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Brain–computer interfaces as an architectural design tool: Feasibility and usability study

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ABSTRACT

The applications of brain-computer interfaces (BCIs) for ideation scenarios in architectural design have not been widely explored. In this paper, a BCI tool was developed and tested with the goal of enabling architectural designers to manipulate the placement and dimensions of windows in a virtual-reality room through the use of self-selected body movements. Usability tests, followed by semi-structured interviews, were conducted to investigate the accuracy of the BCI, the cognitive loads experienced by users, and their subjective reactions to the tool. The findings revealed that a wide range of online binary accuracy (41%–86%) was observed among different participants when the BCI was utilized. The tool was enthusiastically received by the participants, who described it as a rewarding and creativity-enhancing approach. The main challenges reported were high mental loads and confusing visual feedback, both of which may be addressed by future technological adjustments.

1. Introduction

Most computer-aided design (CAD) systems rely on interfaces that use a Window, Icons, Menus, Pointer (WIMP) modality [1]. Empirical research indicates that such interfaces can impede design creativity when compared to traditional approaches such as sketching [2,3]. One commonly noted concern is that WIMP interfaces can influence designers to focus excessively on details and neglect the big picture [4,5]. Other researchers have noted that WIMP promotes premature design idea fixation and may constrain designers' capability for innovation [6]. Because of these constraints, CAD systems are often discouraged in conceptual design and are instead reserved for the later stages of design details and manufacturing [7].

Theories of design thinking and creativity often highlight the importance of design iteration, which is to say, repeated cycles of idea generation and evaluation [8–11]. In this process the time period between idea generation and idea evaluation is crucial. The WIMP-based modality is susceptible to lengthy delays and distorted feedback during this iterative cycle, as it can take a great deal of time to express a design idea in such systems. Hutchins's direct manipulation theory suggests that tools for conceptual design should seek to minimize the gulf of execution, which is the mental gap or delay that occurs when computer users have to translate their intentions into linear and sequential machine-understandable commands [12]. A significant gulf of execution will lead to high latency between idea-generation and realization, interrupting the intuitive process of design feedback. An additional concern in WIMP-based systems has been described as the gulf of evaluation, which is the mismatch between computer-generated visual feedback and reality. The 2D displays typically used in WIMP-based design tools have a high gulf of evaluation compared to VR systems. This is particularly true in architectural design contexts, where information about depth, scale, and first-person experience are important and are often poorly relayed by two-dimensional representations [13].

Virtual Reality (VR) technology has advantages in providing high-fidelity and immersive visualization of space as well as rapid, intuitive interactions, which could shorten the gulfs of evaluation and execution. As a result, VR is increasingly being used in design prototyping, evaluation, and education [14–16]. A recent review paper summarizing the benefits of VR in the design process emphasized its ability to provide more accurate spatial perception, an increase in creative motivation, and a greater sense of presence [17]; and another recent study found that VR was easier to use during early-stage design ideation compared to current WIMP-based CAD tools when creating voxel-based models [18]. Those studies suggest that VR will continue to play an increasing role in design over the upcoming decades, which motivated us to develop and

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test our BCI design tool in a VR context.

Recent developments in the area of brain–computer interfaces (BCIs) have the potential to provide an alternative to the use of WIMP systems. In BCIs, sensors measure users' brain activity and thereby enable mental control of the system's output, either through voluntary commands or through measuring involuntary neural reactions [19]. BCIs could potentially benefit the architectural design process by enabling a more natural and intuitive translation between designers' intentions and CAD outcomes, without the need for menus and pointers. The goal is to shorten the iterative feedback loop and support more fluid and creative design ideation. While BCIs have been developed for use in a variety of applications, we found few studies exploring the possibilities of this approach in design fields. Thus, in the current work, we develop a prototype BCI for use by architectural designers. This early-stage system, which we called MindOpen, allowed the user to adjust the shape, size, and position of a window on the wall of a room by thinking. We conducted a feasibility and usability study of the system with a focus on the following questions:

- What are some of the challenges and concerns that arise when developing a BCI tool for architectural design?
- Will designers who have no prior experience with BCI tools find this approach amiable, and will they view it as potentially useful in their practice?
- How effective will the tool be in allowing designers with no prior BCI experience to accurately implement their design decisions?
- Which tasks within the design process are well-suited for the use of BCIs, and how might these tools be positioned to best augment existing CAD-based design workflows?

2. Related prior work

In evaluating the existing literature on BCIs relevant to architectural design, we identified three broad categories of studies that seemed highly relevant to the current research. First, *classification* research includes studies on brain activity features that have been previously used to identify human experiences of shapes and colors and to manipulate objects using BCIs. Second, *application* studies have explored the use of BCIs in artistic and entertainment contexts adjacent to architectural design. Finally, *user* studies provided insights into how we might enhance the subjective experience of engaging with BCIs, and how such outcomes can be measured. These categories of research are presented respectively in the following sections.

2.1. Classification studies: shape and color identification from EEG

The architectural design process involves intense mental imagination and manipulation of geometric shapes. BCI tools can thus potentially benefit from the use of EEG signals to distinguish between different mentally visualized shapes. A few prior studies have demonstrated that such categorizations are possible. Starting with primitive shapes, Esfahani and Sundararajan [20] asked participants to imagine a cube, sphere, cylinder, pyramid, or cone. The BCI was able to correctly identify the imagined shape with an average of 44% validation accuracy (range: 36–54%), much greater than the random chance of 20%. A similar study by Llorella et al. [21] was able to classify seven shapes—circle, square, hexagon, straight line, parallelogram, triangle, and pentagon—with validation accuracy of 35.14% (range: 25.23–44.06%), with a chance level of 14.3%. When evaluating only two shapes, this study reached a validation accuracy of 69.57% (range: 53.64–81.15%). Combining shapes with color, Bang et al. [22] classified a red circle, white cross, yellow horizontal line, blue triangle, cyan plus shape, and green vertical line (chance level of 16.6%)—and were able to reach an overall average decoding accuracy of 32.56% (range: 27–43%) using convolutional networks. Bose and colleagues [23] used a BCI to identify shape-analogous letters between pairs (p q b d, chance level of 50%) and achieved an average classification accuracy of 86.41 for all 2-class problems. Kosmyna and colleagues [24] trained a BCI to distinguish mental responses to more complex shapes: a flower vs. a hammer, with an average accuracy of 55% (range: 48.06–71.53%), which is only slightly better than 50% random chance. While these classification studies demonstrated the potential of using mental visualizations of shapes for BCI control, their accuracy is still fairly low, and few studies have reported online (real-time) BCI performance based on the visualization of shapes, leaving its applicability in real-life scenarios a bit uncertain.

A better-established approach to the control of BCIs, which we adopted in the current study, involves the use of motor imagery. In this technique, users are asked to visualize moving parts of their bodies (e.g., imagined hand or foot motions) [24] as a means of sending commands to the interface. Accuracy rates in these interfaces are generally higher compared to those based on the visualization of geometric shapes, and there is more robust literature with positive findings for online performance. For example, in a study conducted by Lafleur [25], participants imagined motions of their left or right hands to control the direction of a quadcopter drone. The classification accuracy in Lafleur's study ranged from 69 to 90%, and 82.6% of the participants successfully moved the drone to the target. Other BCI studies using the motor imagery approach have reported task completion rates as high as 94.2% [26]. Since this literature has provided evidence of high reliability for motor-imagery-based BCIs in real-world scenarios, we decided to pursue such an approach for our design-related controls, rather than evaluating mental imagery directly.

Some researchers have suggested that evaluating diverse mental activities and applying user-centered training methods may have the potential to further improve the performance of BCIs [27]. In the current study, we took this approach by asking the users to define relevant mental actions as their imagined motor engagement with a shape (for example, crushing a tin can, or pulling a curtain to the side). While we told the participants that their selected imagery should be related to some form of body movement, we did not impose a specific predetermined motor image for each interface command. Allowing each participant to define the mental tasks that they would associate with each design action is a novel approach, which we believe can enhance both the performance of the BCI and the overall user experience. We theorized that such user-defined visualizations would be more completely envisioned and more cognitively salient compared to external, researcher-defined tasks, and would therefore lead to a greater classification accuracy of the associated neurological signatures.

