

# Analyzing Multimodal Interaction Strategies for LLM-Assisted Manipulation of 3D Scenes

Junlong Chen\*

University of Cambridge

Jens Grubert †

Coburg University of Applied Sciences

Per Ola Kristensson ‡

University of Cambridge



Figure 1: Example workflow for scene editing with our proposed ASSISTVR technique. Left: The user adopts the *bulk modification* strategy to select all blue objects in the original scene to modify their appearance together. Middle: The user adopts the *incremental exploration* strategy to modify the appearance on individual objects. Right: The final scene matches the target scene of one of the tasks in our empirical user study.

## ABSTRACT

As more applications of large language models (LLMs) for 3D content for immersive environments emerge, it is crucial to study user behaviour to identify interaction patterns and potential barriers to guide the future design of immersive content creation and editing systems which involve LLMs. In an empirical user study with 12 participants, we combine quantitative usage data with post-experience questionnaire feedback to reveal common interaction patterns and key barriers in LLM-assisted 3D scene editing systems. We identify opportunities for improving natural language interfaces in 3D design tools and propose design recommendations for future LLM-integrated 3D content creation systems. Through an empirical study, we demonstrate that LLM-assisted interactive systems can be used productively in immersive environments.

**Index Terms:** Virtual reality, large language models, 3D scene editing.

## 1 INTRODUCTION

Large Language Models (LLMs) have gained popularity in assisting task completion in immersive environments. LLMs provide various advantages to improve interaction experience in virtual and augmented reality, such as improving task completion efficiency [30], democratizing VR content creation for non-expert users [12], and improving expressiveness while reducing the user's perceived workload [21]. However, the introduction of LLMs in interaction tasks such as scene editing can also pose barriers and adversely affect the interaction experience due to the current limitations of LLMs and its capability to integrate with 3D scene content. Examples of these barriers include transparency and explainability [23] reflected through user trust in the system, as well as appropriate error handling and timely user feedback [12].

Our central hypothesis is that LLM-assisted 3D scene editing is best carried out through multimodal interaction. To begin investigating this hypothesis we have created the Advanced Speech Support and Interactive System for Virtual Reality (ASSISTVR), which integrates LLMs with multimodal interaction techniques. ASSISTVR uses an off-the-shelf Microsoft Azure Conversational Language Understanding (CLU) Service and GPT-4o to handle user queries. We use this system to study the effects of LLMs on user behaviour patterns in scene editing tasks through an empirical user study with 12 participants. Specifically, we focus on whether user interaction with such LLM-assisted interactive systems reveals certain high-level *interaction strategies*, and if so, was the LLM-assisted interactive system able to assist participants in identifying more efficient interaction strategies without external guidance. We also examine whether the system poses any *interaction barriers*, and suggest design approaches to overcome these. Through this study, we extract observations on user performance and interaction patterns, and provide design implications for future LLM-assisted interactive systems for immersive 3D content and possibly general interactive systems which involve LLMs.

This paper contributes to existing literature by analyzing interaction patterns and strategies through an *exploratory* study. We deliberately chose not to engage in a comparative study since prior work [8, 12, 21] have proposed systems which apply LLMs to immersive content, and the capabilities of LLMs advance in a very rapid speed. Instead of making a technical contribution, this paper provides insights on observed user strategies and behavioural patterns, which generalizes to different types of interactive systems involving LLMs.

## 2 RELATED WORK

### 2.1 Scene Editing and Multimodal Interaction in XR

Rakkolainen et al. [29] reviews recent advances in multimodal interaction technologies for XR content, pointing out how XR technologies introduce new interaction concepts, paradigms, and metaphors and play an important role in addressing accessibility barriers and inequality. Similar views were proposed by Spittle et al. [35], who suggests that multimodal interaction improves selection and manipulation tasks. In 3D editing tasks in virtual reality

\*e-mail: jc2375@cam.ac.uk

†e-mail: jens.grubert@hs-coburg.de

‡e-mail: pok21@cam.ac.uk

(VR), a combined gesture and speech interface can perform on par with a unimodal interface of a radial menu in terms of promoting creativity, usability, and presence [43].

Williams et al. [38] reports on an elicitation study of speech, gesture, and multimodal speech and gesture interactions in unconstrained object manipulation tasks in augmented reality. Zhou et al. [42] found that participants preferred to use the same gesture for one and two-object manipulation in the same task, and revealed associations between speech patterns and gesture strokes during 3D object manipulation. Rodriguez et al. [31] studied natural unimodal and multimodal interaction techniques for 3D sketching in virtual reality.

Plopski et al. [27] reviewed gaze interaction and eye tracking research in XR and outlined how eye gaze has been applied to enhance user interaction with virtual content and interface design. Multimodal interactive systems such as GAZEPOINTAR [22] also demonstrate the possibility of leveraging eye gaze and pointing gestures to provide contextual information for speech queries.

## 2.2 Large Language Models for Extended Reality

A plethora of recent research in AI and XR has focusing on different aspects, including accessibility and inclusion [19, 5], privacy [5], 3D content generation [15], and general applications [12, 25, 8, 34]. Ma et al. [24] reviews integration of LLMs with 3D spatial data as 3D-LLMs and applications. Recent work [16, 17, 3] has further explored how LLMs can assist agents in altering the physical 3D world in various ways.

In terms of 3D content editing, LLM-assisted systems such as LLMR [8] demonstrate a wide range of possible applications in XR, including world creation, multimodal interaction, scene editing, scene query, and integration with other external plugins, platforms, and sensors. DREAMCODEVR [12] is an AI-powered tool for generating code in VR applications during runtime to modify the appearance and behaviour of elements in a 3D scene. Prior work has also studied LLM prompting for immersive content. Roberts et al. [30] show that prompt-based methods can accelerate in-VR level editing and become an integrated part of the gameplay. Aghel Manesh et al. [2] used a Wizard of Oz elicitation study to examine the implicit expectations of users when they prompt generative AI agents to create interactive virtual scenes.

## 2.3 Interaction Pattern Analysis

Interaction analysis is an important part of human-computer interaction (HCI) research. Wright et al. [39] proposed the resources model to analyze human-computer interaction as distributed cognition, where interaction strategies play a crucial role in bringing resources in use to generate actions. Scholz et al. [32] proposed a model to study user behaviour and interaction patterns in online news forums while Guo et al. [13] studied interaction modes and user agency in human-LLM collaboration tasks. Beyan et al. [4] conducted a human-human interaction analysis and identified interaction patterns and behaviours such as nonverbal cues which resulted in effective performance. These interaction patterns are often uncovered through log analysis [36] or audio and video analysis [18].

Interaction patterns have also been studied within the context of extended reality. To support the analysis of interaction patterns, symbolic event visualization methods have been proposed by Rabasahl et al. [28]. Feit et al. [10] and Foy et al. [11] studied ten-finger typing on a physical keyboard and mid-air typing in virtual reality respectively, and summarized common typing behaviours as interaction patterns. Dudley et al. [9] studied the performance envelopes of four alternative text input strategies in virtual reality to provide design implications for novel text entry systems.

## 3 METHODOLOGY

LLM systems have evolved from text-based interaction [7] to vision-language models [37], which support multimodal text and images, to general-purpose multimodal LLMs [40] that support any combination of text, image, video, and audio as inputs and outputs. For immersive 3D environments, while multimodal interactive systems assisted by LLMs have been proposed [8, 20, 12], there is still need to investigate their effects on user behaviour and interaction patterns. We have designed ASSISTVR, an LLM-assisted multimodal interactive system for the purpose of studying typical interaction patterns and interaction barriers in an example task that involves editing an indoor scene to match a given target appearance using multimodal speech commands and raycast selections. The design of ASSISTVR fulfills high-level requirements of multimodal interaction and integration of LLM by incorporating speech and raycast pointing as different interaction modalities for the 3D editing task and follows a method similar to LLMR [8] to integrate LLMs including Azure CLU and GPT-4o with scene graph information and the post-processing pipeline in Unity to provide an integrated scene editing system.

Through a scene editing user study, we gather quantitative usage data and qualitative feedback from post-experience questionnaires. Collectively, these results help us to identify main interaction strategies as well as reoccurring interaction patterns. Through post-hoc analysis of the study data, we identify key barriers in user interaction with LLM-assisted interactive systems in virtual reality and propose design implications for future LLM-assisted interactive systems.

