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RESEARCH ARTICLE

Modulating Frustration and Agency Using Fabricated Input for Motor Imagery BCIs in Stroke Rehabilitation

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ABSTRACT Brain-computer interfaces (BCIs) can serve as a means for stroke rehabilitation, but low BCI performance can decrease agency (users' perceived control), frustrate users and thereby hamper rehabilitation. In such rehabilitative tasks BCIs can implement fabricated input (preprogrammed positive feedback) that improve agency and frustration. Two substudies with healthy subjects and stroke patients investigated this potential through completion of a game and a simple task with: 1) 16 healthy subjects using motor imagery-based online BCI and 2) 13 stroke patients using a surrogate BCI system based on eye-blink detection through an eye-tracker to have a highly reliable input signal. Substudy 1 measured perceived control and frustration in four conditions: 1) unaltered BCI control, 2) 30% guaranteed positive feedback from fabricated input 3) 50% guaranteed negative feedback, and 4) 50% guaranteed negative feedback and 30% guaranteed positive feedback. In substudy 2, stroke patients had 50% control over outcomes and four conditions added from 0% to 50% positive feedback. In both substudies, positive feedback improved participants' perceived control and reduced frustration with increasing improvements when the amount of positive fabricated input increased. The stroke patients did not react as much to the fabricated input as the healthy participants. Fabricated input can be concealed in both online and surrogate BCIs which can be used to improve perceived control and frustration in a game-based interaction and simple task. This suggests that BCI designers can exercise artistic freedom to create engaging motor imagery-based interactions of narrative-based games or simpler gamified interactions to facilitate improved training efforts.

INDEX TERMS Brain–computer interface, stroke rehabilitation, motor imagination, agency, frustration, fabricated input, gamification, motivation, surrogate BCI, research instrument.

I. INTRODUCTION

Stroke patients undergo expensive rehabilitation for months to regain lost motor control with mixed results [1]. Therefore, different new techniques have been proposed such as Brain-Computer Interfaces (BCIs) relying on motor imagery training to restore movement [2]–[5]. The lack of inherent proprioceptive feedback makes BCIs difficult to operate such that patients may experience a loss of control of the BCI during training. The resulting frustration further reduces BCI performance creating a vicious cycle and reduces motivation for subsequent training [6]. BCI research has sought to improve performance of BCIs through novel hardware or signal processing algorithms increasing users' BCI performance (i.e. true positive rate or classification accuracy) [7]. Alternatively, recent studies reduced frustration by creating

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an illusions of control through *fabricated input*, which consists of injections of preprogrammed positive feedback, when the BCI does not recognize valid user input attempts [8], [9]. Most studies investigated fabricated input by employing *surrogate BCI* in which users were led to believe they provided input through BCI, while their input was captured through a reliable input device to gain access to the ground truth of input attempts that are otherwise unavailable in BCI [9], [10]. Hougaard *et al.* [8] equipped users with an electroencephalography (EEG) recording headband and conveyed to the users they were controlling a BCI with eyeblinks, but simultaneously captured the user input through an eye-tracker. So far, fabricated input has only been studied with surrogate BCIs and it is unclear how agency and frustration are affected in real BCI (motor imagery) or when rated by stroke patients. The paper contributes evidence that positive feedback linearly moderates people's frustration and perceived control in both contexts (BCI, stroke patients), including positive feedback from fabricated input and is structured as follows.

Section II includes 1) the relevant background on BCI and its connection with inducing plasticity for stroke rehabilitation, 2) motivates the need for fabricated input to curb frustration, and 3) synthesizes the extant knowledge of fabricated input by discussing its design constraints and details the scientific gap, which the following two substudies address. The methods and results for substudy 1 (online BCI with healthy subjects) are presented in Section III and IV and in section V and VI for substudy 2 (employing a surrogate BCI as a research instrument with stroke patients). Sections VII and VIII provide a cross-study discussion and the conclusions, respectively.

II. BACKGROUND

A BCI system enables users to control external devices and applications using voluntarily produced brain activity [11]. BCIs often record the electrical activity from the scalp (EEG) to pick up specific control signals from the brain that can be evoked either internally such as sensorimotor rhythms and slow cortical potentials or externally such as P300 or steady state visually evoked potentials [11]. BCIs pre-process recorded EEG data to maximize the signal-to-noise ratio to isolate or maximize the control signal of interest. They derive specific features that characterize the control signal to classify them into a number of different classes which maps to commands in different applications. BCIs have been used as a means for communication and control for individuals with severe motor impairments [12], but more recently for applications such as passive brain monitoring and game control [13], [14]. Another major application of BCIs that has evolved over the past 10 years is the induction of neural plasticity [5] - the presumed underlying factor of motor learning [15], and motor recovery of stroke patients [16].

BCIs for stroke rehabilitation detect movement-related cortical activity from the affected brain regions and in response trigger a movement of the affected limb by using a rehabilitation robot, exoskeleton, or electrical stimulation of the muscles. The induced limb movement generates somatosensory feedback back to the brain. Feedback returning with a short temporal delay after the intention to move (resembling the normal motor control loop) fulfills the requirements for inducing Hebbian-associated neural plasticity [5]. The movement-related activity can be evoked through motor imagination (MI) [17] and detected through sensorimotor rhythms or movement-related cortical potentials [18], [19].

Several studies have shown that these control signals can be detected from single-trial EEG in non-disabled and stroke individuals with input recognition rates roughly around 70-80%, but with higher input recognition rates for non-disabled individuals compared to stroke patients [20], [21]. BCI-controlled rehabilitation robots and electrical stimulation can effectively improve motor function in stroke patients [2], [4], [22], [23]. However, the experiments have often been performed under controlled conditions with BCI experienced researchers. Several factors can impede the adoption of this technology in clinical practice and potentially as a home-based rehabilitation tool [24]–[26]. These include the mounting of headsets/caps for recording EEG, lengthy calibrations, poor usability including variable BCI performance, which may be low for several users. Up to 10-30% of users have been labelled BCI illiterate because they could not operate a BCI with sufficient performance (>70%) [27]. It should be noted that this accuracy is for communication and control applications, but not for stroke rehabilitation in which lower accuracy levels can still induce neural plasticity [28].

Control of MI-based BCI systems have been improved and made more robust using various signal processing techniques for improving the signal-to-noise ratio, feature investigations, feature selection, and machine learning techniques see e.g. [20], [21], [29]–[37], but the control of an MI-based BCI could also be improved through proper training protocols adhering to universal learning principles, instructional design, and feedback [38], [39]. However, it may take time to learn to perform MI which may be abstract and new to many patients. Different psychological factors have been reported to be associated with BCI performance. Fear of failure for controlling the BCI has been associated with decreased BCI performance in healthy individuals as well as in individuals with stroke or amyotrophic lateral sclerosis [6], [40]–[42]. Incompetence fear is a component of motivation together with mastery confidence and challenge [43]. Several studies have reported that motivation and BCI performance are associated, (e.g. [6], [40], [44]). Furthermore, factors such as concentration, attention, control beliefs, sense of ownership, and emotions (positive and negative) affect BCI performance [43], [45]–[47].

Two other major factors that are associated with BCI performance are frustration and sense of agency. Decreases in frustration have consistently been associated with higher BCI performance [8], [10], [44], [47], and higher BCI performance with increased agency [8], [10], [44], [45], [48].

But in cases in which people could experience high agency (from continuous feedback) decoupled from the resulting task outcomes, frustration was independent from perceived agency but depended solely on positive task outcomes (negatively correlated) [48]. These factors are important to consider when using a BCI-controlled rehabilitation robot for stroke rehabilitation since they are likely to influence the patients' attitude towards the technology and commitment to the rehabilitation training [49], [50]. Thus, the frustration and sense of agency could affect the amount of time the patient wants to spend on the training with the device, which will determine the potential rehabilitative outcome, higher training intensity should lead to better functional outcomes. Even given proper hardware and software setups, training protocols and environments [51], good BCI performance cannot be guaranteed. Positively biased feedback improved BCI performance for users with BCI recognition <65% while users with higher recognition rates saw their performance decline when exposed to such unwarranted feedback [52]. A study by Gonzalez-Franco *et al.* confirmed this penalty of unwarranted positive feedback for high performers [53] leading to weaker sensorimotor rhythm patterns in subsequent attempts than appropriate negative feedback and thereby decreasing BCI performance. A recent study investigating biased feedback for various personality types found interactions between the bias (positive and negative) and workload, anxiety, and self-control that affect BCI performance suggesting that biased feedback work better/worse for some user types [42]. However, for stroke rehabilitation good control of the BCI may not be needed for inducing neural plasticity but rather, to avoid frustration, a high level of perceived control [5], which is correlated with the actual level of control [10], [48]. The notion of perceived control resembles the sense of agency. Studies have investigated the effect of different levels of BCI performance on the level of frustration and perceived control but relied on surrogate BCI input mimicking BCI performance through keyboard input [9], [10]. This approach provided access to the ground truth, and success rates could be accurately controlled. However, no EEG has been recorded, nor was it conveyed to the participants that they were trying to control a BCI as this was not the aim of the studies. Another approach to simulate a BCI has been followed by using steady state visual evoked potentials where EEG was recorded, but no actual decoding of the EEG was performed, to control success rates [44].

