# Investigating variations and combinations of geospatial visualizations based on spatial dimensionality of attribute space and reference space

by

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## ABSTRACT

The effectiveness of information presentation in different forms plays a vital role in our ability to address challenges and make informed decisions. In this thesis, a focus is placed on the visualization of geospatial data. The study begins with the establishment of a systematic framework that categorizes the presentation space consisting of attribute (data) and reference (terrain) space based on their dimensionality. We also introduce MultiDim, an innovative information visualization system capable of rendering a photo-realistic environment in 2D, 2.5D, and 3D reference spaces. To assess its efficacy, we conducted a comprehensive comparative evaluation of user performance (accuracy and completion time) in different dimensions of attribute and reference space. We also conducted a qualitative analysis where we analyzed with the help of an eye-tracker the different strategies that participants adopted while solving tasks. The eye-tracker enabled us to monitor participants' gaze and discern the preferred views for task-solving. Our findings indicate that the dimensionality of the attribute space (data) has negligible effects on accuracy and task completion time. Conversely, the dimensionality of the reference space (terrain) and the presence of distractors within the environment significantly impact both accuracy and task completion time. Notably, our qualitative analysis reveals a preference for views incorporating 3D terrain. These results offer valuable insights for the future design of geospatial visualizations, guiding decisions on the optimal view selection for enhanced task-solving capabilities.

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# Chapter 1

# Introduction

## 1.1 Context and Motivation

Over the years, researchers have explored various methods for organizing data in spatial representations, each with its unique insights and applications [34]. These representations are categorized as either photorealistic or non-photorealistic [75], static or dynamic [4], and in 3D or 2D [59]. These different methods not only demonstrate the various presentation possibilities but also highlight the importance of conveying information effectively.

The effectiveness of presenting information in its various forms plays an important role in our ability to address challenges and make informed decisions [27]. To be more specific, the suitability of presentation style significantly impacts the speed of problem-solving, the likelihood of errors occurring, and the improvement of our understanding and visual working memory capacity [51]. This relationship between the way we present information and our problem-solving capabilities highlights the importance of diving deep into how we visualize information and its role in shaping our cognitive processes.

Presently, it is estimated that roughly 60-80% of the available data can be categorized as spatial or geo-data [25]. Consequently, this category holds significant importance in the field of visualization and serves as an excellent foundation for further research.

In recent years, electronic maps have progressively replaced traditional paper maps which has also led to the evolution of maps from two-dimensional (2D) to a 2.5-dimensional (2.5D) and even to a three-dimensional (3D) format [41]. In the context of this thesis, we introduce a systematization that focuses only on the dimensionality of the presentation space which includes both attribute space consisting of data, and reference space which consists of maps/terrain. It is an expansion to the foundation laid by Dubel et al. [21] offering us a valuable systematization technique to build upon. We expand the systematization by adding the concept of 2.5D reference space [41].

In the information visualization community, there is an ongoing debate regarding the advantages of 3D versus 2D visualizations. Thus, in this thesis, we conducted a comprehensive assessment of all presentation formats defined in our systematization in Chapter 3 in terms of their accuracy and efficiency. While some researchers argue that the choice between 3D and 2D has no significant impact on task performance [15, 17], others argue that 3D presentations can yield improved task performance [70]. Our study delves into this ambiguity to provide valuable insights into the effectiveness of these visualization approaches.

In this thesis, we conducted a study that extracted exploratory, fixation, and saccade strategies (discussed in Section 5.5.1) that participants employed to solve a domain-related task. These tasks were conducted on a display consisting of all six views integrated on a single screen as illustrated by our system called MultiDim shown in Figure 1.1. The study aims to understand which views participants used at a given point to solve the task and highlights the potential benefits of combining 3D and 2D view types. The varying strengths observed for these views suggest that combining them on a single display could potentially enhance overall performance. Research involving diverse user groups and tasks has indicated that 2D views excel in detailed analysis, precise navigation, and distance measurement [62, 64]. Whereas, 3D views are advantageous for understanding 3D space and shapes, and facilitating navigation [62, 74].

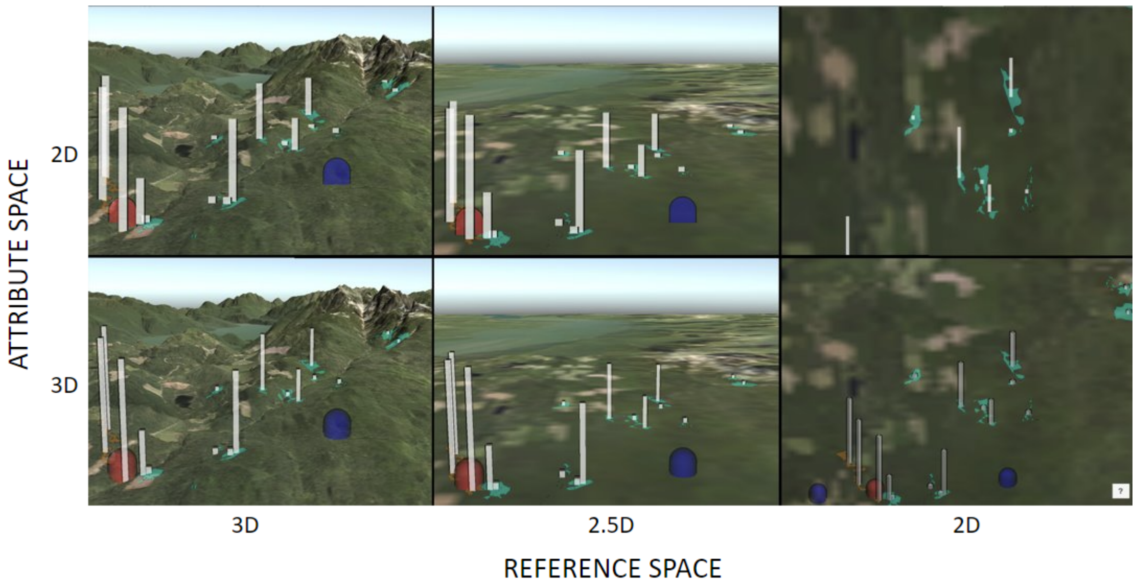



Figure 1.1: Screenshot of our system called MultiDim showing six views in a single display. The views are categorized based on a systematization that is defined by the dimensionality of the attribute space (data) and reference space (terrain)

In this thesis, eye-tracking technology plays an important role. It allows us to precisely measure an individual's visual attention, offering a rich source of data that reveals not only where in the spatial environment their gaze is directed but also when they focus on particular areas, how long they maintain their gaze on each point of interest, and the sequence in which they explore information. In this way, eye-tracking provides a comprehensive understanding of how people engage with spatial data, uncovering patterns and insights that help with the design of a more effective and user-friendly spatial visualization and user interfaces.

## 1.2 Research Question

The thesis aims to answer two overarching research questions:

- **Question 1: Does the dimension of attribute space (data) and reference space (terrain) impact user performance?**

  The term 'user performance' encompasses both the efficiency and accuracy exhibited by users while addressing a task.

  This high-level question can be further broken down into three sub-questions:

  - Question 1.1: Does an increase in difficulty, i.e., an increase in the number of distractors, have an impact on user performance?
  - Question 1.2: Is there an observable influence on user performance when there is a transition in the dimensionality of the attribute space (data)?
  - Question 1.3: Is there an observable influence on user performance when there is a transition in the dimensionality of the reference space (terrain)?

- **Question 2: Are there any benefits in combining multiple views?**

  This high-level question can be further broken down into two sub-questions:

  - Question 2.1: Do people prefer a single view when provided with multiple views?
  - Question 2.2: How do people use multiple views together?

## 1.3 Research Approach

The first research question is: **Question 1: Does the dimension of attribute space (data) and reference space (terrain) impact user performance?**

We start by creating a systematic categorization, which organizes the presentation space based on the dimensionality of the attribute space (data) and the reference space (terrain). We then address this question, by conducting an analysis of quantitative data on a set of simple tasks derived from past literature. These tasks provided valuable insights into the accuracy and task completion time measured across all defined views within our systematization. Expanding on this systematization, the subsequent sections outline our approach for answering the following sub-questions.

*Question 1.1: Does an increase in difficulty, i.e., an increase in the number of distractors, have an impact on user performance?*

Based on the insights derived from Seipel et al.'s study [59], we discover that the degree of difficulty, which was affected by the presence of distractors (number of bars), was established at 15. This led us to categorize three discrete difficulty levels: a lower difficulty level of 5, a medium difficulty level of 15, and an upper difficulty level of 25. We implemented a repeated measures experimental design where each task was conducted thrice at every difficulty level and across all views specified within our systematization, thereby giving us an extensive dataset for comparative examination across the three distinct difficulty levels.

*Question 1.2: Is there an observable influence on user performance when there is a transition in the dimensionality of the attribute space?*

A repeated measures experiment was implemented where each task was conducted across all views specified within our systematization. In our analysis, we logically grouped views that shared similar attribute space dimensions. This strategic grouping allowed us to effectively contrast variations or similarities in the collected data, allowing us to uncover valuable insights and patterns.

*Question 1.3: Is there an observable influence on user performance when there is a transition in the dimensionality of the reference space?*

A repeated measures experiment was implemented where each task was conducted across all views specified within our systematization. In our analysis, we logically grouped views that shared similar reference space dimensions. This strategic grouping allowed us to effectively contrast variations or similarities in the collected data, enabling us to uncover valuable insights and patterns.

The second research question is: **Question 2: Are there any benefits in combining multiple views?**

We start by presenting all the views outlined in our systematization as detailed in Chapter 3. The views are showcased together in a single display as depicted in Figure 1.1. To address this challenge, we conducted a qualitative analysis of eye-tracking data, user interaction, and system logs within the system. This analysis allowed us to identify the strategies users employed to address a series of complex tasks, which were drawn from both existing literature and the specific domain. Expanding on this framework, the subsequent sections outline our approach for answering the following sub-questions.

*Question 2.1: Do people prefer a single view when provided with multiple views?*

Eye-tracking data was integrated with the interaction and system logs to form a unified dataset. An Area of Interest (AOI) timeline was generated from this unified dataset, which served as the foundation for investigating if users preferred a single view to address task-related challenges.

*Question 2.2: How do people use multiple views together?*

Eye-tracking data was integrated with the interaction and system logs to form a unified dataset. Subsequently, an Area of Interest (AOI) timeline was generated from this unified dataset, which allowed us to explore whether users tended to use multiple views to navigate through distinct phases of the task.

## 1.4 Research Contributions

The thesis includes five main research contributions:

- Proposal of a systematic approach that distinguishes the presentation space into attribute space (data) and reference space (terrain) based on their dimensionality. The systematization provides a framework for comparison among various visualizations.
- Introduction of a task categorization framework within the existing literature that categorizes the diverse ranges of task types that have been used in analyzing and comparing 3D and 2D dimensions. This categorization sheds light on the variety of approaches undertaken to explore the complexities between 3D and 2D aspects in the existing body of research.
- Evaluation of user performance across all the views outlined in the systematization in Chapter 3. This evaluation helps us discover the suitability of a specific view for problem-solving, thus offering insights for future research directions.
- Extraction of user strategies in solving complex tasks when presented with a multiple coordinated 3D and 2D display. This investigation explores whether users prefer a particular strategy in task-solving, thus offering insights for future research directions.
- Design recommendations for future geospatial systems that are derived from the outcomes of our experiment. These recommendations provide insights to develop user-centric geospatial technologies.

## 1.5 Thesis Scope

The thesis falls within the field of information visualization. To be specific, it falls within the visualization of geospatial information in different dimensions of presentation space including 3D and 2D attribute space (data) and 3D, 2.5D, and 2D reference space (terrain).

## 1.6 Thesis Overview

The thesis contains six additional chapters. These are described as follows:

- In Chapter Two, an extensive examination of the existing literature on geo-visualization, coordinated multiple views, and eye-tracking is presented. This section specifically dives into the 3D and 2D nature of visualizations providing a deep overview of the relevant research and insights in these domains.
- In Chapter Three, a systematic approach is outlined, serving as the foundation for the subsequent sections of the paper. This framework is structured around the dimensionality of presentation space which consists of both the attribute space (data) and the reference space (terrain). Furthermore, the chapter classifies the referenced literature into distinct task types that have been employed within the field of geo-visualization, providing a structured and insightful organization.
- In Chapter Four, a detailed look into the Multidim's design, exploring its architecture, functionality, and overall design principles in depth.
- In Chapter Five, all the results that we have gathered during the experiment are listed systematically.
- In Chapter Six, a detailed discussion of the findings is listed along with limitations and future design recommendations.
- In Chapter Seven, the thesis concludes with a summary.

# Chapter 2

# Related Work

This chapter explores spatial visualizations presented in both 3D and 2D formats. It dives into the coordination of multiple views and highlights the use of eye-tracking technology within the field. Thus this chapter consists of:

- GIS Technology
- Dimensional Analysis of Space
- Dimensional Analysis of Data
- Coordinated Multiple Views
- Eye tracker

The first section of this chapter is on GIS Technology. It focuses on the utilization of maps in GIS for decision-making across various fields. The discussion includes the use of both 3D and 2D maps. However, the determination of when to apply each dimension remains ambiguous.

The second and third sections of this chapter compare the dimensionality of space and data. The emphasis is on 3D and 2D attribute (data) and reference (terrain) spaces and explores instances when each or both are used to address a specific task. Additionally, these sections also consider whether a particular view proves more effective in solving specific tasks.

The fourth section of this chapter discusses coordinated multiple views, primarily focusing on the visualization of data using both 3D and 2D formats. This section strongly advocates for the use of multiple views, asserting that it enhances the presented information by displaying data from various perspectives.

The last section of this chapter discusses eye-tracking technology and its applications across various domains. It explores the use of eye-tracking technology in utilizing how individuals understand data and identify the focal points of their attention.

## 2.1 GIS Technology

In the present-day problem-solving, an interdisciplinary approach has become increasingly common. This approach is particularly evident in physical planning processes, such as disaster management, and environmental impact studies, like forestry planning, where a diverse range of data is essential for making decisions. This demand to integrate these multifaceted data has given rise to the development of Geographic Information Systems (GIS) [39]. GIS is developed to help solve geographic-related tasks and is ultimately used to enhance spatial understanding and decision-making [19]. Within GIS technology, cartographic expertise plays an important role in the form of visualizations, providing a means to virtually represent data and information [71].

The rise of powerful desktop computers has led to GIS transition into 3D spaces from 2D spaces, offering greater flexibility in rendering details and interacting with spatial data [3]. In a 3D digital environment, users can interpret and understand information from various viewpoints. A 3D, 2D, or a combination of both views can be used to represent information, leading to a better understanding of data [3]. GIS-based urban models, widely utilized in decision support for urban policy-making are generally accepted as a robust framework with system extensibility being a key element in their adoption [44]. However, the systematic approach to representing information initially proposed by Bertin [5] has lagged behind technological advancements. Thus, the development of 3D-specific visual variables, such as animation, light sources, and camera views, alongside the traditional systematic approach to represent information, poses challenges in adapting theory to dynamic 3D environments [24].

Despite the potential advantages offered by 3D visualizations, there is no consensus regarding their effectiveness. Scaife and Rogers [57] concluded that, despite the collective efforts of researchers, there exists a limited understanding of the cognitive impact of interactive displays or graphical representations in improving user comprehension and mental imagery. They also stated the difficulty in validating and generalizing assumptions about how technological advancements in graphical representations facilitate cognitive tasks. This challenge arises, in part, because many graphical representations do not lend themselves well to systematic computational analysis [57]. Despite the extensive research in 3D visualizations, the findings are occasionally contradictory, suggesting that the effectiveness of a specific cartographic approach heavily depends on the task at hand. For example, St. Amant [64] observed that 3D representations outperformed 2D representations in terms of speed and accuracy for shape-understanding tasks involving blocks and terrain, whereas Savage, Wiebe, and Devine [56] found little difference in performance for topographic tasks. This highlights the relationship between 3D visualizations and task-specific effectiveness.

## 2.2 Dimensional Analysis of Space

This section explores the dimensional analysis of reference space. The literature discussed in this section suggests a lack of complete understanding regarding the situations or tasks where a specific dimension proves to be most effective in enhancing user comprehension and problem-solving efficiency within a given environment. The discussion is organized into four subsections. The first subsection focuses on past literature supporting the effectiveness of 2D, while the second focuses on literature supporting the effectiveness of 3D. The third subsection covers literature that equally supports both 2D and 3D. Lastly, the fourth section explores the concept of 2.5D space.

### 2.2.1 Support for 2D

Cockburn et al. [16] conducted an extensive comparison between 3D and 2D interfaces in a document management system and found that 2D display interfaces had a marginal speed advantage over 3D display interfaces.

Seipel et al. [59] investigated the effectiveness of 2D and 3D map presentations in assessing distances within a geographical context. Their experiments indicated comparable efficiencies in weak 3D (2.5D) and 2D presentations. On the other hand, strong 3D presentation led to visual discomfort and decreased task accuracy. Similarly, Cockburn et al.'s study [17] scrutinized spatial memory, revealing that users' performance decreased as their freedom in manipulating the third dimension increased.

In the domain of urban representation, Halik et al. [26] observed user preferences and behaviors in 3D and 2D modes. While there was a general preference for the 3D mode, participants who were engaged in navigational tasks exhibited a slightly higher preference for the 2D mode. Similarly, John et al. [31] reported slight performance differences in planning tasks, with 2D proving more effective for antenna placement. These collective findings highlight the complex relationship between the dimensions of the interface, task requirements, and user preferences.

### 2.2.2 Support for 3D

Cockburn et al. [16] conducted a comparison between 3D and 2D interfaces in a document management system. Despite a marginal speed advantage for the 2D display interface, users exhibited a statistically significant preference for 3D interfaces. This highlights the user-perceived value of the added dimensionality in tasks involving the storage, organization, and retrieval of document representations.

Popelka et al. [52] explored the visual exploration of 3D and 2D map visualizations, revealing a predominant preference for 3D visualization among participants. The study, employing eye-tracking technology and a questionnaire, highlighted the cognitive inequality between the two visualization types. 3D provided a perceptual advantage in tasks related to map understanding, suitability, and aesthetics, thus enhancing the overall user experience.

In the domain of urban representation, Halik et al. [26] observed user preferences and behaviors in 3D and 2D modes. Despite the top-down bird's eye view offered by the 2D mode, participants demonstrated a general preference for the immersive experience of the 3D mode, particularly in scenarios requiring navigation. This preference for 3D highlights the perceived value of the first-person perspective provided by 3D interfaces, even in tasks traditionally associated with 2D representations. Similarly, John et al. [31] presented outcomes from experiments where participants planned routes in 3D and 2D terrains. The 3D perspective view proved advantageous for the initial planning of antenna routes, demonstrating the efficacy of the added dimension in certain tasks.

### 2.2.3 Equal Support

Seipel et al. [59] investigated the effectiveness of 2D and 3D map presentations in assessing distances within a geographical context. The study involved three map presentation formats: 2D, weak 3D (2.5D), and strong 3D. Results from two controlled experiments revealed that participants demonstrated comparable efficiency in both weak 3D (2.5D) and 2D representations.

Lei et al. [41] focused on spatial object search tasks in 2D and 3D electronic maps. With the help of an eye tracker to analyze wayfinding strategies, their study found that 2D electronic maps prompted quicker browsing behaviors, while 3D electronic maps facilitated more prolonged and focused browsing. The extended fixation time in the 3D setting allowed users to acquire more detailed information about the environment, enhancing overall understanding. Despite the differing dynamics, both 2D and 3D settings demonstrated distinct advantages, showcasing the benefits of each approach.

### 2.2.4 2.5D Space

Pettit et al. [49] investigated the diverse visualization techniques with GIS and Cartography tools, ranging from digital globes and virtual simulation environments to building information models and gaming platforms. The paper notably touches upon the concept of 2.5D spaces and emphasizes how a digital perspective can effectively support such a view. The authors of the paper argue that the ease of navigation offered by 2.5D presentations contributes to their widespread popularity among urban researchers, decision-makers, and community groups.

Bladh et al. [7] introduced a pioneering extension of the 2D treemap algorithm into the third dimension with the StepTree visualization system, involving the stacking of graphical representations of sub-directories. In a comparative study with its 2D counterpart, users showcased significantly improved performance in tasks related to interpreting hierarchical structures, while maintaining proficiency in other interpretive and navigational tasks. Similarly, Limberger et al. [43] presented an innovative treemap visualization approach that integrated orthogonal and perspective projections into a unified 2.5D treemap. The advantages of 2.5D maps over 2D counterparts include additional visual variables like transparency, texture, shading, extended shape, and silhouette enhancement techniques [42]. Additionally, 2.5D maps mitigate drawbacks commonly associated with 3D maps such as reduced occlusion, optimal screen space utilization, and the alleviation of perspective foreshortening problems [58].

Cockburn et al. [17] conducted a study exploring spatial memory in both real-world physical models and equivalent computer-based virtual systems, employing 2.5D space as one of the presentation spaces. The choice of presentation space was dependent on the degree of freedom in depth. The findings indicated that subjects' performance declined as their freedom to position items in the third dimension diminished.

## 2.3 Dimensional Analysis of Data

This section explores the dimensional analysis of attribute space. The literature suggests a lack of complete understanding regarding the specific situations or tasks where a specific dimension proves to be most effective in enhancing user comprehension and problem-solving efficiency within a given environment. The discussion is organized into three subsections. The first subsection focuses on past literature supporting the effectiveness of 2D, while the second focuses on literature supporting the effectiveness of 3D. Lastly, the third subsection covers past literature that equally supports both 2D and 3D.

### 2.3.1 Support for 2D

A series of empirical experiments conducted by Bleisch et al. [11] investigated participants' effectiveness in judging the height of various bar combinations within static 2D and 3D desktop virtual environments, both with and without frames. In their study, participants consistently succeeded in identifying the tallest bar across all settings, with significant differences emerging in task completion time rather than accuracy between static 2D and 3D presentations. The findings indicated that tasks in a 3D environment required more time compared to the efficiency observed in the 2D context.