**Apparatus.** To study user behaviour and patterns when interacting with LLM-assisted 3D scene editing systems, we designed ASSISTVR. An outline of the system workflow is provided in Figure 2. The system leverages large language models such as Microsoft Azure Conversational Language Understanding (Azure CLU, as shown in grey) and GPT-4 Omni (GPT-4o, as shown in blue) [26, 1] to process user natural language input.

In the ‘Training Phase’ of Azure CLU, representative utterance data of possible user speech input samples are labelled with intents (such as ‘Select’, ‘Deselect’, ‘Modify’, ‘Undo’, or other intents) and key entities (such as ‘Object of Interest’, ‘Original Color’, ‘Original Material’, ‘Target Color’, and ‘Target Material’), and are used to finetune the default model (2022-09-01 training configuration) provided by the Azure CLU service. Upon training the model, the utterances with labeled intents and entities are adjusted to iteratively improve model performance. The final model with an F1 score of 92.73% on intent classification was deployed. As the GPT-4o model is ready for deployment, there is no training phase for GPT-4o.

In the ‘Deployment Phase’ of Azure CLU and GPT-4o in Figure 2, the system first uses the Azure Speech Recognition service to recognize user speech, then uses the Azure CLU model to classify the recognized speech input into different intents and extracts key entities from the user input. If the intent is classified as ‘Select’, ‘Deselect’, ‘Modify’, or ‘Undo’, the system executes post-processing scripts in Unity to perform object selection, object deselection, color/material modification, or actions to undo the previous color/material editing step. Following De La Torre et al. [8], the system generates a scene graph in JSON format to represent content in the 3D scene. If the intent does not fall under these four categories, the user natural language input, an instructions prompt (providing context about the scene editing task, available colors, and available materials), and a JSON file containing the scene graph of the current 3D scene are sent to the cloud-based GPT-4o model via Application Programming Interface (API) calls. GPT-4o subsequently generates a natural language response, which is then synthesized into speech and sent to the user.

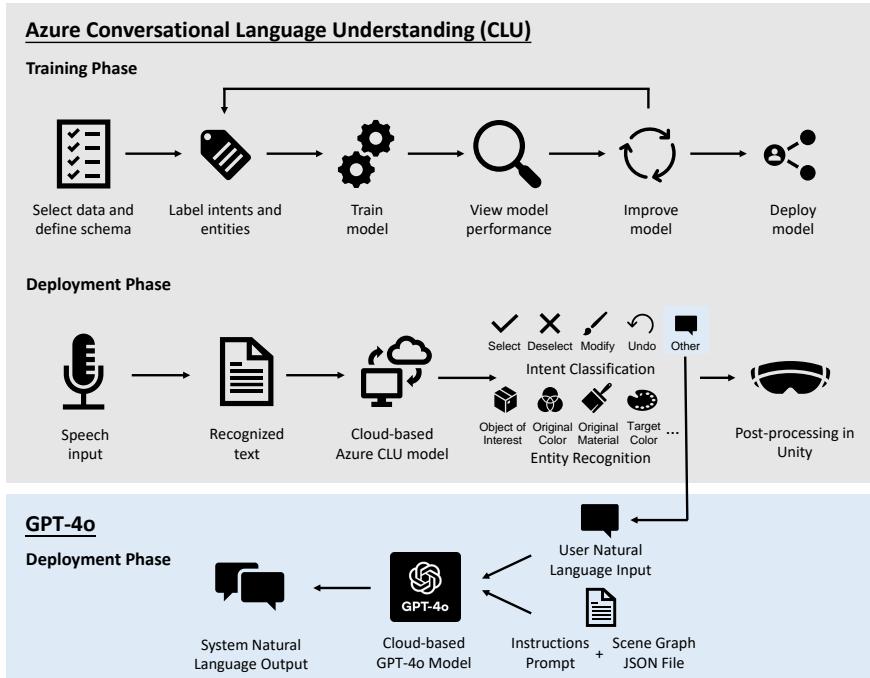


Figure 2: Workflow of the AssistVR system designed for the study. In the training phase, only Azure Conversational Language Understanding (CLU) is involved. The developer labels a number of utterances with intents and entities, and finetunes the Azure CLU model. The model is iteratively improved based on performance metrics. In the deployment phase, Azure CLU classifies user speech input into different intents. If the intent falls under the ‘Select’, ‘Deselect’, ‘Modify’, or ‘Undo’ categories, further post-processing steps to modify the scene are conducted in Unity. If the intent does not fall under these categories, the user speech input and a text file containing the instructions prompt and scene graph of the current scene are sent to GPT-4o, which generates a natural language response synthesized into speech for the user.

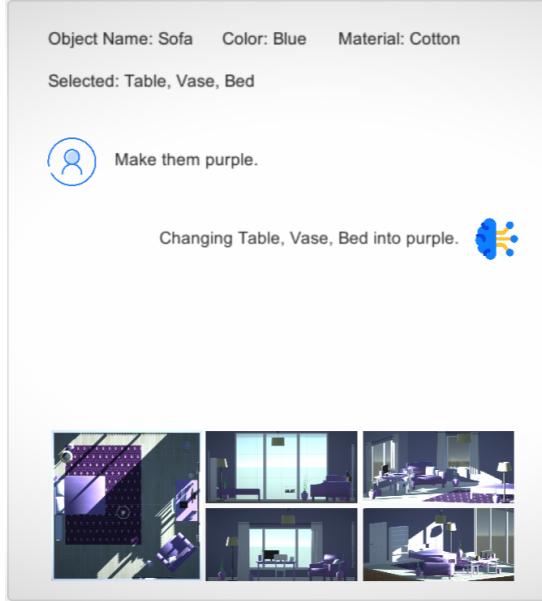


Figure 3: Example of the draggable panel. The panel shows that the current object hit by the raycast is the ‘Sofa’ with ‘Blue’ color and ‘Cotton’ material. Currently, objects ‘Table’, ‘Vase’, and ‘Bed’ are selected. The user says, “Make them purple.” The system responds, “Changing Table, Vase, Bed into purple,” and modifies the color of the selected objects. At the bottom of the panel, screenshots of the target scene at different angles are shown.

Apart from the speech-based interaction powered by Azure CLU and GPT-4o, the system also includes other interaction modalities including selection/deselection of virtual objects via raycast, and a draggable panel to provide feedback by displaying from top to bottom the name, color, and material property of the current object hit by the right raycast, the list of names of all currently-selected objects, the recognized user speech input, the natural language output from the system, as well as screenshots of the target scene at the bottom. An example screenshot of the draggable panel is provided in Figure 3.

Participants wore an Oculus Quest 2 headset and held the right controller during the study. The headset was connected to a Windows 10 laptop PC (Intel i5-9300H CPU, 16GB memory, and GTX 1050 graphics card) via an Oculus link cable. Scenes were implemented with Unity 3D (Version 2022.3.15f1) and publicly available resources<sup>1</sup> on Unity Asset Store.

**Participants.** We recruited 12 participants (6 male and 6 female) aged between 22 and 35. Around 62.5% of participants were familiar with VR, 50% of participants were familiar with speech recognition systems, and around 67% of participants were familiar with 3D modelling or design software. All participants understood and spoke English, and 50% reported themselves as native English speakers. None of the participants reported any form of disability.

**Task.** The task involves matching the original indoor scene to a target scene based on a combination of natural language instructions and image instructions. The scene and task are designed such that there are a number of objects which can be referenced with a common color/material property (such as ‘blue’ or ‘cotton’), and one special object (the carpet) whose target appearance can only be

<sup>1</sup>Source: <https://assetstore.unity.com/packages/3d/environments/interior-house-assets-upr-257122>.

inspected visually by the user. The user is not instructed how to reference the pattern of the carpet verbally at the beginning of the task. The purpose of including this special object in the task is to simulate cases when objects are difficult to reference for the user and to study whether LLM-assisted systems can aid participants in referencing these objects with higher perplexity.