A recent study developed a research instrument mimicking a BCI system, i.e. a surrogate BCI, providing access to the ground truth and allowing for controlling the success rate of the system [8]. An EEG recording headset was mounted on the forehead and conveyed to participants that the system was recognizing specific eye blink patterns from the brain activity. However, instead of using the EEG, an eye tracker was used to recognize the blinks (input) with close to 100% accuracy, i.e. it served as a surrogate BCI research instrument. While not BCI input, this allowed for injecting fabricated input in a BCI-like system to generate different levels of control and modulate the sense of agency and level of frustration with higher modulation precision than possible with online BCI. Special attention must be paid to the design of the fabricated input. To maximize the sense of agency the fabricated input and feedback need to abide by three central principles [50], [54]:

1) temporal congruency - priority principle: minimizing delay between input attempt and feedback
2) spatial congruency - consistency principle: the mapping of feedback to the nature of the input attempt, and
3) be concealed - exclusivity principle: the genuine input attempt seems to be the only plausible cause of the outcome.

Temporal congruency and concealment may be difficult to implement in a true BCI controlled via motor imagery, which provide no access to the ground truth because BCIs may produce false positives and false negatives in addition to true positives from user attempts. The action of a BCI should follow shortly after the intention since long delays can violate the third principle of the user being the sole cause of the effect. The maximum length of permissible delay is unknown but agency can start decreasing even after short delays in the order of 50-300 milliseconds when providing proprioceptive feedback (e.g. from a button press [55]). In a BCI context, the perceived agency decreased with larger temporal delays but remained high even with two second delays [56]. Thus, fabricated input should work best in a synchronous BCI with pre-defined, binary inputs. Another characteristic of fabricated input to consider is its temporal placement during the input time window. In the context of MI-based BCI for stroke rehabilitation, Hougaard *et al.* [8] proposed to 1) avoid placing fabricated input at the beginning of input windows to give users time to attempt input and 2) not deliver it consistently at the same time (e.g. the end of the window) but rather place it randomly (see the original paper on input fabrication [8] for a more thorough discussion on its characteristics). In stroke rehabilitation, a synchronous BCI with binary input (movement intention versus no movement intention) arranged by input windows, creates a context with high probability of users attempting to produce a recognizable movement intention. The input window provides designers a limited time window to inject the fabricated input where this potentially allows for fulfilling the first and third principle of agency. The third principle of agency could be further maximized through instructing the user to keep trying to activate the BCI throughout the input window. The second principle of spatial congruency can be obtained through 1) visual feedback of a rehabilitation robot, 2) an exoskeleton assisting the movement or 3) through virtual reality. However, it could also be a possibility that this principle can be violated so the feedback is more abstract which opens possibilities for enriching the rehabilitation scenario with game contexts and experiences to conceal monotonous repetitive training.

In summary, frustration can reduce patients' ability to generate BCI recognizable MI attempts and their desire to continue BCI training. But previous studies have only used

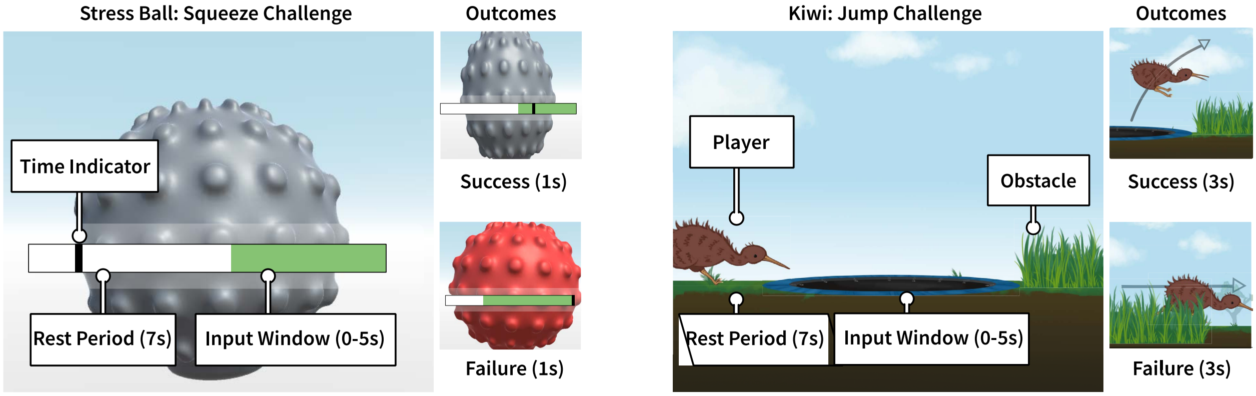

FIGURE 1. Game Screenshots. In the stress ball condition (left), the player must provide input to make the ball squeeze. In the kiwi runner (right), the player must provide input while the kiwi crosses the trampoline, to jump over the obstacle.

surrogate BCI methods with healthy subjects as evidence for the efficacy of fabricated input to increase agency and reduce frustration in both game and non-game contexts. It is not clear whether the benefits of fabricated input apply equally or potentially even more in A) real BCI systems in which users can be less sure about their attempts of triggering actions and for B) stroke patients, who due to their conditions might have lower expectations and different experiences of reduced agency. Two studies tested these aspects between game and non-game contexts. The contribution of this paper is an investigation of agency and frustration with a real online BCI and with the relevant user group, which is people with a stroke; this has not been attempted in the literature.

III. METHODS: SUBSTUDY 1

The study closely followed the design of previously tested interactions [8] to allow for within-subject comparison of two interactions - a simple task (a stress ball, Figure 1, left), and a game-based task with a narrative (kiwi runner) (Figure 1, right). Healthy subjects controlled the interactions through MI-based online BCI. On successful inputs the participants squeezed the stress ball resulting in a squeeze animation with positive audio feedback or blinking red with negative audio feedback on failed attempts (Figure 1, left). In the kiwi runner interaction, the participants controlled a kiwi jumping over obstacles to reach a nest to protect its eggs from a bird of prey (Figure 1, right). Prior to the study, subjects provided their informed consent prior to the experiment which was approved by the local ethical committee (N-20130081), and was in accordance with the Helsinki Declaration.

A. MEASUREMENT OF REAL AND FABRICATED INPUT

The BCI applications utilized an urn model to randomize trials and achieve the target feedback rates, with three possible outcomes: 1) activate on user input (acceptance), 2) fabricated input, or 3) ignore user input (rejection). Activation from user- or fabricated input closed the input window and delivered positive feedback, i.e. ball squeezed or the kiwi jumped. Ignoring user input delivered negative feedback at the end of the input window, (e.g. the ball blinked red or the kiwi walked through the obstacle). For fabricated input the system selected a random point to end the input window between 1.1 sec and 4.9 sec, and delivered positive feedback, as if the participants had activated it. If the participants failed to perform recognizable MI, the urn would count this as a rejection, to get as close to the designated activation rate as possible. The output of the BCI classifier from OpenViBE was sent to Unity for controlling the two interactions. Two different algorithms were used for the output of the BCI classifier to identify an MI event in the two interactions. In the stress ball interaction, an 8-sample ring buffer was used in which eight consecutive outputs from the classifier (that provided an output 16 times per second) had to be above the subject-dependent activation threshold, which made it more difficult to activate the BCI. In the kiwi runner interaction, it was only required that one sample was above the subject-dependent threshold. Regardless of the algorithm, both games controlled the amount of positive and negative feedback users received through the urn model.

