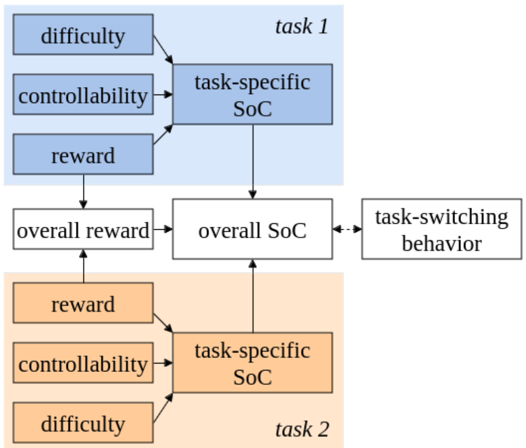

Figure 1: Conceptual diagram for hypothesized influences in SoC construction and task-switching behavior.

Figure 1 shows the assumed constructs and their hypothesized connections. Note that this is not meant to be a process model, but rather a conceptual diagram laying out the assumed components and their connections that should empirically figure as correlations. We believe that task-switching behavior correlates not only with the overall SoC but also with other components such as the reward of each task. However, these connections are not shown in Figure 1, as they are not the focus of the proposed study. In sum, we want to investigate how the SoC is formed in multitasking setups and its potential correlation with task-switching behavior. Thus, our hypotheses are:

H1 In multitasking situations, task-specific SoCs influence an overall SoC.

H2 The overall SoC correlates with task-switching behavior.

Study Design

To investigate how the SoC is formed in multitasking setups and its potential correlation with task-switching behavior, we designed a serial discretionary multitasking setup: Two tasks run continuously and simultaneously, but participants can only see and control one task at a time, which they can switch to voluntarily and at any time. Both tasks were designed to allow for manipulating the components that affect the SoC, namely, controllability, task difficulty and reward.

Tasks

In both tasks, participants navigate a spaceship that descends through the world and can be steered to the left or right or remain in the same position in each frame. *Asteroids* are scattered throughout both worlds, with the number of asteroids determined by the level of difficulty. The world is bounded by walls on both sides and a number on either side indicates the current reward of the current task.

In one task, the spaceship must navigate through the *Dodge Asteroids World* by dodging incoming asteroids. The inlay in Figure 2, bottom left, provides an example image of the world (asteroids in gray). Successfully dodging an asteroid results in a positive reward, while crashing into one results in a negative reward. These rewards are added or subtracted from the current reward. The other task is shown in Figure 2, bottom right. Here, the spaceship is flying in the *Collect Asteroids World* (asteroids depicted in gold), where collecting an asteroid produces a positive reward while missing one incurs a negative reward. In both worlds, level difficulty corresponds to the number and density of asteroids that have to be dodged or collected, resp. The reward values differ for each level of difficulty to ensure a possible total reward ranging from -100 to 100 for each task. Normalizing the reward prevents participants from remaining in a task solely for the possibility of a higher reward. The total reward can range from -200 to 200.

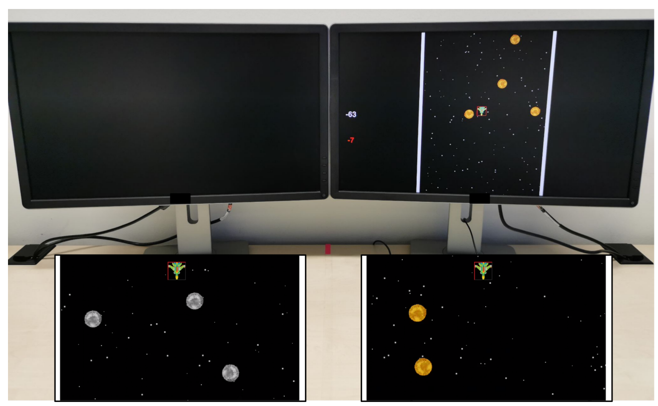

Figure 2: Setup of the in-person experiment with two monitors. One monitor displays the *Dodge Asteroids World* (displayed in the bottom left inlay), while the other one displays the *Collect Asteroids World* (bottom right).

