# *Understanding virtual design behaviors: A large-scale analysis of the design process in Virtual Reality*

*Portia Wang*, Department of Management Science and Engineering, Stanford University, Stanford, CA 94305, United States

*Mark R. Miller*, Department of Computer Science, Illinois Institute of Technology, Chicago, IL 60616, United States

*Eugy Han, Cyan DeVeaux* and *Jeremy N. Bailenson*, Department of Communication, Stanford University, Stanford, CA 94305, United States

*Virtual Reality (VR) is an emerging medium with consequences for studying design processes. In VR, users can design using direct manipulation and move both by walking and using their hands in the physical world and beyond physical spaces using abstract movement such as teleportation. However, research examining VR design processes remains limited.*

*In this work, we present a large-scale analysis of 730 VR designs from 254 students. We built models of VR design processes, selecting features based on previous theoretical and empirical research. By examining these models at scale, we analyzed design behaviors and their relationship with the context and final design. This research provides a tool for describing VR design processes and highlights broader implications for designers and educators.*


*Keywords: design activity, design behavior, human–computer interaction, psychology of design, virtual reality*

Virtual Reality (VR) offers users unique possibilities when creating three-dimensional designs. Unlike computer-aided design (CAD) systems which typically require high levels of software-specific expertise, popular VR applications such as Google's Tilt Brush and ENGAGE XR allow users to more intuitively engage in Schneiderman's definition of direct manipulation (1982) to create and express ideas in 3D space. In contrast to sketching on paper, users are free to draw, create, and manipulate 3D objects in drastically different virtual environments where they can roam around in their virtual avatars, potentially sharing the space with others. Due to the

**Corresponding author:**
Portia Wang
portiaw@stanford.edu

www.elsevier.com/locate/destud
0142-694X *Design Studies* **90** (2024) 101237
https://doi.org/10.1016/j.destud.2023.101237

unique possibilities for design in VR, we believe that VR can become a common design tool in the near future (Kent, Snider, Gopsill, & Hicks, 2021).

To best understand the use of VR as a design tool, we need to understand the design processes it enables. Unsurprisingly, many have designed protocols and coding schemes for analyzing design processes such as sketching tasks for individual architects, designers, and students (Prats, Lim, Jowers, Garner, & Chase, 2009; Suwa, Purcell, & Gero, 1998; Suwa & Tversky, 1997) and collaborative design tasks (Kim & Lee, 2016; Lloyd & Oak, 2018). That said, while works have studied the effects of groups in VR (Han et al., 2023; Khojasteh & Won, 2021; Miller, Sonalkar, Mabogunje, Leifer, & Bailenson, 2021) and the virtual design process for addressing domain-specific problems (Koutsabasis, Vosinakis, Malisova, & Paparounas, 2012; Laing & Apperley, 2020; Shen, Ong, & Nee, 2010), there has been little work studying the VR design process for more open-ended tasks. Moreover, while typical studies look at dozens of designs, examining designs at larger scales (e.g., hundreds at a time) can enable a more comprehensive bottom-up analysis of the VR design process.

Our work aims to fill three research gaps in the study of VR design processes. To start, despite many prior works leveraged the rich VR tracking data from eyes (Shadiev & Li, 2023), and head and hands (Miller et al., 2023), there is no design coding scheme that contextualizes this data for the design process. Therefore, the field lacks a methodology for describing how a user designs in VR. Further, there is no well-established approach that models and compares VR design processes across users and context. Finally, the limited access to VR hardware creates a barrier for researchers to collect and study VR design processes at a large scale and extract design behaviors through bottom-up approaches.

To address these shortcomings, we present a large-scale analysis of the VR design process. We collected and studied 730 unique VR designs from 254 students, developed a VR design coding scheme based on previous frameworks, and proposed a bottom-up analysis pipeline for describing the VR design process. Then, using these techniques, we summarized the common design behaviors and their relationship with the final design and context. This work introduces a tool for describing the VR design process and highlights practical implications for designers and educators.

# 1 Background

## 1.1 Describing and categorizing design processes

### 1.1.1 Design protocol analysis

Ericsson and Simon (1984) first proposed using protocol analysis on verbal data to study cognitive processes, and since then, design researchers have leveraged verbal and retrospective protocols for understanding design processes (Eckersley, 1988; Yen & Jiang, 2009). To do this, design researchers have developed coding schemes and frameworks such as information categories (Suwa et al., 1998; Suwa & Tversky, 1997), linkography (Goldschmidt, 2014; Kan & Gero, 2008), and Function-Behavior-Structure ontology (J. S. Gero & Kannengiesser, 2007; Qian & Gero, 1996).

One seminal framework for performing protocol analysis is information categories. Introduced by Suwa and Tversky's (1997), the approach delineated four information categories — emergent properties, spatial relations, functional relations, and background knowledge, which were used to divide protocols into segments containing coherent statements relating to a single item, space or topic. Through segmenting protocols into smaller processes, this approach enabled analyses of the interconnectivity within the design process and comparisons of protocols such as those between experts and novices. Suwa et al. (1998) later extended information categories into cognitive actions by proposing the categories of Physical, Perceptual, Functional, and Conceptual. Within this framework, the authors coded physical actions into the action of creating depictions (D-action), observing previous depictions (L-action), and other actions such as gesturing and moving pens (M-action). The authors also introduced three types of indices at the perceptual level, the new, continual, and revisited indices, which corresponded to attending to a feature for the first time, continuing to attend to the most recently attended feature, and revisiting a previously attended feature, respectively.

Our work is related to past works on protocol analysis as we propose design coding schemes related to information categories for segmenting and analyzing VR design processes. In contrast to protocol analysis which typically uses manual labeling of verbal protocols and video recordings, our approach that uses VR tracking data does not rely on what designers recall or choose to mention retrospectively nor does it depend on what researchers pick up from video recordings. Instead, tracking data enables automatic labeling and modeling of design processes, which allows us to examine design activities at scale without needing human coders. Finally, another benefit of using VR over these protocol analysis approaches is its ability to track motion and action at a high frequency, which enables more granular analyses of motion in conjunction with changes made to the design.

### 1.1.2 General shape transformations

One theory particularly relevant to our formulation of the design coding scheme is the notion of general shape transformations (Prats et al., 2009). In their work, the authors derived rules that captured the types of shape transformation observed in designers and architects sketching on paper-based digital notepads. Through analyzing changes across sketches, the authors extrapolated seven types of transformations: outline transformation which included transformation of paths between two points and modifications of the length or thickness of a created element, structure transformation such as element translation, rotation, scaling, and reflection, substitute element, add element, delete element, cut element, and change view.

There is a natural analog between designing across sketches and in VR. Rather than iterating through successive sketches, VR users can modify their designs directly. In addition to the clear parallels of creating (add element), manipulating (structure transformation) and deleting 3D objects (delete element) in the virtual environment, viewpoint changes (change view) also become trivial for those without formal design training as VR users can directly walk or teleport to new locations. Because of this, the design coding schemes we proposed in Section 2.2 focused on extracting and labeling design-related actions related to object creation, manipulation, and deletion, as well as user movement that signifies viewpoint changes.

### 1.1.3 Analyzing design behaviors in 3D and virtual environments

Design researchers have also studied design behaviors using 3D modeling programs and VR. Rahman, Xie, and Sha (2021) studied the design sequences of engineering students solving solarized home and parking lot design problems in a desktop CAD environment. After deriving a coding scheme based on the Function-Behavior-Structure ontology (J. Gero, 1990), the authors showed that deep learning approaches were effective in predicting actions and useful in understanding expert-novice differences. More recently, Millán et al. (2022) asked architecture students to design shelters using fixed-size cubes using a desktop 3D modeling program. By fitting decision trees using snapshots collected at six design instants for each design, the authors clustered similar problem-solving pathways to infer common problem-solving behavior. Using the decision trees, the work highlighted properties of high-quality designs and showed that actions taken during the intermediate stage of the task were the most salient predictors of quality. Sopher and Dorta (2023, pp. 423–440) later studied VR design learning by proposing Co-KCA, which extended the Knowledge Construction Activity method (Sopher, Fisher Gewirtzman, & Kalay, 2019) and linkography (Goldschmidt, 2014) to the collaborative setting. Through a case study of a VR codesign studio followed by manual coding of the Co-KCA units and design development links, the authors demonstrated the ability to analyze codesign scenarios involving individuals in different roles.

In our work, we also investigated the VR design process but focused specifically on examining design processes for both individual and collaborative responses to more open-ended design activities. Similar in motivation to previous quantitative approaches (Millán et al., 2022; Rahman et al., 2021), we proposed a bottom-up analysis pipeline that adopted analytical methods such as Hidden Markov Models and Multi-dimensional Scaling for extracting common design behaviors.

## 1.2 *Design activities and ideation in virtual reality*

Researchers have demonstrated the benefits of using VR for design activities. In particular, a body of work compared VR to non-immersive approaches for facilitating design activities. By comparing VR softwares (e.g., Gravity Sketch) to non-immersive ones, works have found that immersivedesign processes were more stimulating and attractive (Houzangbe et al., 2022), induced more holistic approaches to concept generation (E. K. Yang & Lee, 2020), and yielded increased involvement and more rewarding experiences (Obeid & Demirkan, 2020). Works have also demonstrated that VR improved the quality of creative products (X. Yang et al., 2018) and performance on the design and planning, testing and modification, and the thinking and sharing stages of the creative design process (Y.-S. Chang, Kao, & Wang, 2022).

Another corpus of research focused on evaluating specific VR systems for design activities and ideation. While some works evaluated existing VR softwares (Joundi, Christiaens, Saldien, Conradie, & De Marez, 2020), others have developed immersive systems to support classroom activities (Gisli Thorsteinsson & Page, 2007), sketching (Dorta & Pérez, 2006; Drey, Gugenheimer, Karlbauer, Milo, & Rukzio, 2020), co-design (Dorta, Kinayoglu, & Hoffmann, 2016; Mei, Li, de Ridder, & Cesar, 2021), and product design (Berg & Vance, 2017). Many have also explored different ways to facilitate brainstorming and ideation in VR (Bhagwatwar, Massey, & Dennis, 2018; Ide et al., 2021; G. Thorsteinsson & Denton, 2006; Gisli Thorsteinsson, Niculescu, & Page, 2010) and pointed to factors such as immersion and avatars for enhancing creativity during virtual brainstorming (Gong, Lee, Soomro, Nanjappan, & Georgiev, 2022). Collectively, these works presented the possibilities of leveraging VR for ideation and design activities in either individual or collaborative settings, and did so through assessing performance on ideation (Gong et al., 2022) and domain-specific tasks in areas such as product design (Berg & Vance, 2017), and interior and architectural design (Dorta et al., 2016; Dorta & Pérez, 2006).

As prior research advocates for the use of VR in facilitating design activities, it becomes imperative to investigate how people respond to different design tasks in immersive environments. Our work extended past works by studying both the individual and collaborative design processes and focused specifically on their responses towards different open-ended design prompts. Through examining the actions and movements of individuals and groups at scale, we identified common design behaviors that improved our understanding of how people design in VR.

## 1.3 Context in virtual environments

Bailenson, Beall, Loomis, Blascovich, and Turk (2004) referred to situational context as the spatial or temporal structure of those interacting in collaborative virtual environments. Many have studied the psychological effects of situational context, for example the effects of natural environments (Lee et al., 2022; Nukarinen et al., 2022; Yao, Chen, Wang, & Zhang, 2021), indoor and outdoor environments (Han et al., 2023; Minocha & Reeves, 2010), and the amount of visible space through manipulating ceiling heights and spaciousness (Han et al., 2023; Meyers-Levy & Zhu, 2007; Okken, van Rompay, & Pruyn, 2013; Wu, Law, Heath, & Borsi, 2017). Notably, research showed that greater visible space yielded higher levels of entitativity, enjoyment, and self- and spatial presence (Han et al., 2023) and that greater room sizes increased self-disclosure (Okken et al., 2013). Works have also found that higher ceiling height primed thoughts related to the concept of freedom while lower ceiling height primed thoughts related to confinement (Meyers-Levy & Zhu, 2007) and that outdoor environments increased perceived restorativeness and enjoyment compared to indoor environments (Han et al., 2023).

Researchers also examined the effects of task-specific contexts such as group size and activity type. Specifically, Huang, Richter, Kleickmann, and Richter (2022) demonstrated that larger groups increased the heart rates and subjective ratings of stress for instructors in a VR classroom. With regards to task types, Yoon, Choi, Yoon, and Jo (2023) found that groups using VR outperformed those who did not use in VR on tasks centered on communication, interaction, and immediate situational judgments, whereas tasks involving routine handling of physical objects showed no such improvement. Relatedly, in a study of triads collaborating on four design tasks, Miller et al. (2021) found no significant differences of synchrony due to tasks.

Despite these works demonstrating context's influence on human behaviors in virtual environments, and others examining how human behaviors in non-VR settings are shaped by factors such as group size (Renzulli, Owen, & Callahan, 1974) and teaching style (Inayat & Ali, 2020; Michel, Cater, & Varela, 2009), our understanding of how context effects design behaviors in virtual environments remains limited (Sonalkar, Mabogunje, Miller, Bailenson, & Leifer, 2020). Our work bridges this gap by examining the relationship between VR design behaviors and context. Building on the research reviewed here, we focused on the context factors of design prompts, teaching assistants, settings (indoor, outdoor), ceiling heights, amount of visible space, and number of students.

# 2 Methods

## 2.1 Open-ended design activities

We conducted two studies, one focused on the individual design process (N = 670) and another on the collaborative design process (N = 60).

### 2.1.1 Individual design activities

We analyzed the VR field experiment conducted by Han et al. (2023), where 137 university students participated in a 10-week course in VR. For 8 out of the 10 weeks, students engaged in sessions guided by 1 of 3 teaching assistants in groups of size 5 to 8 through the ENGAGE social VR platform. The sessions consisted of an instructor-led discussion and a 15-min open-ended design activity which varied across weeks (Table 1). We focused on these design activities, and specifically the time periods spanning students' design processes (Figure 1). For each design activity, students individually brainstormed, designed, or prototyped responses to the given prompt using the tools provided through ENGAGE, which allows users to create, manipulate, and delete 3D objects, and draw using a 3D pen. During the design activities, users are allowed to walk and teleport around the virtual space, moving to new locations to create new objects or to examine designs from novel viewpoints. Following the end of the design activity, students spent about 5 min sharing their final designs with the group.