2.2. BCI applications in entertainment, art, and environmental control

In reviewing the prior literature, we found that there was little BCI research specific to design workflows, but there were many applications of BCIs in design-related areas such as creative expression and video games. For example, in prior studies BCI users have been able to engage in an electronic ping-pong game [28], in creating a painting [28], and in a "Connect Four" game [29], using only EEG-measured brain activity as the interface. While those prior applications have mostly been tailored for users who have difficulty moving their limbs, the fun and motivational qualities of BCI interactions could potentially be beneficial for non-disabled users as well [29]. Most especially for our research interests, this prior work on BCIs in creative areas has shown the effectiveness of such interfaces for the rapid and intuitive manipulation of shapes, which can potentially be extended to decreasing gulfs of execution and evaluation in design.

We also found interesting prior work on the use of BCIs for manipulating responsive built environments, which has the potential to improve the ability of our homes and workplaces to become more adaptive to the ebb and flow of everyday human needs. For example, Kovacevic and colleagues enabled participants to change the interior atmosphere of a dome by voluntarily alternating between relaxation and concentration [30]. Other researchers have used brain activities to adjust the heights of panels on a ceiling [31] and to introduce ambient stimuli to modulate occupants' alertness levels [27]. While these studies may be considered tangentially related to design processes, we found only two prior publications that directly investigated the application of BCI in design work. Barsan-Pipu used the variable of neurological arousal, operationalized by alpha band power, as a means of prompting designers to explore innovative and unconventional ideas [32]. Shankar developed a BCI design tool that enabled users to model 3D objects through brain activities generated by different facial expressions [1]. Sharing the same basic concept as Shankar's study, our research expanded the BCI potential for fluid interaction with a design space and located that interaction within an immersive VR environment.

2.3. User experiences of BCIs

While much of the current research in BCI development is focused on improving the accuracy of the technology, it is also important to study the related human factors, including how individuals may adapt to BCIs over time (or vice-versa), and how the use of BCIs may fit into existing workflows. Prior research has shown that psychological or affective factors such as current mood, interest in the technology, or nervousness about the technology can affect an individual's accuracy when using BCIs [33,34]. Some studies have also shown that long-term cognitive features or personality traits, such as spatial abilities, feelings of self-reliance, and learning styles, may have a significant correlation with the ability to effectively use BCIs [35–37]. Other researchers have examined learning curves during the sustained use of BCIs, generally finding that accuracy improves over time, but at different rates for different individuals [1]. While there has not been extensive research into user experiences of BCIs, the findings of these prior studies suggest that different users may have a wide range of positive or negative reactions. Botrel [38] is one of the few researchers who has developed a system for rating BCI user experiences. This system includes self-reported measures of cognitive task load, satisfaction, and feelings of control. To the best of our knowledge, there have been no prior studies entailing subjective feedback from designers about the experiences of using BCIs as a design tool. In the current study we collected such feedback, largely following Botrel's measurement approach.

2.4. Research opportunities

Non-invasive BCI applications have created intriguing external visualizations of brain signals, and they are increasingly incorporating the means to customize the relationship between specific neural signals and specific output. However, we argue that some of these BCI interactions can be counterintuitive due to limited mental strategies for BCI control [24] and pre-determined, arbitrary associations between certain brain activities and BCI outputs. For example, limited by the built-in programming interface of EEG headsets, one common system maps motor activities such as looking to the left to commands such as "draw an arc" [1]. Another approach refines brain control by making graphic icons flicker when the user intends to select the command [39]. Such BCI modalities can have tremendous utility, particularly for disabled individuals, but they are still largely embedded within the point-and-click paradigm of WIMP-based interaction, and they do not meet our research goal of directly implementing design visualizations. The use of state-of-the-art EEG classification approaches may open the door to more natural and intuitive BCI interaction by linking design commands with customizable, user-specific mental visualizations [13].

Furthermore, by integrating such approaches with virtual-reality immersion, we hypothesize that designers may be able to work more fluidly within the three-dimensional design space itself. This approach to combining BCI with virtual immersion has the potential to provide high-fidelity feedback to architectural designers while shrinking both the gulf of evaluation and the gulf of execution (Fig. 1). Recent studies support the use of VR as a design development and research tool, showing that human behaviors and responses in such environments are reasonably comparable to how people react to design factors in real-world contexts, especially when contrasted against traditional 2D visualizations [40,41,42]. Architectural design is distinguished from other scenarios such as industrial design because it centers human perceptual reactions to space [43]. In this context, we believe that research into a streamlined BCI-VR approach to architectural design will enable fluid spatial feedback to enhance creativity and innovation.

The current study contributes to the development of this vision and the overall CAD community in several important ways. First, it demonstrates the novel approach of mapping individual users' preferred BCI imagery to corresponding design implementations. This creates a much more fluid experience for designers compared to existing BCI systems; for example, the design action of "move up" will be triggered by motor imagery thought related to "moving up" rather than by a certain pattern of eye blinks. Second, the use of a closed-loop BCI allows users to receive immediate, high-fidelity visual feedback on their design decisions within a three-dimensional virtual workspace, which is a vast improvement over 2D workflows. Finally, our interview feedback provides insights into user-experience concerns in the ongoing pragmatic development of BCI-based tools in the field, along with suggestions about how the use of BCI may best be integrated into design practice.

3. Designing the BCI design tool

Our goal in developing the BCI tool was to focus on a simple yet pragmatically important architectural design task. This task should

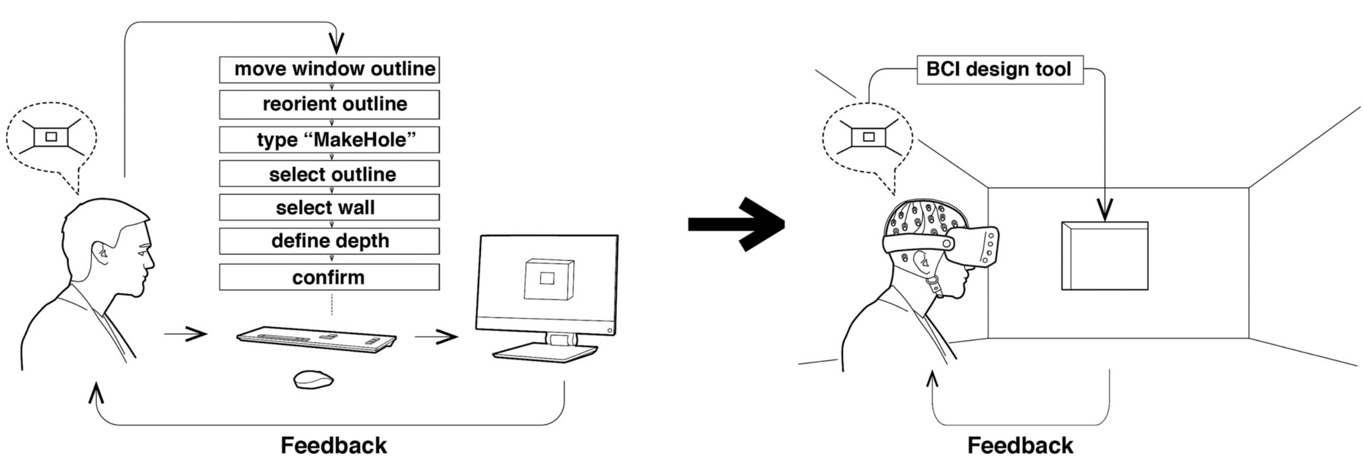

Fig. 1. Shortening the feedback loop of WIMP-based CAD tools by using BCI-VR.

require complicated steps to implement using WIMP-based CAD interfaces. It should cover a diverse array of CAD commands, while also being precise in its scope. Based on those considerations, we decided to start with the task of “adding a window to a room” as an initial representation of the architectural design process. Window designs can have highly consequential impacts on the atmosphere of architectural spaces, and they have been correlated with human health, work performance, and energy consumption, among other important outcomes [44,45]. Thus, fitting a window to a space is a non-trivial design endeavor. In addition, the process of adding a window using traditional CAD tools is rather complex, and the full effects of the window design and its related lighting impacts may be difficult to discern from traditional 2D plans, elevation views, or renderings. Considering these limitations of traditional CAD approaches, we designed MindOpen, a BCI-VR tool to create windows.