Independent and Dependent Variables

Our study setup aims to allow for manipulating the controllability, difficulty and post-hoc reward of each task individually since those aspects were found to affect the SoC. Controllability is manipulated by inducing prediction errors in action intentions and outcomes. To that end, in some blocks, we add an input noise to the steering: Without any input noise, a key input to move left or right is just one step. With input noise, a normally distributed offset ($\mu = 0$, $\sigma^2 = 1.5$) is added to the key input. Level difficulty is operationalized as the number of objects placed in the task, with more objects requiring more planning and action to handle successfully, and therefore requiring more cognitive resources. Finally, we introduce a performance reward for each task. At the end of each trial, we present an overall reward that sums up the rewards of both tasks as post-hoc feedback.

In summary, the experiment employs a $2 \times 2 \times 2$ within-subject design with three independent variables: 1) task 1 difficulty level (easy or hard), 2) task 2 difficulty level (easy or hard) and 3) input noise (applied or not applied).

Dependent variables include questions about the task-specific SoCs to assess whether our manipulations are reflected in participants' subjective ratings. Additionally, a question was included that explicitly measures the construction of an overall SoC. To evaluate the task-specific SoC for the collect task, we asked: *In the last block (3 trials), how strong was your feeling of control when you piloted the spaceship in the collect task?*. The same question was asked for the SoC in the dodge task, replacing 'collect' with 'dodge'. Finally, to assess the overall SoC, we asked: *In the last block (3 trials), how strong was your feeling of control over both spaceships steering?*. Each question has to be answered on a Likert scale from 1 to 7. A score of 1 indicates a feeling of *no control* while a score of 7 indicates a feeling of *full control*.

Another dependent variable is the number of task switches per trial. In theory, a task switch is possible in every frame (ten frames per second), resulting in a maximum of 470 possible task switches per trial. Moreover, the time spent on the collect task is measured and used to calculate the ratio. The ratio of the time spent on the dodge task can be calculated by subtracting the ratio of time spent on the collect task from one and is therefore not considered.

Procedure

After giving their consent to participate, the participants were required to read the instructions displayed on one monitor. The instructions explained both tasks as well as the overall goal of achieving the highest cumulative reward for both tasks. The participants then had to train each task individually once, at an easy level of difficulty and without input noise. Following this, two multitasking training trials were introduced, where both tasks were set at an easy level of difficulty. The first training trial was without input noise, the second one included input noise. The starting display (left or right) and the starting task were randomized.

Following the training, participants completed eight blocks in the $2 \times 2 \times 2$ within-subject design. Each block consisted of a level of difficulty for task 1 (easy or hard) and for task 2 (easy or hard) and whether input noise was present or not. After each block, participants were asked about task-specific SoCs as well as the overall SoC. Pressing [ENTER] started the next block of three trials, each including 470 steps/frames and taking approximately 47 seconds. After each trial, the overall reward (sum of rewards in tasks 1 and 2) was displayed. To begin the next trial, participants had to press [ENTER] to proceed in a self-paced manner. The order of blocks and trials within blocks was randomized. Upon completion of the tasks, participants were asked to fill out a questionnaire regarding their demographic information and gaming behavior. The entire process, including instructions and questionnaire, took approximately 60 minutes for a total of 24 trials.

Participants and Set-Up

The study involved 28 participants (16 male, 12 female) with ages ranging from 18 to 60 and an average age of 28. The experiment lasted for one session and took approximately 60 minutes. Participants in the in-person study were compensated with 12€ and were recruited through various platforms, including mail, contact and social media. A power analysis was conducted using G*Power. We aimed to achieve a power of 0.95 to detect a medium effect size of 0.25 at a standard alpha error probability of 0.05. A post-hoc power analysis revealed a power of 0.82. The preregistration, collected experimental data and analysis code is available at the Open Science Framework (OSF) website[1].