There were 5 context-related variables: the design prompts, teaching assistants, setting (indoor and outdoor), amount of visible space (panoramic and constrained), and number of students in each session. We had varied the movement constraints (passive and active) but it had failed manipulation check due to students not following the instructions, so we excluded it from our analysis. We dropped week 5 from our analysis given that it was a discussion-based activity and users were not instructed to create anything during the session. This yielded 670 unique individual designs in total.

### 2.1.2 Collaborative design activities

We conducted a second study investigating the collaborative design process in VR. We asked 146 university students, 117 of whom consented, to respond to 4 open-ended design prompts in groups of size 2 to 4 over the span of 4 weeks (Table 2). There were in total 40 groups, out of which 26 consented. Each

**Table 1 Individual design study weekly design activities, which groups of students responded to individually during their discussion sections**

| *Week* | *Open-ended Design Activity* |
|---|---|
| 1 | Consider the affordances of VR and create a prototype of something that leverages the uniqueness of VR |
| 2 | Create something frightening that induces a feeling of high presence |
| 3 | Consider the affordances of VR to make a concept that is difficult to understand, easy |
| 4 | Create something that reimagines avatars and representations of the self |
| 5 | Small-group discussions reflecting on various VR empathy experiences |
| 6 | Create a meditation room or "safe-space" |
| 7 | Brainstorm an idea of how to communicate a message about climate change |
| 8 | Create and playtest a VR-based game |

*Figure 1 Groups of students during individual design activities. Students are seen conceptualizing difficult-to-understand concepts (top-left), reimagining avatar and self-representation (top-right), creating meditation rooms or safe-spaces (bottom-left), and designing messages about climate change (bottom-right) using the 3D pen and 3D objects*

week, students met in their pre-assigned groups without the presence of a teaching assistant in ENGAGE for 20 min. During this time, each group discussed a given topic and participated collaboratively in an open-ended design activity that again involved prototyping, creating, or brainstorming using the tools provided by the platform. Similar to Study 1, we again focused our analysis on the design activities (Figure 2). To study the effects of context on the design process, we varied the context of the group sessions, manipulating

**Table 2** Collaborative design study weekly design activities, which groups of students responded to collaboratively during their discussion sections

| *Week* | *Open-ended Design Activity* |
|---|---|
| 1 | Talk about accessibility within the context of ENGAGE (e.g., what are the constraints?). Make a list of things that ENGAGE does well and does not do well (e.g., using sticky notes), and specify the number of sticky notes per person (1 pro and 1 con). |
| 2 | Reimagine what your avatar would look like. Either draw an avatar that you wish represents you or an avatar you would like to embody. Can, but doesn't have to, be a human avatar. |
| 3 | Collaboratively work with your group members to create a meditation room or a safe space using any of the ENGAGE tools (e.g., 3D pen, objects, sticky notes) |
| 4 | Consider a target audience/population (e.g., students of a certain age group, students with a certain learning disability), a goal (e.g., retaining factual information, having students experience something), and a topic of interest (e.g., language, STEM, social skills). Empathize, Define, Ideate, and Prototype an application tailored to your Audience, Goal, and Topic |

the amount of visible space (panoramic and constrained) and ceiling heights (low and tall). We excluded week 1 data from our analysis because it corresponded to a brainstorming activity using shared sticky notes. This resulted in a total of 60 collaborative designs.

## 2.2 VR equipment and tracking data

Students used the Meta Oculus Quest 2 headsets and two hand-held controllers to participate in the activities. Using the ENGAGE platform, we recorded the tracking data of each user, which included the positions (x, y, z) and orientations (row, pitch, yaw) of the head and two hands, as well as object-related information such as the position, orientation, and scale of each object, and drawing actions. The user motion data was recorded at 30 Hz and the object-related information at around 0.21 Hz. An analysis on the changes of object-related information over time allowed us to extract out object-related actions closely related to the shape transformations identified by Prats et al. (2009), such as object creation, manipulation, and deletion. This unit of analysis resembled the notion of segments proposed by Suwa and Tversky (1997), except that ours is extracted temporally and theirs is extrapolated through verbal protocols. For object manipulations, we further determined whether the action is carried out on the most recently created object or a previously created object, mirroring the continual and revisited action categories outlined by Suwa and Tversky (1997).

## 2.3 VR design coding scheme

In this section, we describe the VR Design Coding Scheme for coding the individual and collaborative design processes.

### 2.3.1 Coding individual design

Our VR design coding scheme encodes both object-related activity and user motion. Specifically, for each user, we extracted 12 user-level features each time object-related information is recorded, out of which 6 are object-

*Figure 2 Groups of Students during the collaborative design activities. Students are seen collaboratively creating a meditation room or safe-space (top-left, bottom-right), reimaging avatar representation (top-right), and prototyping an application for a given audience, goal, and topic (bottom-left) using the 3D pen and 3D objects*

related, and 6 are motion-related. The 6 object-related features capture whether certain object-related actions have occurred since the previous recorded timestamp (Figure 3). They were.

1. 3D pen drawing: this binary feature describes whether the user used the 3D pen.
2. Object creation: this binary feature describes whether the user added a new object into the scene.
3. Object deletion: this binary feature describes whether the user removed a previously created object from the scene.
4. Object translation: this feature describes whether the user moved the position of an existing object. The feature takes on one of three categories: (1) the user did not move any object; (2) the user moved the most recently created object; (3) the user moved an object that was not most recently created. The latter two categories mirror the notion of indices proposed by Suwa et al. (1998), where (2) refers to continual actions and (3) corresponds to revisited actions.

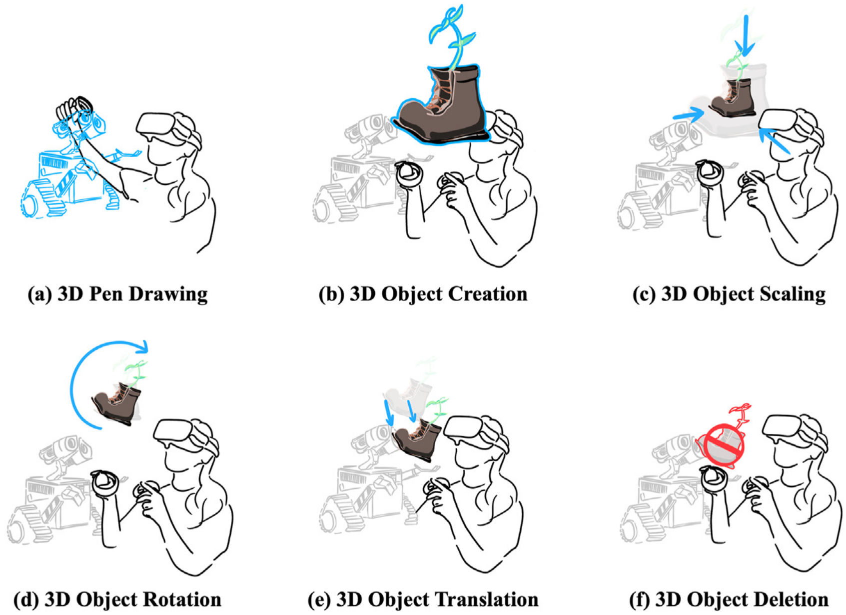


*Figure 3 Toy action sequence demonstrating each of the 6 object-related features encoded in the VR design coding scheme. The VR user (a) begins by drawing using the 3D pen, (b) proceeds to insert a new 3D object into the scene, (c) scales down, (d) rotates, (e) and moves the 3D object to a new location before finally (f) deciding to delete the 3D object from the design*

5. Object rotation: this feature describes whether the user rotated an existing object. The feature can take on one of three categories and is formulated the same way as object translation.
6. Object scaling: this feature describes whether the user scaled an existing object. The feature can take on one of three categories and is again formulated the same way as object translation.

The 6 motion-related features capture body movement since the previous recorded timestamp of object-related information. Specifically, we specified hand motion not by left- and right-hand, but as the *slower* and *faster* hands, so that our coding scheme is less dependent on handedness while still using hand motion as signals to analyze design processes. Further, we encoded head movement into yaw, pitch, and roll rotations because past research suggested that head rotation in different axes corresponds to different cognitive processes (Holzwarth et al., 2021; Slater, Steed, McCarthy, & Maringelli, 1998; Won, Perone, Friend, & Bailenson, 2016). To obtain the 6 features, we first extracted out the following information.

7. Head yaw rotation: the total amount of head yaw rotation in degrees
8. Head pitch rotation: the total amount of head pitch rotation in degrees
9. Head roll rotation: the total amount of head roll rotation in degrees

10. Slower hand movement: the total amount of distance traveled in meters by the hand that has traveled less within the current time period
11. Faster hand movement: the total amount of distance traveled in meters by the hand that has traveled more within the current time period
12. Horizontal plane movement: the total amount of distance traveled by the user in the horizontal plane in meters during the current time period. Users can move either by walking, smooth translation using joysticks, or teleportation.

After obtaining these 6 continuous values, we transformed the values into discrete categories. For a value x of feature i collected at time t, we obtain the transformed value as

$$x_{\text{transformed}} = \text{Max}(\text{Floor}_i, \text{Min}(\text{Ceiling}_i, \log(x)))$$

where the floor and ceiling values are chosen specifically for feature i. The floor and ceiling values can be found in Appendix A. This operation transformed the right-skewed distributions of the motion values into more symmetrical distributions and also accounted for extreme values such as no motion that would have yielded undefined values during the logarithmic operation, and large motion during teleportation. Following this, we binned the transformed values into three equally spaced bins, corresponding to low, moderate, and high motions.

Our decision to bin continuous features allowed us to generate discrete states that can be concatenated with the object-related features into a single descriptive state at every timestamp. To do this, we extracted the 12 features across the recording for each user at a given timestamp and concatenated them into a single state encoding. We then generated the sequence of states for a given user for a given session, which is finally cropped so that the first state of the sequence corresponded to the first object-related manipulation and the last state marked the final object-related manipulation.

### 2.3.2 Coding collaborative design

Collaborative and individual design tasks are different because working in groups allows users to discuss and make design choices collectively, and work on different parts of the design concurrently. The collaborative design process should thus be examined as a collection of actions and motions from all users. We therefore adapted our coding scheme for collaborative designs to account for collaborations in VR. To do this, we began by extracting the sequences of states for all users in each session. Following this, we extracted 27 group-level binary features for each timestamp. There were 12 group-level object-related features, where the first 3 features described whether any user within the group has (1) created an object, (2) deleted an object, or (3) drawn using the 3D pen. We further expanded each of the object translation, object rotation, and object scaling features into 3 binary features, namely (1) whether at least one user has not manipulated any object, (2) whether at least one user manipulated their most recently created object, and (3) whether at least one user manipulated an object that they did not most recently create.

The next 15 features captured group motion. We began by defining a total of 5 features by extracting the 6 user-level motion-related features described in Section 2.3.1, combining the slower and faster hand movements into one feature, as combining the two features improved downstream interpretability. Specifically, we merged the slower and faster hand movement features into a feature that described the mean hand movement by taking the average of the two hand motions and binning the values into equally spaced categories (i.e., low, moderate, high). Then, for each of the 5 motion-related features, we formulated 3 group-level features describing whether at least one user's motion is categorized in the low, moderate, and high categories, respectively.

Upon extracting the 27 group-level features and the sequence of states for a given design, we cropped the sequence so that the first state corresponded to the first object-related manipulation within the group and the last state marked the final object-related manipulation within the group.

## 2.4 Design process modeling

Many approaches exist for mining patterns and sequences of design behaviors, including those using Hidden Markov Models (Hu, McComb, & Goucher-Lambert, 2023; McComb, Cagan, & Kotovsky, 2017a,b), Bayesian optimization frameworks (Chaudhari, Bilionis, & Panchal, 2020; Sha, Kannan, & Panchal, 2015), as well as deep learning approaches such as long short-term memory networks (Rahman et al., 2021) and unsupervised learning techniques (Millán et al., 2022). In particular, extensive research has used Hidden Markov Models (HMMs) to understand additive manufacturing (Mehta, Malviya, McComb, Manogharan, & Berdanier, 2020), design ideation (Hu et al., 2023), as well as proficiency, sequence-learning abilities, and process heuristics in configuration design problems (Brownell, Cagan, & Kotovsky, 2021; McComb et al., 2017a; McComb et al., 2017a). Similarly motivated, we also employed HMMs to model VR design sequences. By analyzing their instantiations using Multi-dimensional Scaling (Ghassempour, Girosi, & Maeder, 2014; Hung, Chiu, Chen, Huang, & Cheng, 2015; Suzuki, Hirasawa, Tanaka, & Fujino, 2007), we extracted design behaviors and further analyzed them in relation to the final design characteristics and context.

For the remainder of this section, we lay out the methodology of using the sequences of states extracted in Section 2.3 to train probabilistic models, construct a distance matrix, and use Multi-dimensional Scaling for identifying common design behaviors. Figure 4 shows an overview of the analysis pipeline used for modeling and analyzing VR design processes.

### 2.4.1 Hidden Markov Models

We used HMMs to describe VR design sequences. Specifically, our approach is similar to that proposed by Ghassempour et al. (2014), who translated the ill-defined distances between two sequences into well-defined distances between two probabilistic models. The authors did so by modeling trajectories of multivariate individual health data using HMMs and clustering trajectories for qualitative interpretation. In our process, we took sequences encoded using our VR coding scheme and trained a corresponding HMM for each unique design process. Our approach differed from that proposed by Ghassempour et al. (2014), in that we trained the HMM of a given design using the number of hidden states that corresponded to the lowest Akaike's information Criteria (AIC). Allowing the models to differ in the number of hidden states, as opposed to fixing them across all design sequences, enabled us to adapt model complexities based on how complicated each design sequence is. For each unique sequence $S_i$, we yielded corresponding model parameters $\lambda_i$. We further denote the probability $P(S_i|\lambda_j)$ as the average likelihood of observing sequence $S_i$ with model parameters $\lambda_j$. Models were built in R, using the "seqHMM" package (Helske & Helske, 2019).