Task type A involves making all blue objects in the original scene into grey and making all cotton objects in the original scene into leather, see [Figure 1](#) (right) for the target scene. Task type A also involves editing the carpet into white pattern, but this requirement was given by showing images of the target scene to the participant. Participants were not instructed that they could use ‘white pattern’ to refer to the target color of the carpet.

Similarly, task type B involves making all blue objects purple, making all leather objects cotton, and making the carpet into purple pattern, see subfigure “T: Target” in [Figure 5](#) for the target scene. The target pattern of the carpet was also given in the form of images and not natural language. During the study, the order of task type A and task type B was counterbalanced across all 12 participants. After rearranging the order of task type A and task type B, the tasks were delivered as Task 1 and Task 2, with Task 1 preceding Task 2.

Additional instructions for participants during Task 1 were to explore list of all available colors and materials and to find the most efficient way to modify color and material. An additional instruction for Task 2 was to modify the scene based on the most efficient way participants found in Task 1. This reason for providing these additional instructions is because we are interested in finding whether LLM-assisted systems help participants obtain any performance improvement, and if so, how is the improvement reflected through the change in interaction strategies and patterns.

**Procedure.** After filling out a consent form and demographics questionnaire, participants were briefed about the study procedure, which involved introducing the goals of Task 1 and Task 2 by showing them images of the original scene and target scene to match the carpet appearance and by giving them verbal instructions to make all blue objects grey (or purple) and make all cotton objects leather (or vice versa). All participants were exposed to both task type A and B in Task 1 and Task 2. Participants were also told that the system supported a list of colors such as red, orange, and yellow and a list of materials such as plastic. Here, only a few examples were given, and the complete list of colors and materials were not given to the user. Users were briefed about the main functions (raycast selection, speech, and assistive panel) of the system, as well as a high-level introduction of the types of supported speech commands (Select/Deselect, Commands to modify appearance, Commands to undo, and Query commands). Participants were not taught about the exact phrases used to elicit these commands. Participants were instructed to think aloud during the study, and to also explore the list of all available colors and materials and find the most efficient way to modify the scene in Task 1.

Participants took their time to explore the scene and attempted to complete the task. Participants also tried to figure out how to use the system efficiently, including which functions/tools to use and what speech commands worked well. During this process, participants were not allowed to obtain additional information from the study moderator but were allowed to ask questions to the system. The task ended when participants were satisfied that the scene matched the target appearance. Participants were then asked to complete a post-experience questionnaire including open-ended questions, SUS [6], NASA-TLX [14], and UEQ-S [33] questionnaires for Task 1 and take a 5-minute break.

Next, participants were given instructions for Task 2, which included making all blue objects purple (or grey), making all leather objects cotton (or vice versa), and modifying the appearance of the carpet to match the target scene. Participants were also instructed to modify the scene based on the most efficient way they found in Task

- After receiving the instructions for Task 2, participants modified the scene and stopped when they were satisfied that the scene matched the target appearance. Participants completed a similar post-experience questionnaire for Task 2, and gave final comments on which features they liked/disliked based on their user experience throughout the entire study. The entire study lasted for around an hour. At the end of the study, participants were thanked for their participation and remunerated.

## 4 RESULTS

Observations and quantitative data from the user study revealed several common patterns in user behaviour. These findings are organized and presented below as overall performance, interaction patterns and interaction barriers. Here, significance tests do not serve to conduct comparisons between different system or interfaces, but instead serve as a tool to indicate how well users can learn to use the system over time.

### 4.1 Overall Performance

**Task Completion Quality.** As the task involves scene editing, and different participants achieved different goal states which match the target scene appearance to different extents, we consider the difference between the color and material of all objects in the current scene and the color and material of all objects in the target scene as the number of **Remaining Elemental Editing Steps (REES)**, a metric to quantify user progress and task completion quality in the scene editing task. This final REES metric measures how close the final state of the scene is compared to the target scene, with a lower final REES value indicating a closer match to the target scene and higher task completion quality. Friedman tests revealed a **significant difference** ( $\chi^2 = 4.50, p < .05$ ) **in the final REES** between TASK1 ( $M = 4.58, SD = 4.72$ ) and TASK2 ( $M = 1.83, SD = 3.69$ ), suggesting that participants were able to match the target scene significantly better in Task 2 compared with their performance in Task 1. Please note, that while it can be expected that participants’ performance improves over time, the scale of this improvement (53.2% reduction in final REES on average) can indicate that users can adopt quickly to the multimodal editing system.

**Task Completion Time.** Another measure for task completion is the time taken for each participant to edit the scene to match the target appearance. Friedman tests revealed a **significant difference** ( $\chi^2 = 5.33, p < .05$ ) **between the completion time** of Task 1 ( $M = 11.2$  minutes,  $SD = 4.85$ ) and Task 2 ( $M = 5.74$  minutes,  $SD = 3.99$ ), suggesting that participants completed Task 2 in a significantly shorter amount of time.

Combining the results for task completion quality and task completion time, we observe that participants were able to match the scene significantly closer to the target scene in a significantly shorter amount of time in Task 2 after familiarizing with the system in Task 1 and making queries to the system to find the most efficient scene editing method. High standard deviations in the results also suggest that different individuals can have a vastly different performance.

### 4.2 Post-Experience Questionnaire Findings

Participants provided task load ratings on mental demand, physical demand, temporal demand, performance, effort, and frustration from a scale of 1 to 10 using the unweighted version of the NASA-TLX questionnaire [14]. A Wilcoxon signed rank test revealed that the **overall task load rating of TASK1 ( $M = 3.97, SD = 1.08$ ) was significantly higher** ( $W = 4, p < .05, |r| = .8$ ) **than that of TASK2 ( $M = 3.35, SD = .983$ )**.

Results from the System Usability Scale (SUS) [6] of TASK1 and TASK2 yielded a higher average SUS score in Task 2 compared with Task 1. However, a Wilcoxon signed rank test did not reveal

a significant difference ( $W = 9.5, p = .073, r = .568$ ) between the SUS ratings of TASK1 ( $M = 72.1, SD = 15.5$ ) and TASK2 ( $M = 75.2, SD = 14.9$ ).

Results from the short version User Experience Questionnaire (UEQ-S) [33] show that TASK1 attains a higher average pragmatic quality score and TASK2 attains a higher average hedonic quality score. Wilcoxon signed rank tests reveal a **significant difference** ( $W = 6, p < .05, |r| = .737$ ) **in the overall UEQ-S score between TASK1 ( $M = 1.50, SD = .590$ ) and TASK2 ( $M = 1.22, SD = .640$ )**. For the subcategories of the UEQ-S ratings, **significant differences were found in the PRAGMATIC quality** ( $W = 6, p < .05, |r| = .738$ ) **between TASK1 ( $M = 1.50, SD = .798$ ) and TASK2 ( $M = .833, SD = .587$ )**.

Following the questionnaires on task load, system usability, and user experience, participants also provided descriptions of the most efficient strategy they found, as well as open comments about the system.

Ten out of 12 participants were able to find an efficient strategy of bulk-editing object properties by interacting with the system without external assistance by the end of the study. Participants who did not find the bulk modification strategy described their strategy as follows:

*"For identical items such as blue walls, blue vases and leather pillows, I tend to use voice command to change their colours/material...For non-repetitive items such as the pen holder and keyboard, I just selected and changed them individually one by one." (P2)*

*"Because I found selecting multiple objects at the same time [being] troublesome, I directly ask[ed] the speech system to help chang[e] the color of multiple objects...I changed 2-3 items together just to make the system work effectively." (P12)*

These two participants either found it more reassuring to change individual objects (P2) or did not find the supported command or workflow to select multiple objects with the same property first and then use another command to modify the appearance of all selected objects (P12). Further analysis on open comments about the system revealed the following trends, which provide further insights on the observed behaviours and interaction patterns:

**System ease of use.** Participants appreciated how easy and efficient it was to complete the scene editing task once they knew how to phrase the commands and which strategy to adopt. P6 found the system to be "*incredibly quick*", and liked how efficient the system was. P6 commented, "I did not need to select anything, which made it really easy. I just told the system what to do and only had to use 5 commands." P8 liked how the system supported multiple ways to complete the task. P10 commented that with speech commands, he could easily tell the system to select objects, then modify their colors and textures. P11 commented, "It was efficient and straightforward to use once the commands were known."