We controlled the amount of positive feedback, which appeared temporally congruent with the participants' input based on the method used in [8]. In each condition, participants played 20 trials in four conditions which manipulated negative and positive feedback as depicted in Figure 3: 0-100%, 30-100% (30% fabricated input), 0-50% (control limited), and 30-80% (control limited, 30% fabricated input). The conditions had a variable continuum of control, as it is not possible to guarantee an exact level of control of the BCI, for example in cases where users tried to create MI, but did not succeed. However, conditions with fabricated input guaranteed at least 30% positive feedback during the trials.

To assist referencing the different conditions between participants and facilitators we color-coded the stress ball and kiwi trampolines. The assignment of colors to the conditions was randomized across participants.

B. EXPERIMENTAL PROCEDURE

The experimental procedure is visualized in Figure 2. Initially, the participants were informed about the experiment and familiarized with the experimental setup,

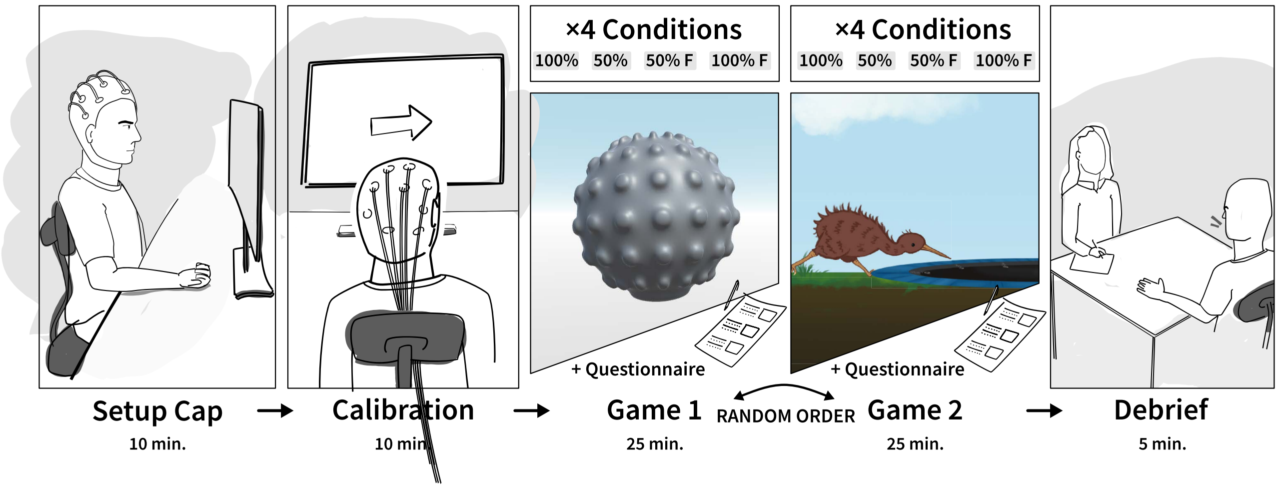

FIGURE 2. **Experimental procedure consisted of 1) mounting the EEG cap, 2) calibration, 3) playing four randomized conditions in each game followed by 4) a debrief interview.**

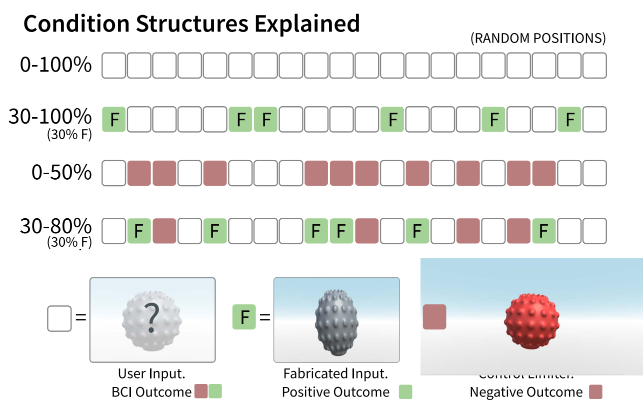

FIGURE 3. **In both games (kiwi, ball), each condition had 20 trials (squares) which were preset with specific behaviours and shuffled. Trials which contained a fabricated input guaranteed a positive outcome (green square). The control limiter (red square) guaranteed low input recognition, unless the BCI already provided low input recognition, in which case control limiting was removed.**

tasks/interaction, and how to perform MI. The participants received approximately five minutes of MI practice before the experiment started. Next, an EEG cap was mounted on the participants' head and lead through a calibration process of the BCI system by a BCI researcher with more than ten years of experience. For calibrating the BCI, the participants performed 30 imaginary palmar grasps (kinesthetic MI) with their right hand. They maintained the imaginary movement for four seconds. Also, 30 time periods with idle activity was recorded, which also lasted four seconds. The participants were visually cued with a red arrow pointing to the right, indicating a palmar grasp with the right hand, for four seconds, and with the text "REST" when the idle activity was recorded. A modified version of the "Motor Imagery BCI" in OpenViBE (an open source platform for BCI development) was used where the left hand MI was replaced with the rest condition [57]. During the recording of the calibration data and use of the online BCI, the participants were instructed to sit as still as possible and avoid both blinking and activating facial muscles. After the BCI calibration, the participants played the two interactions in randomized order. There were four runs of each of the interactions in which different levels of fabricated input were mixed with the output of the BCI. The order of the runs was also randomized, but the interactions were not mixed. After each run the participants filled in a questionnaire. They could see their ratings from the previous runs as a reference. The interaction followed a typical synchronous BCI paradigm with a cue phase (prepare to perform MI) lasting 2 seconds, followed by a 5-second input window where the participants were instructed to perform MI until it was detected, and lastly a rest period of 5 seconds depending on when the MI event was detected in the time window or when the fabricated input was injected (see Figure 1).

After each condition, participants used 7-point Likert scale items to rate their perceived control ("I felt I was in control of when the kiwi jumped/ball squeezed." from strongly disagree (1) to strongly agree (7)) and frustration ("How much frustration did you feel in this condition?" from strongly absent (1) to strongly pronounced(7)). The questions were identical to those used in previous studies of frustration [8], and perceived control [54]. To allow for numerical comparisons, we maintained the Likert item format used in [8] for both questions.

C. ONLINE BRAIN-COMPUTER INTERFACE

Continuous EEG data were recorded from F3, F4, C3, Cz, C4, P3, and P4 according to the International 10-20 System. The EEG was referenced and grounded to CPz and AFz, respectively. The EEG was recorded with a cap with sintered Ag/AgCl electrodes (OpenBCI, USA) and sampled with 250 Hz using a Cyton Biosensing Board (OpenBCI, USA). The signals were transmitted through Bluetooth to a computer on which OpenViBE processed the data using

TABLE 1. Participant demographics (MI Experience denoted with *), mean self-reported measures (perceived control, frustration), MI conversion rate (% of MI events within input windows which resulted in positive outcomes) and mean positive feedback (combined % feedback from MI and fabricated input).

Variable	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
Gender	F	F	M	F	F	F	M	F	F	M	F	M	M	M	M	F
BCI Experience	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes*	No	Yes*	Yes	Yes	Yes	No	No	No
<u>Kiwi</u>																
Perc. Control	0.29	0.75	0.42	0.38	0.54	0.79	0.50	0.71	0.08	0.54	0.50	0.63	0.17	0.46	0.92	0.46
Frustration	0.50	0.17	0.54	0.54	0.50	0.12	0.46	0.50	0.50	0.67	0.44	0.25	0.75	0.54	0.33	0.54
MI Conv. Rate	66%	84%	49%	49%	57%	72%	76%	85%	74%	65%	73%	91%	42%	72%	70%	52%
Pos. Feedback	66%	78%	59%	50%	61%	76%	72%	78%	69%	70%	72%	81%	50%	72%	70%	55%
<u>Stress Ball</u>																
Perc. Control	0.25	0.83	0.54	0.38	0.67	0.50	0.17	0.67	0.21	0.50	0.46	0.67	0.54	0.12	0.62	0.25
Frustration	0.75	0.17	0.58	0.75	0.50	0.38	0.83	0.29	0.62	0.62	0.54	0.29	0.62	0.88	0.62	0.75
MI Conv. Rate	11%	88%	72%	59%	62%	41%	18%	86%	36%	85%	46%	85%	60%	19%	49%	24%
Pos. Feedback	26%	75%	71%	55%	68%	49%	31%	80%	48%	75%	56%	80%	64%	32%	51%	35%