### 2.4.2 Distance matrix construction

Again, following the approach detailed in Ghassempour et al. (2014), we formulated the distance between design sequences using the symmetric Kullback-Leibler (KL) divergence (Kullback & Leibler, 1951) and employed. Specifically, we approximated the distance between sequences $S_i$ and $S_j$ for a dataset with N design sequences by first defining the KL distance:

$$D_{KL}(i,j) = \sum_{i=1}^{N} P\prime(S_i|\lambda_i)\log\frac{P\prime(S_i|\lambda_i)}{P\prime(S_i|\lambda_j)}$$

where $P\prime(S_i|\lambda_j)$ is the normalized probability such that $\sum_{i=1}^{N} P\prime(S_i|\lambda_j) = 1$. The final distance matrix D is constructed using the symmetrized KL distance between all pairwise design sequences:

$$D_{ij} = \frac{1}{2}(D_{KL}(i,j) + D_{KL}(j,i))$$

where i and j denote the indices of the two designs and the corresponding position within the symmetrical distance matrix. For sequences with previously unseen states for a given trained model, we performed smoothing on the

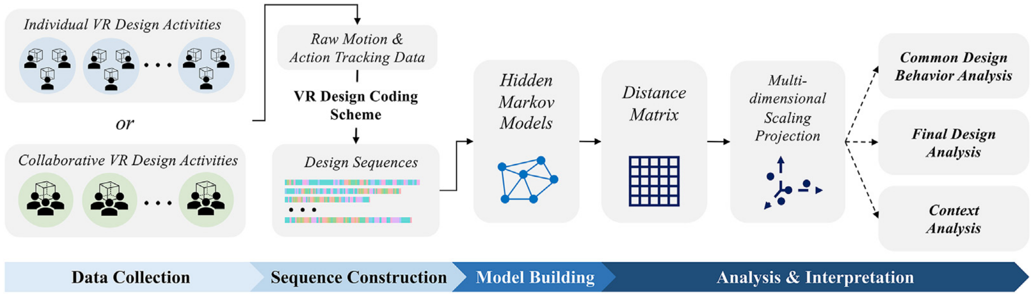


*Figure 4 Analysis pipeline for describing the VR design process*

emission matrix for the trained model. We first included all unseen states to each hidden state, then added a small probability (0.001) to all states within each hidden state, and finally normalized the emission matrix such that the total emission probability for a given hidden state sums up to 1.

### 2.4.3 Multi-dimensional scaling

Consistent with past works that leveraged HMMs to study sequential data (Ghassempour et al., 2014; Hung et al., 2015; Suzuki et al., 2007), we used Multi-dimensional Scaling (MDS) to map design sequences to lower-dimensional representations of n dimensions, all while preserving the pairwise distances computed for the distance matrix D as much as possible. For a given design sequence $S_i$, we calculated an embedding of length n in the Euclidean space, where each index corresponds to a single dimension. Two reasons motivated our decision to use MDS. To start, dimensions are orthogonal, meaning that each dimension describes a different characteristic of the design process. Furthermore, dimensions are extracted in decreasing order of explained variance, meaning that the first dimension explains the most variance and the second dimension, orthogonal to the first, explains the second most variance. We can thus interpret the dimensions as design behaviors in decreasing order of importance.

To determine the number of dimensions to use for further analysis, we examined the scree plots (i.e., eigenvalues against dimension number) for each of the studies and selected the cutoff based on where the eigenvalues began to level off. The scree plot criterion is a common approach for determining the number of dimensions used for describing the underlying data (Ali-Hassan & Nevo, 2009; Hout, Papesh, & Goldinger, 2013; Jaworska & Chupetlovska-Anastasova, 2009). We used the "stats" library in R to perform the MDS. Using the scree plot criterion, we decided to examine the first 4 dimensions for the individual design study and the first 3 dimensions for the collaborative design study.

## 2.5 Bottom-up analysis pipeline

Following the steps of coding tracking data, extracting state sequences, building HMMs from the sequences, calculating the distance matrix, and obtaining the MDS embeddings for each design, we leveraged the MDS dimensions to summarize common design behaviors and analyzed their relationship with the final design and context (Figure 4). Since the individual and collaborative design processes are coded differently, we analyzed their design behaviors separately. To identify common design behaviors, we visualized the feature breakdowns for designs with the highest and lowest 10% values for each of the dimensions for the two studies. For each dimension, we compared ratios of categories that appear within the design sequences across the high-value group and low-value group and described noticeable differences.

To analyze the relationship of design behaviors and the final design and context, we built linear mixed-effects models that predicted each of the dimensions with either the final design characteristics or study-specific contextual factors modeled as fixed effects. The random effect for models built for the individual design study was participants nested within sections and groups for the collaborative design study. If the linear mixed-effects model resulted in a singular fit, which suggested that the random effect accounted for very little of the variance, we dropped the random effect and instead built a linear model for that specific dimension. We also tested models with pairwise interactions and did not find any interaction term that was significant in the majority of the models. We thus report results from the more parsimonious models without interactions. All models were fitted using the "lmer" package in R, and statistical significance evaluated at alpha = 0.05. Given that the numerical values of the dimensions are not directly interpretable, we focus our analysis on the direction and size of effect for significant predictors. Detailed descriptions for the final models can be found in Appendix B.

For each model, we report effect size and their confidence intervals. As there is no universally agreed upon approach for calculating and reporting effect sizes for multilevel and linear mixed effect models (Jaeger, Edwards, Das, & Sen, 2017; Nakagawa & Schielzeth, 2013; Rights & Sterba, 2019), we report the conditional and marginal $R^2$ values as well as their confidence intervals. Marginal $R^2$ ($R^2$m) represents the amount of variance explained by the fixed effects while conditional $R^2$ ($R^2$c) represents the amount of variance explained by both the fixed and random effects. We used the "MuMIn" and "r2glmm" packages in R for calculating the $R^2$ values and confidence intervals, respectively. In cases where we built a linear model for a given dimension, we report its $R^2$ value and confidence interval.

# 3 Results

We report results from the common design behavior analysis (Section 3.1), final design analysis (Section 3.2) and context analysis (Section 3.3). Table 3 summarizes our main findings.

## 3.1 Dimension of VR design behaviors

We examined the MDS dimensions extracted from the individual design study and collaborative design study separately. Following Section 2.5, we compared the feature breakdowns for designs with the highest 10% values (i.e., high-value group) and lowest 10% values (i.e., low-value group) for each of the dimensions (Figures 5 and 6). All breakdown ratios are shown in Appendix C and D.

### 3.1.1 Individual design behaviors

The first dimension is related to whether a user designed more using the 3D pen or through creating 3D objects. Designs with high dimension 1 values are created mostly with the 3D pen − designs in the high-value group spent on average 66.10% of the time drawing, whereas those in the low-value group spent merely 11.96%. We also noticed that design processes that included less 3D pen actions exhibited a higher ratio of fast horizontal plane movement, where the group that drew more (i.e., high-value group) spent 5.57% of the time in the high motion category compared to the group that drew less (i.e., the low-value group) spending 15.34%.

The second dimension captures horizontal plane movement. Those in the high-value group for the second dimension spent on average 3.16% of the time moving in the high motion category while those in the low-value group spent 13.41%.

The third dimension is related to the frequency of manipulation. Specifically, for creation, translation (continual), rotation (continual), and scaling (continual), design processes in the high-value group spent on average 3.56%, 9.25%, 3.08%, and 2.67%, respectively, while those in the low-value group spent 4.81%, 14.92%, 5.36%, 5.68%. We also noticed a difference in horizontal plane movement, where design processes that manipulated more moved more in the horizontal space, as the group that manipulated more (i.e., low-value group) spent 12.84% of the time in the high movement category, in contrast to the 6.24% for the group that manipulated less.

Finally, the fourth dimension is related to head rotation, where those in the low-value group spent on average a greater ratio of time in the low motion categories. Specifically, the low-value group spent on average 8.65%, 8.25%, and 7.21% in the low motion categories for head yaw, roll and pitch features, in

**Table 3 Summary of main findings for each of the MDS dimensions for the Individual and Collaborative Design Processes**

| *Study* | *3.1 Dimension of Design Behaviors* | | *3.2 Design Behaviors and Final Designs* | | | *3.3 Design Behaviors and Context* | | |
|---|---|---|---|---|---|---|---|---|
| | *#* | *Description* | *Main effect(s)* | *Effect size* | *CI* | *Main effect(s)* | *Effect size* | *CI* |
| Individual Design Study | 1 | Designing with 3D objects vs. 3D pen | Total Number of Objects*** Final Design Height*** | $R^2c = 0.30$ $R^2m = 0.13$ | [0.09,0.18] | Design Prompt* Teaching Assistant** Setting* | $R^2c = 0.31$ $R^2m = 0.12$ | [0.09, 0.18] |
| | 2 | Amount of horizontal plane movement | Total Number of Objects* | $R^2c = 0.03$ $R^2m = 0.01$ | [0.00,0.03] | Visible space* | $R^2c = 0.06$ $R^2m = 0.03$ | [0.02, 0.07] |
| | 3 | Frequency of manipulation (i.e., creation, continual translation, rotation, and scaling) | Final Design Projection Area* Final Number of Objects* | $R^2c = 0.06$ $R^2m = 0.02$ | [0.01,0.05] | Teaching Assistant* | $R^2c = 0.07$ $R^2m = 0.03$ | [0.02, 0.07] |
| | 4 | Speed of head rotation (i.e., yaw, roll, and pitch) | *No main effect found* | $R^2c = 0.07$ $R^2m = 0.00$ | [0.00,0.02] | Design Prompt** | $R^2c = 0.11$ $R^2m = 0.03$ | [0.02, 0.08] |
| Collaborative Design Study | 1 | Frequency of manipulation (i.e., creation, continual translation, rotation, and scaling) | Final Design Height** | $R^2 = 0.14$ | [0.05, 0.37] | *No main effect found* | $R^2 = 0.08$ | [0.04, 0.35] |
| | 2 | Designing with 3D objects vs. 3D pen | Total Number of Objects* Final Design Volume* Final Design Projection Area* | $R^2c = 0.27$ $R^2m = 0.19$ | [0.08, 0.41] | *No main effect found* | $R^2c = 0.13$ $R^2m = 0.07$ | [0.03, 0.31] |
| | 3 | Amount of horizontal plane movement | Final Design Height* | $R^2c = 0.19$ $R^2m = 0.09$ | [0.03, 0.31] | *No main effect found* | $R^2c = 0.35$ $R^2m = 0.05$ | [0.03, 0.30] |

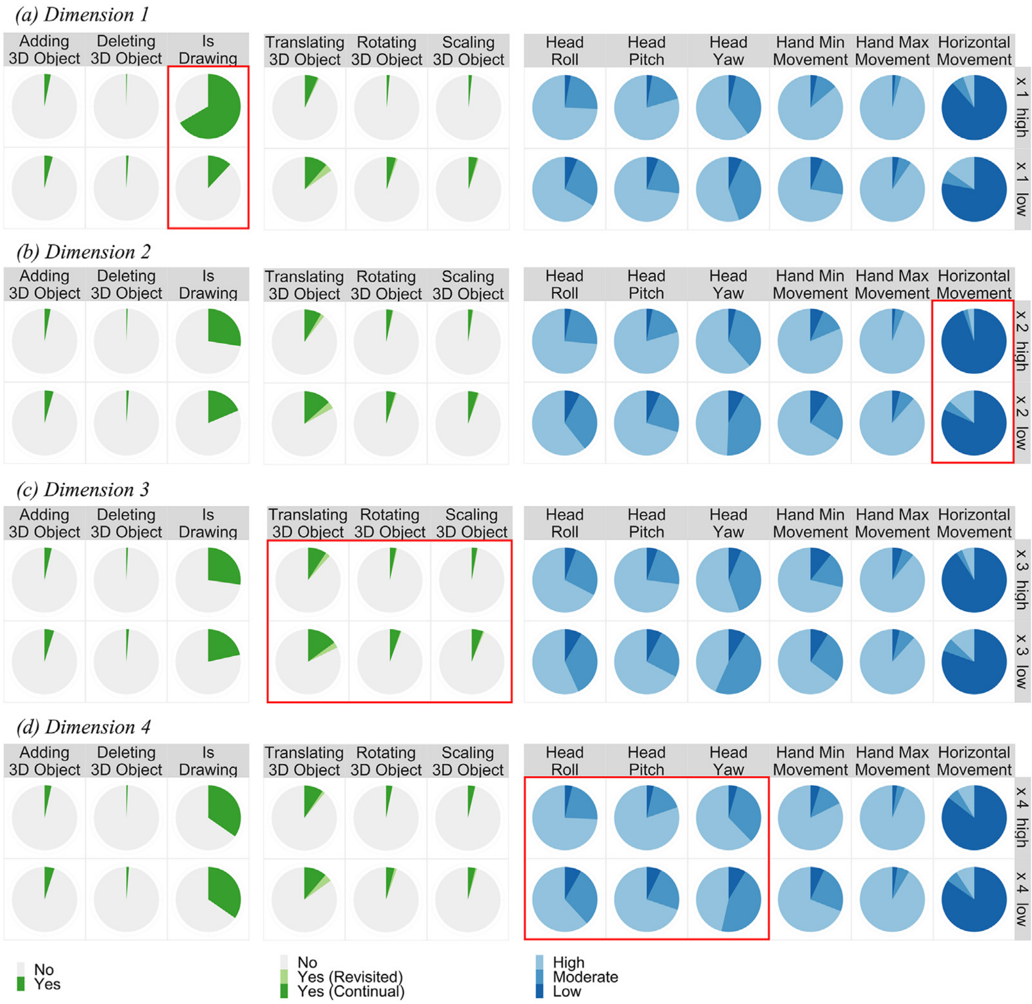


*Figure 5 Individual design study feature breakdowns that show the ratio of different categories for each of the 12 user-level features for the high-value and low-value groups. The main observations are outlined in red (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)*

contrast to the high-value group spending 4.39%, 3.68%, and 3.45%, respectively.