Dialogues between participants and AssistVR during the study revealed that participants found the system useful in providing suggestions to help them find the list of all supported colors, materials, supported speech commands, as well as the efficient bulk modification strategy. For example, P12 asked, "Can you make what I selected into another material," and the system responded, "Yes, you can change the material of the selected objects. Simply use a speech command like 'Make it leather' or 'Make it cotton' to modify the material of the selected objects." P2 asked, "What are the options for colours," and the system responded, "You can change the color of an object to red, orange, yellow, ..., yellow pattern, purple pattern, or white pattern." P6 asked, "What materials can I use," and the system responded, "You can change the material of

an object to plastic, cotton, leather, or concrete." P5 asked, "What is the fastest way to change all the blue objects to purple," and the system responded, "The fastest way to change all the blue objects to purple is to use speech commands. First, press Button A on the right controller and say 'Select all blue objects'. After selecting all blue objects, use the speech command 'Make them purple'." In the post-experience questionnaire, P12 also expressed how she liked how the system 'shows many examples of the exact commands that [she] could say' when asked how to change the color and pattern of the carpet.

**Multimodal Interaction.** In the post-experience questionnaire, participants appreciated how different interaction modalities including speech and raycast worked together to facilitate scene editing tasks. P7 commented that raycast interaction enabled 'precision control' when users do not know the precise name of objects, while speech interaction is helpful when there is little uncertainty around the object name or command. P8 'very much liked the technique' because the speech modality allowed her to select objects in a fast manner, while the raycast modality helped her check object properties easily. Comments from other participants also show how multimodal interaction techniques can be helpful in LLM-assisted interactive systems.

*"I like how intuitive both (speech and raycast) were, this made me more comfortable using them." (P11)*

*"Speech was easiest for this task, but raycast was also useful for selecting the carpet." (P1)*

*"I like the raycast for selecting individual object as it's more accurate, while prefer the speech for selecting multiple identical objects as it's quicker." (P2)*

When asked which features did participants wish to have, P7 further commented, "Maybe if the system is also able to factor in my gaze or selections to provide further context," which further demonstrates that multimodal interaction is not limited to speech and raycast but can instead incorporate a broader range of interaction modalities in future systems.

**User Agency.** Participants commented how sometimes the system did not respond to user speech input as they expected, which negatively affected their sense of agency over the system. P7 commented that he disliked it when the system did not respond as he expected, for example when the system selected all books when he referred to the singular 'book' in his command. During the study, participants were aware of gaining control of their actions and sought to improve user agency by choosing appropriate interaction strategies. For example, P4 preferred to 'select all relevant items' and 'change one property a time, color first and then material,' because she preferred to 'give short and clear instructions and complete the task step by step' and 'avoid complicating the system'.

**User Trust.** Post-experience comments revealed that some participants sought simple ways to verify that the system was processing speech commands correctly before bulk-editing the scene. P6 commented that before starting the task, she saw visually that the system was changing colors correctly for selected objects, and she 'trusted it to select all objects of a certain color at once because it seemed to correctly know the color of every object'. P6 and P8 confessed that they simply trusted the system to do everything correctly upon simple verification that the system seems to be successful in selecting objects and changing their colors, and they would not know if the system made a few mistakes. On the other hand, P2 did not completely trust the system and felt 'better selecting and changing [objects] one by one' if 'things are not entirely identical', such that he does not 'mis-select any item' and 'a larger margin for error can be ensured'. The difference in user trust in the system also

likely led them to choose different interaction strategies. P6 and P8 who trusted the system used *bulk modification* in both Task 1 and Task 2, whereas P2 who did not trust the system did not try *bulk modification* in either Task 1 or Task 2.

**Level of feedback.** Participants appreciated how the system provided an adequate amount of visual feedback via the dragable panel and voice feedback through synthesized speech (see quotes under ‘System ease of use’).

*“The panel shows what I said and what the response will be, so I can confirm if the recognition is correct or not and try again if the recognition is wrong.” (P8)*

Participants also commented how it would be helpful if they received more visual feedback on the list of colors and materials, in addition to their names. P1 commented that it would be helpful to ‘see a sample of the colours’, ‘especially for the patterns’, rather than listing only the names. P12 also suggested providing visual feedback in the form of a progress bar to indicate that the LLM is still processing information, or whether it is unable to complete the task.

### 4.3 Interaction Patterns

The study revealed how participants preferred to iteratively modify the color and material of individual objects in the scene to match the target appearance, or to select a group of objects with a common feature, and change their color/material using a single voice command. Figure 4 plots the number of remaining elemental editing steps for all 12 participants with respect to elapsed time.

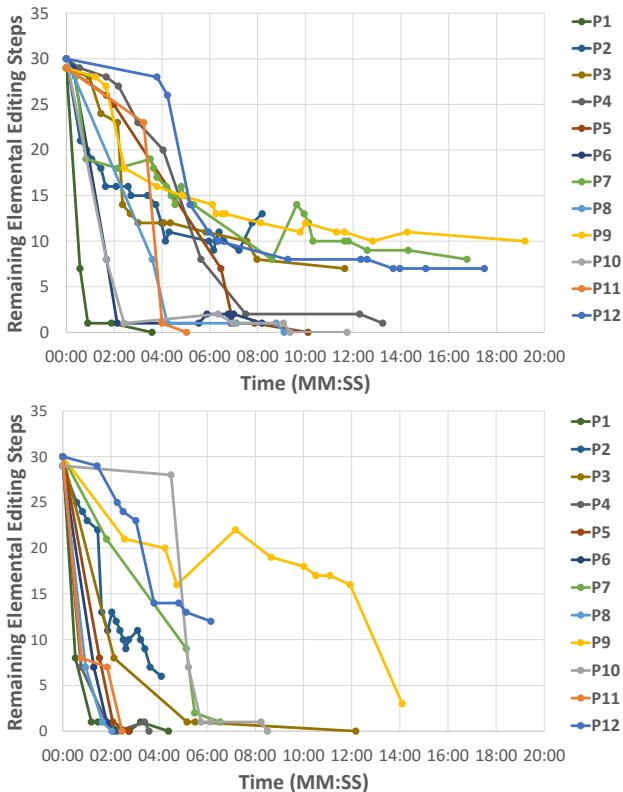


Figure 4: Number of remaining elemental editing steps to match the target scene in Task 1 (top figure) and Task 2 (bottom figure). The horizontal axis is denoting relative time in minutes and seconds.

As shown in Figure 4, in Task 1, in which participants are asked to find the most efficient way to edit the scene to match the target appearance, P2, P3, P7, P9, and P12 preferred to make incremental edits to individual objects. Similarly in Task 2, in which participants are asked to edit the scene based on the most efficient method they found, P2, P9 and P12 also preferred to modify the scene iteratively. We define this high-level scene editing strategy as:

**Incremental Exploration (IE)** This strategy emphasizes visual inspection of individual object properties and combines raycast selection or speech selection of single objects by their names and modifying object appearance using speech commands, or direct modification (without explicit selection) of individual object appearance through speech commands.

In Task 1, P1, P6, P8, P10, P11 used speech commands to select a group of objects via their common color or material property and used a single voice command to bulk edit their appearance. This strategy is also observed in Task 2 within the behaviour of more participants including P1, P3, P4, P5, P6, P7, P8, P10, and P11. We define this high-level interaction strategy as:

**Bulk Modification (BM)** This strategy uses speech to select a group of objects with a shared color/material property, then uses speech to bulk modify their appearance. In this strategy, there is not explicit involvement of visual inspection of individual object properties.

It is important to note that the interaction strategy of a certain user can change over time. For example in Task 1, P4 started the task with *incremental exploration*, then adopted *bulk modification*, before returning to the *incremental exploration* strategy. Therefore, we visualize how interaction strategies have changed (if any) over the course of time in Task 1 and Task 2 for each participant in Figure 5. Based on these interaction patterns, we make the following observations:

Color modification tends to precede material modification in IE and BM. In Task 1, among all 12 participants, 7 edited color before editing material (P1, P3-P6, P8, P10) while none edited material before editing color. The remaining 5 participants did not exhibit a strong preference on editing a certain property before another (P2, P7, P9, P11, P12). In Task 2, 8 participants edited color before editing material (P1, P3-P6, P8, P11, P12) while none edited material before editing color. The remaining 4 participants did not exhibit a strong preference on the editing sequence (P2, P7, P9, P10). This trend in editing sequence regardless of the high-level strategy employed demonstrates how the majority of participants draw attention to the more distinguishable visual features such as object colors and edit these features first in comparison with less distinguishable visual features such as object material.