We further simplified the context by considering only three parameters of the window: its geometrical shape, its size, and its position on the wall. MindOpen allows users to manipulate these parameters by simply thinking about customized visualizations while immersed in a VR environment from a first-person perspective (Fig. 2). There are a total of ten actions that can be taken through the BCI to adjust the window; these actions are: create a rectangular window, create a circular window, move the window up, move the window down, move the window left, move the window right, stretch the shape horizontally, compress the shape horizontally, stretch the shape vertically, and compress the shape vertically (Fig. 3). Those ten actions overlap with three standard categories of commands (creation, navigation, and manipulation) in CAD software [46]. In MindOpen, the users were able to select their own customized mental visualizations for each action, with the instruction that these visualizations should include imagined motor action. For example, one user chose to imagine “crushing a can with both hands vertically” to compress the window vertically. To classify the neural signals associated with each of these visualizations, MindOpen used a machine-learning process tailored to each participant, as discussed in the following section.

4. Methods

4.1. Hardware and software setup

MindOpen consists of an EEG headset, a VR headset, and a combination of commercial, open-source, and custom software. EEG data were collected using a non-invasive, 128-channel, gel-based Actiview System (BioSemi Inc., Amsterdam, Netherlands) with Ag/AgCl active electrodes. An HTC Vive virtual-reality display headset was worn on top of the EEG system (Fig. 2). We used an open-source BCI platform called Openvibe [47] to acquire real-time EEG data and transfer the results to Matlab through the Lab Streaming Layer [48]. Matlab was used to preprocess the EEG data and train the participant-specific machine-learning model. Once the classification model was established, Matlab was used to analyze neural signals associated with users’ motor imagery and send those results to the Unreal Engine in User Datagram Protocol (UDP) format. The Unreal Engine v.4 enabled us to create a high-fidelity, immersive virtual environment to display the design outcomes in real time.

4.2. Participants

To evaluate the performance of the MindOpen system and the experiences of its users, 21 healthy human adults with normal or corrected-to-normal vision were recruited using a convenience sampling method (word-of-mouth and announcements on departmental e-mail lists). Nine of the participants reported as male and 12 as female. The participants’ ages ranged from 18 to 32 ($M = 22.43$, $SD = 3.87$). Since BCI could potentially help to democratize design by lowering technological training barriers, we were interested in evaluating the use of the tool by individuals with a range of professional experience. Our sample included 13 participants who reported no professional design experience, 5 participants who reported having one to three years of professional design experience, and 3 who reported having more than three years of professional design experience. Fourteen of the participants indicated that they had no prior experience using BCI interfaces, while 5 reported having used BCIs one to three times, and 2 reported having used BCIs more than three times.

We did not measure the BCI online accuracy of the first eight participants, because at the time we believed that the system would need additional fine-tuning. However, the informal feedback during this stage was positive, so we decided to continue with the testing without any changes to the system. Thus, the results reported for online accuracy are based on the final 13 participants, while the results of the user experience metrics and interviews include all 21 participants. Among the 13 participants whose data were used to evaluate online accuracy, 10 reported having no design experience, 2 reported having one to three years of design experience, and 1 reported having more than three years of design experience.

Each participant gave informed written consent before participating in the experiment, and the overall study protocol was approved by the Institutional Review Board at **[Deleted for blind review]** before the

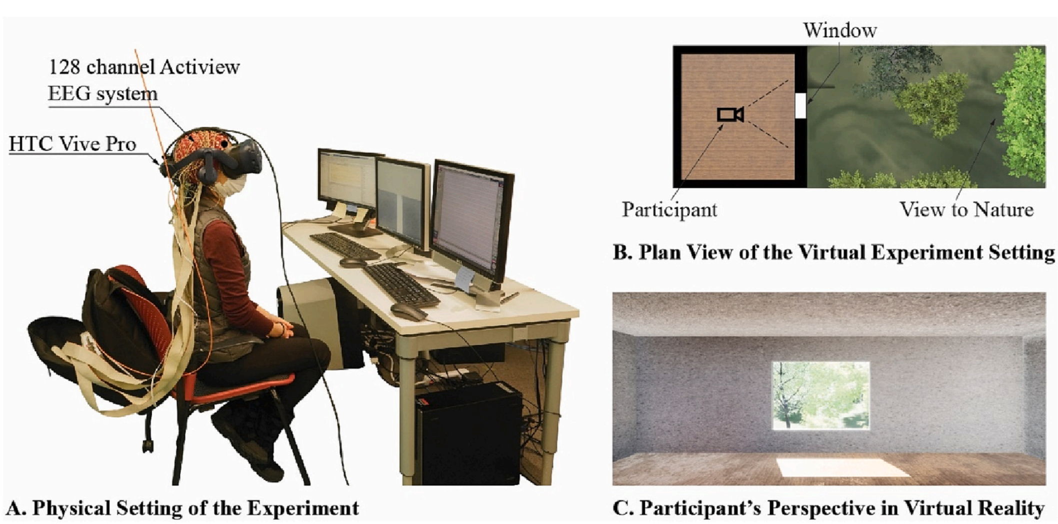

Fig. 2. Physical and virtual setting of the experiment.

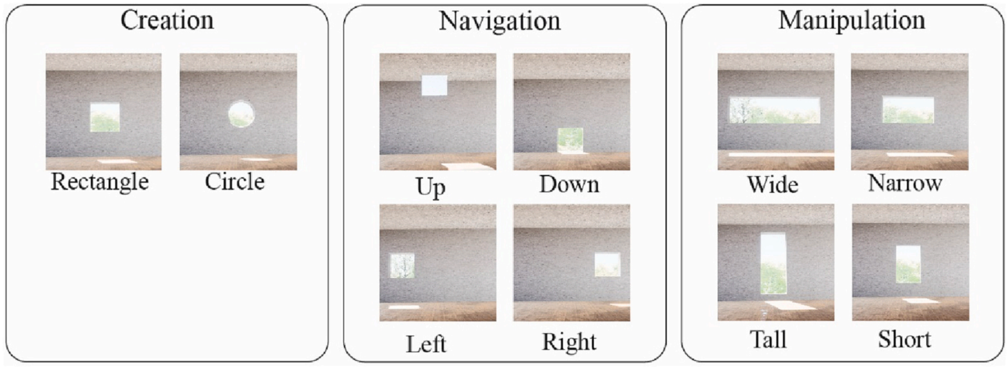

Fig. 3. The ten design actions of the MindOpen BCI tool.

start of research activities. All of the experiment sessions took place at the same physical location in **[Deleted for blind review]**.

4.3. Experiment procedure

Sessions were conducted with one participant at a time and involved a three-stage process (Fig. 4). In the initial setup stage, participants filled out the consent form and a demographic survey. They were then fitted with the EEG cap, followed by the VR headset (worn on top of the EEG cap). After mounting the VR headset, the researcher examined the signal quality to confirm that there were no bad channels. The participants were aware of the goal of the experiment and were told that they would be attempting to design a window using their thoughts alone, via non-invasive EEG technology that responded to their neural activity. A researcher assisted with the equipment setup process and ensured that each participant was comfortable.