### 3.1.2 Collaborative design behaviors

The first dimension for the collaborative design study is related to the frequencies of object-related actions. The design processes in the high-value group spent on average more time creating, deleting, and manipulating objects – the high-value group spent on average 19.28%, 9.11%, 5.28%, and 7.79% translating (continual), rotating (continual), scaling (continual), and adding objects, while in contrast, the low-value group spent 36.13%, 16.23%,

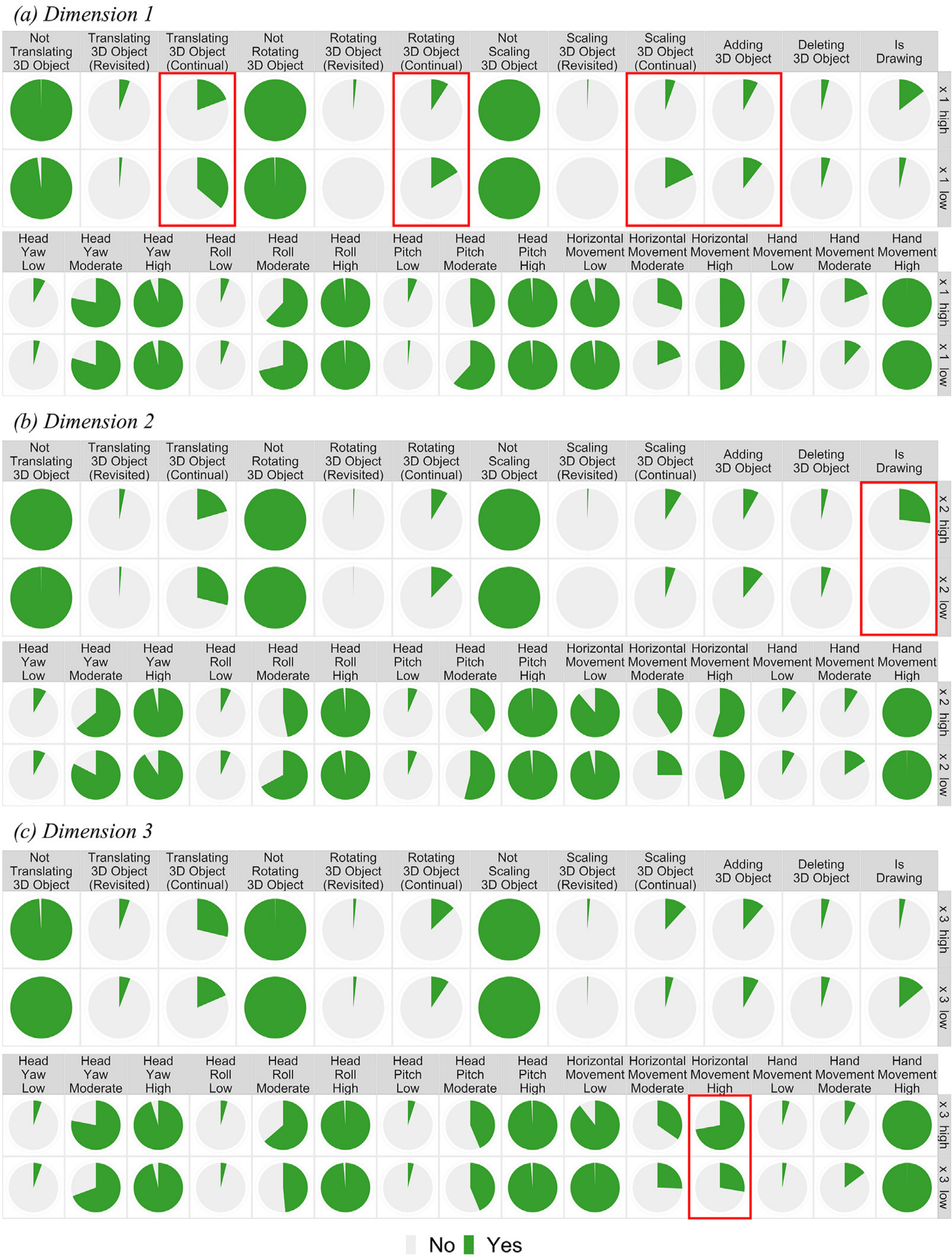


*Figure 6 Collaborative design study feature breakdowns that show the ratio of different categories for each of the 12 group-level action-related and 15 group-level motion-related features for the high-value and low-value groups. The main observations are outlined in red (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)*

17.80%, and 10.47%. Intuitively, we also noticed that design processes with more manipulations drew less, as the high-value group spent 14.51% of time drawing, and the low-value group 3.66%.

The second dimension captures whether the group designed more using the 3D pen or through 3D objects. More specifically, design processes in the high-value group spent on average 26.76% of the time drawing using the 3D pen, whereas the low-value group spent 0.00%. In contrast to our findings for the individual design behaviors, the design processes with less 3D pen actions (i.e., low-value group) exhibited slightly slower motion in the horizontal plane, as they spent on average 96.43% of the time in the low motion category, while the group who drew more spent 88.81%.

Finally, the third dimension is related to the amount of horizontal plane movement. Specifically, the high-value group spent on average 72.13% of the time in the high motion category for horizontal plane movement, in contrast to 27.71% for the low-value group. The high-value group also spent 89.51% of the time in the low category for horizontal plane movement, whereas the low-value group spent 99.62%.

## 3.2 Design behaviors and final designs

To determine how design behaviors led to different final designs, we calculated 4 summary characteristics for each final design. Descriptive measures of these characteristics can be found in Appendix E. The values of the variables are calculated at the last timestamp using all objects and drawings either created by a single user in a given session for the individual design study, or the entire group for the collaborative design study. The 4 summary characteristics were.

1. Total Number of Objects: the number of total objects in the final design
2. Final Design Volume ($m^3$): the volume of a convex hull created using the three-dimensional positions of each object and drawing in the final design
3. Final Design Height (m): the height difference between the highest and lowest object or drawing in the final design
4. Final Design Projection Area ($m^2$): the area of the projection of the created convex hull onto the horizontal plane

Following Section 2.5, we built linear mixed-effects models using the 4 summary characteristics as fixed effects to predict each MDS dimension. Predicting dimension 1 for the collaborative design study resulted in a singular fit, which suggested that group accounted for very little of the variance when predicting dimension 1. We therefore dropped the random effect of group and built a linear model.

### 3.2.1 Individual design behaviors and final designs

For dimension 1, there were significant main effects on the Total Number of Objects ($p < .001$) and Final Design Height ($p < .001$). The directions for both coefficients were negative, and we interpret this as design processes that included more 3D pen actions (higher dimension 1 values) tended to lead to final designs with fewer objects that span a narrower vertical space. The effect size of the model was $R^2c = 0.30$, $R^2m = 0.13$, CI [0.09, 0.18].

For dimension 2, there was a main effect on Total Number of Objects ($p = .043$). The direction of the coefficient was negative. Since lower values in dimension 2 is related to faster horizontal plane movement, this suggests that faster horizontal movements yielded final designs with more objects. For dimension 3, there were main effects of the Final Design Projection Area ($p = .027$) and the Total Number of Objects ($p = .032$). The directions of both coefficients were negative. We interpret this as design processes with a higher frequency of manipulation (lower dimension 3 values) yielding designs with more objects that also spread over a greater area in the horizontal plane. Finally, we found no significant main effect for dimension 4. The effect sizes for the models predicting dimensions 2, 3, and 4 were smaller than that for dimension 1: the effect size for dimension 2 was $R^2c = 0.03$, $R^2m = 0.01$, CI [0.00, 0.03], for dimension 3 was $R^2c = 0.06$, $R^2m = 0.02$, CI [0.01, 0.05], and for dimension 4 was $R^2c = 0.07$, $R^2m = 0.00$, CI [0.00, 0.02].

### 3.2.2 Collaborative design behaviors and final designs

For dimension 1, there was a main effect of Final Design Height ($p = .004$). The direction of effect for the significant predictor was positive, which we interpret as lower frequencies of object-related actions (higher values in dimension 1) resulting in final designs spanning a greater vertical space. The effect size for this model was $R^2 = 0.14$, CI [0.05, 0.37]. For dimension 2, there were main effects on the Total Number of Objects ($p = .040$), Final Design Volume ($p = .018$), and Final Design Projection Area ($p = .023$). The directions of effect for the Total Number of Objects and Final Design Projection Area were positive. The direction of effect for the Final Design Volume was negative. This result suggests that design processes with more 3D pen actions (higher values in dimension 2) will likely yield final designs with less volume, more objects, and a greater projection area in the horizontal space. This model had an effect size of $R^2c = 0.27$, $R^2m = 0.19$, CI [0.08, 0.41]. For dimension 3, there was a main effect on Final Design Height ($p = .044$). The direction of effect was negative, which we interpret as faster horizontal movement (higher values in dimension 3) yielding designs that span a narrower vertical space. The model built for dimension 3 had an effect size of $R^2c = 0.09$, $R^2m = 0.18$, CI [0.03, 0.31].

## 3.3 Design behaviors and context

In this section, we present findings on how contextual-related variables affect students' design behaviors. As the context-related variables differed between the Individual and Collaborative Design Studies, we describe these variables separately in Sections 3.3.1 and 3.3.2.

### 3.3.1 Individual design behaviors and context

There were 5 context-related variables for the individual design study. They were the 7 open-ended design activities spread across each week, the 3 teaching assistants prompting and overseeing the activities, the setting (indoor and outdoor), the amount of visible space (panoramic and constrained), and the number of students in a given session.

For the first dimension, we found main effects of the design prompt ($p = .032$), teaching assistants ($p = .001$), and the setting ($p = .035$). Compared to the reference setting category of indoor, the coefficient found for outdoor was negative, which suggests that those creating in outdoor environments tended to create more using 3D objects and not the 3D pen. The effect size for the model predicting dimension 1 was $R^2c = 0.31$, $R^2m = 0.12$, CI [0.09, 0.18].

For the second dimension, we found a main effect of visible space ($p = .041$). In comparison to the reference category of constrained environments, the coefficient found for panoramic environments was negative, suggesting that students moved more in the horizontal space in panoramic environments. For the third dimension, we found a significant main effect on teaching assistants ($p = .033$), which suggested that instructor style influenced how much a student manipulated throughout their design process. Finally, for the fourth dimension, we found a significant main effect of the design prompt ($p = .003$), suggesting that different design prompts influenced head rotation. The effect sizes for the models predicting dimensions 2, 3, and 4 were again smaller than dimension 1. Specifically, the effect size of the model for dimension 2 was $R^2c = 0.06$, $R^2m = 0.03$, CI [0.02, 0.07], for dimension 3 was $R^2c = 0.07$, $R^2m = 0.03$, CI [0.02, 0.07], for dimension 4 was $R^2c = 0.11$, $R^2m = 0.03$, CI [0.02, 0.08].

### 3.3.2 Collaborative design behaviors and context

For the collaborative design study, there were 4 context-related variables, namely the 3 different design prompts, the ceiling height (tall and low), the amount of visible space (panoramic and constrained), and the number of participants in the group. The linear mixed-effects model predicting dimension 1 resulted in a singular fit, so we dropped the random effect of group and built a linear model. In the three models predicting each of the MDS dimensions based on the context-related variables, we found no significant main effect. We attribute this to a limited number of designs as some of the groups did not load in the virtual environments properly and had to be dropped from this analysis. The effect size for the linear model predicting dimension 1 was $R^2c = 0.08$, CI [0.04, 0.35], while that for the linear mixed-effects models predicting dimensions 2 and 3 had effect sizes of $R^2c = 0.13$, $R^2m = 0.07$, CI [0.03, 0.31] and $R^2c = 0.35$, $R^2m = 0.05$, CI [0.03, 0.30], respectively.

# 4 Discussion

We discuss our findings and their practical design implications in two aspects. First, we contextualize our findings within how designers and educators can leverage VR as a tool to make inferences about design behaviors. Next, we outline considerations regarding the structure of activities and the design of VR systems for practitioners seeking to organize immersive design activities.

## 4.1 VR as a tool to study the design process

Using our coding schemes and analytical approach, we found that the common VR design behaviors closely paralleled the physical action categories outlined by Suwa et al. (1998). In particular, the tools used (i.e., 3D pen or 3D objects) and frequency of manipulation described the making of depictions (D-action), the speed of head rotation was related to the L-action, and the horizontal plane movement was captured by the category of physical actions that do not directly alter the design (M-action). Similarly, we can interpret the design behaviors of horizontal plane movement and head rotation as an extension of the change view transformation described in Prats et al.'s general shape transformations (2009). Despite these similarities, the extrapolated design behaviors are not explicitly described in prior frameworks (Prats et al., 2009; Sopher & Dorta, 2023, pp. 423−440; Suwa et al., 1998), suggesting that practitioners who wish to use VR for characterizing design processes should seek to establish a holistic understanding of the tools and action space made available to individuals in design activities. Failure to capture the relevant parameters of interest can hinder practitioners from extrapolating valuable insights of the design process. While some tools and actions may be platform-dependent, it is also important to consider how broader constraints such as simulator sickness from virtual locomotion, individual differences in physical setups and VR sickness susceptibility, abilities, and disabilities can affect one's utilization of these resources (E. Chang, Kim, & Yoo, 2020; Nabors, Monnin, & Jimenez, 2020; Saker & Frith, 2020).

In this work, we also proposed an approach for translating the granular low-level tracking data into higher-level features characterizing the design process without using verbal protocol analysis, which allowed us to systematically examine design processes at scale. Similar in motivation to works that utilize behavioral and tracking data for studying design processes (Millán et al., 2022; Rahman et al., 2021), we demonstrated that these bottom-up analyses can also be applied to more open-ended design tasks, be adapted to both individual and collaborative tasks, and yield informative insights. Ultimately, as VR immerses individuals in controllable environments while logging granular tracking data (Blascovich et al., 2002), practitioners can leverage our approach to bridge the gap between low-level actions and higher-level design behaviors and extend our understanding of the design processes of individuals with different genders (Baer & Kaufman, 2008; Cheng, Sanchez-Burks, & Lee, 2008), cultures (Thoring, Luippold, & Mueller, 2014), and levels of design expertise (Rahman et al., 2021).