the pre-defined "Motor Imagery BCI" scenario [57]. The continuous EEG was first filtered between 8-30 Hz with a 5^{th} order Butterworth bandpass filter and then with a common spatial pattern filter to maximize the difference in spectral power between the two classes (MI and idle activity). The logarithmic band power was used as input for a linear discriminant analysis classifier [58]. The coefficients of the common spatial pattern filter and the decision boundary of the classifier were determined based on the calibration data. The calibration data were divided into windows with a width of one second which was shifted 1/16 second over the 4-second imaginary movement from the calibration data based on the standard settings in the "Motor Imagery BCI" scenario in OpenViBE. The linear discriminant analysis classifier was calibrated using 5-fold cross-validation. The output of the classifier provided an output between 0 and 1. A subject-dependent threshold was set for the output of the classifier to decide whether it was an MI event or idle activity. Lastly, a short test of the online BCI was performed with the subject-dependent threshold set to balance the true positive rate and number of false positive detections. The starting value for the threshold was based on the classification accuracies for the calibration data, and it could be increased or decreased to allow the balance between the true positive rate and number of false positive detections. During the interaction, the output of the classifier was sent to Unity through a transmission control protocol (TCP) connection for controlling the game. When the classifier output passed the threshold within an input window, an MI event it would be counted towards the total MI rate. If an MI event led to positive feedback, it would be counted towards the MI conversion rate listed in Table 1.

D. DATA ANALYSIS

The BCI games collected continuous data from the BCI interactions and event data from the BCI games which were assembled and post-processed with R Studio. Game events were compared to condition setups to identify potential conditions which did not conform to the experimental design. Afterwards, the quantitative data were analyzed using linear mixed models from the lme4 package [59] and multi-model variance inference from the MuMIn package [60] in terms of conditional (R_c^2) and marginal R-squared (R_m^2). We used linear mixed models to analyze the relationship between the variables listed in Table 2 and described in the table caption, following methods described by Winter [61]. Linear mixed models compare a model of variables, to a null model. In the null model, we used by-participant intercepts, to predict ratings of perceived control and frustration. Visual inspection did not reveal deviations from normality or homoscedasticity. Likelihood ratio tests were used to obtain p-values, by comparing each effect within a full model to models without the effect in question. Tests were considered significant when p was less than 0.05. Qualitative data from post-experiment interviews were transcribed into quotes for an inductive thematic analysis. All of the qualitative data were coded into meaningful groups using open coding analysis [62], where the groups of data were used to define specific themes.

E. PARTICIPANTS

Sixteen non-disabled participants were recruited for the experiment, nine females and seven males with a mean age of 26 years (range: 23-33 years). The experiment took place in an ordinary office environment with no shielding of electromagnetic interference. While some participants have had EEG recorded before, only two participants were familiar with performing MI (P8, P10). P6 disconnected during two conditions in the stress ball (100% +30% and 50%) and therefore experienced very low feedback and MI activations. Due to human error, P11 received six additional fabricated outcomes for a total of 26 trials in the nominally 0-50% condition. In addition, P12 tried a condition (50%) twice in

TABLE 2. Significant likelihood ratio test outcomes of predicting perceived control and frustration from 8 variables: MI rate, fabrication rate, gender, game, condition, BCI experience, condition order and positive feedback rate. The table reports AIC (Akaike information criterion), BIC (Bayesian information criterion), ML (maximum likelihood), χ^2 (significance), R_m^2 (marginal variance) and R_c^2 (conditional variance).

Predicted	Random intercept	Fixed effect	AIC	BIC	ML	χ^2	R_m^2	R_c^2
Perceived Control	Participant	Pos. Feedback	-87.77	-76.39	47.89	<0.001	0.55	0.73
Perceived Control	Participant	MI Rate	-2.36	9.01	5.18	<0.001	0.28	0.43
Perceived Control	Participant	Condition	2.68	19.74	4.66	<0.001	0.18	0.51
Perceived Control	Participant	Fab. Rate	16.87	28.25	-4.44	<0.001	0.10	0.42
Frustration	Participant	Pos. Feedback	-76.87	-65.49	42.43	<0.001	0.52	0.67
Frustration	Participant	MI Rate	-23.45	-12.07	15.72	<0.001	0.35	0.47
Frustration	Participant	Condition	7.71	24.77	2.15	<0.001	0.14	0.40
Frustration	Participant	Fab. Rate	21.66	33.04	-6.83	0.006	0.04	0.29
Frustration	Participant	Game	21.68	33.05	-6.84	0.006	0.04	0.29

the kiwi runner. The conditions (P11 and P12) were excluded from the subsequent analyses. The demographics of each participant and the recorded MI rates are listed in Table 1.

IV. RESULTS: SUBSTUDY 1

A likelihood ratio test of linear mixed models [63] with random intercepts for participants showed that positive feedback rate (from either fabrication or successful inputs) positively affected perceived control (χ^2 = 47.89, p < 0.001). Participants' experienced more control when fabricated input induced higher positive feedback rates. The relationship of feedback rate to perceived control and frustration is visualized in Figure 5. The rate of positive feedback explained most variance (55% R_m^2) of all significant fixed effects listed in table 2. The MI rate measured the number of recognized MI attempts (true positives). MI rate predicted perceived control significantly, but explained much less of the variance in the data compared to the rate of positive feedback. People rated perceived control more according to the feedback they received, than the MI rate they achieved before applying our feedback manipulations. Differences between conditions were significant in isolation but they were not significant when compared in a model with positive feedback predicting perceived control The extent which conditions manipulated positive feedback across participants, is visualized in Figure 4. Gender and interaction type (kiwi vs. stress ball) did not significantly affect perceived control. BCI experience was tested as a random effect, but was not significant.

Frustration ratings were inversely predicted by positive feedback rate (see table 2). Participants rated frustration significantly lower for the kiwi than the stress ball, but participants also experienced higher mean positive feedback when playing the kiwi game ($M = 0.674$ vs. $M = 0.560$). Differences in interaction were significant in isolation, but were not significant compared to a model with positive feedback predicting frustration. People had between 11% - 91% control of the input attempts on average (M = 60%). The stress ball provided only 5 of 16 participants consistent control (P2, P3, P10, P12, P13) in all four conditions (less than 25% variance in recognition rate), while kiwi provided 11 of 16 participants consistent control.

A. INDIVIDUAL-LEVEL ANALYSIS

Due to the nature of the experiment with online BCI, participants' individual experiences of control are not possible to capture in group-level analysis. To demonstrate the experience variation, we performed individual-level analysis to identify how different participant subgroups' experience of MI Rate and feedback variance affected their ratings (see Figure 6). Participants with less than 40% mean MI rate (Group 1, Figure 6), had less than 40% mean positive feedback and high frustration levels as expected (red line, M = 0.64). Due to their low MI rate, the 0-50% condition and 0-100% condition provided the same experience. The injected 30% fabricated input (dark grey bars) made up 52% of the positive feedback this group received on average (light grey bars). The majority of participants in the high MI performance group (group 2 in Figure 6) carried out MI without problems and would have received 75% feedback or higher in all four conditions, if we had not limited the feedback to 50% in some conditions. The mean frustration levels (red lines) were much lower (M = 0.17) as expected and the conditions which limited positive feedback (0-50% and 30-80%) conditions ended up with lowest ratings. Participants with high feedback variance (group 3, Figure 6) were exposed to feedback across the full scale. In contrast to participants with low feedback rates, visual inspection of participant ratings show a stronger inverse correlation between Frustration and Perceived Control in this group - when perceived control is low, frustration becomes high and vice versa. The group