In a study by Hicks et al. [28], the efficacy of one 2D presentation was compared against two 3D presentations in conveying customer behavior information related to telecommunication usage. This study highlighted the importance of presentation style in influencing information retrieval and problem-solving tasks. Hicks et al. [28] in their study found that the 2D presentation had a significant performance advantage over both 3D presentation counterparts in terms of time and accuracy. Similarly, Smallman et al. [62] investigated the optimal use of 2D and 3D displays for operational tasks, highlighting that the choice between formats depends more on information availability rather than the appeal of 3D presentation. The study highlighted the trade-off inherent in 3D displays, introducing realism but simultaneously risking ambiguity and distortion. Particularly in tasks demanding precise spatial judgments, the preference leaned toward 2D displays, highlighting the clarity and precision of data maintained in a 2D format. This finding highlights the significance of prioritizing information availability over the potential advantages of 3D visual realism in operational contexts.

In a similar exploration by Bleisch et al. [10], the effectiveness of different visual representations, including 2D bars, 3D bars, and 2D circles, was examined for displaying quantitative data. The study used reference frames to indicate the largest possible value and revealed that 2D bars consistently emerged as the most efficient and effective option in two telemetry tasks—indicating the largest symbol and comparing symbol sizes. In contrast, 3D bars showed lower efficiency, and 2D circles were identified as the least efficient among the visual representations. These insights contribute to the understanding of the superiority of 2D representations in various tasks, highlighting their efficiency and effectiveness in conveying quantitative information.

### 2.3.2 Support for 3D

Tavanti et al. [65] investigated the spatial memory performance that revealed a significant enhancement in participants' recall of spatial locations with a 3D display compared to a 2D display. The 3D visualizations had an advantage in tasks requiring spatial memory and cognition. This shows the role of display dimensions in cognitive processes.

Amini et al.'s research [2] conducted a study on spatiotemporal movement data visualization. The study revealed distinct advantages of 3D visualizations, with 2D visualizations heavily relying on "scrubbing" the timeline, while 3D views demonstrated proficiency through the predominant use of 3D camera navigation. This preference for 3D mechanisms in handling complex spatiotemporal data implied a unique strength in capturing the complexity of dynamic visual information.

St. John et al. [64] in their study investigated shape understanding tasks and acknowledged challenges posed by distortions in 3D displays when judging relative positions. However, the integration of dimensions in 3D displays proved advantageous for tasks involving shape comprehension, offering a valuable perspective on the effectiveness of 3D presentations in tasks emphasizing shape understanding over positional judgment.

### 2.3.3 Equal support

Bleisch et al. [11] investigated participants' effectiveness in judging the height of various bar combinations within static 2D and 3D desktop virtual environments, both with and without frames. Their study reported high success rates in identifying the tallest bar with significant differences in task completion time rather than accuracy between static 2D and 3D presentations. However, the authors of the paper recognized that the outcomes of the experiment might be dependent on factors such as the complexities of the virtual environment and the introduction of spatial information, highlighting the importance of an evaluation beyond accuracy metrics.

Similarly, Cockburn's experiment [15], directly revisited Tavanti et al.'s study on spatial memory [65], and challenged earlier findings. The results suggested that the effectiveness of spatial memory remained largely unaffected by the presence or absence of 3D perspective effects in monocular static displays, introducing a layer of complexity and questioning previously established relationships between display dimensions and memory performance.

Siepel et al.'s study [60] on visualizations of bar charts in geographic maps revealed that participants exhibited similar levels of speed and accuracy regardless of whether they used 3D or 2D visualizations. Additionally, the study rejected assumptions that frequent game players would experience greater benefits from 3D visualizations, signaling a need for a deeper understanding of the role of visualization formats in specific cognitive tasks.

In summary, the literature suggests a lack of complete understanding regarding the specific situations or tasks where either 3D or 2D visualizations prove to be most effective in enhancing user comprehension and problem-solving efficiency within a given environment. In light of this, we plan to conduct a repeated measured experimental design of the dimensionality in both attribute space and reference space. This approach aims to determine and analyze which dimensionality yields superior performance, providing valuable insights into the effectiveness of 3D versus 2D visualizations.

## 2.4 Coordinated Multiple Views

The importance of implementing multiple views in visualization is highlighted by the contributions of both Wang et al. [72] and Jonathan C. Roberts [54, 55]. Wang et al.'s comprehensive guidelines [72], derived from extensive workshop discussions, offer designers a robust framework to navigate the complexities inherent in designing multiple-view systems. These guidelines provide thorough insights into crucial considerations, contributing to a comprehensive understanding of the complexities involved in crafting effective and user-friendly multiple-view interfaces.

Jonathan C. Roberts advocates for the adoption of multiple views in visualization, asserting that it holds the potential to enhance and clarify presented information. He argues that consolidating too much information into a single view can introduce irrelevant details, leading to confusion in data comprehension. Roberts emphasizes the advantages of dividing information into multiple views to mitigate confusion and enhance the overall effectiveness of visualizations. His survey paper [55] further dives into the evolution of Coordinated Multiple Views (CMV), offering insights into its current landscape and future trajectory. By highlighting the importance of adopting multiple views and providing a comprehensive review of CMV research, Roberts contributes to a comprehensive understanding of the field.

The integration of 3D and 2D views has led to the implementation of new approaches in various studies which has helped to discover new perspectives in data analysis and visualization. Pillay's [50] investigation highlights the benefits of a combined display, demonstrating that incorporating both 2D and 3D views enhances the speed and ease of data analysis. This approach, particularly beneficial in educational settings, facilitates the effective utilization of orthographic views for students working with 3D Computer-Aided Design (CAD) models. Keefe et al.'s [33] dynamic framework further advances this concept by integrating 3D and 2D visualizations in the exploration of bio-mechanical data. Their multi-view strategy supports comparative analysis, employing interactive 3D and 2D tools with an analytical methodology that includes overview-first, zoom and filter, and details-on-demand. Overcoming challenges such as scalability, this framework introduces novel interactive methods for constructing small multiples overview visualizations. Additionally, Bleisch et al.'s [12] prototypical implementation takes a step further by using brushing techniques to connect spatial information in 2D views and 3D virtual environments. This innovative approach not only mitigates shortcomings associated with standalone 3D views but also enhances the exploratory analysis of spatial data, offering new possibilities for evaluating landscapes. Collectively, these studies highlight the significance of integrating 3D and 2D visualization techniques, showcasing their potential across educational, bio-mechanics, and spatial analysis domains.

Tory et al. [69, 66, 68] conducted a series of studies to assess the effectiveness of 3D, 2D, and combined 3D/2D displays. A study conducted in 2004 by Tory et al. [69] demonstrated that the integration of 3D and 2D displays provides distinct advantages, particularly for tasks requiring precise orientation and positioning. Significantly, the performance of combined 3D/2D displays was found to be comparable to or even surpass that of standalone 2D displays.

In a subsequent study also conducted in 2004, Tory et al. [66] reinforced the value of integrating 3D and 2D views, highlighting its significance when both views contribute to task relevance. Both studies converged on the conclusion that a 3D/2D combination display outperforms standalone 3D or 2D displays, proving particularly advantageous for tasks involving rapid switching between 3D and 2D displays or requiring distinct 3D and 2D phases.

A study conducted by Tory et al. [68] in 2005 added another dimension to the discussion, noting that combined displays not only enhance task performance but also instill higher user confidence. Combined displays facilitated a natural and integrated navigation experience, emphasizing the overall benefits of integrating 3D and 2D views. Tory et al. [67] further explored the relative position estimation of objects in 3D space using different arrangements of 3D and 2D views. The findings highlighted the crucial role of 3D views and stated that it was significantly utilized more than individual 2D views in both displays. This emphasized the importance of 3D perspectives for effective task completion. Furthermore, the spatial layout of views in 2D/3D combination displays had a significant impact on users' viewing strategies, highlighting the relationship between display configuration and user behavior.

Convertino et al. [18] conducted a controlled experiment, investigating cognitive strategies and context switching by employing a combination of visualization and various task types as independent variables. The study collected both quantitative and qualitative data, revealing that the time required for context switching in dual-view visualizations may not be significant, and similar visualizations could potentially lead to more interference. Additionally, orthogonal combinations were observed to assist users in pattern recognition and focusing attention on spatial relationships.

North et al. [47] introduced Snap-together visualization, a framework that empowers users to swiftly and dynamically combine various visualizations and coordination elements, creating custom exploration interfaces without the need for programming. In their evaluation of the Snap visualization, the study unveiled a spectrum of outcomes, ranging from benefits to cognitive considerations and usability concerns. Interestingly, data-savvy users demonstrated remarkable efficiency in rapidly constructing powerful coordinated views. The integration of Snapped overview and detail-view coordination emerged as particularly impactful, enhancing user performance by a substantial margin ranging from 30% to 80%, depending on the specific task at hand.

The literature review highlights the efficacy of employing multiple views to enhance and clarify presented information by showcasing data from various perspectives. Furthermore, it advocates for exploiting the strengths of both 3D and 2D displays in a single display, leveraging the advantages of each to effectively address specific tasks. In our study, we introduce a multiple-view display that encompasses various perspectives based on dimensionality. Participants are asked to solve a given task, enabling us to discern their preferences among the provided views. Additionally, we aim to investigate whether participants prefer more than one view to tackle a task and, if so, which specific views they employ. This approach allows us to gain valuable insights into user preferences and the potential connection between different visual perspectives in problem-solving scenarios.

## 2.5 Eye tracker

The eye tracker serves as a recorder of the intricate movements within a user's eyes, offering a reliable method to validate their attentional patterns during interactions with specific stimuli. The data collected through eye tracking proves to be essential in understanding how individuals engage with complex content and visual stimuli, thus making eye-tracker a crucial tool for research and analysis across various fields. Thus, eye-tracking technology has earned widespread acclaim due to its versatile applications in understanding user behavior.

A survey paper conducted by Andrew T. Duchowski [22] sheds light on the extensive reach of eye-tracking technology, spanning domains such as marketing, neuroscience, human-computer interaction, and visualization research and states that this technology emerges as a valuable resource for obtaining objective and quantitative insights into the visual and attentional processes of users. Similarly, Majaranta et al. [46] offer an introduction to cutting-edge eye technology and gaze estimation, by diving into the challenges associated with using eyes as input devices. The authors review real-life applications and explore design solutions derived from research findings, providing an overview of the field. Blascheck et al. [8] complement this research with a survey introducing eye tracking and providing an overview of existing techniques.

The survey papers offer valuable insights into the preceding research conducted across various fields using eye-tracking technology, shedding light on its utility and contributions. These comprehensive reviews serve as a rich source of inputs, connecting and building upon the advancements made in understanding user behavior, cognitive processes, and spatial interactions facilitated by eye-trackers. They provide a foundation for our work, allowing us to draw upon the lessons and findings of previous research studies in leveraging eye-tracking methodologies.

Eye-tracking technology has emerged as an important tool in understanding visual attention and cognitive processes within spatial visualizations, as evidenced by studies conducted by Lei et al. [41], Popelka et al. [52], and Kiefer et al. [35]. Lei et al.'s research [41] delves into the distinct viewing behaviors on 3D and 2D maps, revealing interesting differences in fixation time and saccade amplitude. Meanwhile, Popelka et al. [52] explore user cognition in 2D visualizations with contour lines and perspective 3D views, stating that the experiment's design may influence cognitive processes more significantly than the differentiation between visual formats. In contrast, Kiefer et al.'s survey [35] provides a comprehensive overview of spatial cognition, geographic information science, and cartography, advocating for a robust integration of eye movement analysis. Collectively, these studies highlight the importance of eye-tracking methodologies in uncovering spatial data complexities and offer valuable insights into developing sophisticated, user-centric solutions in diverse spatial domains. In our experiment, we employed an eye tracker to gain insights into user strategies as they navigated and executed tasks within a spatial environment. This application aligns with the existing literature on eye movement analysis in spatial contexts, contributing to the broader understanding of user behavior and decision-making processes. By leveraging eye-tracking technology, we aim to enhance the comprehension of how individuals interact with spatial environments, thus building upon the insights provided by previous studies.

Studies by Tory et al. [67], Popelka et al. [52], and Lei et al. [41] collectively contribute valuable insights into the dynamics of user interactions with 3D and 2D visualizations using eye-tracking technology. Tory et al.'s investigation [67] emphasizes the significance of combined 3D and 2D views, revealing that the 3D perspective was notably more prominent than individual 2D views, highlighting its importance for task completion. While users exhibited distinct viewing patterns, such as frequent transitions through centrally positioned views, these variations did not significantly impact task performance. Popelka et al.'s experiments [52] comparing user cognition in 2D visualizations with contour lines and perspective 3D views revealed that the experiment's design played a more influential role in cognitive processes than the differentiation between 2D and 3D visualizations. Lei et al.'s study [41] delved into fixation time and saccade amplitude differences between 2D and 3D maps, revealing distinct viewing behaviors. Collectively, these studies provide valuable insights into the comparative aspects of eye gaze strategies, cognitive processes, and task performance between 2D and 3D visualizations, thus laying a groundwork for informed design choices in spatial contexts.

A study conducted by Blascheck et al. [9] investigated how individuals explore and uncover the functionality of interactive visualizations. In their research, they organized a laboratory study where participants had the freedom to employ their approaches to discover the features and capabilities of a set of interconnected interactive visualizations representing public energy data. The study collected a rich dataset, including eye movement data, interaction logs, video recordings, and audio recordings, allowing for a comprehensive analysis of participants' behaviors and exploration patterns. Through an integrated analysis of this diverse dataset, the researchers identified distinct exploration strategies employed by the participants to uncover the functionality within the interactive visualizations. These strategies shed light on how individuals approach and engage with such interfaces, providing valuable insights into how to enhance the discoverability of functionality for a broader and more diverse user base.

Jacob et al. [30] delve into the relationship between human factors and technical considerations when attempting to employ eye movements as an input medium. Their argument states that, while the human eye is well-suited for interaction, it is most effective when utilized as an additional input rather than a sole method. The discussion highlights a key challenge wherein eye movements, though a promising input mode, may exhibit a jerky nature, making it challenging for users to maintain focused and precise pointing at objects. This exploration highlights the complexities involved in harnessing eye movements for input and emphasizes the importance of considering both human factors and technical constraints in the design and implementation of such interaction systems.

From the literature, we learn that eye-tracking technology has been applied in different fields to observe how people comprehend data and where they focus their attention the most. In our study, we leverage eye-tracking technology to figure out which views participants rely on when solving a task with multiple views. This technology also gives us a timeline, showing how participants switch between different views over time and during different stages of the task. This helps us to understand if participants have a preference for a particular view when tackling specific parts of the task.

# Chapter 3

# Systematization

This section introduces a systematization that focuses on the dimensionality of the presentation space. The systematization introduced is an expansion to the foundation laid by Dubel et al. [21] that offers us a valuable systematization technique to build upon.

In the first section of this chapter, a systematic categorization is undertaken to distinguish various views based on the dimensionality of the presentation space that consists of both the attribute space (data) and reference space (terrain). We further classify the existing literature by following a categorization approach based on the systematization.

In the second section of this chapter, a systematic categorization presents a list of tasks from past literature that has been used in the field of information visualization.

## 3.1 View Categorization

The presentation space is made up of graphical elements that comprise visual variables such as size, shape, color, and texture. 2D presentations are assembled only from 2D graphical elements, such as points, lines, and polygons whereas 3D presentations use 3D graphical elements. Dubel et al. [21] in their systematization distinguish this presentation space into the presentation of attribute space $A$ and the presentation of the reference space $R$.

We propose a systematization that is an expansion to the foundation laid by Dubel et al. [21] and consists of a combination of 3D and 2D presentations of attribute space ($A$) and 3D, 2.5D, and 2D presentations of reference space ($R$). This is represented as ($A^i$ + $R^j$), with $i \in$ 2,3 and $j \in$ 2, 2.5, 3

- $A^i$: selected attribute space is visualized using i-dimensional graphical elements.
- $R^j$: selected reference space is visualized using j-dimensional graphical elements.

Figure 3.1 shows an overview of our categorization based on the established systematization. The horizontal axis represents the attribute space, categorized as either $A^3$ or $A^2$ and the vertical axis represents the reference space, categorized into $R^3$, $R^{2.5}$, or $R^2$.

(***A***$^{3}$) The data values are depicted as 3D graphical elements directly onto the reference space. Monocular depth cues such as the width and height of the objects are used to ensure that the scene is perceived as 3D. This is similar to desktop-based 3D virtual environment applications that project 3D objects by using monocular depth cues to ensure that the scene is perceived as 3D [36].

(***A***$^{2}$) The data values are depicted as 2D graphical elements placed directly onto the reference space. These objects are essentially flat representations of 3D graphical elements that are always oriented towards the camera [23]. To maintain accuracy in 2D perception of objects, effects like lighting and shading are intentionally excluded from this representation, as they could introduce depth cues that might affect the viewer's perception of the objects. Additionally, the monocular depth cue of width is eliminated by employing the 2D scaling method outlined in Section 4.5.2.

(***R***$^{3}$) In our thesis, we use a perspective camera setup to visually represent the terrain/map within a 3D spatial environment. This approach allows viewers to perceive depth cues naturally, enhancing their understanding of the spatial layout. Such a technique is frequently utilized in fields such as urban planning [38] and landscape planning [48] where the emphasis is on creating realistic visualizations that accurately depict the physical environment.

(***R***$^{2.5}$) The terrain/map is displayed in a 2D spatial context, with 3D geometry which is usually viewed through a perspective camera, which enables depth perception in the environment. The only clues available to the observer are pictorial cues which comprise linear perspective, shading effects, occlusion, relative size, and others. In literature, the definition for this view is ambiguous with some using it as 3D [37], 2.5D [7], or 2D [17].

(***R***$^{2}$) The terrain/map is presented within a 2D spatial context, observed through an orthographic camera, thereby eliminating depth perception within the environment. Additionally, the views in this perspective have a fixed camera angle, restricting rotation. For $A^2 + R^2$ view we adopt a top-down view similar to those commonly found in previous literature [71, 16, 15, 17]. This style of geo-visualization has historically been employed to represent abstract information such as statistical data, utilizing maps as a reference to offer geospatial context (Shepherd et al., 2008). An iconic example of statistical visualization using 2D maps is seen in the depiction of the Cholera Epidemic in London in 1854 (Tufte, 1997). For $A^3 + R^2$ view we opt for an angled view, drawing inspiration from popular games like Age of Empires and Clash of Clans. In these games, the spatial context is presented in a 2D orthographic view, while 3D data is superimposed on top.

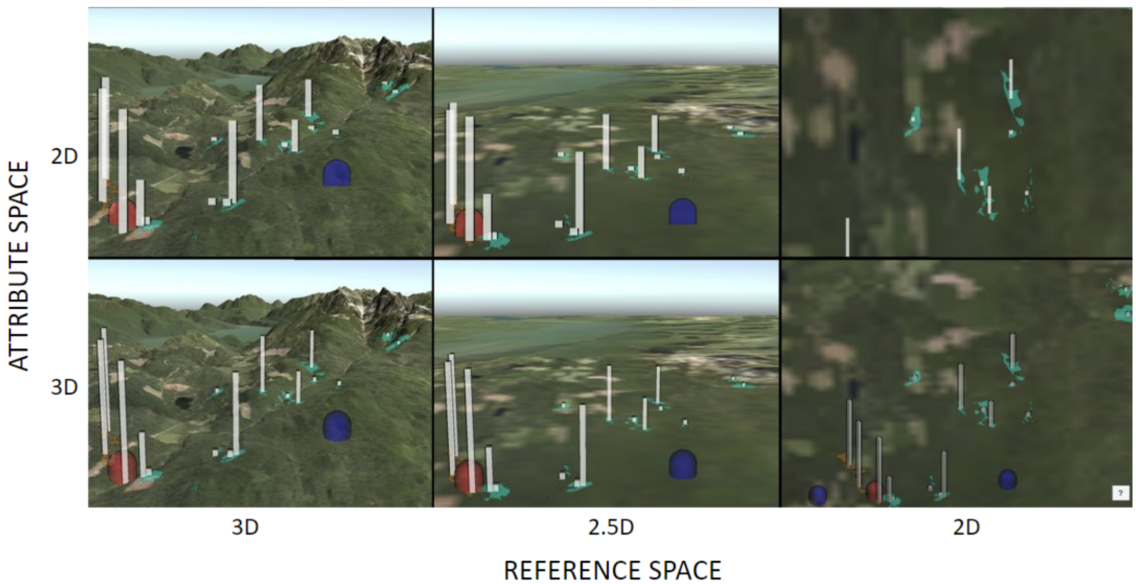



Figure 3.1: Systematization that shows all six views based on a combination of dimensionality of both attribute space (A) and reference space (R). Bottom-left shows $A^3 + R^3$ view. Top-left shows $A^2 + R^3$ view. Middle-bottom shows $A^3 + R^{2.5}$ view. Middle-top shows $A^2 + R^{2.5}$ view. Right-bottom shows $A^3 + R^2$ view. Right-top shows $A^2 + R^2$ view.

Utilizing the systematization illustrated in Figure 3.1, we have systematically classified the literature based on the six different view types. This categorization (Table 3.1) offers an overview of the distribution of research done based on view type.

| Reference Space / Attribute Space | $R^3$ | $R^{2.5}$ | $R^2$ |
|---|---|---|---|
| $A^3$ | 10, 11, 17, 28, 40 | 2, 3, 7, 12, 15, 23, 26, 28, 41, 42, 43, 61, 63 | NA |
| $A^2$ | 10, 11, 12, 21, 24, 29, 31, 35, 53, 57, 72 | 16, 17, 60, 66 | 2, 15, 16, 17, 18, 19, 26, 31, 41, 43, 53, 57, 60, 61, 63, 66, 72 |

Table 3.1: Literature categorized based on presentation space view types as defined in the systematization.