The second stage involved exposing participants to the VR environment and completing the machine-learning process so that the BCI could evaluate their neurological responses. The attending researcher first explained to the participants the ten window transformations they would use their brains to control, and participants were instructed to create mental visualizations to associate with these ten transformations. The researcher also provided some common examples of motor imagery and visualization and gave instructions about how to create effective motor imagery (consistency, duration of the imagery, and embodiment) [49]. After receiving these instructions, the participants were placed into a white VR preparation room and asked to sit quietly for one minute with eyes open so that the system could collect baseline EEG data.

To complete the BCI training, the participants were then moved into another virtual room facing a solid wall with a rectangular window, overlooking a nature scene. Their position in the environment was fixed; that is, the participants could not move around the virtual room. The researchers verbally confirmed that participants had finished conceiving their mental visualizations (described in the supplementary material), and then asked them to attend to the window as the BCI learned about their mental responses. During the training, the window spontaneously moved through a series of transformations, in a pseudo-randomized sequence, and the participants were asked to perform their self-conceived mental visualization associated with each transformation. (The sequence of transformations was randomly intermixed to avoid block-level temporal correlations [50].) This process continued until each of the ten transformations had been shown three times, followed by a one-minute rest session with eyes closed. Then the training continued until each of the ten transformations had been shown additional two times. Finally, we asked the participants to rest in the virtual white preparation room while we completed the machine-learning process in Matlab, which will be discussed in more detail below. The total duration of the training stage was about 20 min for each participant.

Five two-class machine-learning models (two for navigation, two for manipulation, and one for creation) were trained from this EEG data.

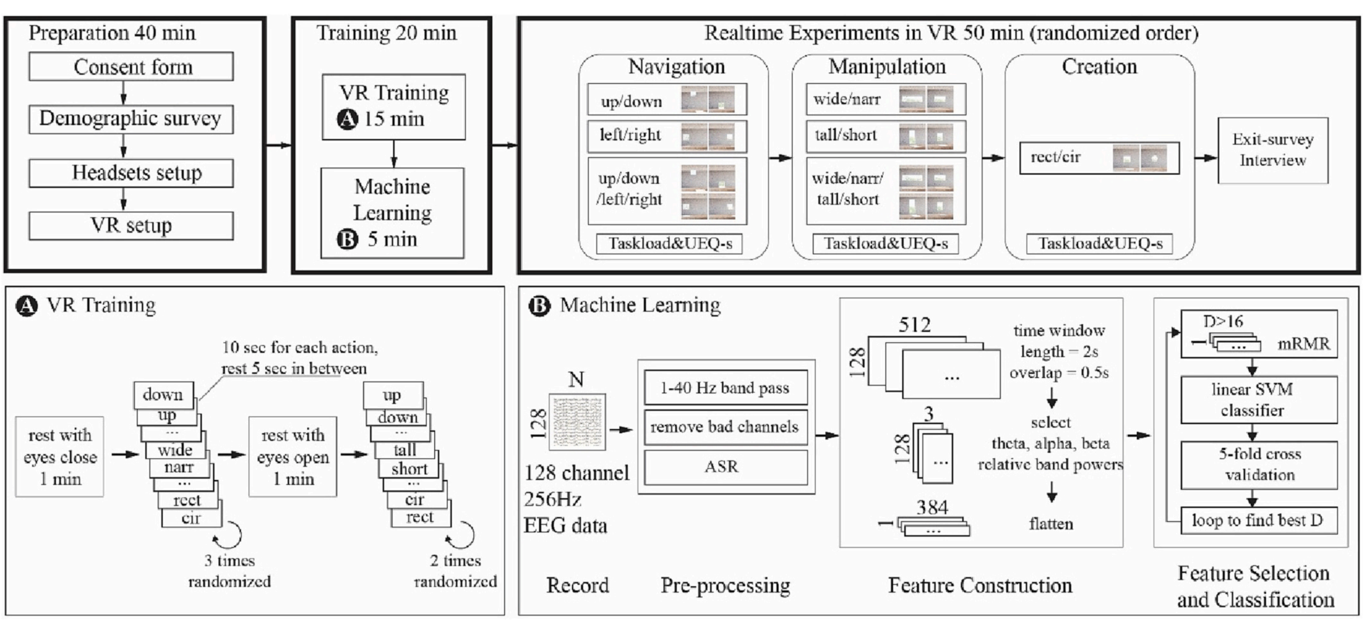

Fig. 4. Experiment protocol and machine learning pipeline.

The two-class models included: (1) navigation up vs. down, (2) navigation left vs. right, (3) manipulation wide vs. narrow, (4) manipulation tall vs. short, and (5) creation rectangle vs. circle.

Finally, in the third stage of the experiment, the participants were asked to experience each of the seven models in a randomized sequence and to use each of the commands in that model. This “online” stage took place in the same overall virtual room as the training sessions. During the “navigate” and “manipulate” sessions, we started with a pre-existing window, and the participants were asked to adjust it using the available commands via motor imagery. In the “creation” sessions, we started in the same room without any windows, and the participants were asked to create a rectangular or circular window. Between each session, the participants were asked to complete measures of cognitive task load and interaction quality.

Because humans can’t voluntarily stop generating brain activity, when participants needed to take a break and didn’t intend to control the windows, the model would continue to output chaotic results. This is commonly known as the “Midas touch problem” in BCI research [51]. To avoid it, the participants in our study held a controller on which they could press a single button to pause or resume the BCI input.

After the completion of the experiment, the researchers assisted the participants with removing the VR headset and EEG cap, and then immediately conducted an exit interview to discuss experiences with using the BCI. The total duration of this third stage was approximately 50 min for each participant.

4.4. Evaluation of the online BCI classification accuracy

Online classification accuracy is an important metric for determining the effectiveness of BCI applications. During the online sessions, participants engaged in each instruction task for 30 s, attempting to modify the window using a predetermined mental command. The BCI refresh rate was 2 Hz, that is, two refreshes per second, which created a total of 60 possible classification outcomes for each instruction task. Outcomes that corresponded to the intended command were identified as successes, and the accuracy was determined by the ratio of successes to total attempts. After each 30-s task, participants were instructed to move on to another command regardless of success or failure (Fig. 4).

4.5. Machine learning classifier

Raw EEG data were recorded at 256 Hz during the training session. At the end of the training session, these data were preprocessed and put through the machine-learning pipeline in Matlab. The preprocessing was conducted to bandpass the preferred frequency band (1–40 Hz), and remove bad channels that had poor contact with the scalp. We applied Artifact Subspace Reconstruction (ASR) [52] to remove noisy channels and artifactual power bursts (SD-threshold = 15). We also visually inspected the data to remove EEG spikes caused by motion artifacts such as blinking, clenching, and body movements, to help further reduce the impact of these actions on the machine-learning model. During the subsequent stage of the experiment when participants attempted to use the BCI to adjust the window design, the EEG data were filtered between 1 and 40 Hz. The ASR algorithm was not used during these online sessions because it introduced excessive lagging in the online performance.

For each of the 128 EEG channels, we extracted the power in three frequency bands: theta (4–7 Hz), alpha (7–15 Hz), and beta (15–30 Hz), yielding a total of 384 frequency band-power features. These features were collected in time windows of 2.0 s, with 0.5 s overlap. Since the duration of each visual transformation was fixed during the training session, the time segments used were identical for all participants.

For analysis purposes, we used five trials, each of which compared two different visualization commands: (1) up vs. down, (2) left vs. right, (3) wide vs. narrow, (4) tall vs. short, and (5) rectangle vs. circle. For each of these trials, we used the Minimum Redundancy Maximum Relevancy (mRMR) algorithm [53] to select the most salient features out of the 384 that we collected. We defined the minimum number of selected features as 16; this relatively large minimum helps to increase the robustness of the subsequent real-time performance as the data of any single channel could be affected by unpredicted events such as body movements from the user. The optimal number of features (above 16) to make each classification was selected by 5-fold cross-validation, looping iteratively using 4 trials to train a Linear SVM classifier and 1 trial as the validation set. As described in the previous sections, this machine-learning process was conducted separately for each participant, thereby allowing them to choose their visualizations and optimize the BCI for individual cognitive factors [27,54,55].