The tasks were programmed in Python using the Pygame library[2]. The experiment was carried out on a desktop PC running Ubuntu 22.04. The experimental setup consists of two Dell P2414H monitors, each with a screen resolution of 1920×1080 and a frame rate of 60 Hz. One monitor was used for each task. The games ran at a frame rate of ten frames per second. The setup is illustrated in Figure 2.

Participants used a standard keyboard to steer the spaceships and answer the questions. The game was controlled using only three keys. [Y] key moved the spaceship to the left and the [M] key moved it to the right. The participants had the freedom to switch between tasks at any time by pressing the [SPACE] key.

Data Analysis

Prior to the data analysis, an exclusion criterion was set for participants who performed less than one task switch in a block. However, this criterion did not lead to any actual exclusions. Linear (mixed) modeling was applied to analyze the data using the SciPy (Virtanen et al., 2020) and statsmodels (Seabold & Perktold, 2010) libraries in Python. We ensured that all assumptions necessary to conduct linear (mixed) models were met. It is important to note that all dependent variables must be continuous variables. The number of task switches per trial and the ratio of mean time spent on the collect task are continuous variables. Additionally, we manipulation-checked the objective SoC defined by task difficulty, input noise and reward, with subjective SoC ratings. The SoC ratings were measured on a Likert scale from 1 to 7, where 1 represents *no control* and 7 represents *full control*. Likert scales are not considered continuous. However, research has shown that parametric tests, such as linear (mixed) models, are robust even when the assumption of continuous dependent variables is violated (Norman, 2010; Johnson & Creech, 1983; Sullivan & Artino Jr, 2013). Our data rejects multicollinearity through a correlation matrix, validates independence of errors through the Durbin-Watson test (Anderson, 1948) and checks for normally distributed residual errors using the Shapiro-Wilks test (Shapiro & Wilk,

[1] `https://osf.io/zsmrx`

[2] `https://github.com/pygame/pygame`

1965). Breusch–Pagan's test for homogeneity of variance validates equal variance between the groups (Breusch & Pagan, 1979). Linear (mixed) models were used to test our first hypothesis. We report interclass correlation coefficients (ICCs) to validate possible random effects and specify fixed effects structures for every individual model in the appropriate paragraphs. Linear models were fitted using the REML criterion, whereas linear mixed models were fitted using the maximum likelihood criterion. A significance level of $\alpha = 0.05$ was used for hypothesis testing. For effects, we report the values of β, p, and the limits of the 95% confidence interval. The second hypothesis was tested using the Spearman correlation (Spearman, 1987).

Variables

We used linear (mixed) models with various covariates to test our hypothesis about *overall SoC* (H1). The categorical variable difficulty of each task (two levels: easy and hard) was used as a predictor for both task-specific *SoCs*. Another predictor was the categorical variable input noise (two levels: true and false) indicating whether noise was applied to the control input. Additionally, the rewards for each task, considered as random effects, as well as the overall reward were included as numerical variables. The task-specific SoCs as predicting ordinal variables or predictors and the overall SoC as a predicting ordinal variable can also be considered as numerical variables in parametric tests, as explained above.

To test our hypothesis regarding *task-switching behavior* (H2), we correlate the number of task switches and the ratio of time spent on collect tasks with task-specific SoCs, overall SoCs and mean overall reward. Note that the ratio of time spent on the dodge tasks is equivalent to the user share and was not included to prevent duplicate testing in the analysis.

Results

In our study, we assume that our manipulations of task difficulty and input noise affect the subjective SoC. Therefore, we first check if our assumptions are met. We then measure the subjective SoC after each block. To include trial-based data, such as the reward, as a fixed effect in linear (mixed) models, we calculate the mean values.