## 3.2 Task categorization

In this section, we list down a set of tasks that have been used in past literature to compare user performance in different dimensional spaces. The tasks are extracted from previous spatial visualization research and selected papers that compared different types of dimensions, whether in attribute space or reference space. Out of the 32 papers reviewed, that met our selection criteria, 27 papers were included in the categorization as they conducted a user study with predefined tasks. Google Scholar was used as the primary search engine, and keywords such as '3D vs 2D,' 'dimensional analysis,' and 'spatial visualization' were used to locate relevant papers. Key papers were identified based on citation count, as well as the reputation of the journal in which they were published. Furthermore, the search extended to papers cited within these key papers, those citing them, and additional papers by the same authors. The tasks from these included papers have been systematically categorized and highlighted in Table 3.2 using grey boxes. Each task type is accompanied by an example, given that the task names are generalized and their specific use cases may vary across research papers. Additionally, Table 3.2 also highlights the tasks implemented in our experiments.

| Task | Example | Used in reference | | | | | | | | | | | | | | | | | | | | | | | | | | Used in our experiment |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | 2 | 4 | 7 | 9 | 10 | 11 | 15 | 16 | 17 | 18 | 26 | 28 | 31 | 41 | 43 | 53 | 57 | 60 | 61 | 63 | 65 | 66 | 67 | 68 | 69 | 72 | |
| Largest object | Out of the given objects find an object with maximum height | | | | | | | | | | | | | | | | | | | | | | | | | | | yes |
| Distance comparison | Identify the closest pair of positions from a set of marked positions | | | | | | | | | | | | | | | | | | | | | | | | | | | yes |
| Comparison between data objects | Find bigger of the two symbol/objects | | | | | | | | | | | | | | | | | | | | | | | | | | | no |
| Search task | Visual search for a specific attribute/symbol/object | | | | | | | | | | | | | | | | | | | | | | | | | | | yes |
| Exploration/Discovery | Participants have freedom to navigate around the space as they want | | | | | | | | | | | | | | | | | | | | | | | | | | | yes |
| Navigation | Navigate from point A to B | | | | | | | | | | | | | | | | | | | | | | | | | | | no |
| Memory task | Memorize as many symbol positions as possible | | | | | | | | | | | | | | | | | | | | | | | | | | | yes |
| Recall task | From the given symbols chose one that matches the given shape | | | | | | | | | | | | | | | | | | | | | | | | | | | no |
| Shape understanding & relative positioning/orientation | Estimate the position of object A relative to the position of object B | | | | | | | | | | | | | | | | | | | | | | | | | | | no |

Table 3.2: Literature categorized based on task type and highlighted using gray boxes. Each task is also provided with an example and if the task has been used in our experiment.

# Chapter 4

# System Design

MultiDim is a visualization system that has been designed with the assistance of Unity. It is an information visualization system that can assist foresters in conducting visual impact assessments that analyze the potential visual effect of the proposed project on the scenic landscape. It is usually conducted in the early/planning stages of the development of projects so that the environmental issues can be addressed and excessive damage to the scenery of the area can be mitigated before the project is even carried out. The Multidim system includes visual representation in all views outlined by the systematization technique discussed in Chapter 3. This chapter explains the step-by-step process of designing and implementing MultiDim. It starts with a description of the available data, detailing its format and the preprocessing steps. Next, the chapter explains the details of the system's design.

## 4.1 Data

To satisfy the design conditions, the following data is required:

- Terrain Data
- Polygon Data
- Viewpoint Data

## 4.2 Data Sources

The dataset was sourced from LlamaZoo Interactive Inc., a technology company headquartered in British Columbia, specializing in the visualization of geospatial, engineering, and IIOT (Industrial Internet of Things) data.

For forestry-related polygon and viewpoint, data originated from the Malcolm Knapp Research Forest, located in British Columbia. The data from this source is publicly accessible and aligns seamlessly with the intended purpose of the thesis.

Data originating from research collaborators at Malcolm Knapp Research Forest in British Columbia offers a more focused scope, limited to the research forest and its immediate vicinity. Despite this confined coverage, the dataset excels in precision, providing detailed and accurate information regarding polygons, viewpoints, and associated parameters.

## 4.3 Data Attributes

MutliDim utilizes a three-dimensional model of a 6x6 km target area encapsulated within a Unity project. This model includes essential terrain features that incorporate details such as height and textures for visual richness.

Both viewpoint and polygon data are acquired in the format of a shapefile, a widely used format for storing geometric information and associated attributes of geographic features. Shapefiles, known for their versatility, store geometric information as vector data that utilize three fundamental spatial elements: points, lines, and polygons.

The polygon data employed in MultiDim comprises a curated selection of polygons within the designated target area, strategically distributed for even coverage. This dataset incorporates information including unit ID, position, shape, and a high-level parameter for each unit. The geometric details embedded in the data are represented through vector polygons, ensuring a robust representation of spatial information within the MultiDim system.

Polygons have one high-level parameter attached:

- Visual Sensitivity Class: Integer number [1,2,3,4,5,6,7,8].

The Visual Sensitivity Class (VSC) measures the sensitivity of a defined area to visual alterations that are based on biophysical and viewing characteristics. The lower the value of VSC, the more sensitive the area is to human-made visual alterations.

The viewpoint data utilized in MultiDim is a subset of the complete viewpoints available in the research forest's database. The geometric details within this dataset are represented using vector points, providing essential information such as viewpoint ID, position, and their respective importance.

## 4.4 Data Processing

MultiDim is integrated with Unity, thus data conversions and processing are required for understanding and integration into the game engine.

For terrain data, we keep it simple. The data is already bundled in a Unity project, so we use Unity's asset exporter. It creates a package with the terrain model and its settings, ready to be imported into any Unity project, including MultiDim.

However, handling polygon and viewpoint data poses a tough challenge. The data is divided into two components: one provides the geometric details like object position, size, and shape, and the other provides forestry-related parameters. To make the geometric part understandable to Unity, a crucial initial step involves converting it into meshes—composed of triangles and vertices—suitable for graphic display.

To accomplish this task, we used an exclusive in-house Unity asset obtained through collaboration with a research partner. This tool is designed to process geojson files, a spatial data format similar to shapefiles. It transforms spatial data into Unity game objects and places them in the 3D environment based on their real-world coordinates. Specifically, the tool converts polygon vectors into game objects with meshes representing their shapes. For point vectors, cube meshes are used as an editable placeholder. Unfortunately, the tool faces limitations with line vectors, as they lack thickness and cannot be represented using meshes.

Since the tool lacks support for shapefiles, we first convert the data from shapefile to geojson format. Notably, for polygons, a dual-mesh requirement arises—one for the actual polygon and another for its boundaries. Given the tool's incapacity to create meshes for line vectors, the boundary mesh is represented as polygon vectors rather than line vectors. These boundary meshes will serve as outlines in the subsequent visualization.

To perform these geospatial data manipulations, we employed QGIS [1], a geographic information system application tailored for viewing and editing geospatial data. Utilizing QGIS, the conversion of shapefiles to geojson files is a straightforward process, requiring no additional manipulation. Simply loading the data into QGIS and saving it as geojson is enough to generate the necessary files for the polygons and viewpoints. However, to create files for the polygon boundaries, additional steps are necessary. Initially, the units must be duplicated and extended outward, then the difference between the duplicated units and the original units is computed, resulting in polygon vectors representing the boundaries. QGIS offers various processing tools, including the buffer and difference tools, which play a role in this process. We set the thickness of the boundary to one centimeter given that the boundaries created using this approach are thin meshes with actual thickness.

In addition to the files for mesh generation, we utilized QGIS to produce a geojson file containing the point vectors of each polygon. MutltiDim uses this data to manipulate visualization based on the computed position of the polygons, providing a more accurate representation than relying on the bounds of the meshes, which can be significantly less precise. QGIS offers various tools for converting polygon vectors to point vectors, with the centroid tool and point-on-surface tool being the most commonly used. Both tools address the same problem but implement different algorithms. While the point-on-surface tool is computationally more intensive, it ensures that the generated points fall within the bounds of the polygon vectors. Despite the longer computation time, we chose the point-on-surface tool, considering that its impact on MultiDim's runtime is negligible. By ensuring points are within the polygons, the visualization generated by Multidim becomes more accurate in terms of position.

Finally, the associated attributes, specifically the forestry-related parameters in this context, are processed by cleaning and then linked to the geojson files containing the point vectors for both polygons and viewpoints. Unnecessary attributes not utilized in MutliDim are removed, and column names are adjusted to align with Unity's naming conventions.

## 4.5 MultiDim

The forestry system, originally developed by Kuan-Cheng Lai [40], underwent a prototyping phase and a formative study with domain experts to understand the task requirements. Designs were implemented considering the available data. MultiDim served as an extension of this system, replicating the existing system in six different views. These views are designed based on the dimensionality of the attribute space (data) and reference space (terrain), as defined in our systematization in Section 3.

### 4.5.1 Visualization Components

Visualization components within MutliDim are termed as elements conveying forestry and visual impact assessment-related data. These components can be classified into attribute space or reference space as follows:

- Attribute Space
  - Polygons
  - Viewpoints
  - Bars that visualize polygon-associated parameter
- Reference Space
  - Terrain

### 4.5.2 Attribute Space

Components in the attribute space have been displayed in $A^3$ and a $A^2$ setting. In $A^3$, they move around on three axes, showing different aspects. In $A^2$, they move around two axes and view the object straight on, eliminating the sense of depth and providing a straightforward representation. The following paragraphs describe the components in detail.

#### Bars

Bars are used as a traditional visualization idiom for data representation [63]. In 3D desktop virtual environments, Bleisch et al. [11] asserted that employing bars with diverse sizes stands out as an effective strategy for conveying quantitative spatial information.

In MultiDim, bars (Figure 4.1) are made out of two layers of rectangular prisms: a smaller, solid one depicting the parameter value, and a larger, transparent one outlining the bar's borders. This design ensured a clear understanding and allowed for an effective communication of data. The Visual Sensitivity Class (VSC), was used for determining the height of each bar and its value corresponded to the height of the bar on the terrain. For experimental flexibility, the heights of the bars were adjusted slightly to meet the specific requirements of the tasks. The opacity of the bars was established at 70%, a decision reached through discussions and testing with members of the research team.

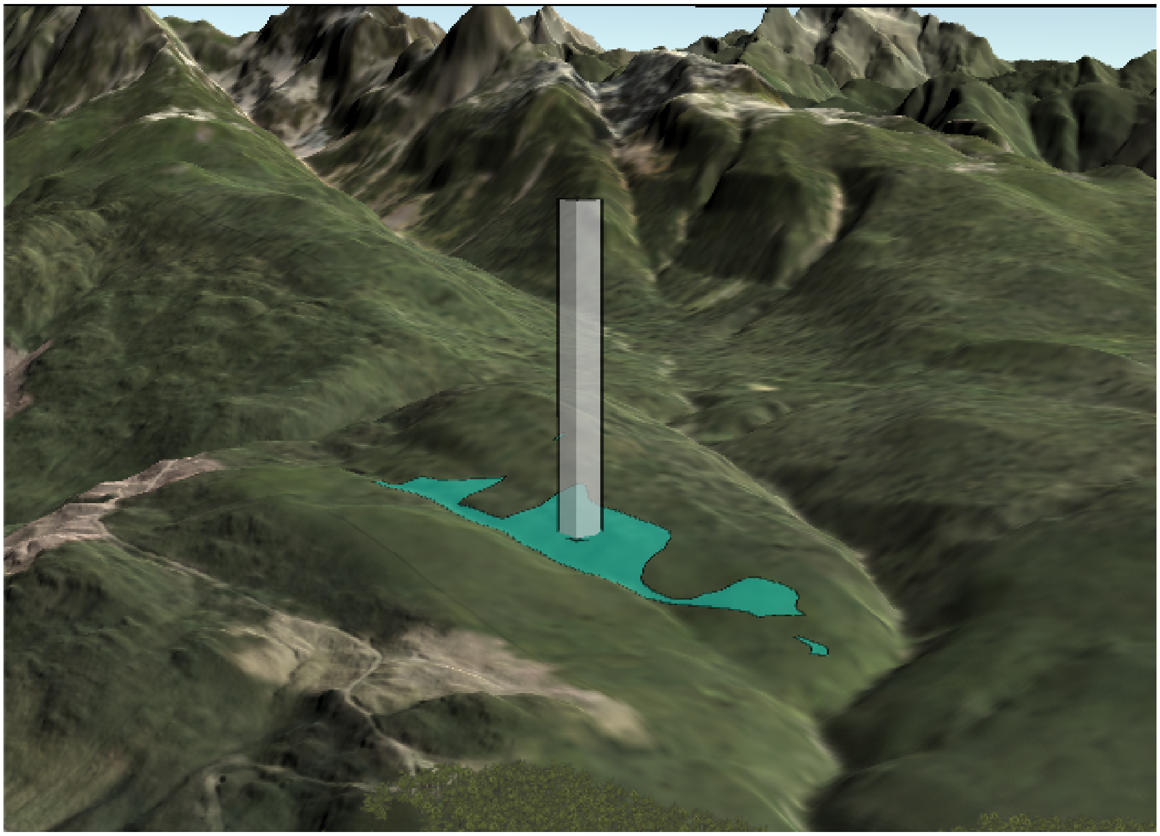


Figure 4.1: Bar visualized in 3D in MutliDim

**Viewpoints**

The viewpoint is also called the observer and is a place or location that is accessible to the general public from which a proposed project/operation is visible. They are also locations of high traffic, such as highways, or a high viewing duration such as parks and campgrounds. Viewpoints (Figure 4.2) are denoted using blue capsules. These capsules are made of two layers of capsules: a smaller, solid one depicting the object, and a larger, transparent one outlining the viewpoint's borders. This design ensured a clear understanding and allowed for an effective communication of data. Positioned at specific coordinates on the terrain as defined in the dataset, each viewpoint undergoes a Raycast operation. This operation involves casting rays towards the center of the polygon, exclusively in the 3D environment. The objective is to determine whether the rays intersect with the polygon or not. Consequently, a dictionary is created, associating each polygon with a value of either 1 (indicating a successful ray-bar intersection) or 0 (representing a missed intersection). Upon clicking a viewpoint, only the polygons (along with their bars) with a corresponding value of 1 in the dictionary are displayed on the screen. This mechanism selectively displays bars visible from the clicked viewpoint, facilitating an effective means of filtering the displayed bars, and can be seen in Figure 4.3. For experimental purposes, the height of the viewpoints, representing the distance of each point above the terrain along the y-axis (the upward axis), was adjusted to align with the specific requirements of the experiment. The opacity of the viewpoints was configured at 50%, a level lower than that of the bars. This decision was reached from discussions with the research team, recognizing that viewpoints were less crucial than bars in our experiments. The lower opacity mitigates potential obstructions in the field of view.

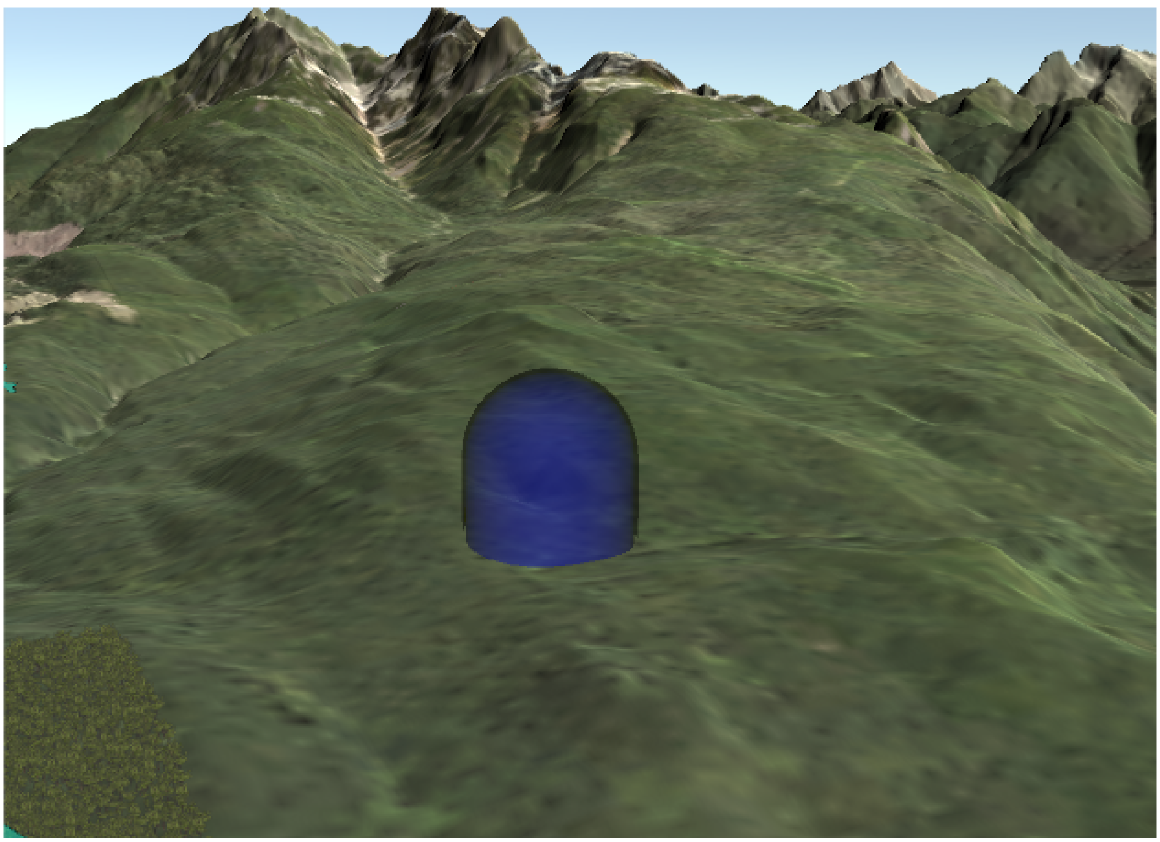
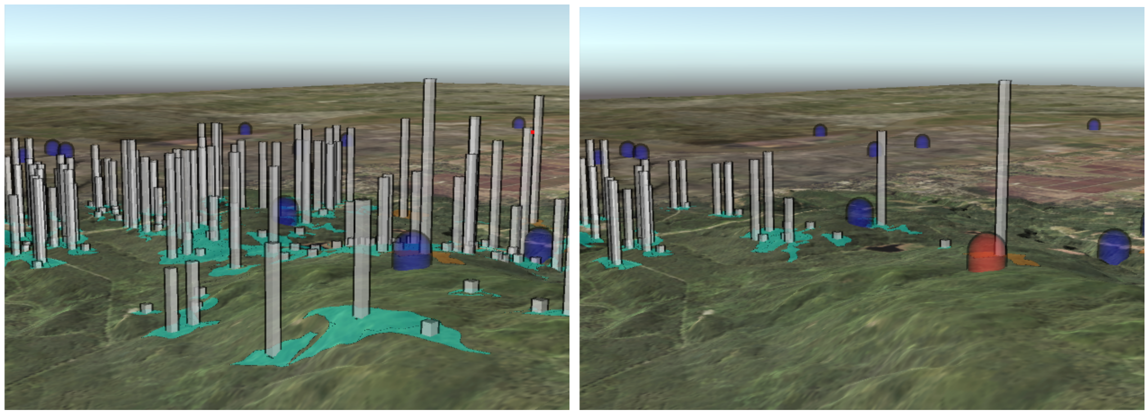


Figure 4.2: Bar visualized in 3D in MutliDim



(a) All bars are visible when no viewpoint is clicked.

(b) Selected bars visible when the viewpoint is clicked.

Figure 4.3: Bar filtering system based on viewpoint

### Polygons

Polygons, as depicted in Figure 4.4, are illustrated as color overlays in shapes positioned on the terrain at their real-world locations. This approach is a standard practice in both 3D and 2D environments. In the context of MultiDim, these overlays convey information about whether further modifications can be applied to the targeted polygon to enhance its visual quality.

The determination of whether additional modifications are allowed is based on a comparison between the polygon's current visual condition and the specified visual quality objective or visual quality class. This evaluation results in two potential outcomes: if additional modifications can be made, it is represented by the color green; if not, it is represented by the color orange. Research findings propose that the optimal opacity for color overlays in 3D photo-realistic environments, as perceived by users, falls within the range of 20% to 70% [29]. In line with this, we have chosen a moderate opacity level of 40%.

Distinct polygons were generated for $R^3$, $R^{2.5}$, and $R^2$ views. These meshes were overlaid onto the terrain and dynamically adjusted in dimensionality based on the type of terrain, providing a visual representation that adapts to the specific characteristics of each terrain format.