### 4.2 Organizing design activities in VR

Our results revealed common design behaviors (i.e., the amount of horizontal plane movement, frequency of manipulation, choice of tool used) across the individual and collaborative design studies. That being said, in line with past findings comparing creative thinking between individuals and groups (Taylor, Berry, & Block, 1958; Youmans, 2011), our findings suggest that practitioners should be mindful of the formulation of design tasks and consider whether the task will be completed individually or collaboratively, with or without an instructor. This is because while the extracted design behaviors for the individual and collaborative design studies overlapped, our findings showed that the same design behavior can lead to different final design characteristics depending on whether the task is completed individually or collaboratively.

For example, we found that design processes with more 3D pen actions yielded final designs with fewer 3D objects spanning a narrower vertical space for the individual design tasks, but more 3D objects spanning a greater horizontal space for the collaborative design tasks. We hypothesize that participants who responded to prompts individually likely used the 3D pen to sketch out their ideas, while those responding in groups likely used 3D pens to label and help explain complex designs with more 3D objects. Another possible reason is that students designing individually were able to explain their designs to the teaching assistant and others during the synchronous discussion sections, whereas those designing collaboratively were under the impression that the final designs will be evaluated asynchronously, and thus warranted more clarity and "labeling" using the 3D pen. Additionally, our results revealed that the amount of horizontal plane movement and frequency of manipulations yielded different effects on the final design characteristics across the two studies. For these two behaviors, we also found that the effect sizes of the models built for the individual design study were substantially smaller than those for the collaborative design study.

Broadly speaking, organizers should be mindful of the context in which design activities occur. In analyzing how context is related to design behaviors, we showed that factors such as design prompts, teaching assistants, amount of visible space, and setting influenced individual design behaviors. Particularly, the effect that context has on whether a student designs with 3D objects or the 3D pen is noticeably greater than the other three dimensions. In demonstrating how contextual factors can also influence dimensions of design behaviors, our results extend past findings on the psychological effects of teaching style (Inayat & Ali, 2020; Michel et al., 2009), visible space (Han et al., 2023), setting (Han et al., 2023; Minocha & Reeves, 2010), and task type (Miller et al., 2021; Yoon et al., 2023).

When organizing design activities for designers and students, it is therefore important to consider whether the activities should be hosted in different environments, and whether their potential effects on design behaviors is desirable and appropriate for the given scenario. For example, for educators hoping to evaluate students through VR design activities, it may be necessary to develop grading rubrics that do not associate performance directly with the one's design behaviors (e.g., amount of virtual movement, choice of tools). As VR can immerse remote users into the same virtual environment across time (Blascovich et al., 2002), another way for mitigating these contextual effects is to instruct students and designers to instantiate the same virtual environment and respond to the same design prompt. Finally, educators and designers can also build VR systems that automatically checks for inconsistencies in context across different virtual sessions and adjust environments accordingly.

# 5 Limitations and future work

There are several limitations to our work. To start, we limited our analysis to the first few dimensions of each of the MDS projections, which captured differences in the aggregated distribution breakdowns of actions and motions. While later dimensions did not capture as much information compared to earlier ones and are therefore not examined based on our scree plot criterion, later dimensions could reveal more subtle design behaviors such as the order and length of operations. When comparing design processes using later dimensions, researchers can consider examining characteristics of the HMMs such as the transition routes, state emission, and transition matrices (Goucher-Lambert & McComb, 2019; Hu et al., 2023; Mehta et al., 2020).

Relatedly, future work should examine other aspects of the final designs such as the spatial arrangement, type, color, and size of the 3D objects and drawings. Additionally, as the design behavior observed in the tracking data is limited to the types of tools and interaction techniques available through the ENGAGE platform, the dimensions of design behavior we identified are platform-dependent. Therefore, we believe that future work should adapt our coding schemes and analysis pipeline to other digital platforms to uncover additional design behaviors and assess the generalizability of our findings.

Furthermore, as we did not collect verbal protocols from the students, we were unable to label action categories beyond the physical and perceptual dimensions (Suwa et al., 1998). Future work can consider leveraging verbal protocol analysis to investigate how action and motion in VR relate to functional and conceptual actions. Since protocol analysis is prone to subjective factors as it inherently relies on the designer's recollection of their thought process and actions, researchers can also integrate objective biometric data such as electroencephalography and eye tracking into the analysis pipeline (Borgianni & Maccioni, 2020; Goucher-Lambert, Moss, & Cagan, 2019; Yu, Schubert, & Gu, 2023). For example, one can encode these measurements as additional features into our coding scheme or analyze them in conjunction with our analysis pipeline. Using biometric measurements and protocol analysis, we envision future research investigating how dimensions of VR design behavior are related to cognitive load, creativity, ideation, and high-level design strategies.

Another area for future work is on extending our coding scheme for collaborative tasks to encode measurements of group dynamics such as synchrony (Miller et al., 2021; Sun, Shaikh, & Won, 2019; Tarr, Slater, & Cohen, 2018), interpersonal distance (Bailenson, Blascovich, Beall, & Loomis, 2003; Kolkmeier, Vroon, & Heylen, 2016), and turn-taking (S. J. Gero & Kan, 2009; Reid & Reed, 2000). Finally, while our approach quantified distances between design processes using KL divergence, future work can explore other ways for defining these distances.

# 6 *Conclusions*

In this work, we collected and studied 730 unique designs from 254 students in VR. Specifically, we (1) developed a VR design coding scheme based on previous theoretical frameworks and (2) proposed a bottom-up analysis pipeline for describing the individual and collaborative VR design processes. Using the proposed techniques, we then summarized the types of design behaviors and examined their relationship with the final designs and context. We found evidence showing that different design behaviors yielded different final designs, and that similar behaviors such as drawing with the 3D pen result in different final design characteristics for those creating individually and collaboratively. Furthermore, in the case of individual design tasks, context (i.e., design activities, setting, amount of visible space, teaching assistants) was closely related to the students' design behaviors. By introducing a tool that leverages the rich tracking data to study the VR design process and outlining the broader practical implications, we hope to encourage further research on the immersive design process and lower the friction for designers and educators to structure and study design activities in VR.

## *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*

The data underlying this work cannot be shared publicly due to the privacy of individuals that participated in the study. The data will be shared on reasonable request to the corresponding author.

## *Acknowledgments*

The authors would like to thank Daniel Scott Akselrad, Tobin Asher, Brian Beams, Hanseul Jun, Ryan Moore, Patricia Jeanne Yablonski, and Mark York for their support with the two VR courses. The authors would also like to thank the team at ENGAGE for providing support throughout the studies. Lastly, the authors would like to thank Ade Mabogunje and Nilam Ram for their feedback. This work was supported by the Sozo Graduate Fellowship.

## *Appendix.*

### *Appendix A. Floor and ceiling values for motion-related features*

| *Motion-related Features* | *Floor* | *Ceiling* |
|---|---|---|
| Head yaw rotation | −10 | 0 |
| Head pitch rotation | −10 | 0 |
| Head roll rotation | −10 | 0 |
| Slower hand movement (Individual design coding scheme) | −10 | 0 |
| Faster hand movement (Individual design coding scheme) | −10 | 0 |
| Horizontal plane movement | −10 | 5 |
| Mean hand movement (Collaborative design coding scheme) | −10 | 0 |

## *Appendix B1. Model equations for analyzing the relationship between the dimensions of design behavior and final design characteristics*

| *Study* | *Dimension* | *Model Type* | *Model Expression* |
|---|---|---|---|
| Individual Design Study | 1, 2, 3, 4 | Linear mixed-effects | Value associated with the design process of student i in section s for design prompt p is modeled as $\text{dimension}_{pis} = \beta_0 + \beta_1(\text{object count}_{pis}) + \beta_2(\text{volume}_{pis}) + \beta_3(\text{height}_{pis}) + \beta_4(\text{projection area}_{pis}) + v_{00s} + u_{0is} + e_{pis}$ where $\beta_0$ represents the intercept, $\beta_1$, $\beta_2$, $\beta_3$, and $\beta_4$ describe how the total number of objects, final design volume, final design height, and final design projection area are related to the dimension value, and $v_{00s}$, $u_{0is}$ and $e_{pis}$ are assumed to be normally distributed with standard deviations $\sigma_v$, $\sigma_u$ and $\sigma_e$, respectively. |
| Collaborative Design Study | 1 | Linear* | Value associated with the design process of group i for design prompt p is modeled as $\text{dimension}_{pi} = \beta_0 + \beta_1(\text{object count}_{pi}) + \beta_2(\text{volume}_{pi}) + \beta_3(\text{height}_{pi}) + \beta_4(\text{projection area}_{pi}) + e_{pi}$ where $\beta_0$ represents the intercept, $\beta_1$, $\beta_2$, $\beta_3$, and $\beta_4$ describe how the total number of objects, final design volume, final design height, and final design projection area are related to the dimension value, and $e_{pi}$ are assumed to be normally distributed with standard deviation $\sigma_e$. |
| | 2, 3 | Linear mixed-effects | Value associated with the design process of group i for design prompt p is modeled as $\text{dimension}_{pi} = \beta_0 + \beta_1(\text{object count}_{pi}) + \beta_2(e_{pi}) + \beta_3(\text{height}_{pi}) + \beta_4(\text{projection area}_{pi}) + u_{0i} + e_{pi}$ where $\beta_0$ represents the intercept, $\beta_1$, $\beta_2$, $\beta_3$, and $\beta_4$ describe how the total number of objects, final design volume, final design height, and final design projection area are related to the dimension value, and $u_{0i}$ and $e_{pi}$ are assumed to be normally distributed with standard deviations $\sigma_u$ and $\sigma_e$, respectively. |

*The linear mixed-effects model built to predict dimension 1 of the collaborative design process resulted in a singular fit, which prompted us to use a linear model instead.

■■■

## *Appendix B2. Model equations for analyzing the relationship between the dimensions of design behavior and context*

| *Study* | *Dimension* | *Model Type* | *Model Expression* |
|---|---|---|---|
| Individual Design Study | 1, 2, 3, 4 | Linear mixed-effects | Value associated with the design process of student i in section s for prompt p is modeled as $\text{dimension}_{pis} = \beta_0 + \beta_1(\text{design prompt}_{pis}) + \beta_2(\text{teaching assistant}_{pis}) + \beta_3(\text{setting}_{pis}) + \beta_4(\text{visible space}_{pis}) + \beta_5(\text{number of student}_{pis}) + v_{00s} + u_{0is} + e_{pis}$ where $\beta_0$ represents the intercept, $\beta_1$, $\beta_2$, $\beta_3$, $\beta_4$, and $\beta_5$ describe how design prompts, teaching assistants, setting (indoor and outdoor), visible space (panoramic and constrained), and the number of students are related to the dimension value, and $v_{00s}$, $u_{0is}$ and $e_{pis}$ are assumed to be normally distributed with standard deviations $\sigma_v$, $\sigma_u$, and $\sigma_e$, respectively. |
| Collaborative Design Study | 1 | Linear* | Value associated with the design process of group i for design prompt p is modeled as $\text{dimension}_{pi} = \beta_0 + \beta_1(\text{design prompt}_{pi}) + \beta_2(\text{ceiling height}_{pi}) + \beta_3(\text{visible space}_{pi}) + \beta_4(\text{number of students}_{pi}) + e_{pi}$ where $\beta_0$ represents the intercept, $\beta_1$, $\beta_2$, $\beta_3$, and $\beta_4$ describe how design prompts, ceiling height (tall and low), visible space (panoramic and constrained), and the number of students are related to the dimension value, and $e_{pi}$ is assumed to be normally distributed with standard deviation $\sigma_e$. |
| | 2, 3 | Linear mixed-effects | Value associated with the design process of group i for design prompt p is modeled as $\text{dimension}_{pi} = \beta_0 + \beta_1(\text{design prompt}_{pi}) + \beta_2(\text{ceiling height}_{pi}) + \beta_3(\text{visible space}_{pi}) + \beta_4(\text{number of students}_{pi}) + u_{0i} + e_{pi}$ where $\beta_0$ represents the intercept, $\beta_1$, $\beta_2$, $\beta_3$, and $\beta_4$ describe how design prompts, ceiling height (tall and low), visible space (panoramic and constrained), and the number of students are related to the dimension value, and $u_{0i}$ and $e_{pi}$ are assumed to be normally distributed with standard deviations $\sigma_u$ and $\sigma_e$, respectively. |

*The linear mixed-effects model built to predict dimension 1 of the collaborative design process resulted in a singular fit, which prompted us to use a linear model instead.