Carpet tends to be edited last. Prior to the study, participants were instructed to match the appearance of the carpet to the appearance shown in an image of the target scene. Participants were not explicitly told how to modify the carpet appearance, or how to reference the target appearance of the carpet. In comparison, the remaining objects were given an explicit target color (grey or purple). The carpet represents objects which are difficult to edit verbally, and the study results revealed that in Task 1, 9 out of 12 participants (P1, P4-P9, P11, P12) chose to edit the carpet last. In Task 2, 9 out of 12 participants (P1, P3-P8, P10, P12) edited the carpet after editing the remaining objects. The results show that in speech-based interfaces, users tend to edit objects with a clear goal state such that the speech commands are easy to enunciate.

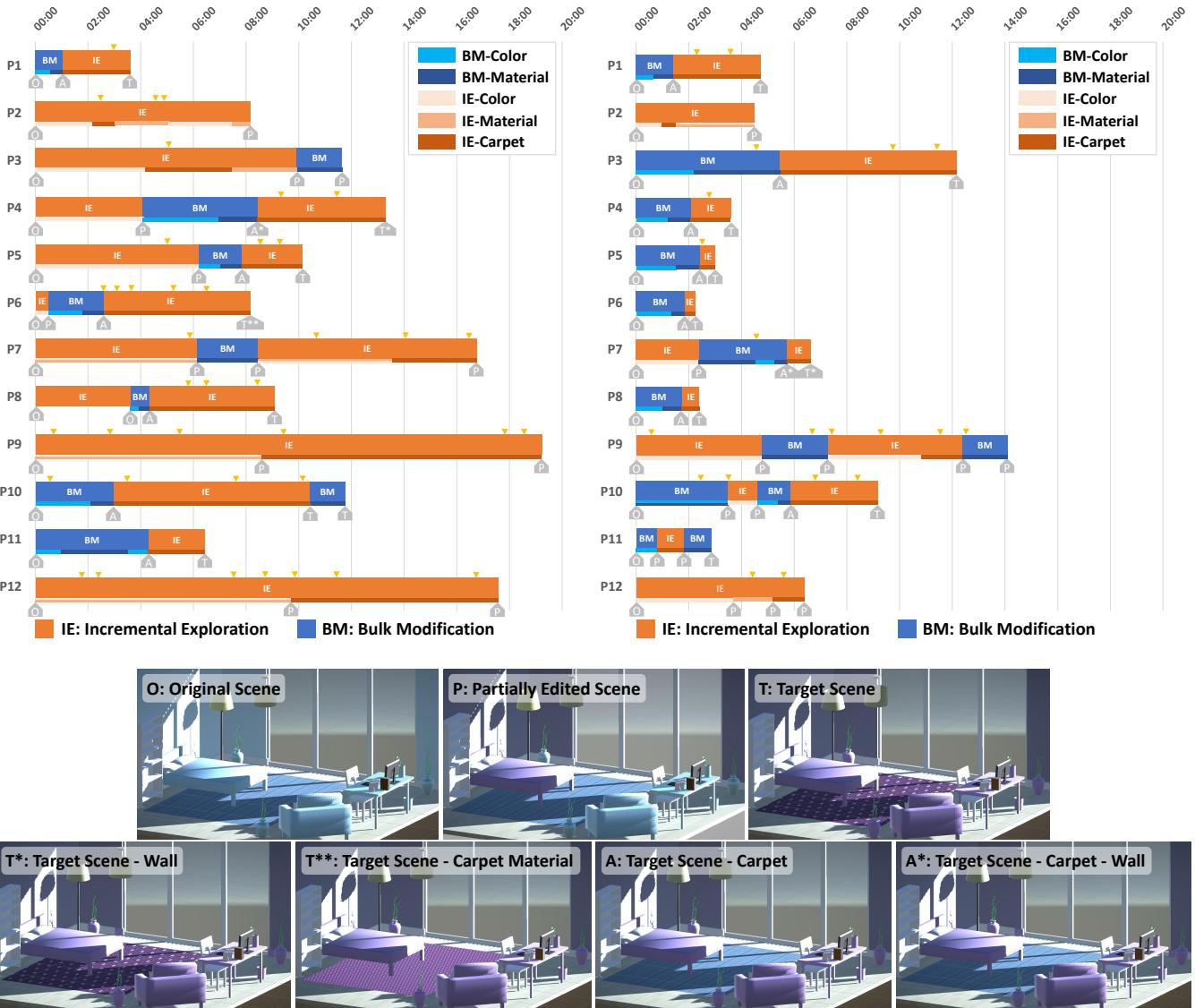


Figure 5: Interaction strategies adopted by different users across the duration of Task 1 (top left) and Task 2 (top right). Time on the horizontal axis is displayed in the format MM:SS (minutes:seconds). Triangles above the timeline of each participant indicate user queries. The main timeline bar for each participant indicates the high-level strategy employed (IE: Incremental Exploration, or BM: Bulk Modification). The secondary timeline bar below the main timeline bar indicates the low-level strategy employed, namely Bulk Modify Color (BM-Color), Bulk Modify Material (BM-Material), Color Editing with Incremental Exploration (IE-Color), Material Editing with Incremental Exploration (IE-Material), or Carpet Editing with Incremental Exploration (IE-Carpet). Grey tags below the timeline bars represent the current scene status (O: Original scene. T: Target scene. P: Partially-edited scene.) The target scene can be the grey scene in Figure 1 (right), or the purple scene shown here. Each participant experienced both target scenes, and the order of the target scene in Task 1 and Task 2 is counterbalanced for all participants. Among partially-edited scenes, some scenes occur frequently and are labelled explicitly. These include: T\*: In addition to T, one of the walls received an extra edit, REES=1. T\*\*: In addition to T, the carpet material is incorrect, REES=1. A: Color/material changed for all objects except the carpet, REES=1. A\*: In addition to A, one of the walls received an extra edit, REES=2. Example screenshots of these scenes are provided below the timeline.

Total time spent on incremental exploration tends to exceed the time spent on bulk modification. Figure 6 (left) provides a box plot of the time spent on incremental exploration and the time spent on bulk modification for all 12 participants. Friedman tests indicate that **the total minutes spent on the incremental exploration strategy ( $M = 9.47, SD = 5.22$ ) in Task 1 is significantly greater ( $\chi^2 = 8.33, p < .05$ ) than the minutes spent on the bulk modification strategy ( $M = 1.78, SD = 1.62$ )**. For Task 2 however, the difference between the time taken on incremental exploration ( $M = 3.38, SD = 2.87$ ) and bulk modification ( $M = 2.36, SD = 1.70$ ) was not significantly different ( $\chi^2 = .33, p = .564$ ).

1.70) was not significantly different ( $\chi^2 = .33, p = .564$ ).

More time was spent on Bulk Modification in Task 2 compared to Task 1. Figure 6 (middle) provides box plots of the percentage of time spent on incremental exploration and bulk modification for each participant. Friedman tests indicate that **the percentage of time spent on bulk modification for each participant significantly increased ( $\chi^2 = 6.40, p < .05$ ) in Task 2 ( $M = .465, SD = .279$ ) compared with Task 1 ( $M = .194, SD = .190$ )**. This suggests that users are likely to have learned about the effi-

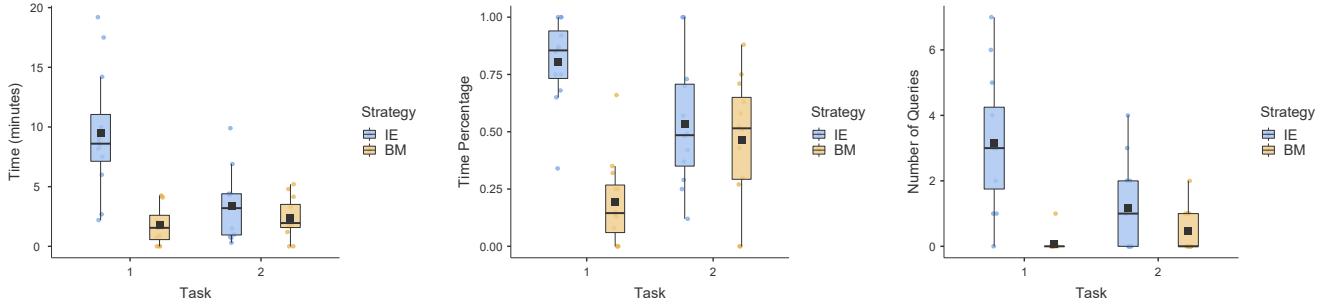


Figure 6: Box plots of the time spent in minutes for all participants on the incremental exploration (IE) strategy and the bulk modification (BM) strategy (left), the percentage of time spent on both strategies for all participants in Task 1 and Task 2 (middle), and the number of queries posed during both strategies for all participants in Task 1 and Task 2 (right). Black squares indicate the mean values.

ciency of the bulk modification strategy and prefer to spend more time on it.