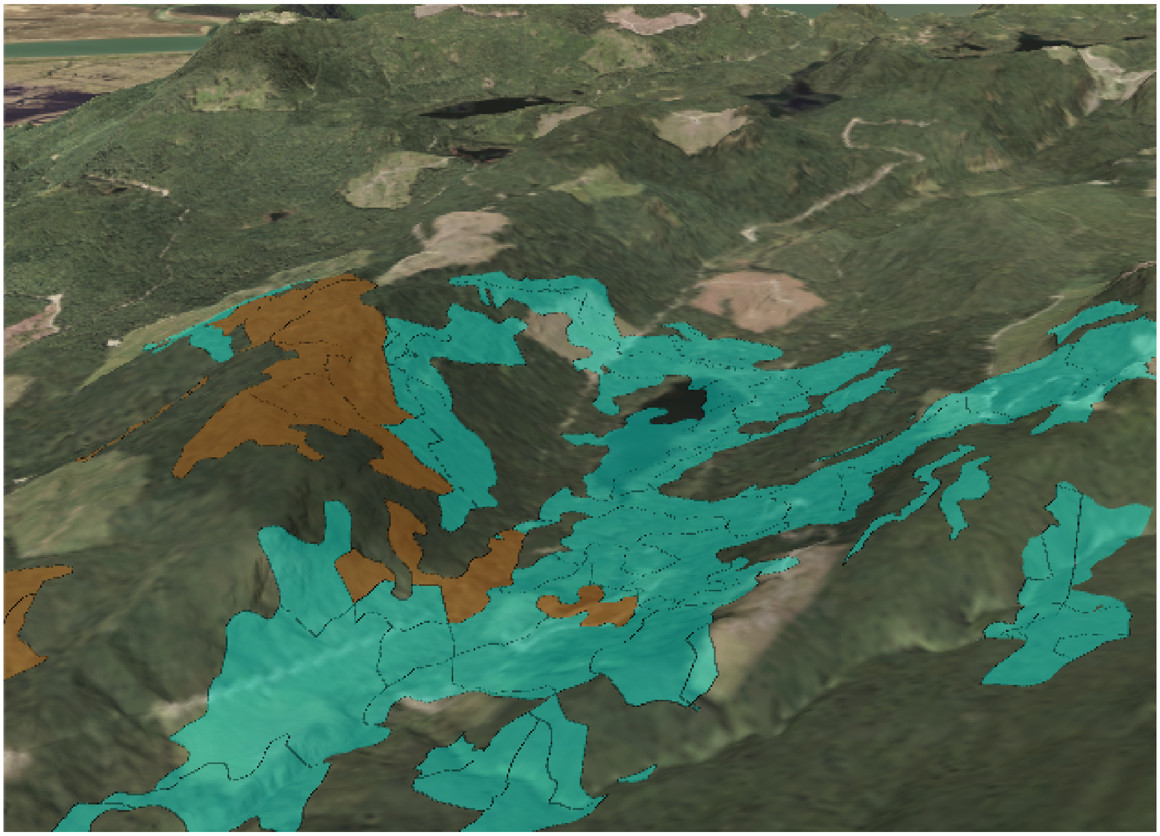
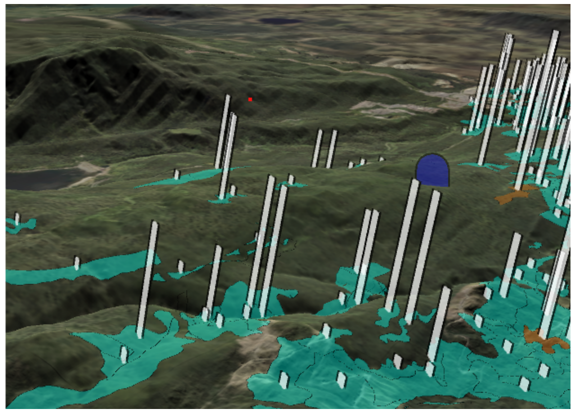


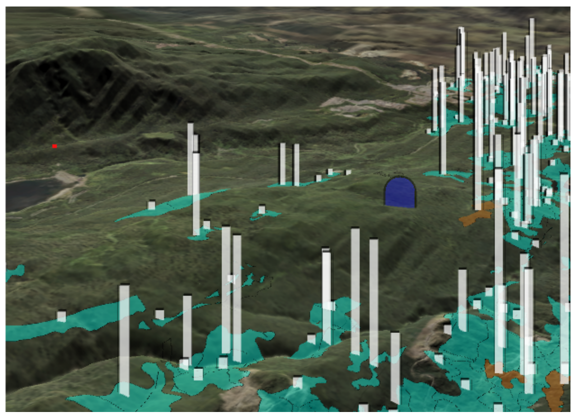
Figure 4.4: Polygon visualized in 3D in MultiDim. A green polygon signifies modifications can be made to the area. An orange polygon represents modifications that cannot be made in the area

### Generation of Gameobjects

Six distinct game objects are generated for each bar and viewpoint, each corresponding to a different view type. These game objects are categorized into $A^3$ and $A^3$ presentations. In both dimensions, a basic game object was utilized to form the bars. In $A^3$, these bars extended into the depth of the environment along the z-axis and remained fixed in position relative to the position of the camera. Whereas, the $A^2$ bars lacked depth along the z-axis and appeared flat, thus lacking a sense of depth. To prevent the $A^2$ bars from being perceived as stationary $A^3$ bars when the camera moves (Figure 4.5a), the Unity-inbuilt LookAt function was used. This function ensured that the normal vector of the front face of the bars was consistently pointed toward the direction of the camera (Figure 4.5b). This prevented the $A^2$ bars from looking like flat $A^3$ objects within the environment.



(a) $A^2$ bars always facing the initial direction when the participant navigates around the system.



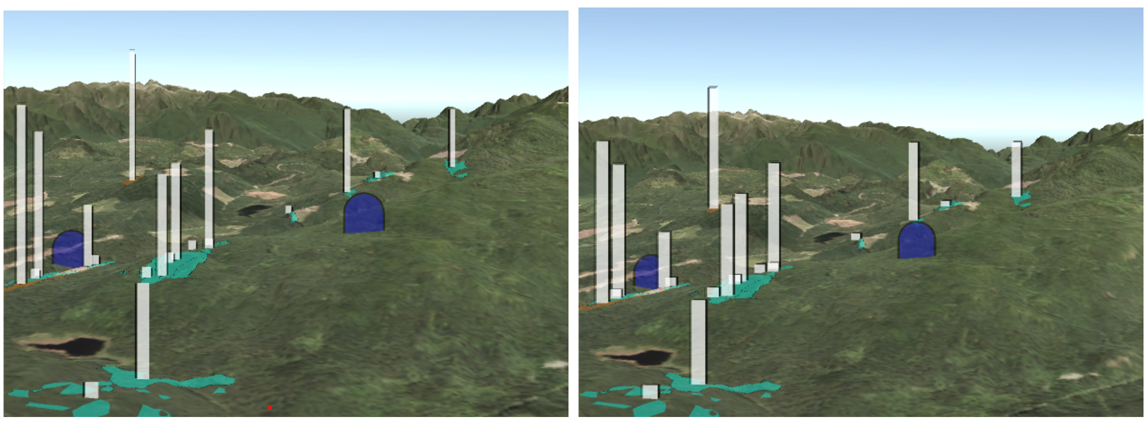
(b) $A^2$ bars always facing in the direction of the camera when the participant navigates around the system.

Figure 4.5: Lookat function for always rotating the front face of $A^2$ bars towards the direction of the camera

Additionally, to maintain clarity in visual representation, lighting effects were deliberately omitted from the $A^2$ objects. This decision aligned with the findings by Engel et al. [23] that stated that lighting and shading could introduce depth cues and potentially impact the accurate perception of the objects.

### 2D Scaling

To eliminate any depth-based cues in the data representation of $A^2$ bars, we developed an algorithm. It calculated the distance of each bar from the point where it intersects the terrain to the center of the camera at each frame. Once the closest and furthest bars from the camera were identified, the distances across all bars could be normalized between 0 and 1. These normalized values could then be further scaled to a consistent range of 50 times the normalized value and applied to each bar. The decision to scale the normalized value to 50 emerged from rigorous testing of the visualization and extensive discussions with other members of the research team. The outcome ensured that the bars maintained a uniform width, regardless of their distance from the camera, as illustrated in Figure 4.6.

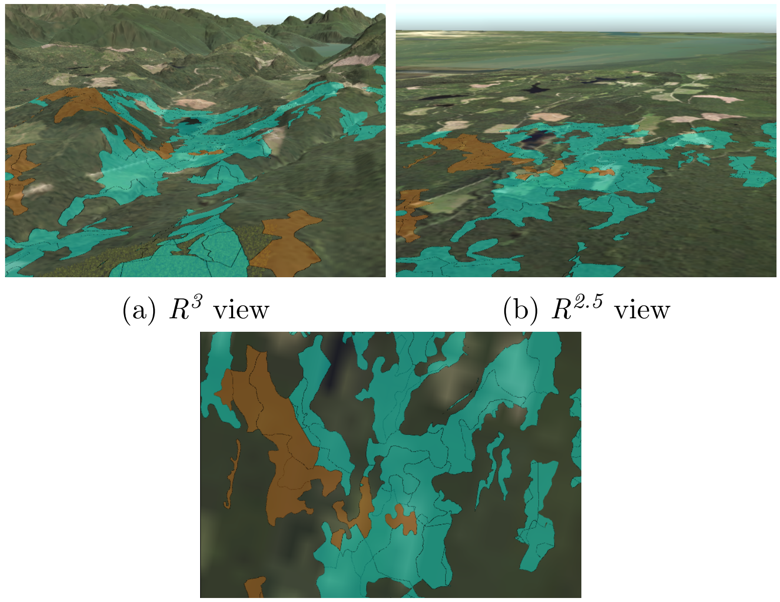


(a) $A^2$ bars without scaling algorithm (b) $A^2$ bars with scaling algorithm

Figure 4.6: $A^2$ bars scaling system

### 4.5.3 Reference Space

In the reference space, components included the terrain which was presented in $R^3$, $R^{2.5}$, and $R^2$ formats. In $R^3$, elevation is represented along the y-axis, introducing a vertical dimension (Figure 4.7a). On the other hand, $R^{2.5}$ and $R^2$ terrains are flat, lacking height along the y-axis, and appear as two-dimensional surfaces. The key distinction lies in the presentation, with $R^{2.5}$ maintaining a perspective camera similar to $R^3$ (Figure 4.7b), while $R^2$ adopted an orthographic camera which eliminated the perception of depth in the scene (Figure 4.7c).



(a) $R^3$ view (b) $R^{2.5}$ view

(c) $R^2$ view

Figure 4.7: Reference space in different dimensions

### 4.5.4 System Components

MultiDim utilized Unity's Camera and LayerMask functionalities to create six distinct view types. These components collaborated to showcase objects specific to each view and contributed to a tailored and context-specific visualization in each instance.

In Unity, six distinct Camera Objects are generated, each dedicated to displaying a unique view. For $R^3$ and $R^{2.5}$ views, a perspective projection was used, providing a realistic visual representation. On the other hand, to showcase $R^2$ view, an orthographic projection was used which ensured an accurate and undistorted depiction of the flat landscape with no depth cues. Henceforth, to simplify nomenclature, both $R^3$ and $R^{2.5}$ terrain views will be collectively denoted as $R^3$ views.

Moreover, the movement of the four cameras dedicated to $R^3$ views was synchronized which ensured identical motion across all the views. In contrast, the two cameras designed for $R^2$ views operate with distinct settings. The camera presenting $A^3 + R^2$ is angled at 30 degrees from the x-axis (horizontal axis), drawing inspiration from gaming perspectives seen in titles like Age of Empires or Clash of Clans. This slanted view is effective in displaying 3D objects on a flat 2D surface. On the other hand, the camera displaying $A^2 + R^2$ adopted a top-down view which looked directly down the y-axis (upward axis) and offered a bird's-eye perspective of the scene. In this view, the bars are always oriented perpendicular to the camera's line of sight. For ease of understanding $A^3 + R^2$ will be denoted as angled view, and $A^2 + R^2$ will be denoted as top-down view.

A LayerMask is assigned to each game object in Unity. These game objects are categorized into one of the six predefined categories manually specified in the Unity system. The camera then selectively filters out objects from the game space by identifying those that align with the LayerMask condition. This process facilitates the display of context-specific views tailored to the predefined categories.

The screen is partitioned into six distinct views by adjusting the Viewport Rect for each display. Specifically, the width of each Viewport Rect is set to 33% of the total screen width, while the height is set to 50% of the screen height. This uniform configuration ensures that all displays maintain the same proportions. Following this, the X and Y coordinates of the Viewport Rect are determined, effectively situating each view in a unique position on the screen.

### 4.5.5 User Control

User control plays a vital role in shaping the overall user experience within any software system as it provides users with a sense of control over their actions and is not only crucial but also enhances their overall satisfaction and engagement [32]. The ability to navigate, customize, and manage their experience empowers users, fostering a more positive and enjoyable interaction with the software.

The utilization of WASD and mouse controls for navigation within an environment is a practice inherited from contemporary video games like Minecraft and Counter-Strike. The preference for the WASD control scheme by experienced players has been highlighted in studies, such as Refai et al. [53]. Moreover, for those who are new to gaming or software navigation, the WASD control scheme is widely regarded as intuitive and easy to learn, as noted in research by Caserman et al. [14]. This familiarity contributes to a natural user experience and caters to both seasoned players and those who are new to the system.

Given the diversity in dimensions among the six views, two variations of the WASD scheme were implemented to cater to the specific requirements of each. Notably, the $R^3$ views followed a shared navigation scheme, while the $R^2$ views followed a different shared navigation scheme. The controls of each scheme are detailed in Tables 4.1 and 4.2.

Table 4.1: User Control for $R^3$ views

| **Navigation Button** | **Action** |
|---|---|
| W | Move forward |
| S | Move behind |
| A | Move left |
| D | Move right |
| Q | Move down |
| E | Move up |
| Left-Mouse click | Select game object |
| Right-Mouse click | Deselect game object |
| Middle-Mouse click | Look around |

Table 4.2: User Control for $R^2$ views

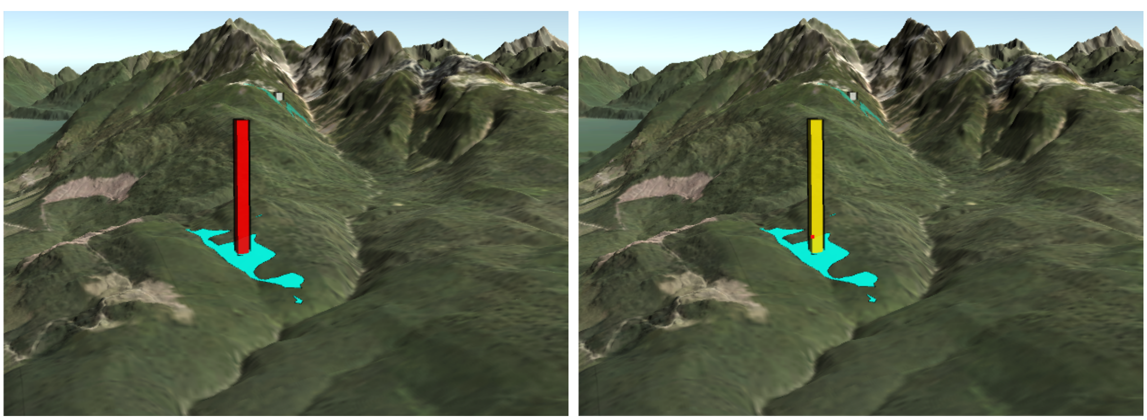
| **Navigation Button** | **Action** |
|---|---|
| W | Move up |
| S | Move down |
| A | Move left |
| D | Move right |
| Q | Zoom in |
| E | Zoom out |
| Left-Mouse click | Select game object |
| Right-Mouse click | Deselect game object |

The key differentiator between the two schemes lies in the utilization of the Q and E keys, as well as the middle mouse button. These variations were carefully designed to optimize navigation and user interaction based on the unique characteristics of each view. These design decisions were taken after conducting thorough testing of the system and several meetings with other members of the research team.

The system incorporated a user-friendly mechanism for changing navigation schemes by dynamically adapting to the user's mouse placement within the desired view. For example, when the mouse was hovered over the $R^3$ views, the navigation scheme automatically switched to the one associated with $R^3$. Conversely, if the mouse hovered over a $R^2$ view, the navigation scheme seamlessly transitioned to the corresponding scheme for $R^2$ views. This system allowed users to adapt to the navigation controls based on their current focus and aimed to enhance the overall accessibility and ease of use by aligning the navigation scheme with the user's visual focus.

Users could interact with the system by using mouse clicks on various objects within the environment, such as bars and viewpoints. Notably, polygons were intentionally excluded from being clickable during the experiment due to their lack of relevance to the assigned tasks.

Additionally, the left mouse button was used for selecting game objects, while the right mouse button was used for deselecting, as detailed in Tables 4.1 and 4.2. To select a bar, users could click on it which caused the bar to turn red (Figure 4.8a) and increase its opacity to 90%. A subsequent click on the already selected bar would trigger a color change to yellow (Figure 4.8b), constituting a double-click action. This double-click functionality is an integral part of tasks conducted in the experiment. Similarly, clicking on a viewpoint, which is initially blue, resulted in a visual indication of it being selected by changing the color to red (Figure 4.9).



(a) Bar turns red on single click (b) Bars turn yellow on double click

Figure 4.8: Bar click system

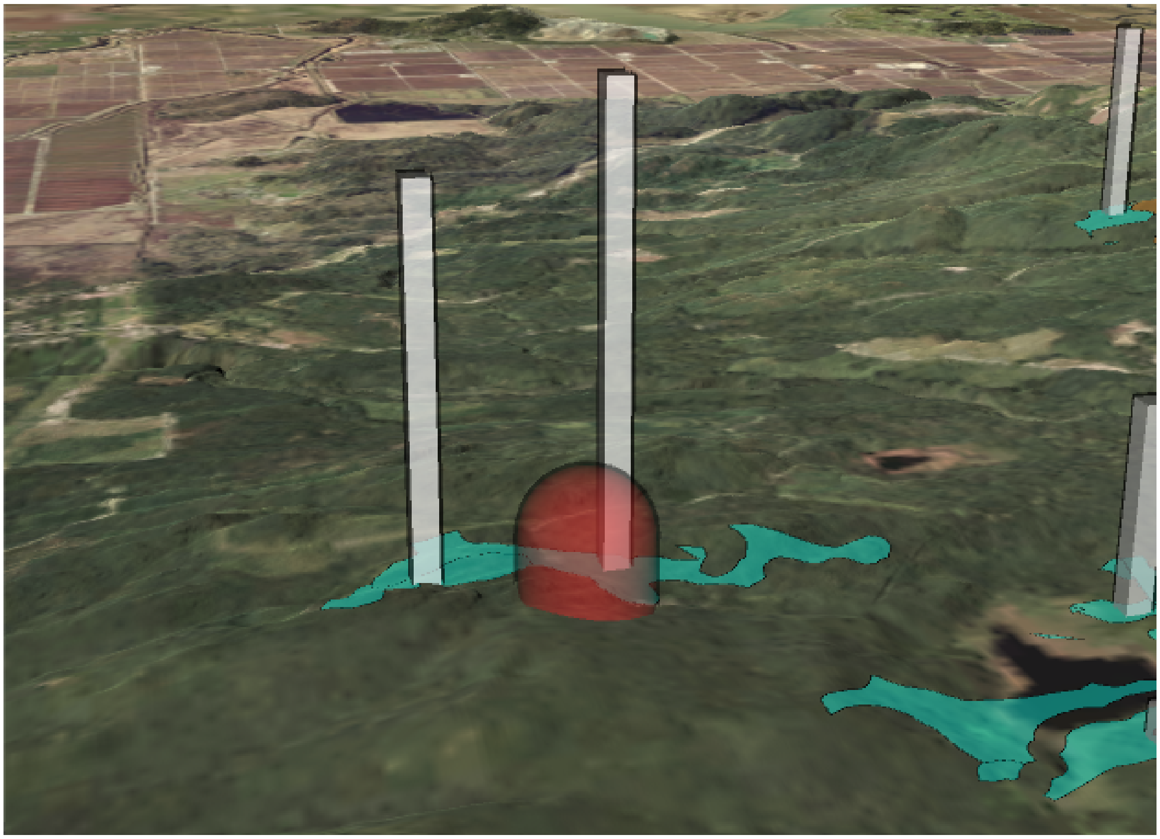


Figure 4.9: Viewpoint turning red on click

## 4.6 View Coordination

Effective coordination of views is a fundamental aspect of the system's functionality. Given that identical data is presented across six different views on the screen, it is important to ensure that there is proper synchronization that maintains meaningful and coherent information for the user throughout their interaction. View coordination in this context is twofold, involving the coordination of clicks and the coordination of the camera.

The coordination of clicks ensured that user interactions, such as selecting bars or viewpoints, were reflected across all six views. This synchronization guaranteed a consistent representation of the selected data in each view and enhanced the user's understanding and interpretation. Similarly, the coordination of the camera ensured that the viewpoint or perspective in all six views was synchronized. This synchronization of the camera perspective contributes to a cohesive and integrated user experience, preventing disorientation or confusion that may arise from disintegrated viewpoints. These coordinations can be seen in Figure 4.10 and are further explained in the sections below.

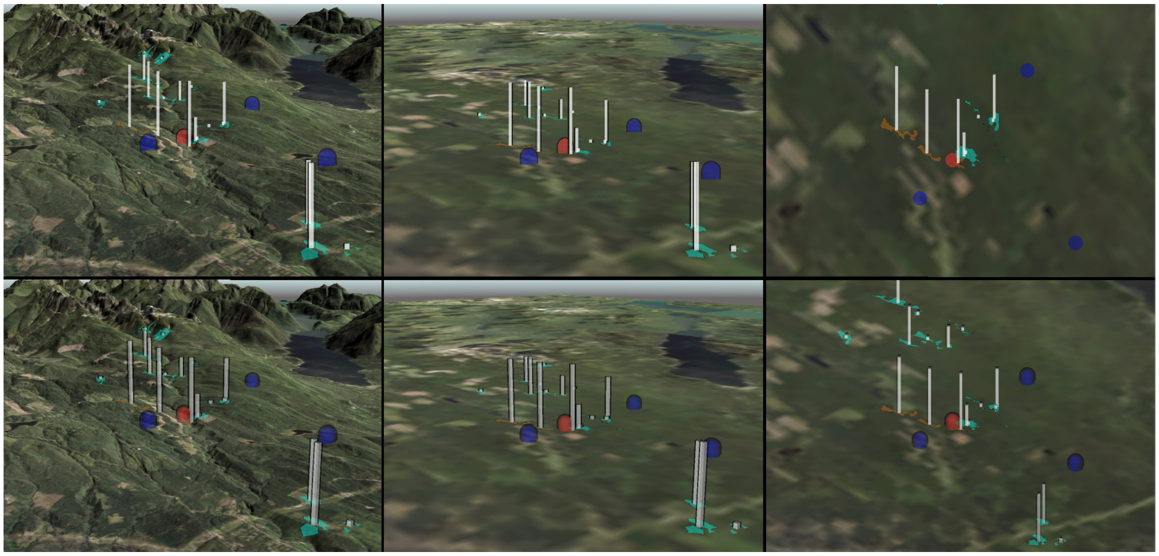


Figure 4.10: Viewpoint clicked being reflected in all six views. Camera angle and position also being coordinated between all the views so that the data is being looked at from the same direction in all the views.

### 4.6.1 Coordination of Clicks

To facilitate the coordination of clicks across all six views, a Manager script generated a dictionary specific to a particular game object, such as a bar. This dictionary served as a mapping tool that associated the object ID with a binary value (in the case of bars it is 0, 1, 2 to account for the double-click functionality). The objective was to keep track of the selection status of each object.

Upon clicking an object in any of the views, the Manager script accessed the dictionary which located the object ID and updated its corresponding value to 1. Conversely, when the object is deselected, the value is set to 0. This tracking mechanism ensured that changes in the selected state were accurately reflected in the dictionary.