## *Appendix C1.Individual design study dimension 1 breakdown ratios*

| *Feature Name* | *Group* | *Feature Value* | *Percentage* |
|---|---|---|---|
| Translating 3D Object | High-value | No | 92.77 |
| | | Yes (Revisited) | 0.70 |
| | | Yes (Continual) | 6.53 |
| | Low-value | No | 84.85 |
| | | Yes (Revisited) | 3.69 |
| | | Yes (Continual) | 11.46 |
| Rotating 3D Object | High-value | No | 98.55 |
| | | Yes (Revisited) | 0.05 |
| | | Yes (Continual) | 1.40 |
| | Low-value | No | 94.55 |
| | | Yes (Revisited) | 0.93 |
| | | Yes (Continual) | 4.52 |
| Scaling 3D Object | High-value | No | 98.31 |
| | | Yes (Revisited) | 0.03 |
| | | Yes (Continual) | 1.66 |
| | Low-value | No | 94.89 |
| | | Yes (Revisited) | 0.75 |
| | | Yes (Continual) | 4.37 |
| Adding 3D Object | High-value | No | 96.82 |
| | | Yes | 3.18 |
| | Low-value | No | 95.86 |
| | | Yes | 4.14 |
| Deleting 3D Object | High-value | No | 99.63 |
| | | Yes | 0.37 |
| | Low-value | No | 98.83 |
| | | Yes | 1.17 |
| Is Drawing | High-value | No | 33.40 |
| | | Yes | 66.60 |
| | Low-value | No | 88.04 |
| | | Yes | 11.96 |
| Head Yaw | High-value | High | 60.04 |
| | | Low | 3.68 |
| | | Moderate | 36.28 |
| | Low-value | High | 55.26 |
| | | Low | 6.66 |
| | | Moderate | 38.08 |
| Head Roll | High-value | High | 74.38 |
| | | Low | 2.91 |
| | | Moderate | 22.71 |
| | Low-value | High | 66.58 |
| | | Low | 6.28 |
| | | Moderate | 27.14 |
| Head Pitch | High-value | High | 79.56 |
| | | Low | 2.65 |
| | | Moderate | 17.79 |
| | Low-value | High | 73.00 |
| | | Low | 5.82 |
| | | Moderate | 21.18 |

(*continued on next page*)

(*continued*)

| *Feature Name* | *Group* | *Feature Value* | *Percentage* |
|---|---|---|---|
| Horizontal Plane Movement | High-value | High | 5.57 |
| | | Low | 88.55 |
| | | Moderate | 5.88 |
| | Low-value | High | 15.34 |
| | | Low | 77.99 |
| | | Moderate | 6.67 |
| Hand Max Movement | High-value | High | 95.68 |
| | | Low | 1.53 |
| | | Moderate | 2.79 |
| | Low-value | High | 90.39 |
| | | Low | 3.20 |
| | | Moderate | 6.40 |
| Hand Min Movement | High-value | High | 86.17 |
| | | Low | 3.24 |
| | | Moderate | 10.59 |
| | Low-value | High | 72.41 |
| | | Low | 6.21 |
| | | Moderate | 21.38 |

## *Appendix C2.Individual design study dimension 2 breakdown ratios*

| *Feature Name* | *Group* | *Feature Value* | *Percentage* |
|---|---|---|---|
| Translating 3D Object | High-value | No | 89.61 |
| | | Yes (Revisited) | 1.90 |
| | | Yes (Continual) | 8.49 |
| | Low-value | No | 83.09 |
| | | Yes (Revisited) | 3.45 |
| | | Yes (Continual) | 13.46 |
| Rotating 3D Object | High-value | No | 96.43 |
| | | Yes (Revisited) | 0.45 |
| | | Yes (Continual) | 3.13 |
| | Low-value | No | 94.78 |
| | | Yes (Revisited) | 0.70 |
| | | Yes (Continual) | 4.52 |
| Scaling 3D Object | High-value | No | 97.43 |
| | | Yes (Revisited) | 0.35 |
| | | Yes (Continual) | 2.22 |
| | Low-value | No | 94.44 |
| | | Yes (Revisited) | 0.60 |
| | | Yes (Continual) | 4.96 |

(*continued on next page*)

*(continued)*

| *Feature Name* | *Group* | *Feature Value* | *Percentage* |
|---|---|---|---|
| Adding 3D Object | High-value | No | 97.09 |
| | | Yes | 2.91 |
| | Low-value | No | 95.58 |
| | | Yes | 4.42 |
| Deleting 3D Object | High-value | No | 99.45 |
| | | Yes | 0.55 |
| | Low-value | No | 98.80 |
| | | Yes | 1.20 |
| Is Drawing | High-value | No | 72.54 |
| | | Yes | 27.46 |
| | Low-value | No | 81.35 |
| | | Yes | 18.65 |
| Head Yaw | High-value | High | 61.42 |
| | | Low | 3.68 |
| | | Moderate | 34.90 |
| | Low-value | High | 49.33 |
| | | Low | 8.10 |
| | | Moderate | 42.56 |
| Head Roll | High-value | High | 73.54 |
| | | Low | 3.21 |
| | | Moderate | 23.26 |
| | Low-value | High | 60.59 |
| | | Low | 7.71 |
| | | Moderate | 31.70 |
| Head Pitch | High-value | High | 79.59 |
| | | Low | 2.96 |
| | | Moderate | 17.46 |
| | Low-value | High | 70.43 |
| | | Low | 6.81 |
| | | Moderate | 22.76 |
| Horizontal Plane Movement | High-value | High | 3.16 |
| | | Low | 94.53 |
| | | Moderate | 2.31 |
| | Low-value | High | 13.41 |
| | | Low | 81.73 |
| | | Moderate | 4.86 |
| Hand Max Movement | High-value | High | 94.01 |
| | | Low | 1.59 |
| | | Moderate | 4.40 |
| | Low-value | High | 88.52 |
| | | Low | 3.98 |
| | | Moderate | 7.50 |
| Hand Min Movement | High-value | High | 81.42 |
| | | Low | 6.58 |
| | | Moderate | 12.00 |
| | Low-value | High | 66.23 |
| | | Low | 9.47 |
| | | Moderate | 24.31 |

## *Appendix C3.Individual design study dimension 3 breakdown ratios*

| *Feature Name* | *Group* | *Feature Value* | *Percentage* |
|---|---|---|---|
| Translating 3D Object | High-value | No | 88.38 |
| | | Yes (Revisited) | 2.37 |
| | | Yes (Continual) | 9.25 |
| | Low-value | No | 82.21 |
| | | Yes (Revisited) | 2.87 |
| | | Yes (Continual) | 14.92 |
| Rotating 3D Object | High-value | No | 96.42 |
| | | Yes (Revisited) | 0.50 |
| | | Yes (Continual) | 3.08 |
| | Low-value | No | 94.22 |
| | | Yes (Revisited) | 0.43 |
| | | Yes (Continual) | 5.36 |
| Scaling 3D Object | High-value | No | 97.01 |
| | | Yes (Revisited) | 0.32 |
| | | Yes (Continual) | 2.67 |
| | Low-value | No | 93.64 |
| | | Yes (Revisited) | 0.68 |
| | | Yes (Continual) | 5.68 |
| Adding 3D Object | High-value | No | 96.44 |
| | | Yes | 3.56 |
| | Low-value | No | 95.19 |
| | | Yes | 4.81 |
| Deleting 3D Object | High-value | No | 99.18 |
| | | Yes | 0.82 |
| | Low-value | No | 98.67 |
| | | Yes | 1.33 |
| Is Drawing | High-value | No | 72.72 |
| | | Yes | 27.28 |
| | Low-value | No | 78.49 |
| | | Yes | 21.51 |
| Head Yaw | High-value | High | 55.39 |
| | | Low | 6.43 |
| | | Moderate | 38.19 |
| | Low-value | High | 43.30 |
| | | Low | 8.73 |
| | | Moderate | 47.97 |
| Head Roll | High-value | High | 67.37 |
| | | Low | 5.62 |
| | | Moderate | 27.00 |
| | Low-value | High | 56.82 |
| | | Low | 8.57 |
| | | Moderate | 34.62 |
| Head Pitch | High-value | High | 72.95 |
| | | Low | 5.41 |
| | | Moderate | 21.64 |
| | Low-value | High | 67.42 |
| | | Low | 7.55 |
| | | Moderate | 25.03 |

(*continued on next page*)

(continued)

| Feature Name | Group | Feature Value | Percentage |
|---|---|---|---|
| Horizontal Plane Movement | High-value | High | 6.24 |
| | | Low | 90.83 |
| | | Moderate | 2.94 |
| | Low-value | High | 12.84 |
| | | Low | 80.51 |
| | | Moderate | 6.65 |
| Hand Max Movement | High-value | High | 88.99 |
| | | Low | 5.12 |
| | | Moderate | 5.89 |
| | Low-value | High | 88.29 |
| | | Low | 3.62 |
| | | Moderate | 8.09 |
| Hand Min Movement | High-value | High | 71.39 |
| | | Low | 10.73 |
| | | Moderate | 17.88 |
| | Low-value | High | 64.87 |
| | | Low | 8.93 |
| | | Moderate | 26.19 |

## *Appendix C4.Individual design study dimension 4 breakdown ratios*

| Feature Name | Group | Feature Value | Percentage |
|---|---|---|---|
| Translating 3D Object | High-value | No | 89.13 |
| | | Yes (Revisited) | 1.36 |
| | | Yes (Continual) | 9.51 |
| | Low-value | No | 84.95 |
| | | Yes (Revisited) | 3.78 |
| | | Yes (Continual) | 11.27 |
| Rotating 3D Object | High-value | No | 96.76 |
| | | Yes (Revisited) | 0.17 |
| | | Yes (Continual) | 3.07 |
| | Low-value | No | 94.67 |
| | | Yes (Revisited) | 1.19 |
| | | Yes (Continual) | 4.14 |
| Scaling 3D Object | High-value | No | 96.28 |
| | | Yes (Revisited) | 0.18 |
| | | Yes (Continual) | 3.54 |
| | Low-value | No | 95.48 |
| | | Yes (Revisited) | 0.78 |
| | | Yes (Continual) | 3.75 |
| Adding 3D Object | High-value | No | 96.63 |
| | | Yes | 3.37 |
| | Low-value | No | 95.11 |
| | | Yes | 4.89 |

(continued on next page)

(*continued*)

| *Feature Name* | *Group* | *Feature Value* | *Percentage* |
|---|---|---|---|
| Deleting 3D Object | High-value | No | 99.37 |
| | | Yes | 0.63 |
| | Low-value | No | 98.77 |
| | | Yes | 1.23 |
| Is Drawing | High-value | No | 65.32 |
| | | Yes | 34.68 |
| | Low-value | No | 65.36 |
| | | Yes | 34.64 |
| Head Yaw | High-value | High | 62.24 |
| | | Low | 4.39 |
| | | Moderate | 33.37 |
| | Low-value | High | 46.47 |
| | | Low | 8.65 |
| | | Moderate | 44.88 |
| Head Roll | High-value | High | 74.24 |
| | | Low | 3.68 |
| | | Moderate | 22.08 |
| | Low-value | High | 61.83 |
| | | Low | 8.25 |
| | | Moderate | 29.92 |
| Head Pitch | High-value | High | 80.28 |
| | | Low | 3.45 |
| | | Moderate | 16.27 |
| | Low-value | High | 69.83 |
| | | Low | 7.21 |
| | | Moderate | 22.97 |
| Horizontal Plane Movement | High-value | High | 8.67 |
| | | Low | 85.59 |
| | | Moderate | 5.74 |
| | Low-value | High | 9.27 |
| | | Low | 84.85 |
| | | Moderate | 5.89 |
| Hand Max Movement | High-value | High | 93.75 |
| | | Low | 2.32 |
| | | Moderate | 3.93 |
| | Low-value | High | 91.44 |
| | | Low | 2.45 |
| | | Moderate | 6.11 |
| Hand Min Movement | High-value | High | 82.40 |
| | | Low | 4.76 |
| | | Moderate | 12.85 |
| | Low-value | High | 69.07 |
| | | Low | 6.88 |
| | | Moderate | 24.04 |

## *Appendix D1.Collaborative design study dimension 1 percentages of positive labels*

We only report the percentage for each of the features being labeled positive as the percentage of the negative label can be obtained by subtracting the positive percentage from 100. For example, the high-value group spent 7.79% of the time adding objects, and 92.21% of the time not adding 3D objects.

| *Feature Name* | *Group* | *Percentage* |
| --- | --- | --- |
| Adding 3D Object | High-value | 7.79 |
| | Low-value | 10.47 |
| Deleting 3D Object | High-value | 4.08 |
| | Deleting 3D Object Low-value | 4.71 |
| Is Drawing | High-value | 14.51 |
| | Is Drawing Low-value | 3.66 |
| Not Translating 3D Object | High-value | 99.75 |
| | Not Translating 3D Object Low-value | 97.91 |
| Translating 3D Object (Revisited) | High-value | 5.53 |
| | Translating 3D Object (Revisited) Low-value | 1.57 |
| Translating 3D Object (Continual) | High-value | 19.28 |
| | Translating 3D Object (Continual) Low-value | 36.13 |
| Not Rotating 3D Object | High-value | 100.00 |
| | Not Rotating 3D Object Low-value | 99.48 |
| Rotating 3D Object (Revisited) | High-value | 1.70 |
| | Rotating 3D Object (Revisited) Low-value | 0.00 |
| Rotating 3D Object (Continual) | High-value | 9.11 |
| | Rotating 3D Object (Continual) Low-value | 16.23 |
| Not Scaling 3D Object | High-value | 100.00 |
| | Not Scaling 3D Object Low-value | 100.00 |
| Scaling 3D Object (Revisited) | High-value | 0.63 |
| | Scaling 3D Object (Revisited) Low-value | 0.00 |
| Scaling 3D Object (Continual) | High-value | 5.28 |
| | Scaling 3D Object (Continual) Low-value | 17.80 |
| Head Yaw Low | High-value | 7.85 |
| | Head Yaw Low Low-value | 4.19 |
| Head Yaw Moderate | High-value | 78.02 |
| | Head Yaw Moderate Low-value | 79.58 |
| Head Yaw High | High-value | 94.79 |
| | Head Yaw High Low-value | 96.34 |
| Head Roll Low | High-value | 5.72 |
| | Head Roll Low Low-value | 5.76 |
| Head Roll Moderate | High-value | 62.06 |
| | Head Roll Moderate Low-value | 71.20 |
| Head Roll High | High-value | 98.43 |
| | Head Roll High Low-value | 98.95 |

(*continued on next page*)

(*continued*)

| *Feature Name* | *Group* | *Percentage* |
|---|---|---|
| Head Pitch Low | High-value | 6.09 |
| | Head Pitch Low Low-value | 1.57 |
| Head Pitch Moderate | High-value | 48.12 |
| | Head Pitch Moderate Low-value | 61.78 |
| Head Pitch High | High-value | 98.56 |
| | Head Pitch High Low-value | 98.43 |
| Horizontal Movement Low | High-value | 95.16 |
| | Horizontal Movement Low Low-value | 97.91 |
| Horizontal Movement Moderate | High-value | 29.77 |
| | Horizontal Movement Moderate Low-value | 19.37 |
| Horizontal Movement High | High-value | 49.81 |
| | Horizontal Movement High Low-value | 49.74 |
| Hand Movement Low | High-value | 4.77 |
| | Hand Movement Low Low-value | 2.62 |
| Hand Movement Moderate | High-value | 19.22 |
| | Hand Movement Moderate Low-value | 11.52 |
| Hand Movement High | High-value | 99.94 |
| | Hand Movement High Low-value | 100.00 |