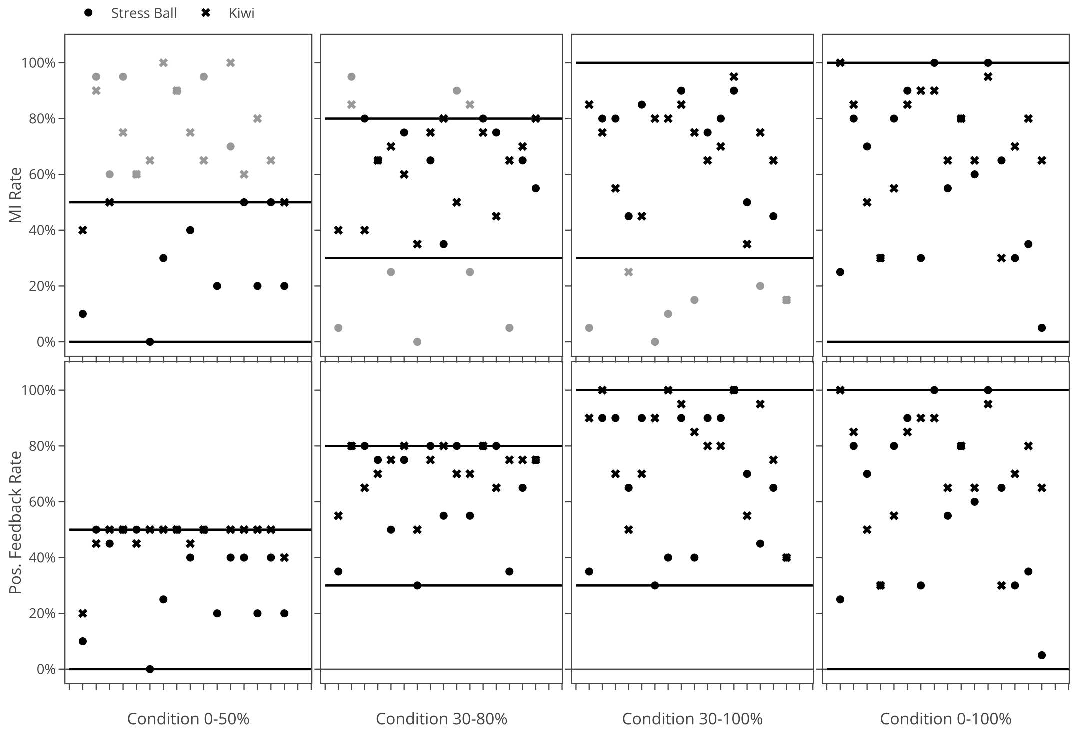

FIGURE 4. Participants 1-16 (x-axis) went through four conditions (0-100%, 30-100%, 0-50%, 30-50%) which moderated their feedback rate (y-axis). The conditions 30-100% and 30-80% included fabricated input which guaranteed a baseline 30% positive feedback, as indicated by the shift of the lower black line.

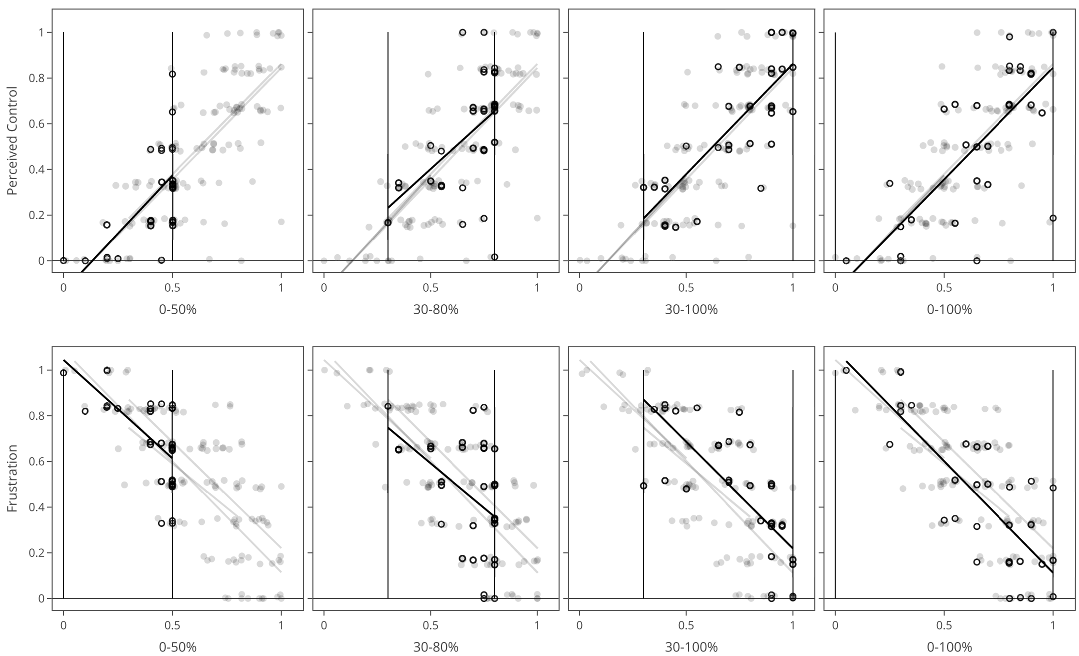

FIGURE 5. Regression plots depicting feedback rate from the kiwi and stress ball combined on the x-axis to user ratings of perceived control (upper) and frustration (lower) on the y-axis (jittered). Vertical black lines depict upper and lower bounds of positive feedback provided in the condition. The condition (black line and markers) is compared to all data points (grey line and markers).

demonstrates how giving participants access to a broad range of low to high feedback rates, makes participants able to reliably discriminate the experiences from each other.

In the qualitative post-experiment interview, five participants (P3, P6, P7, P11, and P15) revealed that they tried other strategies than MI after experiencing successive failures, for

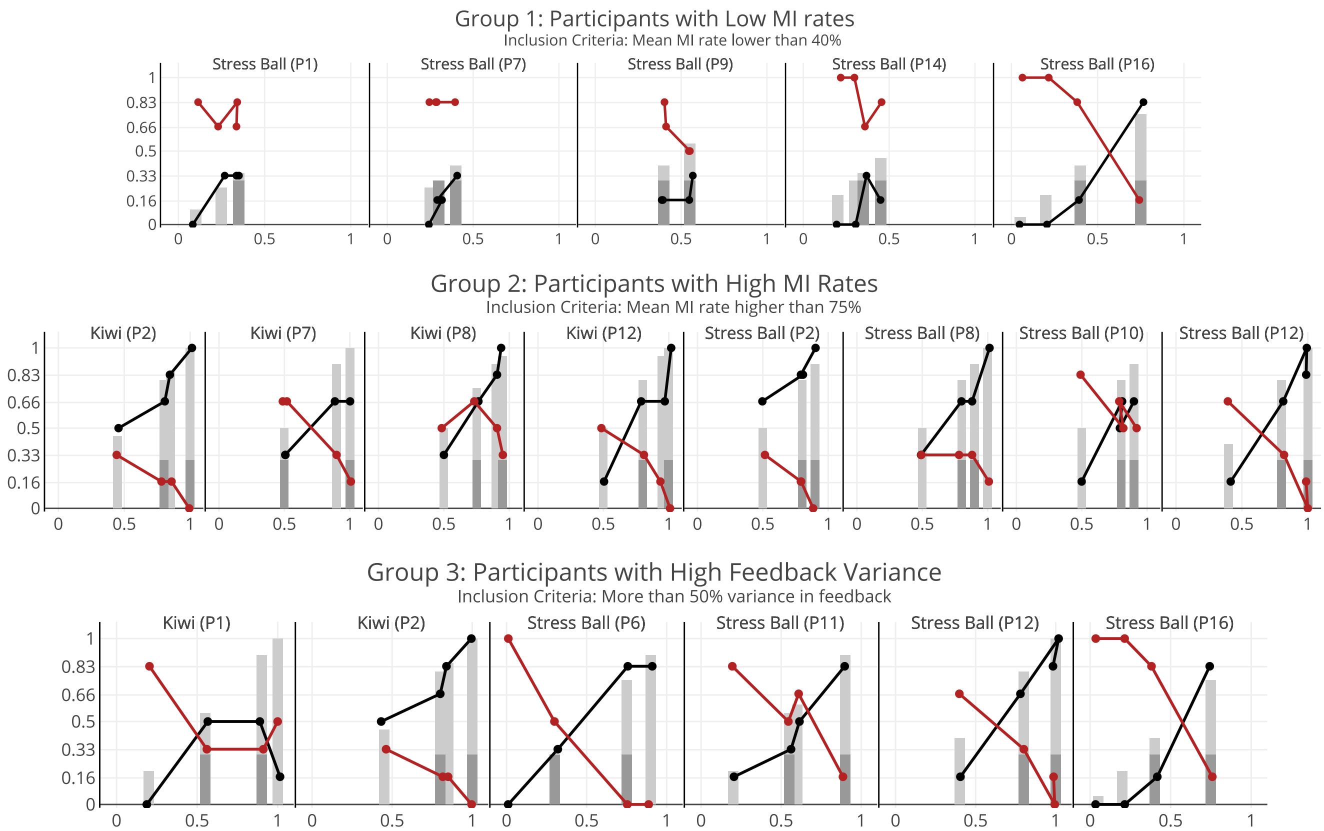

FIGURE 6. Individual play-throughs grouped by 1) low MI recognition (mean below 40%), 2) high MI recognition (mean above 75%) and 3) high variance between conditions (more than 50%). Light grey bars indicate the feedback level. Dark grey bars indicate how much feedback was fabricated input. The red line indicates frustration and the black perceived control ratings. The x-axis plots MI rates achieved.