4.6. Rationale for machine learning model selection and time-window length

A classical machine learning classifier such as the linear SVM is a good candidate for the automatic identification of predefined EEG frequency band-power features. SVMs have been extensively used for EEG classification [56–58], often outperforming other machine learning algorithms. Preliminary trials with training and validation sets from the first few participants showed that both a kernel-SVM with the polynomial kernel of degree two, and the linear SVM performed well. We decided to continue with the simpler algorithm, the linear SVM, to improve potential generalizability.

The time window of data to analyze is a hyper-parameter to optimize. Time windows of 2 s have been used successfully to decode EEG data in prior motor imagery studies [59–63]. Often in BCI paradigms, a time window of 1 s is preferred [56,64,65], but this window is contingent upon the specific type of experimental task. Longer time windows of 4–6 s are often implemented to identify creative action planning and execution, especially when using functional connectivity features in conjunction with band-power features [31,66,67]. Such longer periods are also common when studying navigation in an environment under different design conditions [68,69], and in motor imagery classification paradigms with complex features [70,71]. In this study, a 2-s time window was selected to optimize the number of data points to obtain for online classification, minimize the delay between intended command and execution, and have enough data to achieve accurate performance.

4.7. Outcome measures

BCI performance was measured by offline 5-fold validation accuracy, as well as by online performance accuracy as discussed in section 4.4. To obtain quantitative measures of user experience, we relied on the NASA Task Load Index (NASA-TLX) [72] and the short version of the User Experience Questionnaire (UEQ—S) [73]. The NASA-TLX assesses subjective workload associated with human–machine interfaces; it contains six subscales: mental demand, physical demand, temporal demand, performance, effort, and frustration. The UEQ-S assesses the quality of interactive products; it is divided into three “pragmatic” subscales (dependability, efficiency, and perspicuity), along with two “hedonic” subscales (stimulation and novelty). We used the short version of the UEQ-S since it has been found to approximate the full version relatively well and is preferred when participants have to complete the scale multiple times, as is the case in our experiment [73]. In addition to providing a quantitative overview of participants’ responses to the BCI, using these scales multiple times allowed us to compare responses after each category of design commands (move, manipulate, and create) to determine if any of these three types imposed a higher task load or a different user experience.

Qualitative data were gathered during semi-structured exit interviews based on the following five questions: “[Q1] Could you describe your BCI experience just then?” “[Q2] What is the greatest challenge you faced in the experiment when using BCI as a design tool?” “[Q3] Would you prefer to use BCI-based design tools rather than standard computer design tools in your daily life? Why or why not?”

"[Q4] Based on your knowledge and the experiment, to what other design scenarios do you think BCIs can be applied?" "[Q5] If you had magic, what changes would you wish to make in BCI-based tools for designers, considering the overall experience?" The interview data were analyzed using the Naturalistic Inquiry Method, which involves sorting text segments into emerging themes [74].

5. Results

5.1. Validation accuracy and performance accuracy

The mean offline validation accuracy of all two-class models was above the chance level (50%). Among the tested participants the *Up* vs. *Down* model achieved 75.1% (*SD* = 6.6%); the *Left* vs. *Right* model achieved 74.2% (*SD* = 5.6%); the *Tall* vs. *Short* model achieved 73.8% (*SD* = 6.6%); the *Wide* vs. *Narrow* model achieved 69.5% (*SD* = 6.4%); and the *Circle* vs. *Rectangle* model achieved 72.4% (*SD* = 7.0%). These are all robust outcomes that indicate a good ability to distinguish between neural features in these two-way comparisons.

Regarding the online performance accuracy of the two-class models, the 13 participants' commands for *Up* vs. *Down* were correctly identified by the BCI 53.0% of the time (*SD* = 8.9%, range = 43.4%–78.1%). The *Left* vs. *Right* commands achieved 53.5% accuracy (*SD* = 6.1%, range = 41.0%–62.9%); the *Tall* vs. *Short* commands achieved 57.8% accuracy (*SD* = 10.9%, range = 45.1%–85.9%); the *Wide* vs. *Narrow* commands achieved 51.8% accuracy (*SD* = 6.6%, range = 42.6%–64.2%); and the *Circle* vs. *Rectangle* commands achieved 50.0% accuracy (*SD* = 0.041, range = 59.5%–44.0%).

The online performance accuracy on these tests showed a wide range of outcomes among different participants (Fig. 5). Six of the 13 participants were able to achieve online accuracy above 60% on at least one of the two-way comparisons, and a few outliers were extremely successful on one or more of the tests. Overall, however, the average accuracy outcomes in these two-way comparisons were only slightly better than random chance (50%). The performance rates were particularly poor for the window-creation commands *Circle* vs. *Rectangle*, in which none of the participants achieved greater than 60% accuracy. Data for one of the most successful participants are shown in Fig. 6.

5.2. User experience

Overall scores on the NASA-TLX were calculated from all 21 participants (Fig. 7). These scores were moderate-to-low for *Physical Demand* (*M* = 4.52, *SD* = 2.72), *Temporal Demand* (*M* = 3.14, *SD* = 1.76), and *Performance* (*M* = 4.10, *SD* = 2.35). However, the participants indicated relatively high levels of *Mental Demand* (*M* = 7.43, *SD* = 2.34), *Effort* (*M* = 7.05, *SD* = 2.56), and *Frustration* (*M* = 5.90, *SD* = 2.59). An ANOVA test showed no significant differences in these scores between the different types of design commands (navigation, manipulation, and creation).

For UEQ—S, overall scores for the 21 participants on the *Hedonic* subscales (combined Stimulation and Novelty) were within the range that the scale classifies as "good" (*M* = 1.38, *SD* = 0.89). However, the overall scores on the *Pragmatic* subscales (combined Dependability, Efficiency, and Perspicuity) were in the range defined as "below average" (*M* = -0.37, *SD* = 1.49) [75]. When comparing UEQ-S scores between the different design commands (navigation, manipulation, and creation), an ANOVA showed no significant differences (Fig. 8). A *T*-Test indicated that the Hedonic scores for the BCI were significantly higher than the Pragmatic scores ($p < 0.001$) (Fig. 9).

5.3. Qualitative analysis

Interviews with all 21 participants were recorded and transcribed, broken down into text segments, and ultimately categorized into six themes. *Applications* (30 mentions) were a major topic in the replies when participants discussed potential uses of BCI in design fields. *Devices* (3 mentions) included comments about the BCI and VR hardware. *Experiences* (5 mentions) focused on emotional feelings about the BCI. *Feedback* (12 mentions) included comments about how the BCI gave visual feedback on design commands. *Learning* (9 mentions) was an unanticipated theme, as multiple participants spontaneously discussed how they explored and adapted to the BCI. Finally, *Limitations* (19 mentions) were a concern as users mentioned potential drawbacks of using BCI in design.

We identified three central topics in these responses that are worth consideration by developers of BCI design tools in the future. One particular concern that emerged in the interviews was the presence of Opposite Visual Feedback, referring to an unintended visualization caused by classification error. For example, if the window moved left when the participant intended to move it right. When this error phenomenon occurred it tended to confuse the participants and derail their mental visualization. One participant stated that "Opposite visual feedback makes me feel confused, overcorrect myself, and makes it more difficult to switch classes." Another participant stated, "I wish there was some feedback telling me how good I have been doing." Overall, 11 out of the 21 participants commented on this aspect of the BCI feedback, indicating that the opposing visuals created confusion and distraction when trying to control through mental visualizations.

Despite the complaints about opposite feedback and other difficulties in engaging with the BCI, six participants indicated that it was a Rewarding Interaction. For example, one participant stated that "I was actively exploring how to think and learn the tricks during the experiment," and another indicated that "the BCI experience was very intuitive." Two participants indicated that they were intrigued by the novelty of the idea and felt that it would improve the experience of intellectual and artistic reward in design as well as their ability to intuitively explore new design ideas.