## *Appendix D2.Collaborative design study dimension 2 percentages of positive labels*

| *Feature Name* | *Group* | *Percentage* |
|---|---|---|
| Adding 3D Object | High-value | 8.16 |
| | Adding 3D Object Low-value | 10.86 |
| Deleting 3D Object | High-value | 3.57 |
| | Deleting 3D Object Low-value | 5.00 |
| Is Drawing | High-value | 26.76 |
| | Is Drawing Low-value | 0.00 |
| Not Translating 3D Object | High-value | 100.00 |
| | Not Translating 3D Object Low-value | 99.86 |

(*continued on next page*)

(*continued*)

| *Feature Name* | *Group* | *Percentage* |
|---|---|---|
| Translating 3D Object (Revisited) | High-value | 3.08 |
| | Translating 3D Object (Revisited) Low-value | 1.14 |
| Translating 3D Object (Continual) | High-value | 20.54 |
| | Translating 3D Object (Continual) Low-value | 28.86 |
| Not Rotating 3D Object | High-value | 100.00 |
| | Not Rotating 3D Object Low-value | 100.00 |
| Rotating 3D Object (Revisited) | High-value | 0.65 |
| | Rotating 3D Object (Revisited) Low-value | 0.14 |
| Rotating 3D Object (Continual) | High-value | 8.70 |
| | Rotating 3D Object (Continual) Low-value | 12.14 |
| Not Scaling 3D Object | High-value | 100.00 |
| | Not Scaling 3D Object Low-value | 100.00 |
| Scaling 3D Object (Revisited) | High-value | 0.65 |
| | Scaling 3D Object (Revisited) Low-value | 0.00 |
| Scaling 3D Object (Continual) | High-value | 8.76 |
| | Scaling 3D Object (Continual) Low-value | 5.29 |
| Head Yaw Low | High-value | 8.54 |
| | Head Yaw Low Low-value | 7.86 |
| Head Yaw Moderate | High-value | 64.22 |
| | Head Yaw Moderate Low-value | 82.57 |
| Head Yaw High | High-value | 96.86 |
| | Head Yaw High Low-value | 90.71 |
| Head Roll Low | High-value | 6.86 |
| | Head Roll Low Low-value | 6.57 |
| Head Roll Moderate | High-value | 47.08 |
| | Head Roll Moderate Low-value | 67.14 |
| Head Roll High | High-value | 98.59 |
| | Head Roll High Low-value | 97.14 |
| Head Pitch Low | High-value | 6.27 |
| | Head Pitch Low Low-value | 6.00 |
| Head Pitch Moderate | High-value | 39.35 |
| | Head Pitch Moderate Low-value | 53.86 |

(*continued on next page*)

(*continued*)

| *Feature Name* | *Group* | *Percentage* |
|---|---|---|
| Head Pitch High | High-value | 99.14 |
| | Head Pitch High Low-value | 98.29 |
| Horizontal Movement Low | High-value | 88.81 |
| | Horizontal Movement Low Low-value | 96.43 |
| Horizontal Movement Moderate | High-value | 40.97 |
| | Horizontal Movement Moderate Low-value | 25.00 |
| Horizontal Movement High | High-value | 54.70 |
| | Horizontal Movement High Low-value | 46.86 |
| Hand Movement Low | High-value | 9.57 |
| | Hand Movement Low Low-value | 8.29 |
| Hand Movement Moderate | High-value | 8.86 |
| | Hand Movement Moderate Low-value | 15.57 |
| Hand Movement High | High-value | 100.00 |
| | Hand Movement High Low-value | 99.86 |

## *Appendix D3.Collaborative design study dimension 3 percentages of positive labels*

| *Feature Name* | *Group* | *Percentage* |
|---|---|---|
| Adding 3D Object | High-value | 11.21 |
| | Low-value | 8.21 |
| Deleting 3D Object | High-value | 4.31 |
| | Low-value | 4.55 |
| Is Drawing | High-value | 3.16 |
| | Low-value | 13.95 |
| Not Translating 3D Object | High-value | 98.85 |
| | Low-value | 100.00 |
| Translating 3D Object (Revisited) | High-value | 5.46 |
| | Low-value | 5.74 |
| Translating 3D Object (Continual) | High-value | 28.74 |
| | Low-value | 18.50 |
| Not Rotating 3D Object | High-value | 99.86 |
| | Low-value | 100.00 |
| Rotating 3D Object (Revisited) | High-value | 1.58 |
| | Low-value | 1.77 |
| Rotating 3D Object (Continual) | High-value | 12.79 |
| | Low-value | 9.41 |
| Not Scaling 3D Object | High-value | 100.00 |
| | Low-value | 100.00 |

(*continued on next page*)

(*continued*)

| *Feature Name* | *Group* | *Percentage* |
|---|---|---|
| Scaling 3D Object (Revisited) | High-value | 1.44 |
| | Low-value | 0.44 |
| Scaling 3D Object (Continual) | High-value | 11.78 |
| | Low-value | 4.23 |
| Head Yaw Low | High-value | 5.32 |
| | Low-value | 5.49 |
| Head Yaw Moderate | High-value | 78.02 |
| | Low-value | 69.38 |
| Head Yaw High | High-value | 95.26 |
| | Low-value | 96.28 |
| Head Roll Low | High-value | 4.45 |
| | Low-value | 3.85 |
| Head Roll Moderate | High-value | 63.65 |
| | Low-value | 48.48 |
| Head Roll High | High-value | 98.99 |
| | Low-value | 98.61 |
| Head Pitch Low | High-value | 4.89 |
| | Low-value | 3.85 |
| Head Pitch Moderate | High-value | 43.68 |
| | Low-value | 43.81 |
| Head Pitch High | High-value | 99.14 |
| | Low-value | 98.74 |
| Horizontal Movement Low | High-value | 89.51 |
| | Low-value | 99.62 |
| Horizontal Movement Moderate | High-value | 34.63 |
| | Low-value | 25.57 |
| Horizontal Movement High | High-value | 72.13 |
| | Low-value | 27.71 |
| Hand Movement Low | High-value | 4.74 |
| | Low-value | 2.84 |
| Hand Movement Moderate | High-value | 7.33 |
| | Low-value | 14.77 |
| Hand Movement High | High-value | 100.00 |
| | Low-value | 99.94 |

## *Appendix E.Individual design study and collaborative design study means and standard deviations (in parentheses) of the 4 final design summary characteristics*

| | *Individual Design Study* | *Collaborative Design Study* |
|---|---|---|
| Total Number of Objects | 5.37 (5.49) | 13.22 (18.90) |
| Final Design Volume ($m^3$) | 396.87 (8082.14) | 1870.03 (11 972.94) |
| Final Design Height (m) | 2.89 (13.30) | 3.99 (7.15) |
| Final Design Projection Area ($m^2$) | 11.54 (83.59) | 40.73 (151.60) |

## *References*


. Ali-Hassan, H., & Nevo, D. (2009). Identifying social computing dimensions: A multidimensional scaling study. In *Proceedings of the International Conference on Information Systems, ICIS 2009, Phoenix, Arizona, USA, December 15-18, 2009, 148*. unknown.

Baer, J., & Kaufman, J. C. (2008). Gender differences in creativity. *Journal of Creative Behavior, 42*(2), 75–105.

Bailenson, J. N., Beall, A. C., Loomis, J., Blascovich, J., & Turk, M. (2004). Transformed social interaction: Decoupling representation from behavior and form in collaborative virtual environments. *Presence: Teleoperators & Virtual Environments, 13*, 428–441.

Bailenson, J. N., Blascovich, J., Beall, A. C., & Loomis, J. M. (2003). Interpersonal distance in immersive virtual environments. *Personality and Social Psychology Bulletin, 29*(7), 819–833.

Berg, L. P., & Vance, J. M. (2017). Industry use of virtual reality in product design and manufacturing: A survey. *Virtual Reality, 21*(1), 1–17.

Bhagwatwar, A., Massey, A., & Dennis, A. (2018). Contextual priming and the design of 3D virtual environments to improve group ideation. *Information Systems Research, 29*(1), 169–185.

Blascovich, J., Loomis, J., Beall, A. C., Swinth, K. R., Hoyt, C. L., & Bailenson, J. N. (2002). Immersive virtual environment technology as a methodological tool for social psychology. *Psychological Inquiry, 13*(2), 103–124.

Borgianni, Y., & Maccioni, L. (2020). Review of the use of neurophysiological and biometric measures in experimental design research. *Artificial Intelligence for Engineering Design, Analysis and Manufacturing, 34*(2), 248–285.

Brownell, E., Cagan, J., & Kotovsky, K. (2021). Only as strong as the strongest link: The relative contribution of individual team Member proficiency in configuration design. *Journal of Mechanical Design, 143*(8), 081402.

Chang, Y.-S., Kao, J.-Y., & Wang, Y.-Y. (2022). Influences of virtual reality on design creativity and design thinking. *Thinking Skills and Creativity, 46*, 101127.

Chang, E., Kim, H. T., & Yoo, B. (2020). Virtual reality sickness: A review of causes and measurements. *International Journal of Human-Computer Interaction, 36*(17), 1658–1682.

Chaudhari, A. M., Bilionis, I., & Panchal, J. H. (2020). Descriptive models of sequential decisions in engineering design: An experimental study. *Journal of Mechanical Design, 142*(8), 081704.

Cheng, C.-Y., Sanchez-Burks, J., & Lee, F. (2008). Connecting the dots within: Creative performance and identity integration. *Psychological Science, 19*(11), 1178–1184.

Dorta, T., Kinayoglu, G., & Hoffmann, M. (2016). Hyve-3D and the 3D cursor: Architectural co-design with freedom in virtual reality. *International Journal of Architectural Computing, 14*(2), 87–102.

Dorta, T., & Pérez, E. (2006). Immersive drafted virtual reality a new approach for ideation within virtual reality. ACADIA proceedings. In *Presented at the ACADIA 2006: Synthetic landscapes, Louisville (Kentucky), USA*. https://doi.org/10.52842/conf.acadia.2006.304.

Drey, T., Gugenheimer, J., Karlbauer, J., Milo, M., & Rukzio, E. (2020). VRSketchIn: Exploring the design space of pen and tablet interaction for 3D sketching in virtual reality. In *Proceedings of the 2020 CHI conference on human factors in computing systems* (pp. 1–14). New York, NY, USA: Association for Computing Machinery.

Eckersley, M. (1988). The form of design processes: A protocol analysis study. *Design Studies, 9*(2), 86–94.
Ericsson, K. A., & Simon, H. A. (1984). *Protocol analysis: Verbal reports as data*. MIT Press.
Gero, J. (1990). Design prototypes: A knowledge representation schema for design. *AI Magazine, 11*(4), 26–36.
Gero, S. J., & Kan, W. T. J. (2009). Learning to collaborate during team designing: Some preliminary results fromMeasurement-based tools. In *ICORD 09: Proceedings of the 2nd international conference on research into design, Bangalore, India 07.-09.01.2009* (pp. 560–567).
Gero, J. S., & Kannengiesser, U. (2007). A function–behavior–structure ontology of processes. *Artificial Intelligence for Engineering Design, Analysis and Manufacturing, 21*(4), 379–391.
Ghassempour, S., Girosi, F., & Maeder, A. (2014). Clustering multivariate time series using Hidden Markov Models. *International Journal of Environmental Research and Public Health, 11*(3), 2741–2763.
Goldschmidt, G. (2014). *Linkography: Unfolding the design process*. MIT Press.
Gong, Z., Lee, L.-H., Soomro, S. A., Nanjappan, V., & Georgiev, G. V. (2022). A systematic review of virtual brainstorming from the perspective of creativity: Affordances, framework, and outlook. *Digital Creativity, 33*(2), 96–127.
Goucher-Lambert, K., & McComb, C. (2019). Using hidden Markov models to uncover underlying states in neuroimaging data for a design ideation task. *Proceedings of the Design Society: International Conference on Engineering Design, 1*(1), 1873–1882.
Goucher-Lambert, K., Moss, J., & Cagan, J. (2019). A neuroimaging investigation of design ideation with and without inspirational stimuli—understanding the meaning of near and far stimuli. *Design Studies, 60*, 1–38.
Han, E., Miller, M. R., DeVeaux, C., Jun, H., Nowak, K. L., Hancock, J. T., et al. (2023). People, places, and time: A large-scale, longitudinal study of transformed avatars and environmental context in group interaction in the metaverse. *Journal of Computer-Mediated Communication: JCMC, 28*(2). https://doi.org/10.1093/jcmc/zmac031.
Helske, S., & Helske, J. (2019). Mixture hidden Markov models for sequence data: The seqhmm package in R. *Journal of Statistical Software, 88*(1). https://doi.org/10.18637/jss.v088.i03.
Holzwarth, V., Schneider, J., Handali, J., Gisler, J., Hirt, C., Kunz, A., et al. (2021). Towards estimating affective states in Virtual Reality based on behavioral data. *Virtual Reality, 25*(4), 1139–1152.
Hout, M. C., Papesh, M. H., & Goldinger, S. D. (2013). Multidimensional scaling. *Wiley Interdisciplinary Reviews. Cognitive Science, 4*(1), 93–103.
Houzangbe, S., Masson, D., Fleury, S., Gómez Jáuregui, D. A., Legardeur, J., Richir, S., et al. (2022). Is virtual reality the solution? A comparison between 3D and 2D creative sketching tools in the early design process. *Frontiers in Virtual Reality, 3*. https://doi.org/10.3389/frvir.2022.958223.
Huang, Y., Richter, E., Kleickmann, T., & Richter, D. (2022). Class size affects preservice teachers' physiological and psychological stress reactions: An experiment in a virtual reality classroom. *Computers & Education, 184*, 104503.
Hu, M., McComb, C., & Goucher-Lambert, K. (2023). Uncovering hidden patterns of design ideation using hidden Markov modeling and neuroimaging. *Artificial Intelligence for Engineering Design, Analysis and Manufacturing, 37*, e8.
Hung, Y.-W., Chiu, Y.-H., Chen, W.-H., Huang, K.-Y., & Cheng, K.-S. (2015). Acoustic monitoring of daily activities based on hidden Markov model and