SoC Results A null model predicting the subjective task-specific *SoC in the dodge task* was defined with the mean reward in this task as a random effect. The reward in the dodge task explains a sufficient amount of the total variance ($ICC_{\text{reward of dodge task}} = 0.222$). To check for influences of the collect task on the SoC in the dodge task, we entered the difficulties of both tasks, the input noise and the mean reward of the collect task as predictors, as well as defined the interaction between each difficulty with the input noise. The linear mixed model did not converge, but the finite coefficients demonstrate that the difficulty of the dodge task ($\beta = -0.820$, $p = .002$, $[-1.333, -0.306]$), the difficulty of the collect task ($\beta = -0.539$, $p = .036$, $[-1.043, -0.036]$) and the input noise ($\beta = -0.681$, $p = .023$, $[-1.266, -0.096]$) significantly reduce the task-specific SoC in the dodge task. However, the mean reward of the collect task ($p = .198$) as well as the interactions between the difficulty of the dodge task and input noise ($p = .265$) and the difficulty of the collect task and input noise ($p = .105$) are not significant.

In the same way, we analyzed the subjective task-specific *SoC in the collect task*. The null model indicates that the total variance can be partly explained by the mean reward of the collect task ($ICC_{\text{reward of collect task}} = 0.115$). Furthermore, the task-specific SoC in the collect task is significantly decreased by the difficulty of the collect task ($\beta = -0.683$, $p = .019$, $[-1.254, -0.112]$) and the input noise ($\beta = -1.110$, $p = .001$, $[-1.764, -0.457]$). Again, the mean reward of the dodge task ($p = .170$), the interaction between the difficulty of the dodge task and input noise ($p = .840$) and the difficulty of the collect task and input noise ($p = .506$) are not significant. In contrast to the SoC in the dodge task, the difficulty of the other task (here: the dodge difficulty) does *not* significantly influence the SoC in the collect task ($p = .186$).

To test the first hypothesis H1 that a *overall SoC* can be explained by task-specific SoCs, we conduct a linear model explaining the overall SoC by the SoCs in the dodge task and collect task. Additionally, we add the mean overall reward as a fixed effect. Although the mean overall reward is not statistically significant ($p = .278$), the SoC in the dodge task ($\beta = 0.422$, $p < .001$, $[0.353, 0.490]$) and the SoC in the collect task ($\beta = 0.473$, $p < .001$, $[0.412, 0.534]$) indeed significantly increase the overall SoC. The formula for calculating the overall SoC is shown in Equation 1. Figure 3 shows the relation between each task-specific SoC and the overall SoC.

$$\text{SoC}_{overall} = 0.215 + 0.422 * \text{SoC}_{dodge} + 0.473 * \text{SoC}_{collect} \tag{1}$$

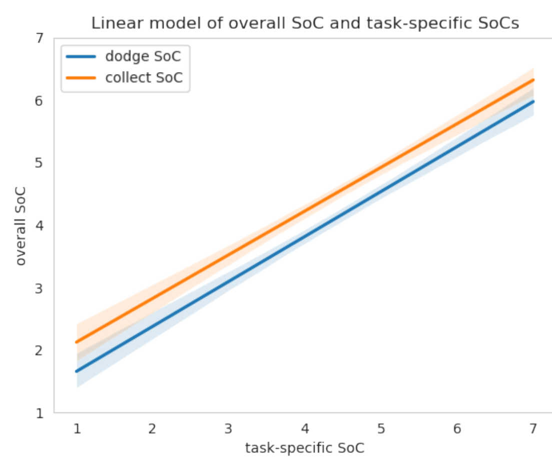

Figure 3: Linear Model predicting overall SoC from task-specific SoCs.

Task-Switching Behavior Results For testing hypothesis H2 that SoC correlates with task-switching behavior, we calculate the Spearman correlation between the *mean number of task switches* and the overall SoC. Further, we correlate the mean number of task switches with the mean overall reward because it was not significant for explaining the overall SoC. While the overall SoC does not correlate significantly with the mean number of task switches ($p = .587$), the overall reward correlates positively with the mean number of task switches ($r(26) = .426, p < .001$). In another exploratory analysis, we checked if the mean number of task switches also correlates with the task-specific SoCs. Results show that the SoC in the dodge task does not correlate significantly with the mean number of task switches ($p = .941$), but the SoC in the collect task correlates positively with the mean number of task switches ($r(26) = .155, p = .020$).