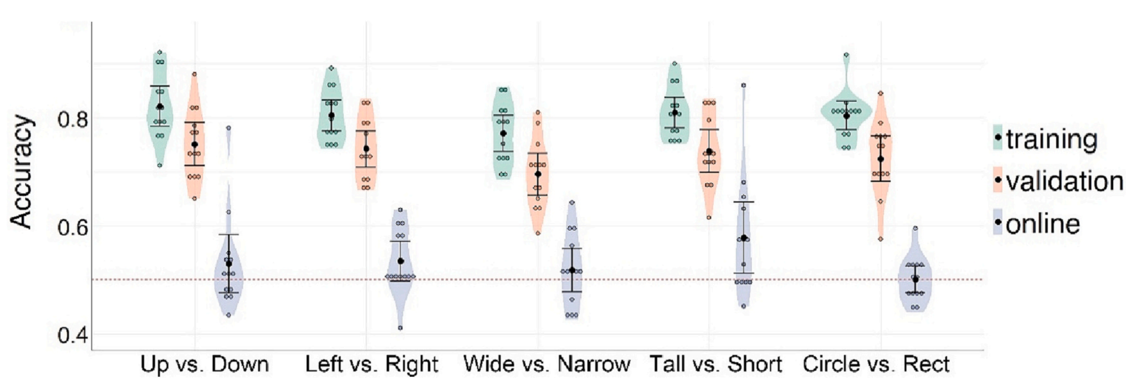

Fig. 5. Training, validation, and online classification accuracy of the five 2-class scenarios.
Note: The black dot represents the mean value. The error bar represents a 95% confidence interval. The horizontal dotted line represents the chance level (50%).

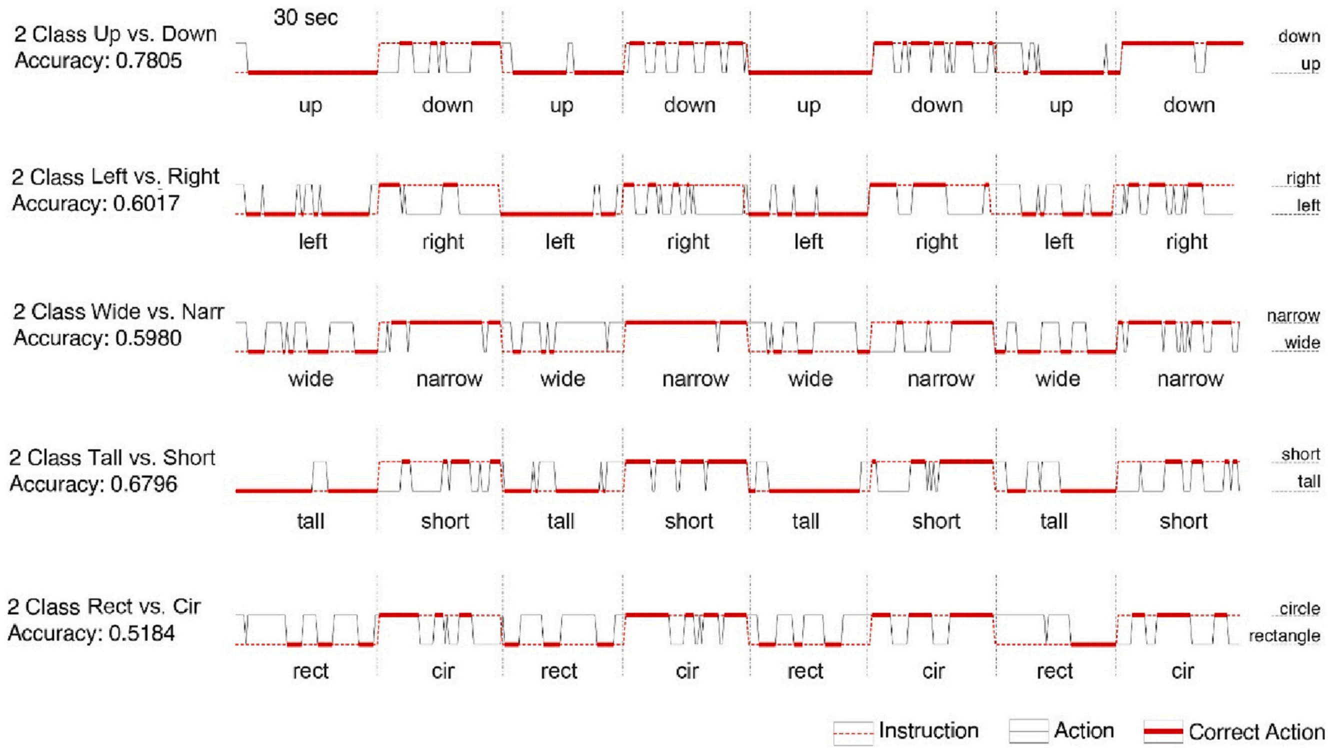

Fig. 6. Online BCI performance of the most successful participant.

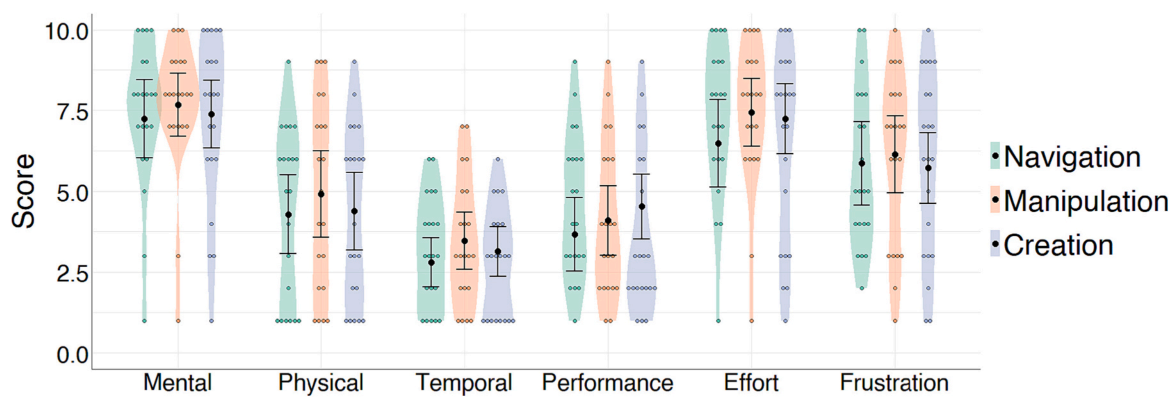

Fig. 7. Overall NASA-TLX Scores for the Three Types of Design Commands.
Note: Each hollow point represents a participant's response. The solid black dot represents the mean value. The error bar represents a 95% confidence interval.

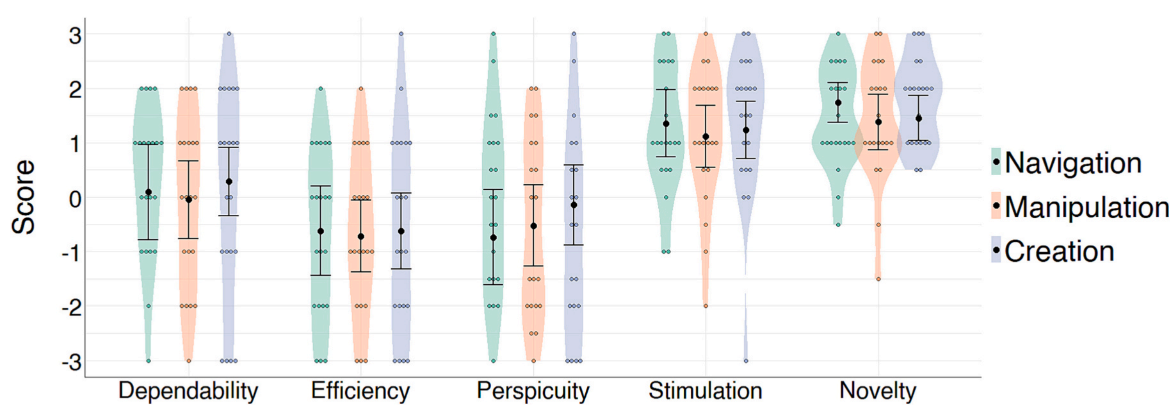

Fig. 8. Overall UEQ-S Scores for Three Types of Design Commands.
Note: Each hollow point represents a participant's response. The solid black dot represents the mean value. The error bar represents a 95% confidence interval.