example imagining stretching fingers, swearing at the blue kiwi bird in their head while clenching their hand, or clenching the stomach: *"I clenched my stomach at two times, where the yellow ball got squeezed both times, and then I thought I should stop doing that [as it felt like cheating]"* (P15). Six participants (P2, P4, P7, P9, P12, and P16) felt that activation of the squeeze/jump was random or uncontrollable: *"it was a bit frustrating. When my strategy worked, I thought I could use the same strategy again, but then it didn't work."* (P4). Three participants (P3, P8, and P12) felt that *"the stress ball helped recall contraction, which made it easier to control."* Three participants (P2, P9, and P16) got the feeling of *"the ball sometimes squeezed before I even started thinking"* (P2), which invoked a feeling of *"did I even do this?"* (P9), whereas P12 had the same feeling but with a different explanation: *"some algorithms were more sensitive than others, while some did not even respond."* We discuss the results of this substudy jointly with those of substudy 2.

V. METHODS: SUBSTUDY 2

Substudy 2 studied fabricated input in a hospital setting with stroke patients using a similar surrogate BCI hardware setup, experimental procedure and interaction by Hougaard *et al.* [8] to allow for comparison. The study provided patients control of two games (kiwi, ball) through a surrogate BCI system - a system, which resembled BCI in appearance and input behavior, but recognized input through blink recognition. The blink recognition gave ground truth access to user input attempts and was practicable for experimental designs in a rehabilitation setting because of minimal setup time and reduced complexity (no MI training) to reduce the risk of physical and mental fatigue of the patients. Similar to substudy 1, this within-subject study asked patients to rate perceived control and frustration in four conditions for two interaction types (kiwi and ball). The participants provided their informed consent prior to the experiment. The experiment was approved by the local ethical committee (N-20130081), and was in accordance with the Helsinki Declaration.

A. EXPERIMENTAL PROCEDURE

The study explored how stroke victims, in a within-subject experiment design, rated perceived control and frustration while controlling two surrogate BCI games using blinks captured by an eye-tracker (Tobii EyeX[2]). A therapist fetched each patient from their room, and was not further involved in the study. The participants were equipped with a MyndPlay band and were explained that they controlled the game by blinking in a specific way, similar to a previous study [8]. The participants played four conditions in the kiwi runner and the stress ball games in randomized order.

We manipulated user input for the purpose of creating a controlled experiment. In each game, the participants played four conditions: 50% real control, 50% real control +15% fabricated input, 50% real control +30% fabricated input, and 50% real control +50% fabricated input. Similar to substudy 1, real control was measured as % of input events (eye blinks) within an input window which led to positive feedback. Fabricated input was measured as the % of system-injected input events, which led to positive feedback. The conditions were visually distinguished by a random color, to make it easy for participants to recall and talk about them.

The questionnaire was identical to the questionnaire used in substudy 1. The facilitator helped reading the questionnaire to assist the patients and offered to fill in the questionnaire answers based on patients' verbal answers.

In each condition, players had 20 trials. The BCI games were designed to follow an interaction paradigm similar to substudy 1 (see Figure 1), but used a eye-blinks as the input modality.

B. SURROGATE BRAIN-COMPUTER INTERFACE

Both BCI games utilized the same urn model to roll between three possible outcomes. The three possible outcomes were: 1) activate on user input (acceptance), 2) ignore user input (rejection) or 3) fabricated input. Acceptance outcomes ended the input window and delivered positive feedback, for example making the kiwi jump or the ball squeeze. Ignoring the user input delivered negative feedback at the end of the input window, for example the kiwi walked through an obstacle slowing it down, and the ball blinked red. For fabricated input the system selected a random point to end the input window and deliver positive feedback, as if the user had activated it. If the user failed to perform a blink throughout the input window, the urn counted it as a rejected outcome and saved the drawn decision.

C. DATA ANALYSIS

The collected data included notes taken during the study, audiovisual recordings of the participants' game-screen, their face when performing the blinks, and answered questions in the debrief interview. Data from the input device and the BCI games were logged locally. We followed a similar approach as in substudy 1 in terms of data processing for quantitative and qualitative analysis, except that recognized attempts were now calculated from blink recognition.

D. PARTICIPANTS

Thirteen stroke patients were recruited for a within-subject experiment of all four conditions, five females and eight males with a mean age of 65 years (range: 34-87 years). The participants were recruited from the neurorehabilitation center (Neuroenhed Nord) in Brønderslev, Denmark. Three of the participants had experience with BCI (P1, P4, P12).

Table 5 lists the demographics and achieved input rates of all participants. Due to moving out of the eye-tracking range, three participants (P2-P4) missed inputs within a window and experienced only 40% control in terms of accepted blinks (one condition for P2 and P4, two conditions for P3) leading to lower positive feedback than designed. In addition, P4 remained out of the eye tracking range for a whole condition, resulting in 0% control in the 50% + 30% fab. input condition. We checked all analyses without the conditions, but found no differences in terms of the results, so the conditions were included in analysis.

VI. RESULTS: SUBSTUDY 2

A likelihood ratio test of linear mixed models with random intercepts by participant showed that positive feedback significantly increased perceived control and reduced frustration (see Table 3 and 5). Positive feedback and fabrication rates separately explained equal amounts of R_m^2 and R_c^2 variance in perceived control and frustration (relationship to fabrication rate visualized in Figure 7). Delays between blinks and fabricated feedback ranged from 0 to 4.4 seconds (see Table 5) but affected neither perceived control. Mean delay affected frustration significantly, but was not significant, when tested against a model which included positive feedback. Interaction type (kiwi vs. stress ball) and play order did not affect self-reports.

TABLE 3. The experimental conditions with added fabrication rates to a baseline of 50% successful task outcomes and the means of the participants' normalized frustration and perceived control ratings.

Control	Fab. Input	Frust.	Perc. Control
Kiwi			
50%	0%	0.51	0.54
50%	15%	0.33	0.60
50%	30%	0.29	0.74
50%	50%	0.15	0.87
Stress ball			
50%	0%	0.38	0.59
50%	15%	0.41	0.53
50%	30%	0.30	0.63
50%	50%	0.21	0.78

An intra-rater reliability analysis (ICC3, [64]) showed poor agreement [65] between participant ratings for perceived control (kappa = 0.26, $p < 0.001$) and frustration (kappa = 0.24, $p < 0.001$), which is lower than in a previous study using the same surrogate BCI [8].