More queries were posed during IE. Figure 6 (right) provides box plots of the number of queries posed during incremental exploration ( $M = 3.17, SD = 2.08$ ) and bulk modification ( $M = .083, SD = .289$ ) for all participants in Task 1 and the number of queries posed during incremental exploration ( $M = 1.25, SD = 1.36$ ) and bulk modification ( $M = .417, SD = .669$ ) for all participants in Task 2. Friedman tests indicate that **significantly more queries were posed during incremental exploration, as compared to bulk modification in both Task 1 ( $\chi^2 = 11.0, p < .001$ ) and Task 2 ( $\chi^2 = 4.50, p < .05$ )**.

Queries did not necessarily guide participants to find the BM strategy. P2, P9, and P12 who did not try the bulk modification strategy in Task 1 posed 3, 6, and 7 queries respectively, but only P9 shifted to a combination of the incremental exploration strategy and bulk modification strategy in Task 2, while P2 and P12 continued with the incremental exploration strategy and were not successful in matching the scene to the target appearance.

Participants who tried BM in Task 1 achieved high performance in Task 2. P1, P3, P4, P5, P6, P7, P8, P10, and P11 tried the bulk modification strategy in Task 1. All these participants were able to complete Task 2 to match exactly the target scene (P1, P3-P6, P8, P10, P11) or match sufficiently close ( $T^*$ ) to the target scene (P7). Friedman tests on the task completion time of these participants also revealed a **significantly shorter ( $\chi^2 = 2.78, p < .05$ ) completion time of Task 2 compared with Task 1**.

#### 4.4 Interaction Barriers

The study also revealed certain interaction barriers which adversely affected the completion quality of scene editing tasks or the completion efficiency of the tasks.

**Speech Recognition/Processing Issues.** The misrecognition and processing errors of certain words by the system required participants to repeat their queries multiple times, which ultimately resulted in a delay in task completion. Interaction barriers under this category can be due to an recognition error from the Microsoft Azure Speech Recognition service, or due to a processing error in the misrecognition of user intents or key entities by Azure CLU or an error occurred when matching key entities to the GameObjects or textures in Unity during the Unity post-processing step.

**Feedback Clarity.** In the user study, participants were often confused when the system failed to respond to user speech input according to user expectations. In such circumstances, the system does not always provide clear feedback on why a command did not work or instruct participants on how to phrase it correctly. For

queries that were not categorized as ‘Other’, the Azure CLU model did not have the capability to provide feedback to users. For speech input that were processed by GPT-4o, the model lacked enough contextual information on the current status of each object (such as whether they are selected or not) in the scene and could not provide enough feedback. Participants also commented how visual feedback could be further improved by, for example, adding images to describe colors and materials in addition to text, or adding a progress bar to indicate that the LLM is processing the user query.

**Command Phrasing.** Some participants struggled with finding the correct phrasing for some commands, especially for changing patterns or materials. This is because the training data of the Azure CLU model only labelled commands with a certain sentence structure as selection or editing commands. Commands with different phrasing are processed by GPT-4o, but it often replied that it did not have the capability to select or modify objects, which resulted in confusion among participants. This example shows how special considerations should be included in the GPT prompt to instruct LLMs to incorporate information from other sources, such as information directly from the 3D scene or the Azure CLU model. This will guide users to find the correct command instead of providing a misleading response to state that the system is incapable of completing the selection or editing task.

## 5 DISCUSSION

This study highlights the promising potential of LLM-assisted interactive systems in guiding users towards more efficient multi-modal interaction strategies, thereby improving user performance in typical interaction tasks such as scene editing in virtual reality.

**User Performance.** Performance indicators, such as the number of remaining elemental editing steps and task completion time reported in Section 4.1, reveal how user performance significantly improved in Task 2 compared with Task 1. First, as shown by performance indicators, the study exemplifies the impact of choosing the correct interaction strategy on task completion quality. While **431.3%** more time was used on *incremental exploration* as compared to *bulk modification* in Task 1, *bulk modification* resulted in a **66.38%** reduction in the remaining elemental scene editing steps compared with the *incremental exploration* strategy in Task 1. Second, the performance indicators reveal how LLM-assisted interactive systems help to guide users to select better interaction strategies which result in improved performance. In several cases for P12, P2, P6, and P5, the LLM-assisted scene editing system was able to give constructive feedback in response to user queries on the supported speech commands, available colors, available materials, and the most efficient way supported by the system for users to complete the scene editing task, with examples provided below.

This demonstrates how LLM-assisted interactive systems have the strong potential of handling various types of natural language user input and providing a response to the best of its customized knowledge base to guide users to improve their interaction strategy.

**Interaction Patterns.** Results from Section 4.3 also revealed certain interaction patterns. First, users tend to edit visually-distinguishable features, such as color properties, first before editing features with less distinct visual features, such as material properties. Second, when using the LLM-assisted interactive system for scene editing, participants preferred to edit objects with clear target states which could be edited through simple voice commands (i.e., ‘Make this purple’, ‘Make them leather’), as opposed to objects with goal states that are difficult to enunciate and issue voice commands, such as the carpet. Third, queries were mainly posed during incremental exploration as opposed to during bulk modification. More queries did not necessarily guide participants to find the bulk modification strategy. Instead, participants (i.e., P3–P6, P8) who tried some form of bulk modification in Task 1 and who posed some queries to the system were more successful in finding the most efficient strategy combination (bulk modification for most objects followed by incremental exploration to modify carpet pattern) in Task 2. Finally, the study also revealed that participants tended to adhere to a single interaction strategy or a single pattern of interaction modalities. Even when Task 1 and Task 2 explicitly encourage participants to find the most efficient way of scene editing, P2 and P12 adhered to the incremental exploration strategy throughout the entire study and adhered to two interaction modality patterns: (1) modifying single objects directly through speech commands; or (2) using raycast to select one or several objects, then modifying the selected object(s) through a single speech command.

### 5.1 Implications for LLM-assisted Interactive system design

Results from this study shed light on design implications for future LLM-assisted interactive systems. While the study is conducted in a VR environment, design implications are applicable to 3D content applications in general, and even possibly applicable to general interactive systems where LLMs are involved. Based on results from the study, we formulate design implications as follows.

**First, effective use of multimodal input is critical for improving the user experience for LLM-assisted interactive systems.** In the study, many participants stumbled upon providing clear descriptions on how to edit the carpet. This corroborates findings from Liao et al. [23] who state that interaction with LLM systems with only the natural language modality can be easily affected by subtle language and communication cues. To cope with this issue, Tsimpoukelli et al. [37] allowed language models to support multimodal image and text input in addition to original natural language prompts. Wu et al. proposed NExT-GPT [40], a general-purpose any-to-any MM-LLM system which supports inputs and outputs of any combination of text, image, video, and audio, demonstrating the importance of LLM-assisted interactive systems to leverage different information modalities to specify user intent. In the study, we also found cases where participants would like to use a combination of raycast selection and speech interaction to make queries about the selected object. For example, P7 asked, ‘Is this a leather object?’ when using raycast to point at different objects. Many participants also used raycast to point at the object of interest when asking questions, which further emphasizes the importance of leveraging multimodal information in interaction design. Associating with the comment by P7 on including eye gaze under ‘Multimodal Interaction’ in Section 4.2, this demonstrates the promise of using additional input such as eye gaze to contextualize a query.