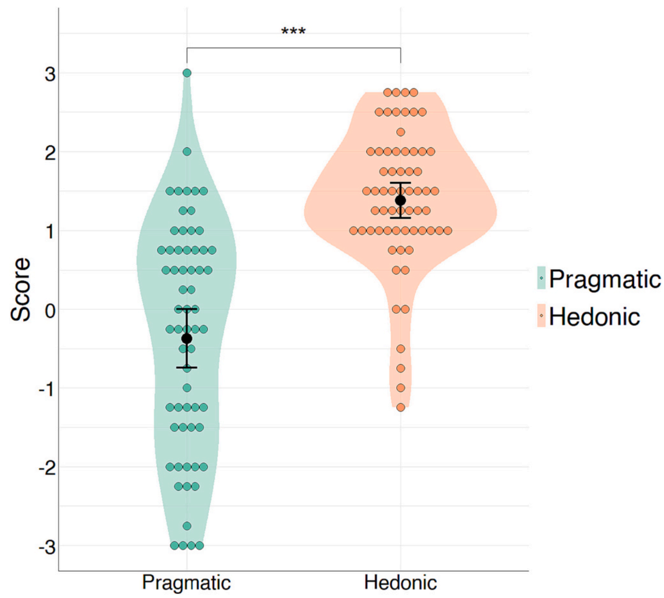

Fig. 9. Overall UEQ-S Scores, Pragmatic vs. Hedonic Factors.
Note: Each hollow point represents a participant's response to a design scenario. The solid black dot represents the mean value. The error bar represents a 95% confidence interval.

Ten participants recommended the use of Multi-modality Interaction, for example indicating that "the WIMP interface is more reliable" and "we should use both WIMP and BCI." Two participants were skeptical about the possibility of matching the full variety of CAD commands to specific mental visualizations and suggested that other modalities of interaction would always need to be retained. Four participants strongly believed that WIMP-based interfaces would continue to be necessary for detailed design.

6. Discussion

The design tool developed in this study and the outcomes of the user testing provide a variety of insights about the potential applications of BCIs in design fields. The study demonstrates that it is feasible to let participants define their mental visualizations to associate with BCI commands, provided that they are given adequate instruction in this process and can understand the types of visualizations that are effective. This has important implications for the fluidity and intuitiveness of BCI use, which is vital for the goal of reducing the gulf of evaluation and the gulf of execution in the design process. The technological ability to combine BCI with VR immersion was successfully demonstrated in this study; this combination may be particularly useful for decreasing the gaps between design conceptualization and high-fidelity feedback.

For our best 2-class online classification model, we achieved an average of 57.8% performance accuracy, and in our least successful model, we achieved an accuracy of 50%. Notably, there was a wide range of accuracy across the participants, ranging from as high as 86% to as low as 41% for different commands and different individuals. Despite the wide range of performance, the participants, who were mostly first-time BCI users, reported that they felt they were able to control the tool well and that they found it enjoyable. It is notable that while the results of our machine-learning validation accuracy are in the same range as other BCI classification studies [21,24,76], the performance accuracy of MindOpen was relatively low, never rising above an average of 60% for our two-command tests (where random chance would have yielded 50% accuracy).

The drop in accuracy in the test set, compared to the validation set, is probably due to the overfitting of the machine learning models to the training and validation data. In addition, when the online experiment took place, the participants had already been exposed to the VR setting for a prolonged period, which may have resulted in mental fatigue. Notably, our training and test tasks were somewhat different from each other—while the training consisted of watching videos of the shape change and attaching specific motor imagery to those movements, the test set had the shape directly responsive and manipulated by the user. In addition, during the online test, there was a greater possibility of EEG artifacts, while the training set had most of them removed with ASR (only those over 15 standard deviations). As noted above, we found it impossible to use ASR during real-time sessions due to the response lag that it created, though this might be improved with future technological development.

The interview results also indicate that technological adjustments might help to improve online accuracy, for example by limiting the distracting effects of opposite visual feedback (this might be done by having the display resist movement in an opposite direction from the prior movement). More research will be needed to determine if such adjustments can increase the effectiveness and usability of the system. The participants' emphasis on a learning curve in the interviews is also very notable, as it indicates that performance might improve with more extensive practice sessions, a view that is supported by some of the prior BCI literature [36,49].

Another consideration is effective instruction or practice to help users understand what visualizations are most effective with the BCI system. While we did not investigate this as a study variable, evidence from the interviews suggested that some participants were uncertain about their visualizations and might wish to change or adjust them in future encounters with the technology. Some participants stated that they had the most trouble thinking of an appropriate mental visualization for the "create a window" tasks, which in turn had the lowest performance accuracy. This can only be considered anecdotal evidence, but in future work, the researchers plan to investigate the use of MindOpen over time and with greater personalized instruction, to determine how participants adapt to the system and if they can develop greater performance accuracy during multiple sessions.

The wide range of performance findings for different participants in our study suggests that specific BCIs may not be suitable for use by all individuals, even when they include options for customization. The researchers suspect that this may be an aspect of natural human diversity, operating in combination with the limited range of BCI research that has so far been conducted in this field. As BCI technology continues to expand and improve, we will likely discover additional customization options and modalities for issuing mental commands through these systems, some of which may rely on alternative neural processes besides motor or geometric visualization. At the same time, researchers and practitioners should be aware that BCI usability may vary among different individuals, and we should ensure that a broad range of design tools remain in play so that diverse designers can leverage their strengths.

Our findings from the NASA-TLX and UEQ-S surveys were intuitive and relatively unexceptional. The use of MindOpen was associated with significant *mental load* and *effort* on the NASA-TLX, and the UEQ-S scores were high on *novelty* and *stimulation* while rating lower on pragmatic utility. These findings are similar to Botrel's original study (in the context of using BCIs for painting) on which we based our user-experience evaluation strategy [38]. One finding that is of particular concern in our results is the moderately high *frustration* level reported by participants on the NASA-TLX. The interviews suggest that this frustration may be an outcome of the low performance accuracy of the system, as participants commonly expressed exasperation and even a sense of personal failure when the BCI's output did not reflect their visualized commands. These experiences of frustration need to be contextualized within the high hedonic ratings of the BCI, which indicate that the overall experience remained enjoyable. It is likely to become even more so if the system's performance accuracy can be improved, or if the system is adjusted so that binary accuracy is not such an essential feature.

6.1. Broader implications: the use of BCIs in the design process

Design can be seen as a problem-solving process with ill-defined variables, and as an embodied creative activity involving both the body and the mind [78]. The value of BCIs in design is to increase the efficiency of this process, and thus reduce the latency of the design feedback loop, encourage exploration and experimentation, and alleviate design fixation. An ideal BCI would be able to directly map user intentions and ideas to corresponding expressions. However, this technology is still in the early stages of development, and there is no certainty that it will ever improve to the point of becoming a true "mind-reader." For the time being, designers should consider how best to incorporate imperfect BCIs into existing creative workflows, and how to enable switching between BCIs and WIMP-based tools smoothly.

WIMP-based design tools might be viewed as loyal agents that do exactly what they are asked and nothing more, and that work predictably so long as they are given precise instructions. In contrast, BCI-based tools might be viewed as opinionated agents that are likely to offer some resistance to the designer's plans and may even suggest unexpected solutions. This process makes BCIs most useful as a creativity-enhancing tool that can be engaged during the initial brainstorming and conceptual-design stages of a project when designers can afford uncertainty and benefit from novel insights. In this role, it will be important to separate the basic technological capacities of the system (such as "save the file") from the amorphous and uncertain realm of the human creative process. Overly enthusiastic interpretation of basic commands is likely to lead to frustration, anxiety, and distrust; whereas greater autonomy in the system for interpreting creative decisions and displaying alternative design variations may prompt users to more fully explore the possibility space and alleviate design fixation, perhaps leading toward collaborative AI design approaches [78].