The significance of this approach lies in its ability to transfer data to the individual bars displayed in each view. By maintaining a synchronized record of selected and deselected states through the dictionary, the system ensured that these changes were consistently propagated to all views. Consequently, this method played a crucial role in achieving unified and coordinated user interactions across all the views of the system.

### 4.6.2 Coordination of Camera

The coordination of cameras involved the development of algorithms to ensure uniform navigation across all six views. Four of the cameras, responsible for displaying $R^3$ views, shared a similar navigation scheme and were treated accordingly. The challenge arose when the camera movement was to be adapted for the other two cameras dedicated to the $R^2$ views. Additionally, these $R^2$ views featured two distinct camera positioning types, as outlined in Section 4.5.4.

#### Camera Rotation

The rotation took place using the middle mouse button as described in Table 4.1. The decision to disable the middle mouse button in $R^2$ views stemmed from the recognition that camera rotation lacks meaningful functionality within this context. Unlike $R^3$ views, where rotation occurs around the camera position, $R^2$ views rotation pivots around the center point on the terrain. This pivot point is established by a line extending from the terrain center to the camera's center, making the locking of the middle mouse button in $R^2$ views a logical choice.

In previous versions of the system, the choice was made to refrain from rotating $R^2$ views in alignment with the camera rotation applied to $R^3$ views. However, through several pilot studies and discussions within the research team, it became evident that maintaining a static orientation for $R^2$ views disintegrated the overall visualization. This was particularly evident as the angles and direction from which the data was observed were not cohesive across all views. Thus, the decision was reached to synchronize the rotation of $R^2$ views with the camera rotation in $R^3$ views, ensuring a cohesive and integrated visualization across all views.

#### Camera Displacement

A transformation algorithm was devised to convert camera metrics between the different views as explained in Figure 4.11. During navigation in $R^3$ views, a ray was cast from the center of the screen to the terrain, and the intersection on the $R^3$ terrain. From this terrain position given by point A, the algorithm calculated the camera position for displaying the angled view by placing it at a height of 'd' on the y-axis directly above the terrain position.

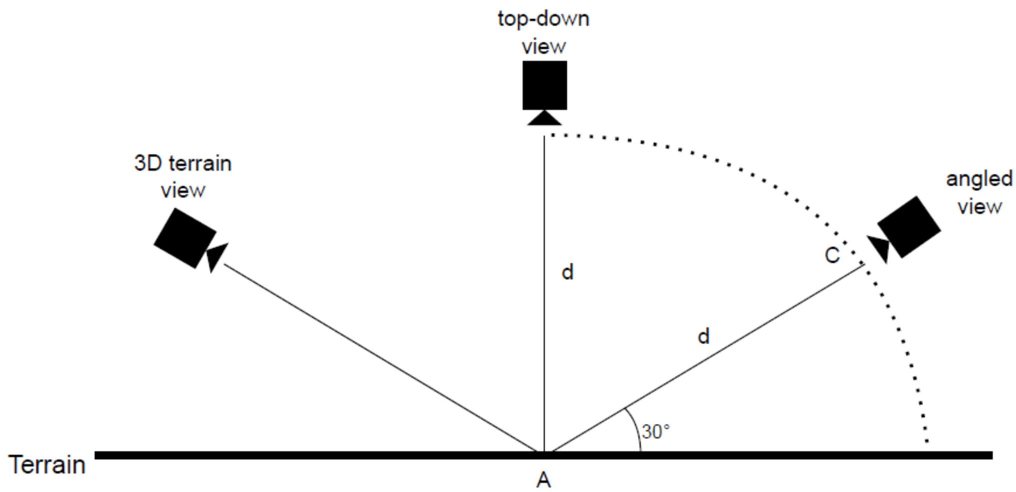



Figure 4.11: Camera displacement transformation logic

The initial step involved a calculation of the camera's distance from a specific point on the terrain. This distance, denoted as 'd,' can be determined given that it remains consistent even for a top-down view camera, as illustrated in Figure 4.11. The reason behind this consistency lies in the fact that both the top-down view camera and the angled view camera share the same arc of a circle, thereby sharing an identical radius. This symmetry enables a straightforward calculation of the distance for the angled camera by using the known distance between the top-down view camera and the corresponding point on the terrain.

Now that we know the distance 'd', we can easily calculate the displacement for the angled view camera (Figure 4.12). Given the constant distance 'd' from the camera to point A, we use the trigonometric properties of sine and cosine functions to compute the x and y coordinates. This approach exploits the relationships within the triangle formed by point ABC where the angled view camera is at point B. Point A is where the camera is initially looking at, and point C is the new position where the camera is now looking at. This forms angle $\theta$ at point B. To calculate the x and y for this new line BC, we use the following equations:

$x = \cos\theta \cdot d$

$y = \sin\theta \cdot d$

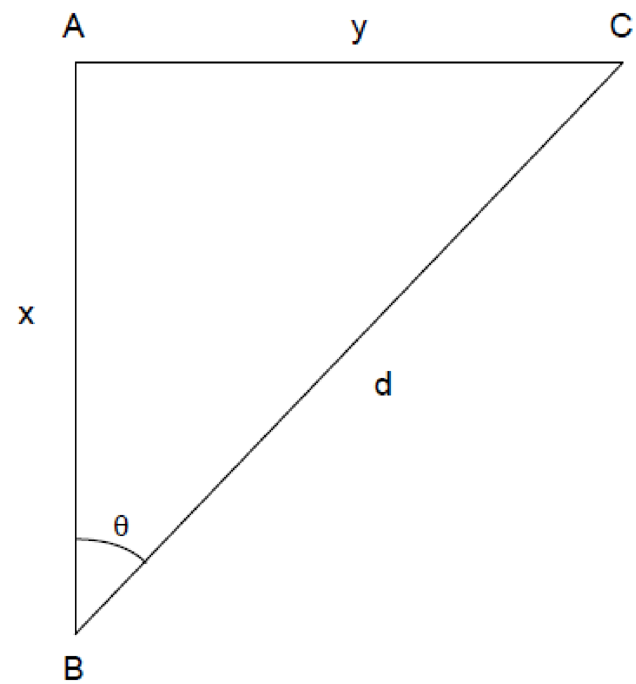



Figure 4.12: Camera displacement for angled view based on camera rotation

**Camera Zoom**

The $R^2$ view camera incorporated a functionality known as zooming, a feature executed through the use of the Q and E buttons, as outlined in Table 4.2. Q was used to zoom in while E was used to zoom out. This functionality was achieved by manipulating the OrthographicSize function within the Unity framework.

To convert this into a $R^3$ view camera, the calculation of the vector distance between the center of the $R^3$ view camera and the ray cast to the center of the terrain plays an important role in the system. This distance serves as a key parameter for mapping to the orthographic size property in $R^2$ view cameras, effectively creating a zoom effect in the orthographic camera. During the conversion from a $R^3$ view camera to a $R^2$ view camera, the distance is scaled down by a factor of 4.5. Conversely, when transitioning the value from orthographic size to distance, it undergoes a scaling up by the same factor of 4.5. This scaling factor was determined through rigorous testing and discussions with research team members, ensuring that it aligned with the system's requirements and contributed to the desired visual outcomes.

# Chapter 5

# Evaluation, Analysis, and Comparisons

In this chapter, we describe how we designed our study to understand the properties of different views as well as the various methods and strategies participants used to solve different tasks. Our study involved 24 participants who were given a series of tasks. The study was divided into two phases: a quantitative phase consisting of a repeated measure experiment to compare different views, and an exploratory qualitative phase to understand how participants used all views together. Our analysis of the data provides insights into the advantages and disadvantages of different dimensional views and how they can be used to further improve future systems.

## 5.1 Participants

We used the university's departmental mailing lists and distributed university-approved posters across bulletin boards on campus to recruit participants. Participants who replied to the invite were sent initial screening questions designed to identify suitable candidates. Our screening criteria necessitated that participants be at least 19 years of age and possess the capability to view a screen from a distance without the need for glasses, which was a prerequisite for our eye-tracking procedures.

A total of 24 participants (10 males and 14 females) were recruited for the study, ranging in age from 21 to 41 with a mean age of 25.96 and median of 25. Among them, seven were undergraduates, thirteen were graduate students, and four were pursuing doctoral degrees. Notably, the majority of participants, totaling 16 individuals, had backgrounds in computer science and engineering. Moreover, 17 participants, using a 5-point Likert scale, rated their 3D experience as 2 or lower. Conversely, 18 participants gave a rating of 4 or higher for their frequency of using maps.

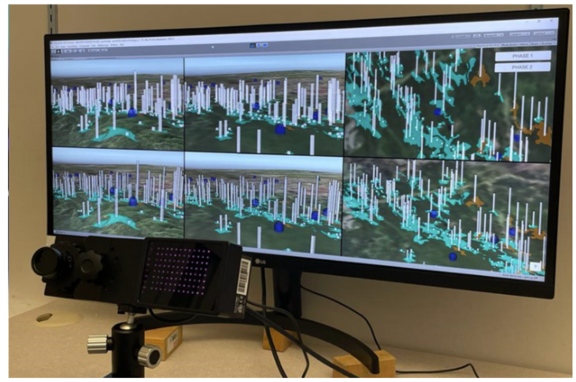
## 5.2 Experiment Setup

The experiment took place in a controlled environment, in an enclosed room with no natural lighting. Participants were asked to fill out a demographic survey form before the start of the experiment. The experimenter was present in the room throughout the session and provided a comprehensive explanation of the procedure to participants before commencing the experiment. Participants were encouraged to seek clarification by asking questions during the experiment if needed. Participants were also given a small break of two minutes after the end of phase one (Quantitative phase) of the study.

The visualization system was built in Unity version 2019.1.14f1. For eye-tracking EyelinkPlus 1000 eye-tracker was used. It was connected with Unity using C# libraries provided by the eye-tracking company. A 34" ultra wide screen of resolution 2560 x 1080 pixels per inch was used to display the data. The participants were seated at a distance of approximately 125 cm (1.5 times the width of the screen) from the screen for accurate eye calibration. We positioned the eye-tracker directly in front of the screen, minimizing the distance between the two components, and adjusted its height to align with the screen's lower edge for optimum functionality (Figure 5.1b).

The EyelinkPlus 1000 system included a dedicated PC known as the host PC (Figure 5.1a), and the setup involved the use of two Ethernet cables. One Ethernet cable was used to establish a connection between the eye-tracker and the host PC, while the other Ethernet cable was employed to connect the eye-tracker to the system machine. This configuration effectively established a network for seamless data transfer between these two machines.


(a) Host-PC screen that displayed Eye-LinkPlus software

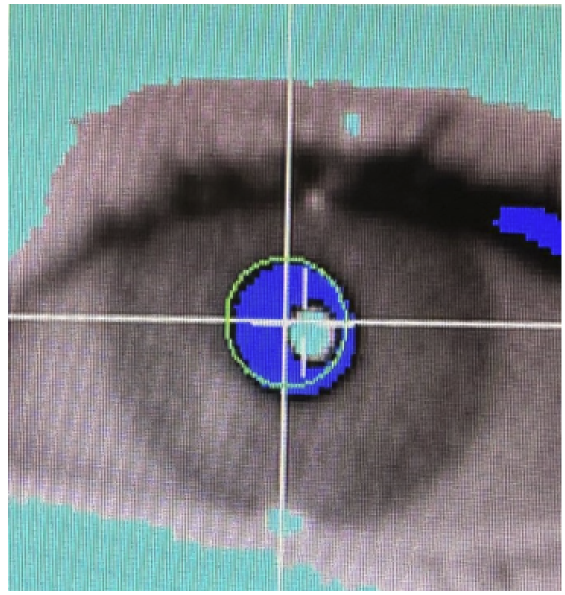


(b) EyelinkPlus 1000 being set up with display monitor.

Figure 5.1: Experiment setup along with eye-tracker machine

The eye-tracker operated at a sampling rate of 500Hz and used a monocular lens with a 25mm focal length for eye tracking. To facilitate eye tracking, we used the eye tracker in Desktop Free mode which required participants to attach a marker to their foreheads at all times as seen in Figure 5.2a and was used to track the head movement of the participant. Before starting the second phase (Qualitative phase) of the experiment, we conducted a calibration procedure to ensure precise tracking of participants' eye movements. The calibration process was standardized, with the left eye being used for all participants (Figure 5.2b).

(a) Marker that was required to be stuck to participant's forehead during the experiment for accurate tracking of the eye in Desktop Free mode.



(b) Eye being focused for accurate calibration of the eye.

Figure 5.2: Eye-tracking technology

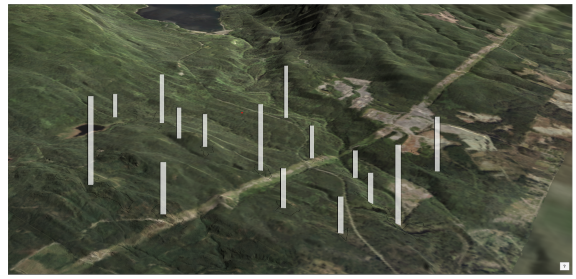
The study comprised two distinct phases: a Quantitative phase for evaluating and comparing the accuracy and efficiency of different views and a Qualitative phase for analyzing the various strategic approaches employed by participants when solving a set of tasks. The rest of this chapter is thus divided into the Quantitative phase and the Qualitative phase.

## 5.3 Quantitative Phase

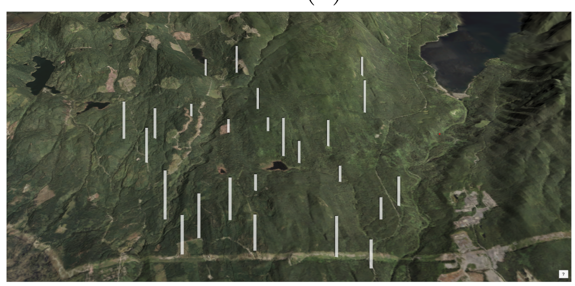
### 5.3.1 Study Design

The quantitative phase comprised two distinct tasks, each executed individually in six different views. These views are carefully designed to present a progressive increase in task difficulty, primarily driven by varying numbers of distractors (Figure 5.3). In alignment with the findings from Seipel et al.'s research [59], the difficulty level, influenced by the presence of distractors, was assessed at 15. Therefore, we categorized three distinct difficulty levels: a lower level of 5 (denoted as $D_5$) (Figure 5.3a), a moderate level of 15 (denoted as $D_{15}$) (Figure 5.3b), and an upper level of 25 (denoted as $D_{25}$) (Figure 5.3c). Each task is then performed three times at each difficulty level, resulting in a total of 54 iterations for each task. The order of the views is determined based on the Latin Square methodology [20].

(a) Task with 5 distractors on the screen.



(b) Task with 15 distractors on the screen.



(c) Task with 25 distractors on the screen.

Figure 5.3: Tasks with increasing difficulty based on number of distractors.

### Measurements

The data collection was facilitated through the Unity system, and after each iteration, a system log generated a row of essential information. This log included details such as the system timestamp, participant number, task number, iteration number, the active view, the selected answer, the actual answer, and the time taken (in seconds). For each participant, a distinct .txt file was generated. Following the conclusion of the study, these individual files were then preprocessed and consolidated into a .csv file to facilitate data analysis.

### Tasks

This phase of the study employs two distinct tasks. The task comprised two simple low-level tasks based on the abstract visualization task typology defined by Brehmer et al. [13]. These tasks are derived from past literature and are defined in detail in the below paragraphs.

- Task 1:

  Participants are shown a group of bars displayed on the screen and are directed to select one bar that they believe has the greatest vertical length (Figure 5.4). The purpose of this task is to assess their ability to perceive variations in height among multiple bars positioned in different geographic locations. This particular task has been previously employed in existing literature, as referenced in Table 3.2, to investigate the differences in perceptual effects when comparing presentations with different dimensions. In each iteration of the task, a singular definitive answer is identified, while the remaining bars are set to heights ranging between 30% and 90% of the result bar's height, as stated by Bleisch et al. [11] in their study.

Figure 5.4: Task of selecting bar with maximum vertical length. Participants must click on one bar as depicted in the screenshot

- Task 2:

  Participants are presented with a set of bars on the screen and are instructed to choose a pair of bars that, in their estimation, are the closest to each other in terms of distance (Figure 5.5). While selecting the bars participants should consider the distance measured between the bottom of the bars. The purpose of this task is to assess their ability to perceive variations in distance among multiple bars positioned in different geographic locations. This particular task has been previously employed in existing literature, as referenced in Table 3.2, to investigate the differences in perceptual effects when comparing presentations with different dimensions. There exists a distinct pair of bars that are closest to each other.

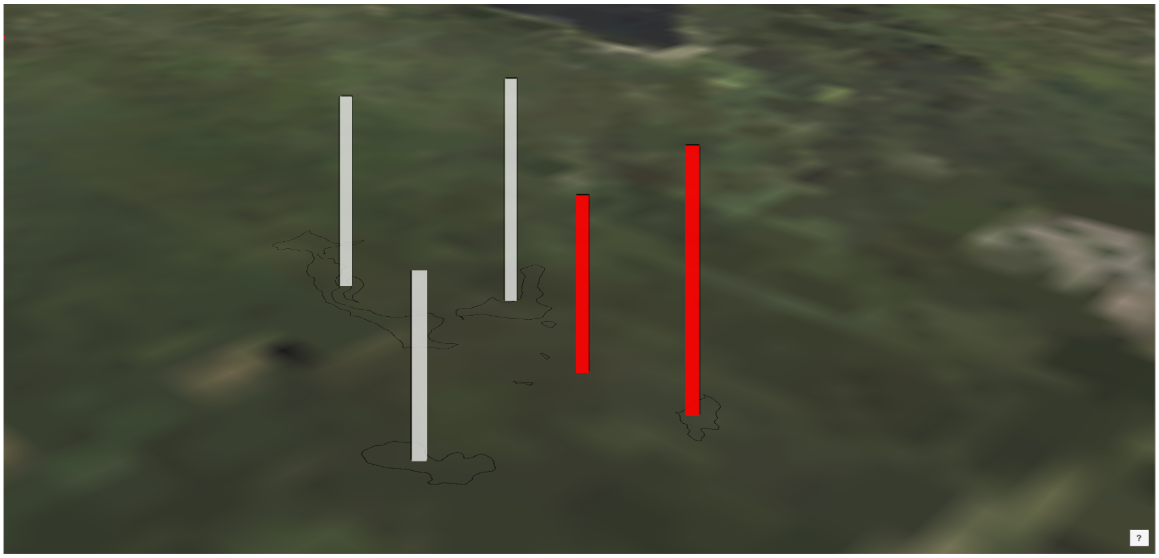


Figure 5.5: Task of two bars that are closest to each other in terms of distance. Participants must click on two bars as depicted in the screenshot

### Hypothesis

We have formalized 12 hypotheses for the quantitative phase:

- Height Task:
  - H1: Time taken by $D_5$, $D_{15}$, and $D_{25}$ will induce the same result as in the study conducted by Cockburn et al. [16]. Time taken will increase with an increase in the number of distractors. $D_{25}$ will have the largest time, $D_{15}$ will have lesser time, and $D_5$ will have the least time.
  - H2: Accuracy will not be affected by an increase in the number of distractors. $D_5$, $D_{15}$, and $D_{25}$ will have similar accuracy. We hypothesize this as we think that distractors will not affect selecting maximum height.
  - H3: Time taken by $A^3$ and $A^2$ will induce the same result as in the study conducted by Seipel et al. [60]. $A^3$ and $A^2$ will have similar task completion time.
  - H4: Accuracy by $A^3$ and $A^2$ will induce the same result as in the study conducted by Seipel et al. [60]. $A^3$ and $A^2$ will have similar accuracy.

  - H5: Time taken by $R^3$, $R^{2.5}$ and $R^2$ will induce the same result in the study conducted by Seipel et al. [59]. $R^3$, $R^{2.5}$ and $R^2$ will have similar times.
  - H6: Accuracy by $R^3$, $R^{2.5}$ and $R^2$ will induce the same result as in the study conducted by Seipel et al. [59]. $R^{2.5}$ and $R^2$ will have a similar accuracy and will be greater than that of $R^3$.

- Distance Task:
  - H7: Time taken by $D_5$, $D_{15}$, $D_{25}$ will induce the same result as in the study conducted by Cockburn et al. [16]. Time taken will increase with an increase in the number of distractors. $D_{25}$ will have the largest time, $D_{15}$ will have lesser time, and $D_5$ will have the least time.
  - H8: Accuracy will decrease with an increase in the number of distractors. $D_5$, $D_{15}$, and $D_{25}$ will have similar accuracy. We hypothesize this as we think that the number of distractors will increase the number of pair selections for estimating minimum distance.
  - H9: Time taken by $A^3$ and $A^2$ will induce the same result as in the study conducted by Seipel et al. [60]. $A^3$ and $A^2$ will have similar task completion time.
  - H10: Accuracy by $A^3$ and $A^2$ will induce the same result as in the study conducted by Seipel et al. [60]. $A^3$ and $A^2$ will have similar accuracy.
  - H11: Time taken by $R^3$, $R^{2.5}$ and $R^2$ will induce the same result as in the study conducted by Seipel et al. [59]. $R^3$, $R^{2.5}$ and $R^2$ will have similar times.
  - H12: Accuracy y $R^3$, $R^{2.5}$ and $R^2$ will induce the same result as in the study conducted by Seipel et al. [59]. $R^{2.5}$ and $R^2$ will have a similar accuracy and will be greater than that of $R^3$.

### 5.3.2 Data Analysis

The data was collected after each iteration, capturing both the total time spent and the participant's selected answers. Python scripts were used to analyze the data. For each hypothesis, we computed for each participant the mean of all trials for a given task for a given condition. These participant means were then bootstrapped to calculate their corresponding 95% Confidence Intervals (CIs). Finally, these results were visually represented on a bar chart with mean estimates and 95% confidence intervals.

**Data Visualization**

Bar charts have been employed as a visual aid to effectively convey information about the mean accuracy and time across different groups. In Figure 5.6, we utilize this visualization to illustrate the mean values within these distinct groups. Each bar in Figure 5.6 represents the mean value and the black line is used to represent the 95% CI associated with that specific group.