multidimensional scaling. *Journal of the Chinese Institute of Engineers, 38*(4), 447–457.
Ide, M., Oshima, S., Mori, S., Yoshimi, M., Ichino, J., & Tano, S. (2021). Effects of avatar's symbolic gesture in virtual reality brainstorming. In *Proceedings of the 32nd Australian conference on human-computer interaction* (pp. 170–177). New York, NY, USA: Association for Computing Machinery.
Inayat, A., & Ali, A. Z. (2020). Influence of teaching style on students' engagement, curiosity and exploration in the classroom. *Journal of Education and Educational Development, 7*(1), 87.
Jaeger, B. C., Edwards, L. J., Das, K., & Sen, P. K. (2017). An R2 statistic for fixed effects in the generalized linear mixed model. *Journal of Applied Statistics, 44*(6), 1086–1105.
Jaworska, N., & Chupetlovska-Anastasova, A. (2009). A review of multidimensional scaling (MDS) and its utility in various psychological domains. *Tutorials in Quantitative Methods for Psychology, 5*(1). https://doi.org/10.20982/tqmp.05.1.p001.
Joundi, J., Christiaens, Y., Saldien, J., Conradie, P., & De Marez, L. (2020). AN explorative study towards using VR sketching as a tool for ideation and prototyping in product design. *Proceedings of the Design Society: DESIGN Conference, 1*, 225–234.
Kan, J. W. T., & Gero, J. S. (2008). Acquiring information from linkography in protocol studies of designing. *Design Studies, 29*(4), 315–337.
Kent, L., Snider, C., Gopsill, J., & Hicks, B. (2021). Mixed reality in design prototyping: A systematic review. *Design Studies, 77*, 101046.
Khojasteh, N., & Won, A. S. (2021). Working together on diverse tasks: A longitudinal study on individual workload, presence and emotional recognition in collaborative virtual environments. *Frontiers in Virtual Reality, 2*. https://doi.org/10.3389/frvir.2021.643331.
Kim, K. M., & Lee, K. P. (2016). Collaborative product design processes of industrial design and engineering design in consumer product companies. *Design Studies, 46*, 226–260.
Kolkmeier, J., Vroon, J., & Heylen, D. (2016). Interacting with virtual agents in shared space: Single and joint effects of gaze and proxemics. *Intelligent Virtual Agents*1–14, Springer International Publishing.
Koutsabasis, P., Vosinakis, S., Malisova, K., & Paparounas, N. (2012). On the value of Virtual Worlds for collaborative design. *Design Studies, 33*(4), 357–390.
Kullback, S., & Leibler, R. A. (1951). *On information and sufficiency*. *Annals of mathematical statistics*. https://doi.org/10.1214/aoms/1177729694.
Laing, S., & Apperley, M. (2020). The relevance of virtual reality to communication design. *Design Studies, 71*. https://doi.org/10.1016/j.destud.2020.100965.
Lee, M., Kim, E., Choe, J., Choi, S., Ha, S., & Kim, G. (2022). Psychological effects of green experiences in a virtual environment: A systematic review. *Forests, 13*. https://doi.org/10.3390/f13101625. MDPI.
Lloyd, P., & Oak, A. (2018). Cracking open co-creation: Categories, stories, and value tension in a collaborative design process. *Design Studies, 57*, 93–111.
McComb, C., Cagan, J., & Kotovsky, K. (2017a). Capturing human sequence-learning abilities in configuration design tasks through Markov chains. *Journal of Mechanical Design, 139*(9). https://doi.org/10.1115/1.4037185.
McComb, C., Cagan, J., & Kotovsky, K. (2017b). Mining process heuristics from designer action data via hidden Markov models. *Journal of Mechanical Design, 139*(11). https://doi.org/10.1115/1.4037308.

Mehta, P., Malviya, M., McComb, C., Manogharan, G., & Berdanier, C. G. P. (2020). Mining design heuristics for additive manufacturing via eye-tracking methods and hidden Markov modeling. *Journal of Mechanical Design, 142*(12), 124502.

Mei, Y., Li, J., de Ridder, H., & Cesar, P. (2021). CakeVR: A social virtual reality (VR) tool for Co-designing cakes. In *Proceedings of the 2021 CHI conference on human factors in computing systems* (pp. 1–14). New York, NY, USA: Association for Computing Machinery.

Meyers-Levy, J., & Zhu, R. (2007). The influence of ceiling height: The effect of priming on the type of processing that people use. *Journal of Consumer Research, 34*(2), 174–186.

Michel, N., Cater, J. J., III, & Varela, O. (2009). Active versus passive teaching styles: An empirical study of student learning outcomes. *Human Resource Development Quarterly, 20*(4), 397–418.

Millán, E., Belmonte, M. V., Boned, F. J., Gavilanes, J., Pérez-de-la-Cruz, J. L., & Díaz-López, C. (2022). Using machine learning techniques for architectural design tracking: An experimental study of the design of a shelter. *Journal of Building Engineering, 51*. https://doi.org/10.1016/j.jobe.2022.104223.

Miller, M. R., Han, E., DeVeaux, C., Jones, E., Chen, R., & Bailenson, J. N. (2023). *A large-scale study of personal identifiability of virtual reality motion over time*. Retrieved from. http://arxiv.org/abs/2303.01430.

Miller, M. R., Sonalkar, N., Mabogunje, A., Leifer, L., & Bailenson, J. (2021). Synchrony within triads using virtual reality. *Proceedings of the ACM on Human-Computer Interaction, 5*(CSCW2). https://doi.org/10.1145/3479544.

Minocha, S., & Reeves, A. J. (2010). Design of learning spaces in 3D virtual worlds: An empirical investigation of second life. *Learning, Media and Technology, 35*(2), 111–137.

Nabors, L., Monnin, J., & Jimenez, S. (2020). A scoping review of studies on virtual reality for individuals with intellectual disabilities. *Advances in Neurodevelopmental Disorders, 4*(4), 344–356.

Nakagawa, S., & Schielzeth, H. (2013). A general and simple method for obtainingR2from generalized linear mixed-effects models. *Methods in Ecology and Evolution/British Ecological Society, 4*(2), 133–142.

Nukarinen, T., Rantala, J., Korpela, K., Browning, M. H. E. M., Istance, H. O., Surakka, V., et al. (2022). Measures and modalities in restorative virtual natural environments: An integrative narrative review. *Computers in Human Behavior, 126*. https://doi.org/10.1016/j.chb.2021.107008. Elsevier Ltd.

Obeid, S., & Demirkan, H. (2020). The influence of virtual reality on design process creativity in basic design studios. *Interactive Learning Environments*. https://doi.org/10.1080/10494820.2020.1858116.

Okken, V., van Rompay, T., & Pruyn, A. (2013). Room to move: On spatial constraints and self-disclosure during intimate conversations. *Environment and Behavior, 45*(6), 737–760.

Prats, M., Lim, S., Jowers, I., Garner, S. W., & Chase, S. (2009). Transforming shape in design: Observations from studies of sketching. *Design Studies, 30*(5), 503–520.

Qian, L., & Gero, J. S. (1996). Function–behavior–structure paths and their role in analogy-based design. *Artificial Intelligence for Engineering Design, Analysis and Manufacturing, 10*(4), 289–312.

Rahman, M. H., Xie, C., & Sha, Z. (2021). Predicting sequential design decisions using the function-behavior-structure design process model and recurrent neural networks. *Journal of Mechanical Design, 143*(8). https://doi.org/10.1115/1.4049971.

Reid, F. J. M., & Reed, S. (2000). Cognitive entrainment in engineering design teams. *Small Group Research, 31*(3), 354−382.
Renzulli, J. S., Owen, S. V., & Callahan, C. M. (1974). Fluency, flexibility, and originality as a function of group size. *Journal of Creative Behavior, 8*(2), 107−113.
Rights, J. D., & Sterba, S. K. (2019). Quantifying explained variance in multilevel models: An integrative framework for defining R-squared measures. *Psychological Methods, 24*(3), 309−338.
Saker, M., & Frith, J. (2020). Coextensive space: Virtual reality and the developing relationship between the body, the digital and physical space. *Media, Culture & Society, 42*(7−8), 1427−1442.
Shadiev, R., & Li, D. (2023). A review study on eye-tracking technology usage in immersive virtual reality learning environments. *Computers and Education, 196*. https://doi.org/10.1016/j.compedu.2022.104681.
Sha, Z., Kannan, K. N., & Panchal, J. H. (2015). Behavioral experimentation and game theory in engineering systems design. *Journal of Mechanical Design, 137*(5), 051405.
Shen, Y., Ong, S. K., & Nee, A. Y. C. (2010). Augmented reality for collaborative product design and development. *Design Studies, 31*(2), 118−145.
Shneiderman, B. (1982). The future of interactive systems and the emergence of direct manipulation. *Behaviour & Information Technology, 1*(3), 237−256.
Slater, M., Steed, A., McCarthy, J., & Maringelli, F. (1998). The influence of body movement on subjective presence in virtual environments. *Human Factors, 40*(3), 469−477.
Sonalkar, N., Mabogunje, A., Miller, M., Bailenson, J., & Leifer, L. (2020). Augmenting learning of design teamwork using immersive virtual reality. In C. Meinel, & L. Leifer (Eds.), *Design thinking research : Investigating design team performance* (pp. 67−76). Cham: Springer International Publishing.
Sopher, H., & Dorta, T. (2023). *Collaborative-knowledge construction activity method to analyse design-learning in VR Co-design crits*. Design Computing and Cognition'22, −. Springer International Publishing.
Sopher, H., Fisher Gewirtzman, D., & Kalay, Y. E. (2019). Going immersive in a community of learners? Assessment of design processes in a multi-setting architecture studio. *British Journal of Educational Technology: Journal of the Council for Educational Technology, 50*(5), 2109−2128.
Sun, Y., Shaikh, O., & Won, A. S. (2019). Nonverbal synchrony in virtual reality. *PLoS One, 14*(9). https://doi.org/10.1371/journal.pone.0221803.
Suwa, M., Purcell, T., & Gero, J. (1998). Macroscopic analysis of design processes based on a scheme for coding designers' cognitive actions. *Design Studies, 19*, 455−483.
Suwa, M., & Tversky, B. (1997). What do architects and students perceive in their design sketches? A protocol analysis. *Design Studies, 18*(4), 385−403.
Suzuki, N., Hirasawa, K., Tanaka, K., & Fujino, Y. (2007). Learning motion patterns and anomaly detection by Human trajectory analysis. In *Systems, Man and Cybernetics, 2007. ISIC. IEEE International Conference on* (pp. 498−503), unknown.
Tarr, B., Slater, M., & Cohen, E. (2018). Synchrony and social connection in immersive Virtual Reality. *Scientific Reports, 8*(1), 3693.
Taylor, D. W., Berry, P. C., & Block, C. H. (1958). Does group participation when using brainstorming facilitate or inhibit creative thinking? *Administrative Science Quarterly, 3*(1), 23−47.
Thoring, K., Luippold, C., & Mueller, R. M. (2014). The impact of cultural differences in design thinking education. In *DRS biennial conference series*.

Retrieved from. https://dl.designresearchsociety.org/drs-conference-papers/drs2014/researchpapers/49/.

Thorsteinsson, G., & Denton, H. (2006). Ideation in a virtual reality learning environment: A pilot project from Iceland in innovation education. *The Design and technology association international research conference*. Retrieved from. https://www.semanticscholar.org/paper/5101a85a1aa944ac137d78ffe4e59c590d89ae62.

Thorsteinsson, G., Niculescu, A., & Page, T. (2010). Using virtual reality for developing design communication. *Studies in Informatics and Control, 19*(1), 93–106.

Thorsteinsson, G., & Page, T. (2007). Creativity in technology education facilitated through virtual reality learning environments: A case study. *British Journal of Educational Technology: Journal of the Council for Educational Technology, 3*(4), 74–87.

Won, A. S., Perone, B., Friend, M., & Bailenson, J. N. (2016). Identifying anxiety through tracked head movements in a virtual classroom. *Cyberpsychology, Behavior, and Social Networking, 19*(6), 380–387.

Wu, X., Law, S., Heath, T., & Borsi, K. (2017). Spatial configuration shapes student social and informal learning activities in educational complexes. In *Proceedings of the 11th Space Syntax Symposium*.

Yang, E. K., & Lee, J. H. (2020). Cognitive impact of virtual reality sketching on designers' concept generation. *Digital Creativity, 31*(2), 82–97.

Yang, X., Lin, L., Cheng, P.-Y., Yang, X., Ren, Y., & Huang, Y.-M. (2018). Examining creativity through a virtual reality support system. *Educational Technology Research & Development: ETR & D, 66*(5), 1231–1254.

Yao, W., Chen, F., Wang, S., & Zhang, X. (2021). Impact of exposure to natural and built environments on positive and negative affect: A systematic review and meta-analysis. *Frontiers in Public Health, 9*. https://doi.org/10.3389/fpubh.2021.758457.

Yen, C. C., & Jiang, H. (2009). Protocol analysis in design research: A review. In *Proceeding of IADSR 2009*. unknown. Retrieved from.

Yoon, M., Choi, K., Yoon, S., & Jo, I.-H. (2023). Task type matters: The impact of virtual reality training on training performance. *Journal of Computer Assisted Learning*. https://doi.org/10.1111/jcal.12874.

Youmans, R. J. (2011). The effects of physical prototyping and group work on the reduction of design fixation. *Design Studies, 32*(2), 115–138.

Yu, R., Schubert, G., & Gu, N. (2023). Biometric analysis in design cognition studies: A systematic literature review. *Buildings, 13*(3), 630.