**Second, the design of LLM-assisted interactive systems should place special considerations on fostering user trust and improving user agency.** Processing steps in LLM-assisted systems

can easily become a black box to users as it is not evident how the system handles natural language input from the user. It was observed that when some participants first began using the system, they preferred to ask some simple questions to the system to verify that the system is processing their request as they expected, which is an important step for users to build trust with the system.

When asked about what made them to believe that the bulk modification strategy yielded correct results, some participants (P6, P8) confessed that they simply chose to trust the system but were not able to completely rule out the possibility that some editing steps might have gone wrong.

In the post-experience questionnaire, P2 and P12 used the incremental exploration strategy in both Task 1 and Task 2. P2 commented preferring this strategy over bulk modification because selecting individual objects provided more visual confirmation which consequently fostered trust with the system that it was making the correct editing step. P12, on the other hand, chose the incremental exploration strategy because it provided more user agency and sense of control over the system. P12 commented that the system was not able to respond to her commands to select all blue objects, which affected her sense of agency and control over the system through speech commands.

While we used a draggable panel to assist users in verifying the correctness of the system output, we believe that there are many more possibilities to increase user trust and agency, for example, by overlaying or blending (future or already conducted) changes of 3D objects directly in the 3D scene and to allow for quick assertion and undo of previous actions.

**Finally, LLM-assisted interactive systems should implement measures to convey the fundamental uncertainties that emerge from LLM interaction, such as hallucination.** In the study, there were some instances when hallucination occurred, which resulted in inaccurate or incomplete information provided by the system. In this regard, immersive environments could help to address the hallucination problem by providing additional contextual information to reduce uncertainty, which might help in minimizing the chances of hallucination compared to text-only input.

P9 asked, “Is there a bin in this room,” and received the response “Based on the provided context, there is no information indicating the presence of a bin in the room.” In this case, there is a bin in the room but the system provided inaccurate information. P9 also asked, “How many blue cotton items are there,” and the system responded, “There is one blue cotton item, which is the pen holder.” In this example, there were several blue cotton items in the room, but the system provided incomplete information to list only the pen holder. While LLMs inherently have limitations in hallucinating information [41], it is important to signpost to the user when such information can be inaccurate or incomplete.

## 6 CONCLUSION AND FUTURE OUTLOOK

This work has provided an analysis of user interaction patterns and strategies with LLM-assisted interactive systems through an example scene editing task in virtual reality. As evidenced by the results in Section 4.1, LLM-assisted interactive systems have the potential to guide users to find more effective and efficient interaction strategies and improve task performance without external guidance. Results from the post-experience questionnaire corroborate findings in prior work [21, 12] on the strengths of LLM-assisted interactive systems for immersive content in perceived workload, usability, and user experience. Based on post-experience questionnaire comments, we summarize design considerations for LLM-assisted interactive systems in terms of multimodal interaction, user trust, user agency, and appropriate feedback to cope with uncertainty and hallucination. We also summarize interaction patterns such as the fact that visually distinguishable features tend to be edited first, and objects with an obscure goal state tend to be edited last. Interaction

patterns further reveal how participants were able to improve their strategy through interaction with the system. Based on these qualitative and quantitative observations, we proposed a set of design implications for LLM-assisted interactive systems.

Novelty effects possibly inflated usability perceptions and thus results have to be treated with caution and we encourage replication efforts. This study provides a promising outlook for LLM-assisted interactive systems and provides a reference for future work on interaction analysis of LLM-assisted systems. We envision that these interaction pattern findings and design implications will be applicable to LLM-assisted interactive systems in general to guide a broad range of future designs in VR and beyond.

## ACKNOWLEDGMENTS

The authors wish to thank A, B, and C. This work was supported in part by a grant from XYZ.