Moreover, we considered the *ratio of mean time spent on the collect task* as a second variable to measure task-switching behavior. A correlation was calculated to correlate this ratio with the overall SoC and the mean overall reward. The overall SoC does not correlate significantly ($p = .145$), while the mean overall reward ($r(26) = .438, p < .001$) correlates positively with the ratio of mean time spent on the collect task. We conduct a similar correlation as above where the ratio of mean time spent on the collect task is correlated with task-specific SoCs. Neither SoC in the dodge task ($p = .074$) nor SoC in the collect task ($p = .474$) are significant.

Discussion

The subjective task-specific SoC ratings indicate that our manipulation of controllability through the difficulty of the task and input noise was successful. Interestingly, the SoC rating for the dodge task was also significantly reduced by the difficulty of the collect task, but not the other way around. The collect task requires more effort (i.e. more key presses, more time spent on the task) to achieve a higher reward than the dodge task. The ratio of time spent on the collect task for each block ranges between 49.87% and 70.13%, indicating that it is attended at least half of the time even if the dodge task is currently difficult. It could be that participants perceived less control in the dodge task when the collect task was harder due to carry-over effects from the previous task-set of the collect task. On the contrary, the reward obtained in one task did not significantly influence the task-specific SoC in the other task.

Moreover, we found that the overall SoC can be predicted from the task-specific SoCs (cf. Eq. 1), where each task-specific SoC contributes significantly to the overall SoC ($\beta = 0.422$ and $\beta = 0.473$). We can thus confirm hypothesis H1 that task-specific SoCs influence an overall SoC. Similar to the results above, the collect task has a greater influence than the dodge task (see Figure 3). The mean overall reward does not significantly influence the overall SoC. This finding is consistent with Dewey (2023), where post-hoc feedback did not influence SoC ratings, although other research has shown otherwise (Metcalfe et al., 2012). Further analysis is needed to determine how post-hoc feedback might influence the SoC in general.

Hypothesis H2, which suggests that overall SoC correlates with task-switching behavior, is not supported. However, further analysis reveals that not only the overall reward correlates with the number of task switches but also the SoC in the collect task. Again, one assumption is that the influence of the collect task is higher because more actions are needed there. Further exploratory analysis showed that the ratio of mean time spent on the collect task does not correlate with the overall SoC or by task-specific SoCs, but by the mean overall reward. These findings suggest that task-switching behavior is explained by multiple divers factors which are not completely covered by SoCs.

Re-visiting Figure 1, we would need to add a link indicating a correlation between the overall reward and task-switching behavior, while removing the mediating link via the overall SoC. Moreover, the connection between the overall SoC and task-switching behavior does not hold. Finally, we found differentiated influences of different tasks. To distinguish between the dodge and the collect task, an arrow should be added connecting the difficulty of the collect task to the task-specific SoC in the dodge task. Furthermore, a dashed connection between the SoC in the collect task and task-switching behavior would show that task-specific SoCs correlate in parts with task-switching behavior.

Conclusions

We conducted a study to explore how humans form a SoC in serial discretionary multitasking scenarios, and how it might correlate with their task-switching behavior. Our results indicate the presence of task-specific SoCs, affected by the difficulty and controllability of the respective task. Furthermore, an overall SoC is found to be largely determined by the task-specific SoCs with certain tasks having a larger impact. Future research should investigate whether other predictors beyond task-specific SoCs can further explain the overall SoC. Additionally, different tasks should be used in the multitasking scenario to verify if the impact of a task-specific SoC is consistent or depends on relative differences to the second task. Finally, the use of more than two tasks would provide even more insight into the composition of an overall SoC in multitasking problems.

Furthermore, our results suggest that SoC does not correlate with task-switching behavior in multitasking scenarios. The overall SoC was not found to correlate with the number of task switches or with the ratio of time spent on one task. Future work should check if the hypothesis does not hold for further measures of task-switching behavior as well as manipulating a local SoC during a trial, rather than just a general SoC per block. A measure of task-switching behavior that could be considered is switching after subgoal completion. This would help to elucidate the cognitive mechanisms at work in multitasking and what role an actually complex SoC plays in these situations.

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