Results from the thematic analysis of the debrief interviews revealed that all but four participants (P1, P10, P12, and P13) felt that the game was at fault for most of their experienced rejections. Two participants (P4 and P11) blamed it on the game cheating them, showing a lack of trust towards the game. One participant blamed the game because of feeling

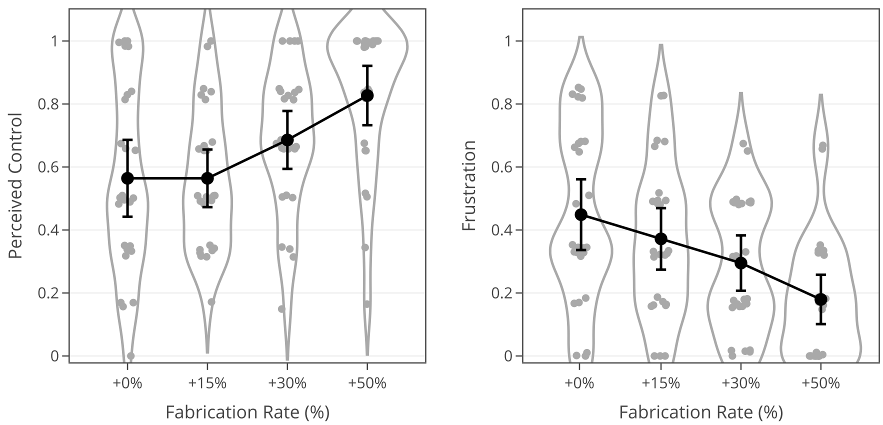

FIGURE 7. **Perceived Control and Frustration means (substudy 2), jittered for better visibility and their distribution (violin plots) by fabrication rate (the conditions) added to a 50% of actual control. Error bars denote 95% confidence intervals.**

protective towards their functionality in the brain. As P11 explained *"my nurse told me that my brain functions completely normal even though I've had a stroke, which convinces me that the game is cheating me"*. Not trusting the game influenced the frustration of two participants (P7 and P11): *"I am not that frustrated, because I just think to myself that it's the games' fault"* (P7). A couple of participants (P4 and P5) had a perceived learning curve when playing first with +0% fabricated input, and then with +50% fabricated input after, *"I have figured it out! Slow blinks work."* (P5). This has a connection to uncertainty of strategy as well, where several participants (P1, P2, P4, P5, and P9) were trying to figure out how to play the game, *"Do I need to press [my eyelids] harder for it [the game] to react?"* (P2) and *"Is it true that I need to blink more with my left eye?"* (P5). These comments mostly came after consecutive rejections, which made participants question their blinking approach.

VII. DISCUSSION

Fabricated input increased perceived control and lowered frustration in an online BCI study with healthy participants (substudy 1) and in a surrogate BCI study with stroke patients (substudy 2). Both substudies showed a strong negative Spearman correlation (r=-0.78 for substudy 1 and r=-0.62 for substudy 2) between perceived control and frustration (see Figure 8). This provided evidence that system-generated fabricated input can be useful in 1) surrogate studies with healthy and stroke participants, 2) surrogate and online BCI studies with healthy participants, and 3) in interactions both without (stress ball) and with a larger narrative frame in which progress to a larger goal was at stake (rescuing the kiwi's babies). In both studies, participants perceived their control based on positive feedback, rather than underlying control indications (MI rate, blink rate). Positive feedback rates predicted both perceived control and frustration linearly in line with previous work using binary, discrete feedback [8] unlike when feedback gets generated continuously and perceived control becomes independent from experiencing discrete, positive feedback events [66].

A. ONLINE VS. SURROGATE BCI

The online BCI study yielded similar ratings for perceived control and frustration compared to a previous surrogate BCI study [8] (see the intercepts (α) and slopes (β) for both variables in Table 6). While Hougaard *et al.*'s found that the variable delay from fabricated input reduced perceived control over stress ball squeezes in healthy participants [8] results from neither substudy showed delay-related penalties in perceived control or frustration. The random placement of fabricated events during the later parts of the input window did not significantly affect the experience for stroke patients and online BCI users. The reduced perceived control in that study [8] could be due to a violation of temporal congruency [54]. For the participants to be able to penalize a potential delay, they need to have access to ground truth to register the delay. While online BCIs introduce a constant delay from the used algorithm, which theoretically might appear variable, as users do not know whether and when their MI attempts passes the necessary thresholds, they do not provide access to the ground truth due to lack of sensory feedback. The surrogate BCI studies both past and presented here, concealed the ground truth by asking participants to blink in a specific way to make it more difficult for them to be aware if they succeeded.

In future studies, it would be interesting to investigate if similar ratings of perceived control and frustration can be obtained when using participants that are skilled in performing MI and may be more aware if and when they have performed it correctly. In this study only two participants were familiar with MI, although everyone performed a short MI familiarization session prior to the BCI calibration.

TABLE 4. Participant demographics and means averaged across the four conditions of frustration (Likert scale), perceived control (Likert scale), blink conversion rate (% of registered blinks within input windows which resulted in positive outcomes), blink recognition (% of unaltered trials which had registered blinks) and delay (mean delay between blink and positive feedback across all trials).

Variable	1	2	3	4	5	6	7	8	9	10	11	12	13
Gender	F	M	M	M	M	M	F	M	F	F	M	F	M
BCI Experience	Yes	No	No	Yes	No	No	No	No	No	No	No	Yes	No
Kiwi													
Perc. Control	0.92	0.46	0.67	1.00	0.58	0.88	0.58	0.67	0.46	0.71	0.79	0.62	0.62
Frustration	0.00	0.42	0.42	0.17	0.33	0.42	0.29	0.25	0.46	0.58	0.17	0.42	0.29
Blink Conv. Rate	45%	65%	89%	84%	46%	63%	70%	38%	48%	77%	49%	28%	50%
Blink Recognition	98%	100%	90%	90%	100%	100%	100%	98%	100%	100%	98%	100%	100%
Pos. Feedback	74%	74%	69%	71%	74%	74%	74%	74%	74%	74%	74%	74%	74%
Pos. Feedback Delay (s)	0.3	0.3	0.3	0.4	0.3	0.5	0.4	0.2	0.3	0.3	0.4	0.2	0.3
Stress Ball													
Perc. Control	0.87	0.46	0.46	1.00	0.67	0.83	0.46	0.75	0.71	0.67	0.71	0.25	0.38
Frustration	0.00	0.62	0.46	0.17	0.25	0.42	0.25	0.21	0.33	0.46	0.04	0.46	0.54
Blink Conv. Rate	37%	81%	31%	26%	28%	66%	43%	41%	30%	50%	36%	26%	33%
Blink Recognition	100%	92%	100%	75%	100%	100%	100%	100%	100%	100%	100%	100%	98%
Pos. Feedback	74%	71%	74%	61%	74%	74%	74%	74%	74%	74%	74%	74%	74%
Pos. Feedback Delay (s)	0.3	0.8	0.3	0.2	0.3	0.7	0.3	0.4	0.2	0.4	0.7	0.2	0.4

TABLE 5. Significant likelihood ratio test outcomes of predicting perceived control and frustration from 8 variables: blink rate, fabrication rate, delay, gender, game, condition, condition order and positive feedback rate. The table reports AIC (Akaike information criterion), BIC (Bayesian information criterion), ML (maximum likelihood), χ^2 (significance), R^2_m (marginal variance) and R^2_c (conditional variance). Significant variables were modeled with positive feedback as fixed effects, but no combinations were significant.

Predicted	Random Intercept	Fixed Effect	AIC	BIC	ML	χ^2	R^2_m	R^2_c
Perceived Control	Participant	Condition	-15.42	0.45	13.71	<0.001	0.17	0.50
Perceived Control	Participant	Fab. Rate	-16.51	-5.93	12.25	<0.001	0.15	0.49
Perceived Control	Participant	Pos. Feedback	-14.29	-3.71	11.14	<0.001	0.14	0.49
Perceived Control	Participant	Blink Rate	-6.89	3.69	7.45	<0.001	0.11	0.44
Frustration	Participant	Condition	-25.10	-9.23	18.55	<0.001	0.16	0.48
Frustration	Participant	Fab. Rate	-29.07	-18.49	18.53	<0.001	0.16	0.48
Frustration	Participant	Pos. Feedback	-27.32	-16.74	17.66	<0.001	0.15	0.48
Frustration	Participant	Blink Rate	-16.34	-5.76	12.17	<0.001	0.10	0.46
Frustration	Participant	Delay	-6.14	4.44	7.07	0.046	0.04	0.33

TABLE 6. Cross-study comparison of normalized results from substudy 1 and 2 predicting agency and frustration with results from Hougaard *et al.* [8].

Games	BCI input	Participants	Agency (α)	Agency (β)	Frustration (α)	Frustration (β)	ICC Score
Kiwi, stress ball	BCI (MI)	Healthy	-0.11	0.97	1.06	-0.88	0.25/0.28
Kiwi, stress ball	Blinks	Stroke	0.31	0.49	0.68	-0.50	0.24/0.26
Kiwi [8]	Blinks	Healthy	-0.03	0.72	0.90	-0.64	0.31/0.36
Stress ball [8]	Blinks	Healthy	-0.07	0.92	1.09	-0.78	0.72/0.78

B. PERCEIVED CONTROL AND FRUSTRATION IN STROKE PATIENTS

Stroke patients in substudy 2 reported having more control over the kiwi and stress balls and were less frustrated than healthy participants with the same number of successful outcomes in a study using eye-blink surrogate input [8] (see Table 6). The differences were mostly due to stroke patients having higher baselines (intercepts) of perceived control (and lower frustration) than healthy participants. In return, the ratings of stroke patients did not change as much as those of healthy participants [8] when positive feedback increased (see Table 6).