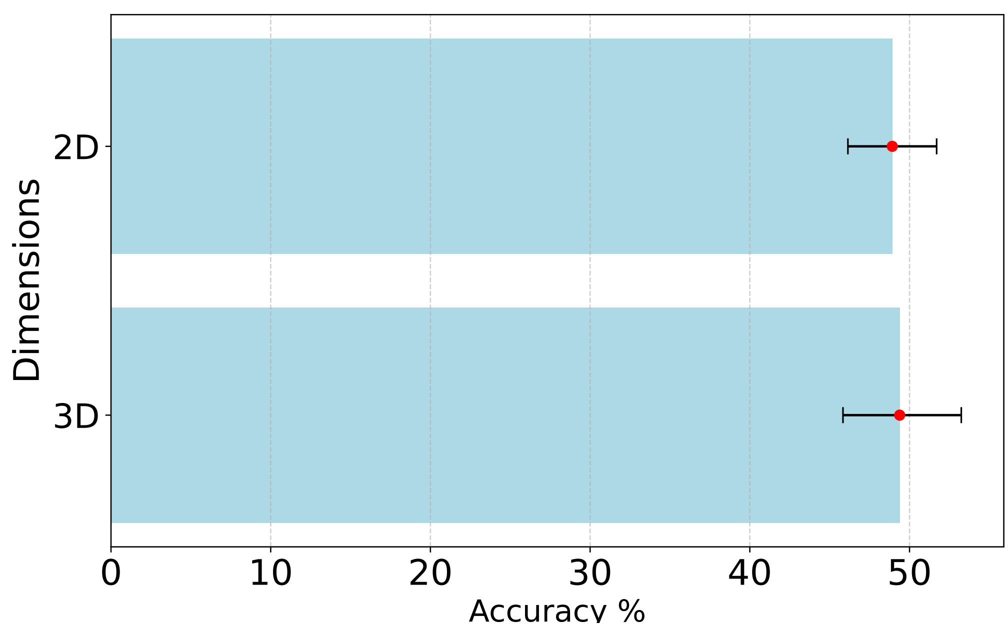



Figure 5.6: Bar chart representing mean accuracy (%) and 95% CI for two dimension groups

In Figure 5.7, we utilize a different chart to analyze pairwise differences - the differences in means and 95% CIs between groups. This visual representation serves as a means to determine whether there are significant differences between the groups based on the measured parameters.

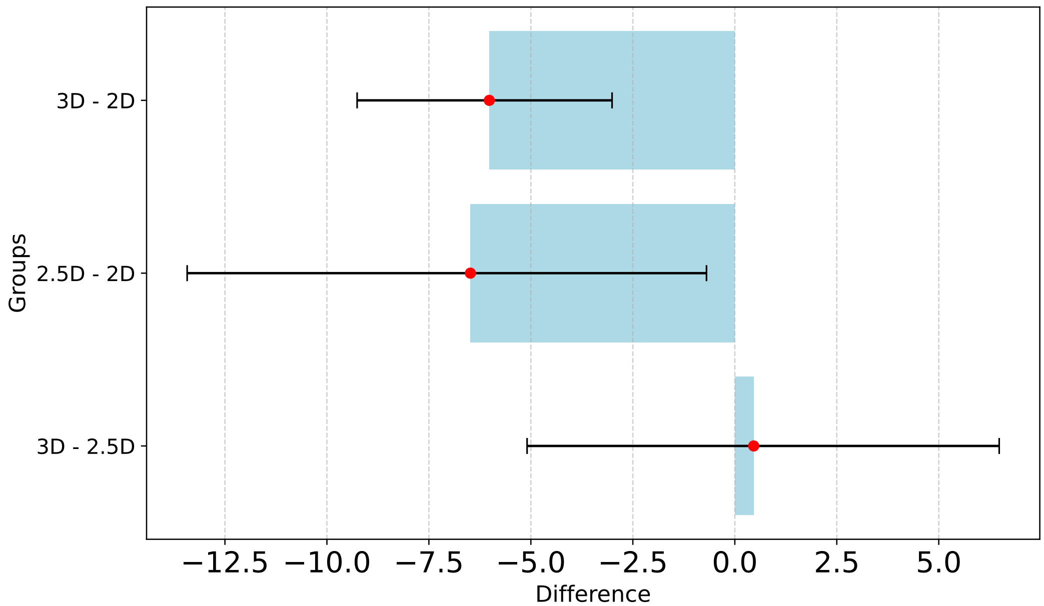



Figure 5.7: Bar chart representing differences in means and CI for a combination of the two distinct dimensions.

From Figure 5.7, we can determine the significance of the difference between the groups. For instance, considering the group '3D-2D', we can observe that the CI does not include 0. Therefore, we infer there exists a significant difference between the two groups.

On the other hand, if we examine the group '3D - 2.5D', we observe that the CI does include 0. This means that the results do not indicate a significant difference between these two groups. However, it's important to note that this does not imply the equivalence of the groups. If the study were to be conducted again, the CI might not overlap with 0.

Furthermore, from Figure 5.6, we can evaluate the magnitude of the effect by calculating the difference between the means of the two groups. In this thesis, we consider an effect to be 'large' if the mean difference between two groups is greater than or equal to 10%, and 'small' otherwise.

### 5.3.3 Method

Bootstrap estimation of confidence interval is a statistical technique that uses resampling from a limited sample to make inferences about a broader population. Since our experimental data only represents a fraction of the entire population, bootstrap estimation becomes important in understanding population characteristics [45]. Employing a 95% bootstrapped confidence interval allows us to construct an interval that through resampling should cover the true population parameter in 95% of the cases. We use the bootstrapping method that does not require normal distribution as our experiment represents a fraction of the entire population.

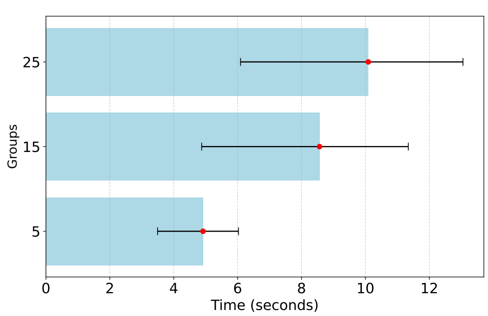
This method offers advantages such as rather than having a simple binary dimension of ’significant’ and ’non-significant’ findings, bootstrapped confidence interval provides a continuous dimension of effect size [6]. By encapsulating the variability inherent in the data to resampling, bootstrap provides us with a better understanding of the broader population. Thus, it is a powerful tool for concluding results with limited sample sizes.

### 5.3.4 Result

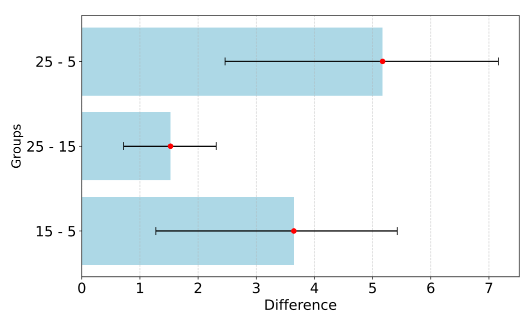
For this study, The entirety of our recruited participants (24) were included in the analysis.

This section will systemically present and analyze the results of the study. Specifically, the section will be divided into points with each point dedicated to a hypothesis. This detailed breakdown will enable us to examine the data closely and get a deeper understanding of the study’s outcomes.

- **H1**




(a) Mean time (seconds) with 95% CI for three distinct distract groups.




(b) Pairwise difference of mean time duration (seconds) with 95% CI for combination of all three distractor groups.

Figure 5.8: Bar chart representing mean and pairwise difference of the time taken (seconds) along with 95% CI for three distinct distractors.

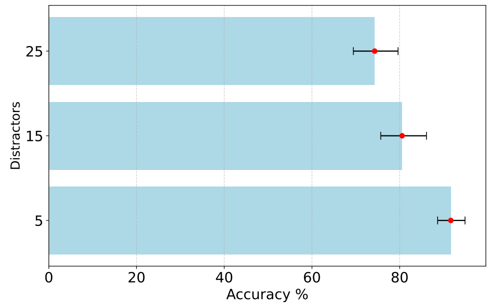
Figure 5.8a shows three distinct distractor groups - $D_5$, $D_{15}$, and $D_{25}$, along with their mean time duration (seconds) and 95% CI - 4.92 (CI [3.47, 5.06]), 8.56 (CI [4.82, 11.04]), and 10.09 (CI [5.05, 13.05]) respectively. Figure 5.8b represents the average pairwise difference (seconds) of mean time duration along with 95% CI for a combination of all three distractor groups.

In the comparison between $D_{15}$ and $D_5$, we have evidence to strongly accept H1. This conclusion is based on the observed pairwise difference of 3.65 (CI [1.24, 5.40]) in Figure 5.8b. The gap between the lower bound of the CI with 0, along with the absence of any overlap with the reference point 0, supports the evidence that the time required for $D_{15}$ exceeds that of $D_5$. Referring to Figure 5.8a we can also say that this effect is large as there is a difference of 40% between the mean estimates.

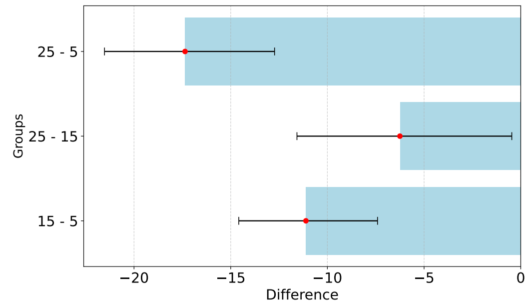
In comparison between $D_{25}$ and $D_{15}$, we have evidence to strongly accept H1. This conclusion is based on the observed pairwise difference of 1.53 (CI [0.72, 2.29]) in Figure 5.8b. The gap between the lower bounds of the CI, along with the absence of any overlap with the reference point 0, supports the evidence that the time required for $D_{15}$ exceeds that of $D_5$. Referring to Figure 5.8a we can also say that this effect is large as there is a difference of 15% between the mean estimates.

Lastly, in the comparison between $D_{25}$ and $D_5$, we have evidence to strongly accept H1. This conclusion is based on the observed pairwise difference of 5.17 (CI [2.51, 7.17]) in Figure 5.8b. The gap between the lower bounds of the CI, along with the absence of any overlap with the reference point 0, supports the evidence that the time required for $D_{25}$ exceeds that of $D_5$. Referring to Figure 5.8a we can also say that this effect is large as there is a difference of 50% between the mean estimates.

- **H2**




(a) Mean accuracy (%) with 95% CI for three distinct distract groups.




(b) Pairwise difference of accuracy (%) with 95% CI for combination of all three distractor groups.

Figure 5.9: Bar chart representing mean and pairwise difference of accuracy (%) along with 95% CI for three distinct distractor groups.

Figure 5.9a, shows three distinct distractor groups - $D_5$, $D_{15}$, and $D_{25}$, along with the mean accuracy (in percentage) and 95% CI - 91.67 (CI [88.6, 94.91]), 80.56 (CI [75.69, 86.11]), and 74.31 (CI [69.44, 79.63]) respectively. Figure 5.9b represents the average pairwise difference (%) of mean accuracy along with 95% CI for a combination of all three distractor groups.

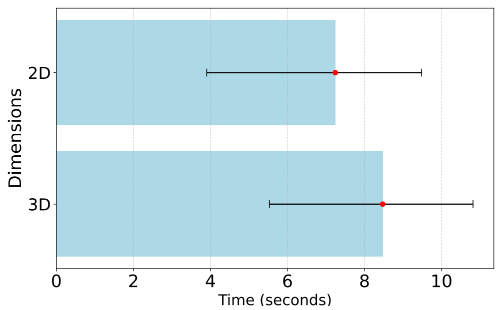
For the comparison between $D_{15}$ and $D_5$, we have evidence to strongly reject H2. This conclusion is based on the observed pairwise difference of -11.11 (CI [-7.41, -14.58])) in Figure 5.9b. The gap between the upper bound of the CI with 0, along with the absence of any overlap with the reference point 0, supports the evidence that the accuracy for $D_{15}$ is more than that of $D_5$. Referring to Figure 5.9a we can also say that the difference in mean accuracy is large as there is a difference of 13.70% between the mean estimates.

For the comparison between $D_{25}$ and $D_{15}$, we have evidence to weakly reject H2. This conclusion is based on the observed pairwise difference of -6.25 (CI [-0.69, -11.57]) in Figure 5.9b. The small gap between the upper bound of the CI with 0, along with the absence of any overlap with the reference point 0, supports the evidence that the accuracy for $D_{25}$ is less than that of $D_5$. Referring to Figure 5.9a we can also say that the difference in mean accuracy is small as there is a difference of 7.75% between the mean estimates.

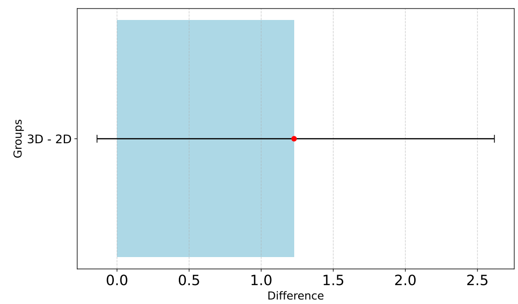
Lastly, for the comparison between $D_{25}$ and $D_5$, we have evidence to strongly reject H2. This conclusion is based on the observed pairwise difference of -

17.36 (CI [-12.96, -21.53]) in Figure 5.9b. The gap between the upper bound of the CI with 0, along with the absence of any overlap with the reference point 0, supports the evidence that the accuracy for $D_{25}$ is less than that of $D_{15}$. Referring to Figure 5.9a we can also say that the difference in mean accuracy is large as there is a difference of 23.36% between the mean estimates.

- **H3**




(a) Mean time (seconds) with 95% CI for two distinct attribute space groups.



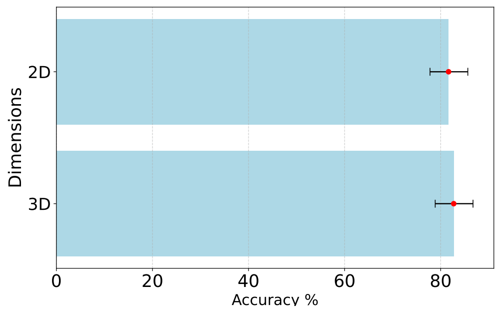

(b) Pairwise difference of mean time duration (seconds) with 95% CI for a combination of the two attribute space groups.

Figure 5.10: Bar chart representing mean and pairwise difference of the time taken (seconds) along with 95% CI for two distinct attribute space groups.

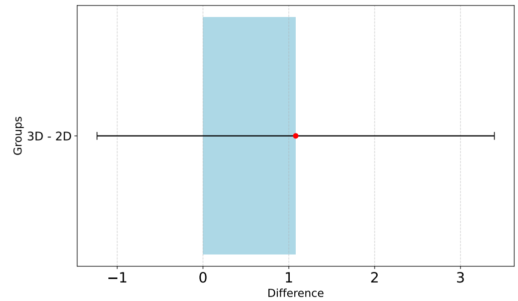
Figure 5.10a shows two distinct data groups - $A^3$, and $A^2$, along with their mean time duration (seconds) and 95% confidence interval (CI) - 8.47 (CI [5.53, 10.82]), and 7.24 (CI [3.90, 9.48]) respectively. Figure 5.10b represents the average pairwise difference (seconds) of mean time duration along with 95% CI for a combination of both data groups.

In the comparison between $A^3$, and $A^2$, we have evidence to weakly accept H3. This conclusion is based on the observed pairwise difference of 1.23 (CI [-0.11, 2.62]) in Figure 5.10b. The overlap of CI with reference point 0, does not show evidence of a difference between $A^3$ and $A^2$. We are 95% confident that the difference between the two conditions is between -0.11 and 2.62 and the slight overlap with 0 is minimal, therefore it is possible that replicating the experiment would show a significant difference between these two views. Referring to Figure 5.10a we can also say that the effect has a significant difference of 16.98% between the mean estimates.

- **H4**




(a) Mean accuracy (%) with 95% CI for two distinct attribute space groups.



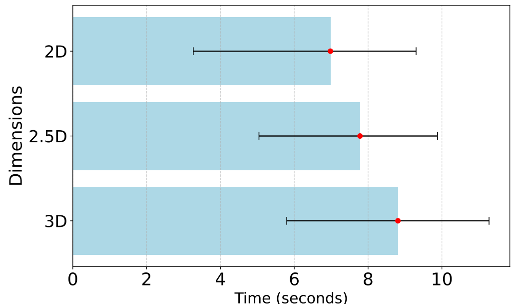

(b) Pairwise difference of accuracy (%) with 95% CI for a combination of the two attribute space groups.

Figure 5.11: Bar chart representing mean and pairwise difference of accuracy (%) along with 95% CI for two distinct attribute space groups.

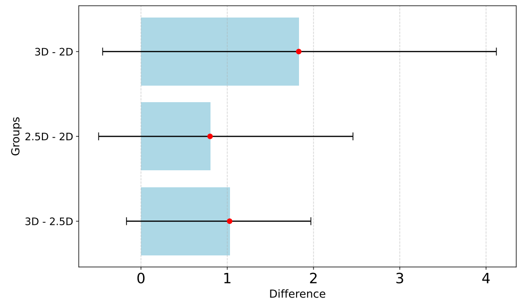
Figure 5.11a shows two distinct data groups - $A^3$, and $A^2$, along with their mean accuracy (%) and 95% CI - 82.72 (CI [78.86, 86.73]), and 81.64 (CI [77.78, 85.65]) respectively. Figure 5.11b represents the average pairwise difference (in percentage) of mean accuracy along with 95% CI for a combination of both data groups.

In the comparison between 81.64 (CI [77.78, 85.65]), we have evidence to accept H4. This conclusion is based on the observed pairwise difference of 1.08 (CI [-1.23, 3.40]) in Figure 5.11b. The overlap of CI with reference point 0, does not show evidence of a difference between $A^3$ and $A^2$. We are 95% confident that the difference between the two conditions is between -1.23 and 3.40. Referring to Figure 5.11a we can also say that the difference of 1.04% between the mean estimates would be very small. This tells us that not only is it unlikely there is a difference between these two conditions, if there was one, it would be very small and practically insignificant.

- **H5**




(a) Mean time (seconds) with 95% CI for three distinct reference space groups.




(b) Pairwise difference of mean time duration (seconds) with 95% CI for combinations of all three reference space groups.

Figure 5.12: Bar chart representing mean and pairwise difference of the time taken (seconds) along with 95% CI for three distinct reference space groups.

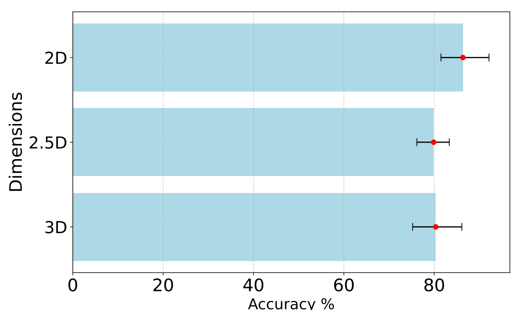
Figure 5.12a shows three distinct terrain groups - $R^3$, $R^{2.5}$, and $R^2$, along with their mean time duration (seconds) and 95% CI - 8.81 (CI [5.80, 11.28]), 7.78 (CI [5.04, 9.88]), and 6.98 (CI [3.26, 9.30]) respectively. Figure 5.12b represents the average pairwise difference (seconds) of mean time duration along with 95% CI for a combination of all three terrain groups.

In the comparison between $R^3$ and $R^{2.5}$, we have evidence to weakly accept H5. This conclusion is based on the observed pairwise difference of 1.03 (CI [-0.18, 1.97]) in Figure 5.12b. The slight overlap of CI with reference point 0, does not show evidence of a difference between $R^3$ and $R^{2.5}$. We are 95% confident that the difference between the two conditions is between -0.18 and 1.97 and the slight overlap with 0 is minimal, therefore it is possible that replicating the experiment would show a significant difference between these two views.

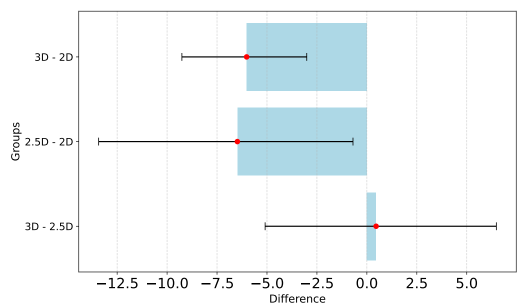
In the comparison between $R^{2.5}$ and $R^2$, we have evidence to weakly accept H5. This conclusion is based on the observed pairwise difference of 0.80 (CI [-0.49, 2.46]) in Figure 5.12b. The slight overlap of CI with reference point 0, does not show evidence of a difference between $R^{2.5}$ and $R^2$. We are 95% confident that the difference between the two conditions is between -0.49 and 2.46 and the slight overlap with 0 is minimal, therefore it is possible that replicating the experiment would show a significant difference between these two views. Referring to Figure 5.12a we can also say that the effect is significant as there is a difference of 11.46% between the mean estimates.

In the comparison between $R^3$ and $R^2$, we have evidence to weakly accept H5. This conclusion is based on the observed pairwise difference of 1.83 (CI [-0.40, 4.16]) in Figure 5.12b. The overlap of CI with reference point 0, does not show evidence of a difference between $R^3$ and $R^2$. We are 95% confident that the difference between the two conditions is between -0.40 and 4.16 and the slight overlap with 0 is minimal, therefore it is possible that replicating the experiment would show a significant difference between these two views.

- **H6**




(a) Mean accuracy (%) with 95% CI for three distinct reference space groups.




(b) Pairwise difference of accuracy (%) with 95% CI for combinations of all reference space groups.

Figure 5.13: Bar chart representing mean and pairwise difference of accuracy (%) along with 95% CI for three distinct reference space groups.