## REFERENCES

- [1] J. Achiam, S. Adler, S. Agarwal, L. Ahmad, I. Akkaya, F. L. Aleman, D. Almeida, J. Altenschmidt, S. Altman, S. Anadkat, et al. Gpt-4 technical report. *arXiv preprint arXiv:2303.08774*, 2023. [2](#)
- [2] S. Aghel Manesh, T. Zhang, Y. Onishi, K. Hara, S. Bateman, J. Li, and A. Tang. How people prompt generative ai to create interactive vr scenes. In *Proceedings of the 2024 ACM Designing Interactive Systems Conference*, pp. 2319–2340, 2024. [2](#)
- [3] M. Ahn, A. Brohan, N. Brown, Y. Chebotar, O. Cortes, B. David, C. Finn, C. Fu, K. Gopalakrishnan, K. Hausman, et al. Do as i can, not as i say: Grounding language in robotic affordances. *arXiv preprint arXiv:2204.01691*, 2022. [2](#)
- [4] C. Beyan, A. Vinciarelli, and A. D. Bue. Co-located human–human interaction analysis using nonverbal cues: A survey. *ACM Computing Surveys*, 56(5):1–41, 2023. [2](#)
- [5] E. Bozkir, S. Özdel, K. H. C. Lau, M. Wang, H. Gao, and E. Kasneci. Embedding large language models into extended reality: Opportunities and challenges for inclusion, engagement, and privacy. In *Proceedings of the 6th ACM Conference on Conversational User Interfaces*, pp. 1–7, 2024. [2](#)
- [6] J. Brooke et al. Sus-a quick and dirty usability scale. *Usability evaluation in industry*, 189(194):4–7, 1996. [4](#)
- [7] T. Brown, B. Mann, N. Ryder, M. Subbiah, J. D. Kaplan, P. Dhariwal, A. Neelakantan, P. Shyam, G. Sastry, A. Askell, S. Agarwal, A. Herbert-Voss, G. Krueger, T. Henighan, R. Child, A. Ramesh, D. Ziegler, J. Wu, C. Winter, C. Hesse, M. Chen, E. Sigler, M. Litwin, S. Gray, B. Chess, J. Clark, C. Berner, S. McCandlish, A. Radford, I. Sutskever, and D. Amodei. Language models are few-shot learners. In H. Larochelle, M. Ranzato, R. Hadsell, M. Balcan, and H. Lin, eds., *Advances in Neural Information Processing Systems*, vol. 33, pp. 1877–1901. Curran Associates, Inc., 2020. [2](#)
- [8] F. De La Torre, C. M. Fang, H. Huang, A. Banburski-Fahey, J. Amores Fernandez, and J. Lanier. Llmr: Real-time prompting of interactive worlds using large language models. In *Proceedings of the CHI Conference on Human Factors in Computing Systems*, pp. 1–22, 2024. [1, 2](#)
- [9] J. Dudley, H. Benko, D. Wigdor, and P. O. Kristensson. Performance envelopes of virtual keyboard text input strategies in virtual reality. In *2019 IEEE International Symposium on Mixed and Augmented Reality (ISMAR)*, pp. 289–300. IEEE, 2019. [2](#)
- [10] A. M. Feit, D. Weir, and A. Oulasvirta. How we type: Movement strategies and performance in everyday typing. In *Proceedings of the 2016 chi conference on human factors in computing systems*, pp. 4262–4273, 2016. [2](#)
- [11] C. R. Foy, J. J. Dudley, A. Gupta, H. Benko, and P. O. Kristensson. Understanding, detecting and mitigating the effects of coactivations in ten-finger mid-air typing in virtual reality. In *Proceedings of the 2021 CHI conference on human factors in computing systems*, pp. 1–11, 2021. [2](#)
- [12] D. Giunchi, N. Numan, E. Gatti, and A. Steed. Dreamcodevr: Towards democratizing behavior design in virtual reality with speech-driven programming. In *2024 IEEE Conference Virtual Reality and 3D User Interfaces (VR)*, pp. 579–589. IEEE, 2024. [1, 2, 9](#)
- [13] J. Guo, V. Mohanty, J. H. Piazentin Ono, H. Hao, L. Gou, and L. Ren. Investigating interaction modes and user agency in human–llm collaboration for domain-specific data analysis. In *Extended Abstracts of the CHI Conference on Human Factors in Computing Systems*, pp. 1–9, 2024. [2](#)
- [14] S. G. Hart and L. E. Staveland. Development of nasa-tlx (task load index): Results of empirical and theoretical research. In *Advances in psychology*, vol. 52, pp. 139–183. Elsevier, 1988. [4](#)
- [15] K. He, A. Lapham, and Z. Li. Enhancing narratives with saymotion’s text-to-3d animation and llms. In *ACM SIGGRAPH 2024 Real-Time Live!*, pp. 1–2. 2024. [2](#)
- [16] W. Huang, P. Abbeel, D. Pathak, and I. Mordatch. Language models as zero-shot planners: Extracting actionable knowledge for embodied agents. In *International conference on machine learning*, pp. 9118–9147. PMLR, 2022. [2](#)
- [17] W. Huang, F. Xia, T. Xiao, H. Chan, J. Liang, P. Florence, A. Zeng, J. Tompson, I. Mordatch, Y. Chebotar, et al. Inner monologue: Embodied reasoning through planning with language models. *arXiv preprint arXiv:2207.05608*, 2022. [2](#)
- [18] A. Jebeli, L. K. Chen, K. Guerrero, S. Papparotto, L. Berlin, and B. J. Harden. Quantifying the quality of parent-child interaction through machine-learning based audio and video analysis: Towards a vision of ai-assisted coaching support for social workers. *ACM Journal on Computing and Sustainable Societies*, 2(1):1–21, 2024. [2](#)
- [19] L. Jiang, M. Phutane, and S. Azenkot. Beyond audio description: Exploring 360 video accessibility with blind and low vision users through collaborative creation. In *Proceedings of the 25th international ACM SIGACCESS conference on computers and accessibility*, pp. 1–17, 2023. [2](#)
- [20] M. Konenkov, A. Lykov, D. Trinitatova, and D. Tsetserukou. Vrgpt: Visual language model for intelligent virtual reality applications. *arXiv preprint arXiv:2405.11537*, 2024. [2](#)
- [21] R. Kurai, T. Hiraki, Y. Hiroi, Y. Hirao, M. Perusquia-Hernandez, H. Uchiyama, and K. Kiyokawa. Magicitem: Dynamic behavior design of virtual objects with large language models in a consumer metaverse platform. *arXiv preprint arXiv:2406.13242*, 2024. [1, 9](#)
- [22] J. Lee, J. Wang, E. Brown, L. Chu, S. S. Rodriguez, and J. E. Froehlich. Gazepointar: A context-aware multimodal voice assistant for pronoun disambiguation in wearable augmented reality. In *Proceedings of the CHI Conference on Human Factors in Computing Systems*, pp. 1–20, 2024. [2](#)
- [23] Q. V. Liao and J. W. Vaughan. AI transparency in the age of llms: A human-centered research roadmap. *arXiv preprint arXiv:2306.01941*, pp. 5368–5393, 2023. [1, 9](#)
- [24] X. Ma, Y. Bhalgat, B. Smart, S. Chen, X. Li, J. Ding, J. Gu, D. Z. Chen, S. Peng, J.-W. Bian, et al. When llms step into the 3d world: A survey and meta-analysis of 3d tasks via multi-modal large language models. *arXiv preprint arXiv:2405.10255*, 2024. [2](#)
- [25] G. Manfredi, U. Erra, and G. Gilio. A mixed reality approach for innovative pair programming education with a conversational ai virtual avatar. In *Proceedings of the 27th International Conference on Evaluation and Assessment in Software Engineering*, pp. 450–454, 2023. [2](#)
- [26] OpenAI. Hello GPT-4o, May 2024. Available at <https://openai.com/index/hello-gpt-4o>. [2](#)
- [27] A. Plopski, T. Hirzle, N. Norouzi, L. Qian, G. Bruder, and T. Langlotz. The eye in extended reality: A survey on gaze interaction and eye tracking in head-worn extended reality. *ACM Computing Surveys (CSUR)*, 55(3):1–39, 2022. [2](#)
- [28] S. Rabsahl, T. Satzger, S. Kalamkar, J. Grubert, and F. Beck. Symbolic event visualization for analyzing user input and behavior of augmented reality sessions. 2023. [2](#)
- [29] I. Rakkolainen, A. Farooq, J. Kangas, J. Hakulinen, J. Rantala, M. Turunen, and R. Raisamo. Technologies for multimodal interaction in extended reality—a scoping review. *Multimodal Technologies and Interaction*, 5(12):81, 2021. [1](#)
- [30] J. Roberts, A. Banburski-Fahey, and J. Lanier. Steps towards prompt-based creation of virtual worlds. *arXiv preprint arXiv:2211.05875*,

2022. 1, 2
- [31] R. Rodriguez, B. T. Sullivan, M. D. Barrera Machuca, A. U. Batmaz, C. Tornatzky, and F. R. Ortega. An artists' perspectives on natural interactions for virtual reality 3d sketching. In *Proceedings of the CHI Conference on Human Factors in Computing Systems*, pp. 1–20, 2024. 2
- [32] F. Scholz, T. E. Kolb, and J. Neidhardt. Classifying user roles in online news forums: A model for user interaction and behavior analysis. In *Adjunct Proceedings of the 32nd ACM Conference on User Modeling, Adaptation and Personalization*, pp. 240–249, 2024. 2
- [33] M. Schrepp, A. Hinderks, and J. Thomaschewski. Design and evaluation of a short version of the user experience questionnaire (ueq-s). *International Journal of Interactive Multimedia and Artificial Intelligence*, 4 (6), 103–108., 2017. 4, 5
- [34] J. Song, B. Wang, Z. Wang, and D. K.-M. Yip. From expanded cinema to extended reality: How ai can expand and extend cinematic experiences. In *Proceedings of the 16th International Symposium on Visual Information Communication and Interaction*, pp. 1–5, 2023. 2
- [35] B. Spittle, M. Frutos-Pascual, C. Creed, and I. Williams. A review of interaction techniques for immersive environments. *IEEE Transactions on Visualization and Computer Graphics*, 29(9):3900–3921, 2022. 1
- [36] J. R. Trippas, S. F. D. Al Lawati, J. Mackenzie, and L. Gallagher. What do users really ask large language models? an initial log analysis of google bard interactions in the wild. In *Proceedings of the 47th International ACM SIGIR Conference on Research and Development in Information Retrieval*, pp. 2703–2707, 2024. 2
- [37] M. Tsimpoukelli, J. L. Menick, S. Cabi, S. Eslami, O. Vinyals, and F. Hill. Multimodal few-shot learning with frozen language models. *Advances in Neural Information Processing Systems*, 34:200–212, 2021. 2, 9
- [38] A. S. Williams and F. R. Ortega. Understanding gesture and speech multimodal interactions for manipulation tasks in augmented reality using unconstrained elicitation. *Proceedings of the ACM on Human-Computer Interaction*, 4(ISS):1–21, 2020. 2
- [39] P. C. Wright, R. E. Fields, and M. D. Harrison. Analyzing human-computer interaction as distributed cognition: the resources model. *Human-Computer Interaction*, 15(1):1–41, 2000. 2
- [40] S. Wu, H. Fei, L. Qu, W. Ji, and T.-S. Chua. Next-gpt: Any-to-any multimodal llm. *arXiv preprint arXiv:2309.05519*, 2023. 2, 9
- [41] Y. Zhang, Y. Li, L. Cui, D. Cai, L. Liu, T. Fu, X. Huang, E. Zhao, Y. Zhang, Y. Chen, et al. Siren's song in the ai ocean: a survey on hallucination in large language models. *arXiv preprint arXiv:2309.01219*, 2023. 9
- [42] X. Zhou, A. S. Williams, and F. R. Ortega. Eliciting multimodal gesture+ speech interactions in a multi-object augmented reality environment. In *Proceedings of the 28th ACM Symposium on Virtual Reality Software and Technology*, pp. 1–10, 2022. 2
- [43] C. Zimmerer, E. Wolf, S. Wolf, M. Fischbach, J.-L. Lugrin, and M. E. Latoschik. Finally on par?! multimodal and unimodal interaction for open creative design tasks in virtual reality. In *Proceedings of the 2020 international conference on multimodal interaction*, pp. 222–231, 2020. 2