Design decisions are not always a binary "yes" or "no," and it is common for designers (as well as other creative practitioners) to work with a certain amount of randomness and serendipity in developing novel solutions. In one prior study focused on form generation through BCI, the researchers included a chance of combining uncertain neural classifications to generate a hybrid form, which can be regarded as an in-between or unexpected solution [79]. We think that future BCI design tools for ideation scenarios should consider this approach and provide continuous or fuzzy visual feedback so that designers can use them to explore a wide spectrum of options rather than a discrete choice of commands. Furthermore, in addition to active BCI that requires users to voluntarily manipulate certain brain activities, other BCI paradigms for design may include passive and reactive interpretations that respond to broad aspects of the designer's experience and mental/emotional states [19]. In both passive and active BCI, there is much room to explore the numerous types of neurological signals that could potentially be incorporated into the system's responses.

Thus, the applications of BCI in the context of design should primarily be evaluated not in terms of their predictable and precise response to commands, but rather in terms of their potential for enhancing the creative process and empowering the designer to explore new perspectives. To better adapt broad BCI research into the specific real-world application of design ideation, functionalities such as immediate high-fidelity responsiveness and the representation of complex, non-binary mental states are often more important than complete accuracy in implementing precise commands. We advocate that future work in this area should focus on conducting performance tests of design-oriented BCIs in the context of their creative utility rather than relying purely on the training set accuracy measurements that are common in other types of BCI applications [24,50]. Adapted from Zeisel's diagram of the design process that shows the spiral flow of image, present, and test [11], Fig. 10 indicates a potential vision of how such BCIs can be integrated into key design processes.

6.2. Limitations and future work

Most of the participants in the current study were college students with limited design experience. Additional insights about the potential integration of BCIs into professional design practice could be obtained

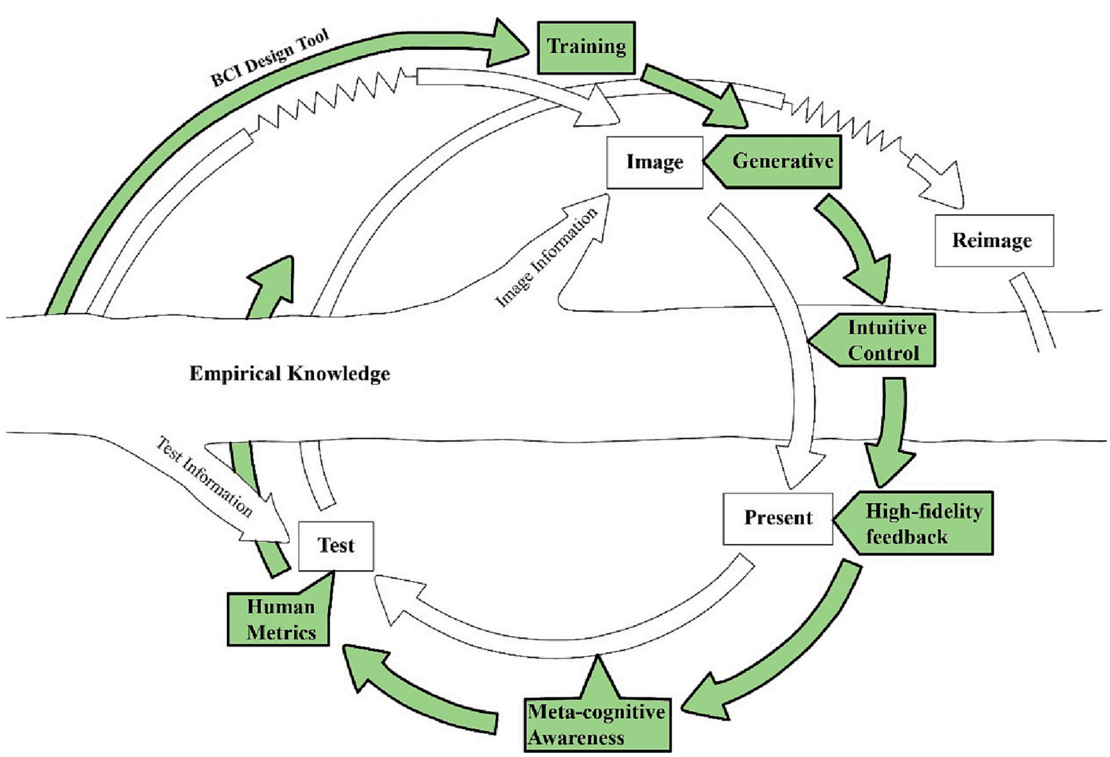

Fig. 10. How BCI design tools can change and benefit the design process.

by testing the system with a broader population of experienced designers. It should also be noted that the design activity of placing and adjusting a window is a very small part of the overall integrated design process and that much additional technological development will be needed before BCIs are capable of reflecting more complex design intentions and instructions. Mapping additional mental imageries to a wide range of design actions, and integrating these actions into a single, fluid system, is a daunting task that will have to contend with longer training sessions, increased mental loads during use, and a likely decrease in the system's reliability and usability. There are likely upper limits of mental imagery capacity that a user can effectively retain without experiencing confusion. In our experiment, some participants found it hard to decide on appropriate and intuitive motor imagery for the "create a window" commands, and such problems are only likely to increase at higher levels of abstraction (such as "group items together" or "change the lattice pattern").

The researchers propose two potential approaches to explore this question further. The first approach involves dividing mental imageries into smaller groups based on different design scenarios so that each scenario contains an appropriate quantity of mental imageries. This may be most effective when combined with generative and/or AI-assisted design techniques. The second approach involves considering multimodal interaction. We think it is doubtful that near-future designers will rely solely on BCI technologies. Instead, we anticipate that designers will use BCI commands for high-level control while integrating other modalities for more nuanced operations. More work is needed in this context to examine the viability of the BCI design tool, the scope of its applicability, and the practical value of integrating it into actual design workflows. The ongoing development of this tool into a viable design application may need to take novel directions as its scope expands, such as integrating AI helper utilities to generate options for design details. The researchers also recommend that future research in this area emphasizes longer practice sessions and longitudinal studies to better understand how designers might put BCI tools into practice.

7. Conclusions

In this article, we described the development and the user-testing of MindOpen, a design tool that applies an EEG-based brain–computer interface in combination with virtual-reality immersion. The goal of the study was to make progress toward a more natural and intuitive design feedback loop using BCI and to evaluate the prospects of such technologies in the design field. The study monitored participants' brain activities using a 128-channel EEG headset and applied a machine-learning approach to map user-selected mental imageries to design commands, which were then realized within the VR workspace.

A feasibility study for the use of this tool was conducted with 21 participants. The average performance accuracy of the BCI was relatively low, and it varied widely among different individual participants. Users reported high mental load and effort when using MindOpen for all design commands, but they also reported that the tool was pleasurable and rewarding to use. The BCI design tool received significantly higher "hedonic" (Stimulation and Novelty) scores compared to "pragmatic" (Dependability, Efficiency, and Perspicuity) scores on the UEQ-S survey instrument. Participants noted that some aspects of the system, such as the use of opposite visual feedback, tended to create frustration and make the BCI harder to use. Such aspects of the system will likely be altered in future work.

The researchers argue that BCI technology has the greatest potential for impact in the design field in the context of early creative design ideation processes, where it may alleviate design fixation and encourage exploration. In the future, such approaches may be combined with collaborative AI tools. The current exploratory and proof-of-concept study demonstrated the feasibility of using BCIs in the architectural design process, and we hope that it will prompt greater discussion and interest in this emerging technology among design researchers.

Declaration of Competing Interest

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

Data availability

Data will be made available on request.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.autcon.2023.105011.

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