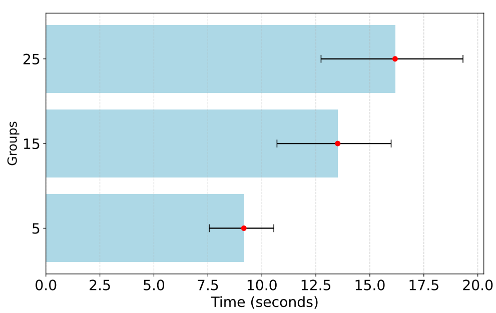
Figure 5.13a shows three distinct terrain groups - $R^3$, $R^{2.5}$, and $R^2$, along with their mean accuracy (%) and 95% CI - 80.32 (CI [75.23, 86.11]), 79.86 (CI [76.16, 83.33]), and 86.34 (CI [81.48, 92.13]) respectively. Figure 5.13b represents the average pairwise difference (in percentage) of mean accuracy along with 95% CI for a combination of both data groups.

In the comparison between $R^3$ and $R^{2.5}$, we have evidence to strongly reject H6. This conclusion is based on the observed pairwise difference of 0.46 (CI [-5.09, 6.48]) in Figure 5.13b. The overlap of CI with reference point 0, does not show evidence of a difference between $R^3$ and $R^{2.5}$. We are 95% confident that the difference between the two conditions is between -5.09 and 6.48. Referring to Figure 5.13a we can also say that the difference of 0.57% between the mean estimates is very small. This tells us that not only it is unlikely there is a difference between these two conditions, but also that if there was one, it would be very small and practically insignificant.

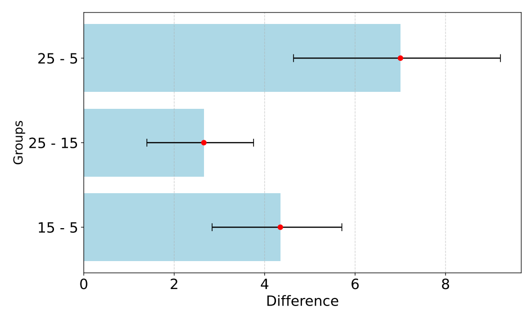
In the comparison between $R^{2.5}$ and $R^2$, we have evidence to weakly reject H6. This conclusion is based on the observed pairwise difference of -6.48 (CI [-13.19, -0.69]) in Figure 5.13b. The gap between the upper bound of CI and 0 along with the overlap of CI with reference point 0, supports the evidence that the accuracy for $R^{2.5}$ is less than that of $R^2$. Referring to Figure 5.13a we can also say that this effect is small as there is a difference of -8.11% between the mean estimates.

In the comparison between $R^3$ and $R^2$, we have evidence to strongly accept H6. This conclusion is based on the observed pairwise difference of -6.02 (CI [-9.03, -3.01]) in Figure 5.13b. The gap between the upper bound of CI and 0 along with the overlap of CI with reference point 0, supports the evidence that the accuracy for $D_{3D}$ is less than that of $D_{2D}$. Referring to Figure 5.13a we can also say that this effect is small as there is a difference of -7.49% between the mean estimates.

- **H7**




(a) Mean time (seconds) with 95% CI for three distinct distract groups.




(b) Pairwise difference of mean time duration (seconds) with 95% CI for combination of all three distractor groups.

Figure 5.14: Bar chart representing mean and pairwise difference of the time taken (seconds) along with 95% CI for three distinct distractors.

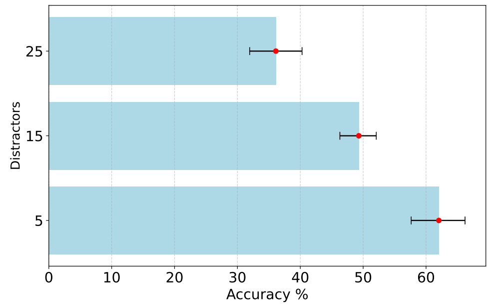
Figure 5.14a shows three distinct distractor groups - $D_5$, $D_{15}$, and $D_{25}$, along with their mean time duration (seconds) and 95% CI - 9.17 (CI [7.56, 10.55]), 13.51 (CI [10.70, 15.99]), and 16.17 (CI [12.74, 19.31]) respectively. Figure 5.14b represents the average pairwise difference (seconds) of mean time duration along with 95% CI for a combination of all three distractor groups.

In the comparison between $D_{15}$ and $D_5$, we have evidence to strongly accept H7. This conclusion is based on the observed pairwise difference of 4.34 (CI [2.80, 5.67]) in Figure 5.14b. The gap between the lower bound of the CI with 0, along with the absence of any overlap with the reference point 0, supports the evidence that the time required for $D_{15}$ exceeds that of $D_5$. Referring to Figure 5.14a we can also say that this effect is large as there is a difference of 32.12% between the mean estimates.

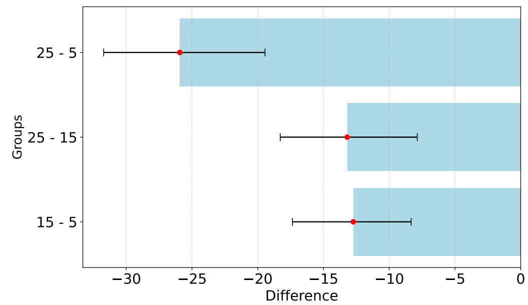
In comparison between $D_{25}$ and $D_{15}$, we have evidence to strongly accept H7. This conclusion is based on the observed pairwise difference of 2.66 (CI [1.39, 3.75]) in Figure 5.14b. The gap between the lower bounds of the CI, along with the absence of any overlap with the reference point 0, supports the evidence that the time required for $D_{25}$ exceeds that of $D_{15}$. Referring to Figure 5.14a we can also say that this effect is small as there is a difference of 16.45% between the mean estimates.

Lastly, in the comparison between $D_{25}$ and $D_5$, we have evidence to strongly accept H7. This conclusion is based on the observed pairwise difference of 7.00 (CI [4.62, 9.18]) in Figure 5.14b. The gap between the lower bounds of the CI, along with the absence of any overlap with the reference point 0, supports the evidence that the time required for $D_{25}$ exceeds that of $D_5$. Referring to Figure 5.14a we can also say that this effect is large as there is a difference of 43.29% between the mean estimates.

- **H8**




(a) Mean accuracy (%) with 95% CI for three distinct distract groups.




(b) Pairwise difference of accuracy (%) with 95% CI for combination of all three distractor groups.

Figure 5.15: Bar chart representing mean and pairwise difference of accuracy (%) along with 95% CI for three distinct distractor groups.

Figure 5.15a shows three distinct distractor groups - $D_5$, $D_{15}$, and $D_{25}$, along with the mean accuracy (in percentage) and 95% CI - 62.04 (CI [57.87, 66.44]), 49.31 (CI [46.30, 52.08]), and 36.11 (CI [31.94, 40.28]) respectively. Figure 5.15b represents the average pairwise difference (%) of mean accuracy along with 95% CI for a combination of all three distractor groups.

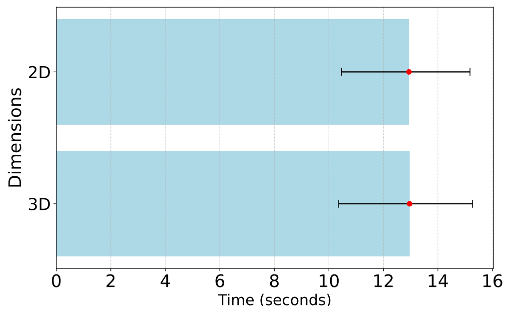
For the comparison between $D_{15}$ and $D_5$, we have evidence to strongly accept H8. This conclusion is based on the observed pairwise difference of -12.73 (CI [-17.36, -8.10]) in Figure 5.15b. The gap between the upper bound of the CI with 0, along with the absence of any overlap with the reference point 0, supports the evidence that the accuracy for $D_{15}$ is less than that of $D_5$. Referring to Figure 5.15a we can also say that the difference in mean accuracy is large as there is a difference of -25.81% between the mean estimates.

For the comparison between $D_{25}$ and $D_{15}$, we have evidence to strongly accept H8. This conclusion is based on the observed pairwise difference of -13.19 (CI [-18.28, -7.87]) in Figure 5.15b. The gap between the upper bound of the CI with 0, along with the absence of any overlap with the reference point 0, supports the evidence that the accuracy for $D_{25}$ is less than that of $D_{15}$. Referring to Figure 5.15a we can also say that the difference in mean accuracy is large as there is a difference of -36.56% between the mean estimates.

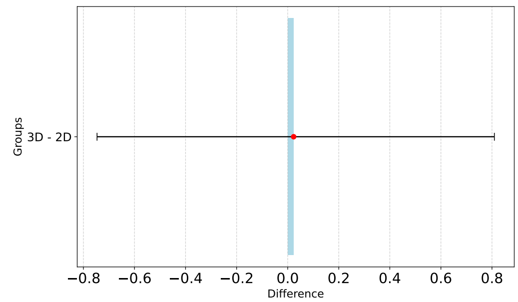
Lastly, for the comparison between $D_{25}$ and $D_5$, we have evidence to strongly accept H8. This conclusion is based on the observed pairwise difference of -

25.92 (CI [-31.71, -19.67]) in Figure 5.15b. The gap between the upper bound of the CI with 0, along with the absence of any overlap with the reference point 0, supports the evidence that the accuracy for $D_{25}$ is less than that of $D_{15}$. Referring to Figure 5.15a we can also say that the difference in mean accuracy is large as there is a difference of -71.80% between the mean estimates.

- **H9**




(a) Mean time (seconds) with 95% CI for two distinct attribute space groups.



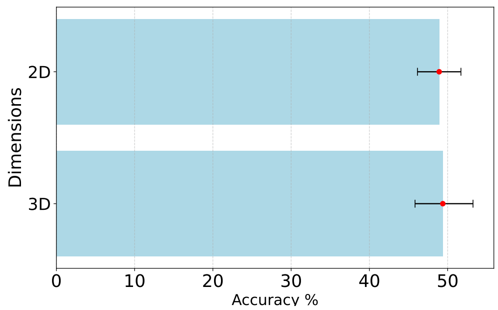

(b) Pairwise difference of mean time duration (seconds) with 95% CI for a combination of the two attribute space groups.

Figure 5.16: Bar chart representing mean and pairwise difference of the time taken (seconds) along with 95% CI for two distinct attribute space groups.

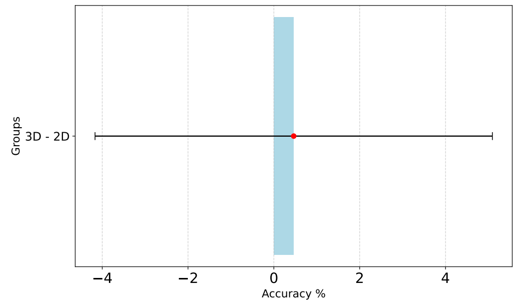
Figure 5.16a shows two distinct data groups - $A^3$, and $A^2$, along with their mean time duration (seconds) and 95% CI - 12.96 (CI [10.34, 15.17]), and 12.93 (CI [10.41, 15.17]) respectively. Figure 5.16b represents the average pairwise difference (seconds) of mean time duration along with 95% CI for a combination of both data groups.

In the comparison between $A^3$, and $A^2$, we have evidence to accept H9. This conclusion is based on the observed pairwise difference of 0.02 (CI [-0.77, 0.80]) in Figure 5.16b. The overlap of CI with reference point 0, does not show evidence of a difference between $A^3$ and $A^2$. We are 95% confident that the difference between the two conditions is between -0.77 and 0.80. Referring to Figure 5.16a we can also say that the effect is negligible as there is a difference of 0.18% between the mean estimates. These conditions tell us that not only it is unlikely there is a difference between these two conditions but if there was one, it would be very small and practically insignificant.

- **H10**




(a) Mean accuracy (%) with 95% CI for two distinct attribute space groups.



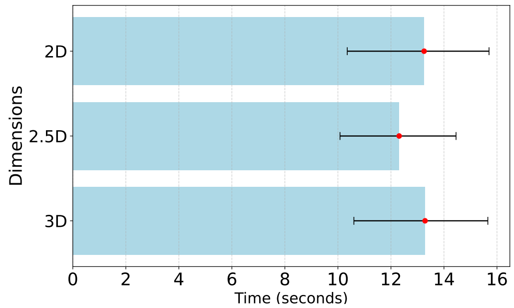

(b) Pairwise difference of accuracy (%) with 95% CI for a combination of the two attribute space groups.

Figure 5.17: Bar chart representing mean and pairwise difference of accuracy (%) along with 95% CI for two distinct attribute space groups.

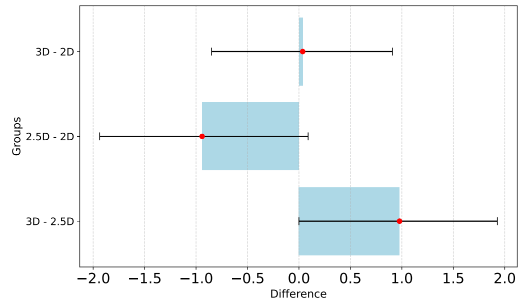
Figure 5.17a shows two distinct data groups - $A^3$, and $A^2$, along with their mean accuracy (in percentage) and 95% confidence interval (CI) - 49.38 (CI [45.83, 53.24]), and 48.92 (CI [46.14, 51.70]) respectively. Figure 5.17b represents the average pairwise difference (in percentage) of mean accuracy along with 95% CI for a combination of both data groups.

In the comparison between $A^3$, and $A^2$, we have evidence to accept H10. This conclusion is based on the observed pairwise difference of 0.46 (CI [-4.16, 5.09]) in Figure 5.17b. The overlap of CI with reference point 0, does not show evidence of a difference between $A^3$ and $A^2$. We are 95% confident that the difference between the two conditions is between -4.16 and 5.09. The difference of 0.94% between the mean estimates (Figure 5.17a) is also very small. This tells us that not only is it unlikely there is a difference between these two conditions but if there was one, it would be very small and practically insignificant.

- **H11**




(a) Mean time (seconds) with 95% CI for three distinct reference space groups.



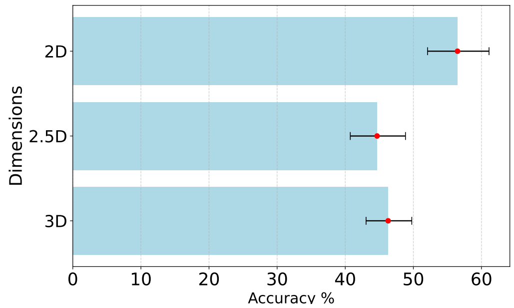

(b) Pairwise difference of mean time duration (seconds) with 95% CI for combinations of all three reference space groups.

Figure 5.18: Bar chart representing mean and pairwise difference of the time taken (seconds) along with 95% CI for three distinct reference space groups.

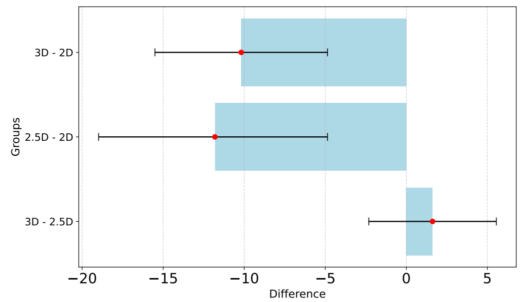
Figure 5.18a shows three distinct terrain groups - $R^3$, $R^{2.5}$, and $R^2$, along with their mean time duration (seconds) and 95% CI - 13.29 (CI [10.60, 15.66]), 12.31 (CI [10.08, 14.46]), and 13.25 (CI [10.35, 15.70]) respectively. Figure 5.18b represents the average pairwise difference (seconds) of mean time duration along with 95% CI for a combination of all three terrain groups.

In the comparison between $R^3$ and $R^2$, $R^3$ and $R^{2.5}$, and $R^{2.5}$ and $R^2$, we have evidence to weakly accept H11 (see Figures 5.18b and 5.18a). In all cases, there is some overlap with reference point 0, which tells us that there is no statistical evidence of a difference between these conditions. Although the minimal overlap with 0 tells us that it is likely that replicating the experiment with more power would yield differences, these differences would be of small practical significance given the small differences between mean estimates for these three comparisons.

- **H12**




(a) Mean accuracy (%) with 95% CI for three distinct reference space groups.




(b) Pairwise difference of accuracy (%) with 95% CI for combinations of all reference space groups.

Figure 5.19: Bar chart representing mean and pairwise difference of accuracy (%) along with 95% CI for three distinct reference space groups.

Figure 5.19a shows three distinct terrain groups - $R^3$, $R^{2.5}$, and $R^2$, along with their mean accuracy (in percentage) and 95% CI - 46.30 (CI [43.06, 49.77]), 44.68 (CI [40.74, 48.84]), and 56.84 (CI [52.08, 61.11]) respectively. Figure 5.19b represents the average pairwise difference (in percentage) of mean accuracy along with 95% CI for a combination of both data groups.

In the comparison between $R^3$ and $R^{2.5}$, we have evidence to reject H12. This conclusion is based on the observed pairwise difference of 1.62 (CI [-2.31, 5.55]) in Figure 5.19b. The overlap of CI with reference point 0, does not show evidence of a difference between $R^3$ and $R^{2.5}$. We are 95% confident that the difference between the two conditions is between -2.31 and 5.55. Referring to Figure 5.19a we can also say that this effect is small as there is a difference of 3.62% between the mean estimates. These conditions tell us that not only it is unlikely there is a difference between these two conditions but if there was one, it would be very small and practically insignificant.

In the comparison between $R^{2.5}$ and $R^2$, we have evidence to strongly reject H12. This conclusion is based on the observed pairwise difference of -11.81 (CI [-18.98, -4.86]) in Figure 5.19b. The gap between the upper bound of CI and 0 along with the absence of any overlap with the reference point 0, supports the evidence that the accuracy for $R^{2.5}$ is less than that of $R^2$. Referring to Figure 5.19a we can also say that this effect is large as there is a difference of -20.89% between the mean estimates.

In the comparison between $R^3$ and $R^2$, we have evidence to strongly accept H12. This conclusion is based on the observed pairwise difference of -10.18 (CI [-15.27, -4.86]) in Figure 5.19b. The gap between the upper bound of CI and 0 along with the absence of any overlap of CI with reference point 0, supports the evidence that the accuracy for $R^3$ is less than that of $R^2$. Referring to Figure 5.19a we can also say that this effect is large as there is a difference of -18.02% between the mean estimates.

## 5.4 Qualitative Phase

The qualitative phase consisted of two tasks, with each task having two iterations of similar difficulty levels. A mosaic of all 6 views was displayed on the screen and the position of each view was determined using a Latin Square [20].

The displayed view was dynamic, and the participant could navigate around with the help of a keyboard and a mouse. The placement and number of bars and viewpoints were manually selected and hard-coded in the system beforehand. The bars were visually selected such that they were well spread out throughout the study area.

Once the experiment was completed for all participants, we generated one Area of Interest (AOI) timeline for each participant. We then analyzed those AOI timelines with the aim to categorize first participant exploration strategies, and then fixation and saccade strategies.

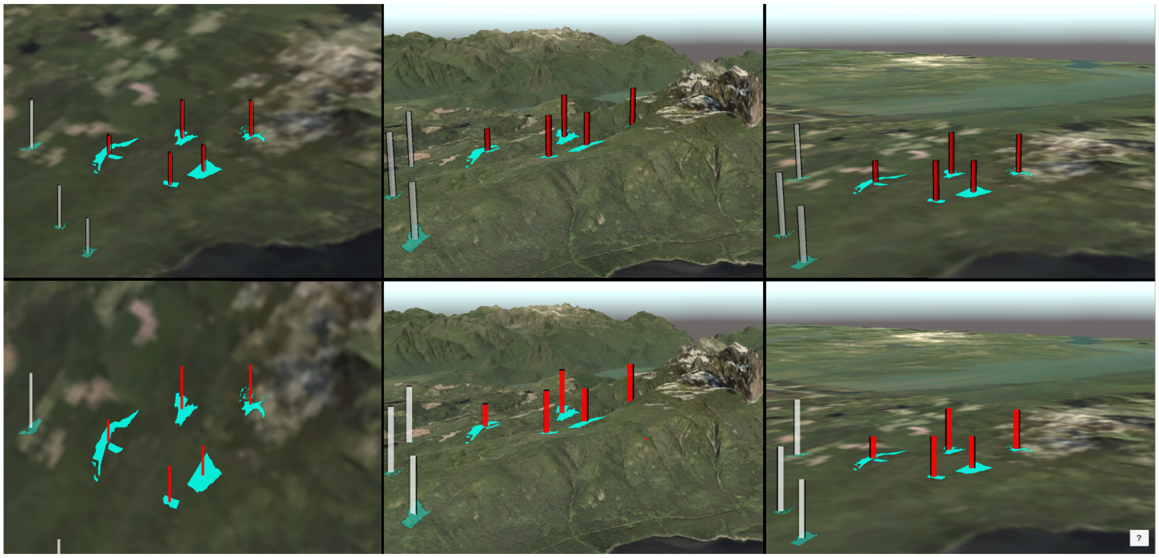
### 5.4.1 Tasks

This phase of the study employed two complex, high-level tasks based on the abstract visualization task typology defined by Brehmer et al. [13]. These tasks were derived from past literature as well as domain-specific tasks defined by Kuan-Cheng Lai [40]. The tasks are divided into two parts, with the initial phase involving a domain-related task, and the subsequent phase involving a straightforward task similar to the quantitative phase tasks outlined in Section 5.3.1. The tasks are defined in detail next.