Stroke patients did not penalize delays between intention and system output as much as the healthy participants in the surrogate BCI. Due to their age, the stroke patients may have lower expectations to the technology due to their presumable reduced exposure to computer interaction in general compared to the healthy participants in in Hougaard *et al.*'s study [8]. However, this is just a speculation that has not been tested.

Moreover, potential cognitive impairments such as spatial neglect, and deficits in magnitude estimation, self-awareness or abstraction ability can confound the validity of self-reported measurements from stroke patients [67]. Stroke patients may face low self-awareness [68] and therefore may not want to articulate any frustration that they actually feel in fear of acknowledging their own deficit. Physiological measures such as galvanic skin response could potentially complement the self-reported measures.

In substudy 2, an intra-rater reliability analysis (ICC3, [64]) across kiwi and stress ball showed poor agreement [65] in ratings for perceived control (kappa $= 0.26$, $p < 0.001$) and frustration (kappa $= 0.24$, $p < 0.001$) than in a previous study using the same surrogate BCI approach and interactions [8]. Comments from some of the stroke patients indicated that special attention to wording and explanation is necessary to avoid measuring ill-defined constructs.

P11 was not frustrated over a bird not jumping inside a game, as they mentioned, *"It is not frustrating at all. The bird can decide for itself if it wants to listen or not"*. The number of stroke participants was fairly small for the findings to be representative for the entire stroke population, which is very heterogeneous. Future studies should investigate how fabricated input modulates perceived control and frustration in patients with varying cognitive impairments.

C. STUDY LIMITATIONS

Both studies increased the external and ecological validity over previous work [8] but yielded lower experimental control. In substudy 1, we used online BCI instead of surrogate BCI in a study with healthy subjects. This introduced variable input and blocked analytical access to the ground truth. Although we could measure MI rate from the participants, it could have contained false positives and negatives and thereby not accurately reflecting intentional user input attempts. Hence it might be reasonable to expect how the MI rate only explain a low amount of variance (28% R_m^2) in users' ratings of perceived control. From an experimental design point of view, the benefits of using surrogate BCI includes allowing for *known-groups validation* [69] for example by measuring a well-known construct such as 100% control known beforehand to be distinct. The participants, many without prior MI experience, described trying various other approaches when they realized MI did not work consistently, including focusing on the fingertips or clenching their stomach; this could reduce the actual MI recognition rate. The low rater reliability could potentially be improved by including reference conditions with 100% or 0% control as anchoring points for the Likert scale ratings of the perceived control and frustration (e.g. see Hougaard *et al.* [8]). In real-life rehabilitation scenarios, high levels of input fabrication could be counter-productive and degrade rehabilitation outcomes if they hindered learning of MI and produced weaker sensory-motor rhythm patterns [52], [53]. But motor cortical activity through MI is an integral part of inducing neural plasticity [3], [28], [70]–[72], and fabricated input would only serve to improve the patient's agency and frustration to maintain sufficient engagement and motivation in the rehabilitation. Lastly, the use of fabricated input is likely most relevant for BCI applications within neurorehabilitation for inducing plasticity or binary input tasks in synchronous BCIs with pre-defined input windows. Because it would not be possible to predict what type of fabricated input would be relevant, and when to inject it, in BCI applications for communication and control purposes such as wheelchair control, cursor movement, and speller devices.

D. IMPLICATIONS

This study showed that fabricated input can be used to improve perceived control and frustration in online and surrogate BCI use in healthy participants and stroke patients, and that it can be concealed without being noticed by the user. This simplifies the implementation of fabricated input in systems with time-bounded input windows (five seconds in our studies) as designers do not need to worry much about delays between randomly system-injected inputs and the most recent unrecognized MI attempts. Especially in BCI systems in which 1) processing and aggregation delays can be quite high (0.5 seconds in substudy 1), 2) participants are meant to maintain imaginary movements until recognition, and 3) triggering MI-BCI lacks proprioceptive and somatosensory feedback.

The fabricated input could be implemented in task realistic training, for example for grip strength with a stress ball and in a game context with a narrative. The results from the studies did not indicate group-level differences in perceived control or frustration based on the game or simple task, but participants indicated individual preferences during interviews. This provides evidence that in these interactions participants evaluated frustration in relation to their ability to affect change rather than the bigger goal or that the provided narrative framing was not strong enough to affect their frustration.

In both surrogate BCI and online BCI, most participants preferred the kiwi game to the stress ball (8/13), but the MI contractions felt more natural when squeezing the ball than making the kiwi jump. Designers can integrate fabricated input in BCI-based training to reduce frustration and maintaining patients' engagement for patients with low BCI performance (<65% recognition rate) as for patients with higher performance fabricated input might lead to a reduction in

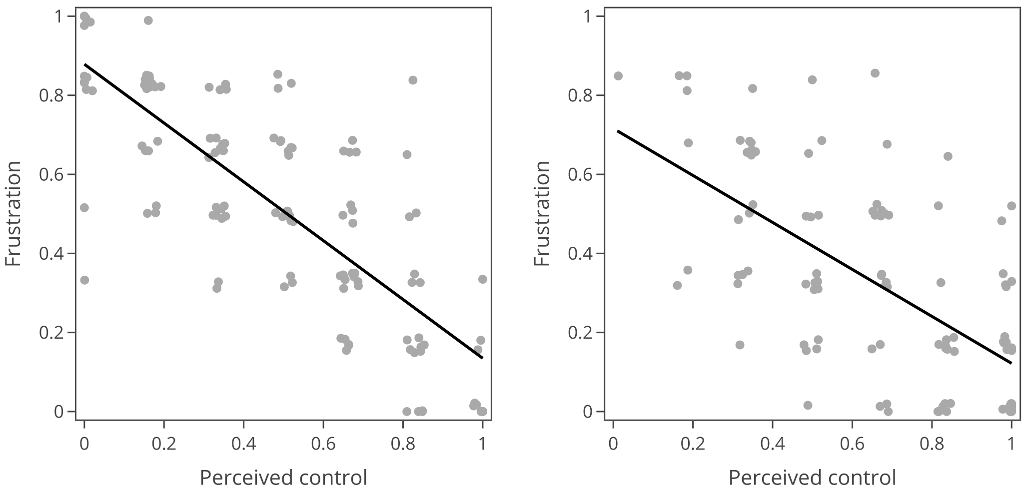

FIGURE 8. **Perceived control to frustration for substudy 1 (left) and substudy 2 (right).**

their ability to perform MI [38], [52], [53]. Other avenues to increase BCI users agency include leveraging realistic feedback rather than abstract representations [73] and continuous instead of discrete feedback depending on the preferences of the learner [48]. These concepts can be combined with fabricated input to dynamically modulate perceived agency and to some degree frustration depending on the user's performance. This could for example be different games and potentially introducing multiplayer experiences with other patients to motivate them to train more.

VIII. CONCLUSION

Fabricated input can be implemented in online MI-based BCIs and in surrogate BCI studies to reduce frustration and increase perceived control of healthy and stroke participants. Stroke patients reacted not as much to the variations in fabricated input as healthy participants which could be due to differences in expectations to the technology/interaction. For discrete, binary input the rate of positive feedback linearly moderates both the perceived agency and frustration. From an experimental point of view, surrogate BCIs are useful since they provide access to ground truth and reduce the effect of confounding factors to isolate the factor(s) under investigation. Lastly, fabricated input work, at least for binary input, both in game and non-game contexts, allowing developers to promote patient training by concealing monotonous and repetitive training regimes through game contexts. Future studies should investigate the reasons for these differences with larger patient groups and varying cognitive impairments.

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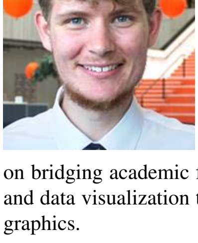

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