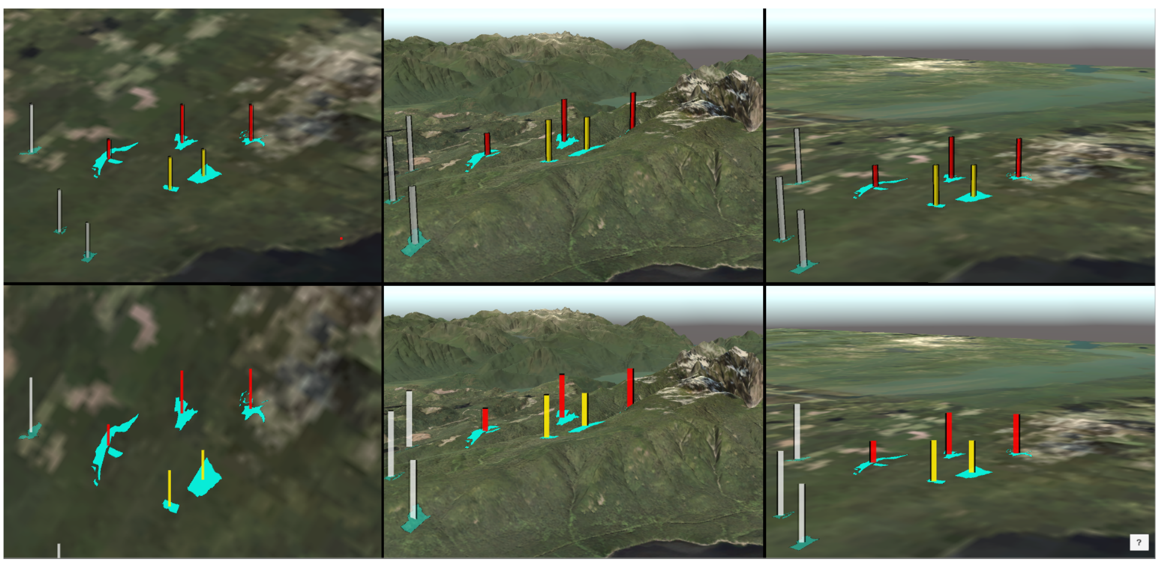
- Elevation Task:

  Participants are presented with a set of bars and tasked with identifying the top 5 bars they believe are situated at the highest elevation (Figure 5.20). Elevation serves as a factor in calculating the VSC rating of the polygon. After selecting the top 5 bars, participants are then required to choose 2 out of the 5 selected bars that they perceive to be closest to each other in terms of distance. To complete the task, participants must complete the following sub-tasks:

- Navigate in the environment and adjust the camera position and angle. This sub-task is drawn from past literature, as detailed in Table 3.2.
- Compare the elevation of bars on the terrain. This sub-task is drawn from past literature, as detailed in Table 3.2.
- Select five bars with the highest terrain elevation. This sub-task is drawn from past literature, as detailed in Table 3.2.
- Compare the distance between selected bars. This sub-task is drawn from past literature, as detailed in Table 3.2.
- Select two bars with the closest distance. This sub-task is similar to the task in Section 5.3.1.



(a) Phase 1 of the task where participants have to first select 5 bars that are on the highest elevation on the terrain.



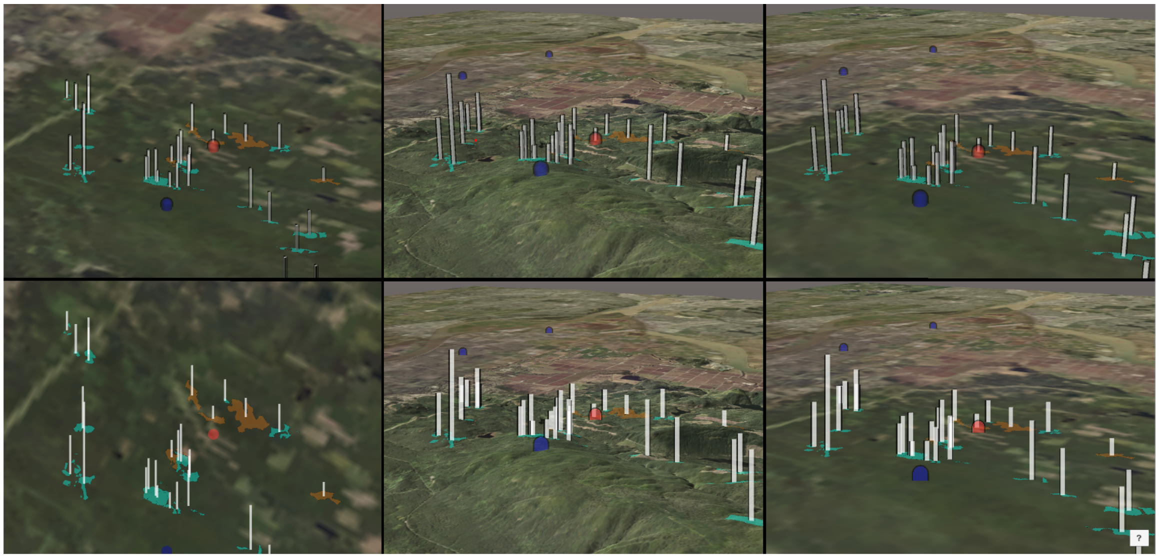
(b) Phase 2 of the task where participants have to select 2 bars out of the 5 already selected bars that according to them are closest to each other in terms of distance.

Figure 5.20: Elevation Task

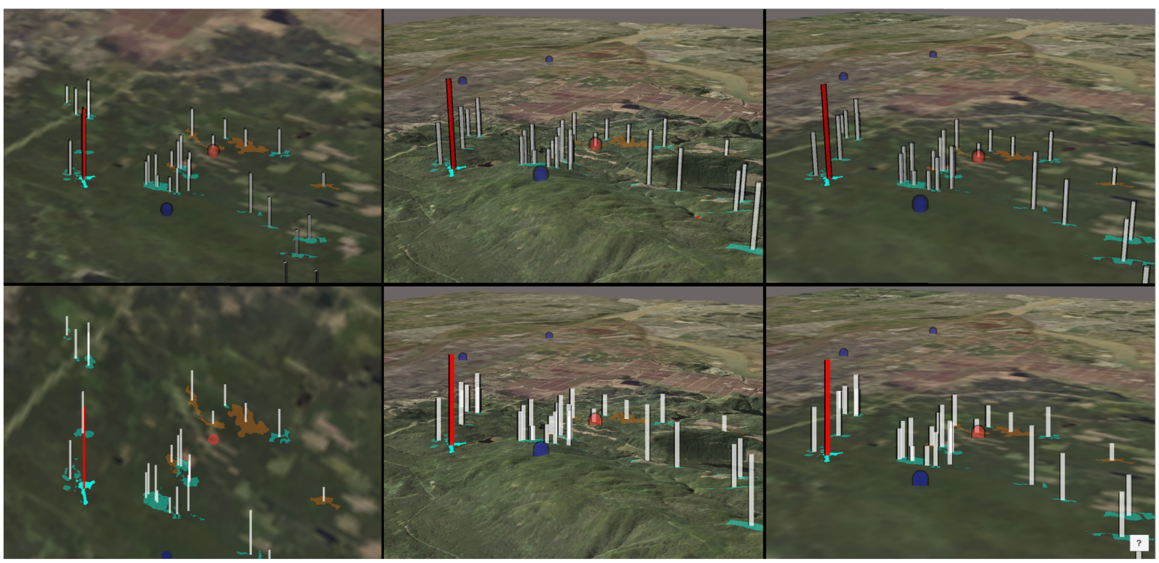
- Viewpoint Task:

  Participants are presented with a set of bars and viewpoints and are tasked to compare and choose a viewpoint that in their judgment filters the fewest bars on the screen. The count of visible bars from a chosen viewpoint determines its priority or ranking. Following the selection of the viewpoint, participants are then required to choose a bar from the filtered set that they perceive to have the longest vertical length. To complete the task, participants must complete the following sub-tasks:

- Navigate in the environment and adjust the camera position and angle. This sub-task is drawn from past literature, as detailed in Table 3.2.
- Select viewpoints and compare the number of bars visible on the screen. This sub-task is drawn from past literature, as detailed in Table 3.2.
- Select viewpoint with a minimum number of bars visible. This sub-task is drawn from past literature, as detailed in Table 3.2.
- Compare the vertical length of bars that are visible. This sub-task is drawn from past literature, as detailed in Table 3.2.
- Select the bar with the longest vertical length. This sub-task is similar to the task in Section 5.3.1.



(a) Phase 1 of the task where participants have to select a viewpoint from which a minimum number of bars are visible on the terrain.



(b) Phase 2 of the task where participants have to select a bar that has the longest vertical length out of the bars that are visible on the terrain.

Figure 5.21: Viewpoint Task

### 5.4.2 Measurements

Data was gathered from both the eye-tracker and the Unity system, and these datasets were merged to create a unified dataset. Interaction and system logs were systematically collected from the Unity system at a consistent rate of 30 frames per second, resulting in the collection of 30 logs every second.

System logs encompassed information such as the system timestamp, eye-tracking timestamp, camera positions, and angles, task number, iteration number, participant identification, and elapsed time (in seconds) for the specific task. In parallel, interaction logs documented keyboard inputs, mouse movements, and objects clicked providing insights into user actions and interactions.

Gaze data was obtained through the eye-tracker, where the display was partitioned into six categories, each corresponding to a specific view, as defined in the eye-tracking system. The eye position was recorded at a rate of 500Hz, enabling precise determination of the section of the display where the eye was concentrated or fixated during the task.

For each participant, a separate log file and eye-tracking file were generated, and these individual files were subsequently preprocessed and merged to create a unified dataset, laying the foundation for comprehensive analytical assessments and investigations.

### 5.4.3 Data Analysis

#### Eye Movement Visualization

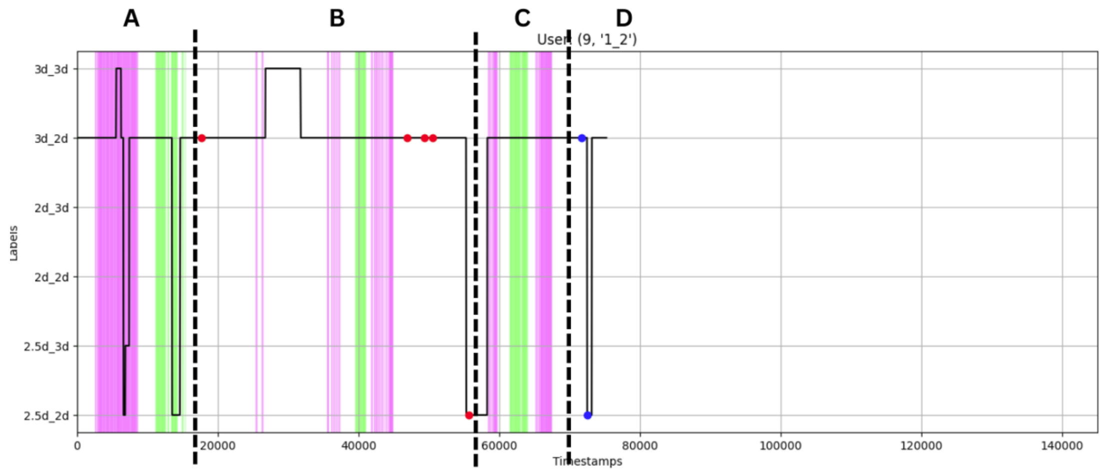
We have used AOI timelines as shown in Figure 5.22. It effectively visualizes the fixation and the saccade periods for an individual participant, as well as provides an overview of that participant's interactions with the system in a single time-based view.

The Y-axis of the chart in Figure 5.22 indicates the different views of the Multidim system and is represented by horizontal lines in the AOI timeline. To enhance clarity, we have colored the background of the chart based on the type of navigation used by the participants: green for mouse-based navigation and purple for keyboard-based navigation.

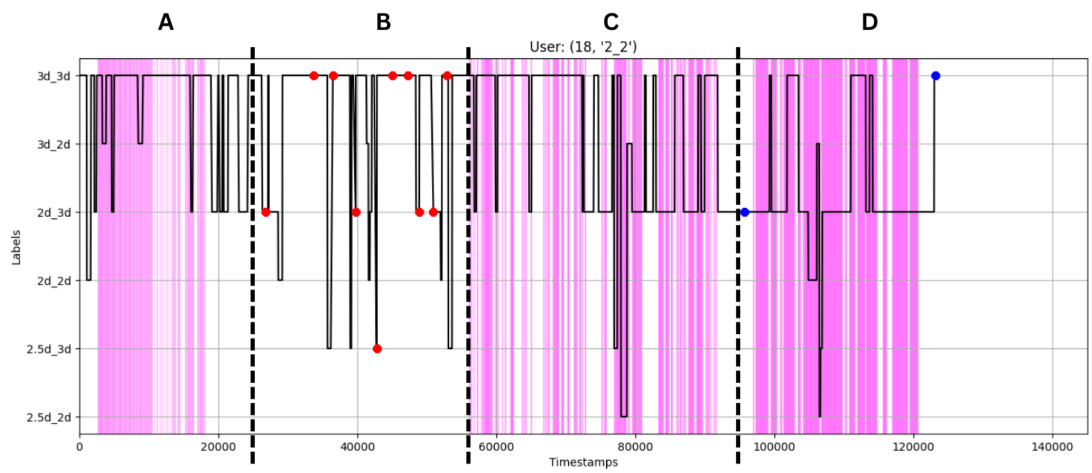
The black line within the chart signifies the fixation periods. The duration of the fixation is directly visualized using the length of this line, with longer lines indicating extended periods of focused attention within a specific AOI.

Within this visual representation, dots along the timeline denote instances when participants have clicked on objects within the system. Specifically, red dots signify objects clicked during the first phase of the task, whereas blue dots represent objects clicked during the second phase. This color-coded scheme enhances the clarity of participant interactions and provides a visual distinction between the two phases of the task throughout the AOI timeline.

Moreover, the choice to segment the AOI timeline, as discussed in Section 5.4.4, is based on the division of the complex task into sub-tasks, as detailed in Section 5.4.1. This approach breaks down the AOI timeline into more manageable segments, that correspond to the simpler tasks participants undertake to accomplish the overall complex task. Thus, dividing the AOI timeline into smaller segments provides us with a clearer interpretation of participants' actions and behaviors as seen in Figure 5.22.




(a)




(b)

Figure 5.22: Two examples of AOI timelines. Exploration is indicated by the green and purple vertical lines in the background of the AOI timeline, which denote navigation using a mouse and keyboard respectively. The selection of an object is indicated with the red and blue dots on the black lines. Red dots denote objects clicked in phase one of the task and blue dots denote objects clicked in the second phase of the task. The AOI timelines are divided into four parts, A, B, C, and D, based on different exploration strategies. Part A refers to phase $P_a^E$ as participants explore the environment in phase one of the task. Part B refers to $P_a^S$ where participants select objects as in Figure 5.22b or $P_a^{E+S}$ select and explore the environment as in Figure 5.22a in phase one of the task. Part C refers to $P_b^E$ where participants explore the environment in phase two of the task. Part D refers to $P_b^S$ where participants select objects as in Figure 5.22a or $P_a^{E+S}$ select and explore the environment as in Figure 5.22b in phase two of the task.

### 5.4.4 Coding Process

During the coding process, the second iteration of each task was chosen for analysis. This selection was made due to the participants' increased familiarity with the task during the second iteration, which allowed for a better understanding of their problem-solving strategies. AOI timelines were color-printed on paper for all participants and screen recordings were also employed as a means to validate the accuracy of the AOI timelines. This step was taken to ensure the precise and faithful representation of the AOI timeline.

After the preparation of the AOI timeline, a series of initial meetings were held, during which the collaborative categorization of the AOI timeline was carried out in group settings, with active involvement from both myself and my supervisor. As the process advanced, the categorization transitioned to an individual setting, undertaken by me. These individual categorizations were then subjected to regular scrutiny in weekly meetings with my supervisor, who carefully reviewed and verified their accuracy to ensure they were correctly executed.

As discussed in Section 5.4.1, the complex tasks are divided into two distinct parts, labeled as $P_a$ and $P_b$ respectively. The AOI timelines, illustrated in Figure 5.22, are segmented into four phases - A, B, C, and D. $P_a$ consists of phases A and B. The decision to partition $P_a$ into phases A and B was made by observing user interactions with the system. Phase B commences when participants click on the first object in part $P_a$ and concludes after they click on the last object, with the preceding portion referred to as phase A. Similarly $P_b$ consists of phases C and D and the decision to partition it into these two phases was made by observing user interactions with the system. Phase D commences when participants click on the first object in $P_b$, with the preceding portion referred to as phase C which begins immediately after the end of phase B.

Phases A and C are characterized as the 'exploration phase' and are denoted by $P_a^E$ and $P_b^E$ respectively as participants engaged in navigational activities. This can be observed in Figure 5.22 by observing the background of the chart during these phases where green shows mouse-based navigation and purple shows keyboard-based navigation.

Phases B and D are characterized as either 'selection phase' and denoted as $P_a^S$ and $P_b^S$ or 'exploration and selection' phase and are denoted as $P_a^{E+S}$ and $P_b^{E+S}$. We term the phase as the' selection phase' when participants only click on objects and do not use any of the navigational functionalities of the system. As observed in Figure 5.22a phase D and 5.22b phase B is characterized as the 'selection phase' as participants only clicked on objects during this phase. On the other hand, as observed in Figure 5.22a phase B and Figure 5.22b phase D is characterized as the 'exploration and selection' phase as participants click on objects as well as use the navigational functionalities of the system to explore the environment.

## 5.5 Results

In this section, we list the results of the qualitative phase of the study. Reports are organized according to the smaller phases extracted by the overall exploration strategy, and it is further organized based on the task.

As mentioned in Section 5.4.1, this phase of the study had two high-level complex tasks. Due to issues with the proper collection of eye-tracking data, certain participants had to be excluded from the analysis. Specifically, from the Elevation task, two participants, and from the Viewpoint task, three participants were excluded from the study.

This section will systematically present and analyze the results of the qualitative phase of the study. Specifically, the chapter will be divided into three sections with the first section defining the different user strategies - overall exploration strategy, fixation strategy, and gaze-shift/saccade strategy. The other two sections then list the results for each task. Within each task, we will further partition the content based on the three strategies. This detailed breakdown will enable us to examine the data closely and provide a better understanding of the study's outcome.

### 5.5.1 User Strategies

We have defined three types of strategies: overall exploration strategy, fixation strategy, and gaze-shift/saccade strategy. These three strategies are explained in detail below:

- **Overall exploration strategy:** The exploration strategy is devised based on the method described in Section 5.4.4. This method divides the AOI timeline into smaller manageable segments which provide us with a clearer interpretation of participants' actions and behaviors. The exploration strategies are described in Section 5.5.2 for the Elevation task and Section 5.5.3 for the Viewpoint Task.

- **Fixation strategy:** The AOI timeline, already segmented based on exploration, can now be further categorized based on the view participants fixated on during each exploration phase, indicating the most gazed-at view during that exploration phase. This categorization provides insights into participants' preferences for selecting specific views during different parts of the task. We denote the Fixated view as $F_v$ where v ∈ {$A^3$ + $R^3$, $A^2$ + $R^3$, $A^3$ + $R^{2.5}$, $A^2$ + $R^{2.5}$, $A^3$ + $R^2$, $A^2$ + $R^2$}.

- **Saccade or gaze-shifting strategy:** The AOI timeline, already segmented based on exploration, can now be further categorized based on the participants' gaze shifts between views for each phase of the exploration that indicated if they used multiple views during that exploration phase. This categorization provides insights into participants' using multiple views for different parts of the task. We denote the gaze shifts as $G_s^f$ where f is the first view and f ∈ {$A^3$ + $R^3$, $A^2$ + $R^3$, $A^3$ + $R^{2.5}$, $A^2$ + $R^{2.5}$, $A^3$ + $R^2$, $A^2$ + $R^2$}, whereas s is the second view and s ∈ {$A^3$ + $R^3$, $A^2$ + $R^3$, $A^3$ + $R^{2.5}$, $A^2$ + $R^{2.5}$, $A^3$ + $R^2$, $A^2$ + $R^2$}.

### 5.5.2 Elevation Task

Out of the 22 participants for whom eye-tracking data was accurately collected during Task 1, we analyzed a subset of 20 participants. The reason for excluding the remaining two individuals from the analysis was their inconsistent task-solving strategies, which prevented us from categorizing them alongside the rest of the participants.

#### Exploration Strategy

In the process of solving the given task, participants demonstrated diverse approaches, revealing four predominant strategies (Figure 5.23). The sequence of exploration, along with the percentages of participants who followed that strategy, is outlined in the diagram below:

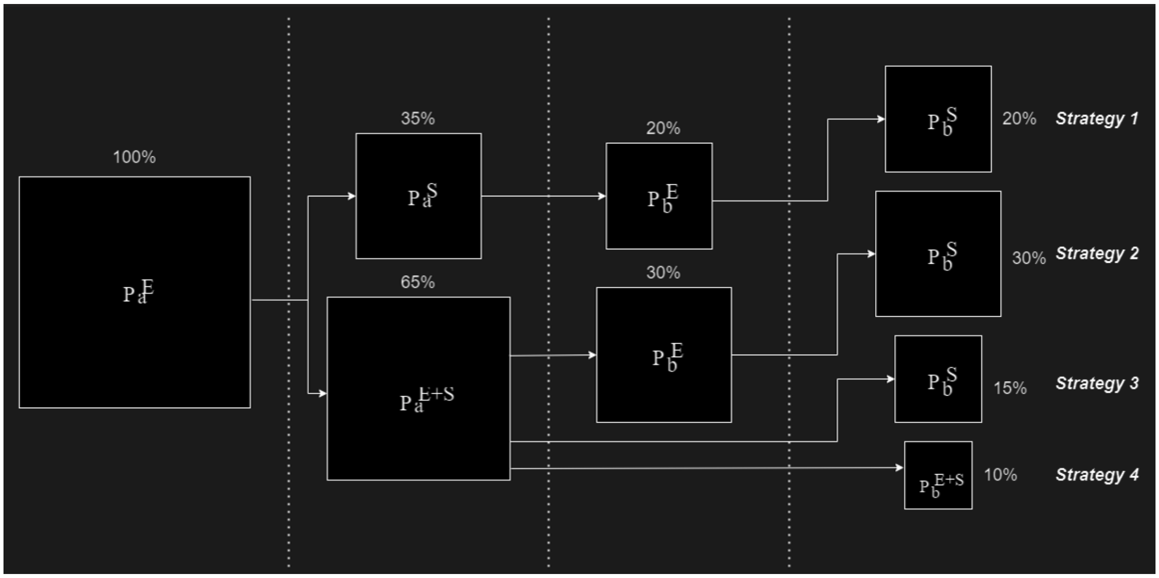
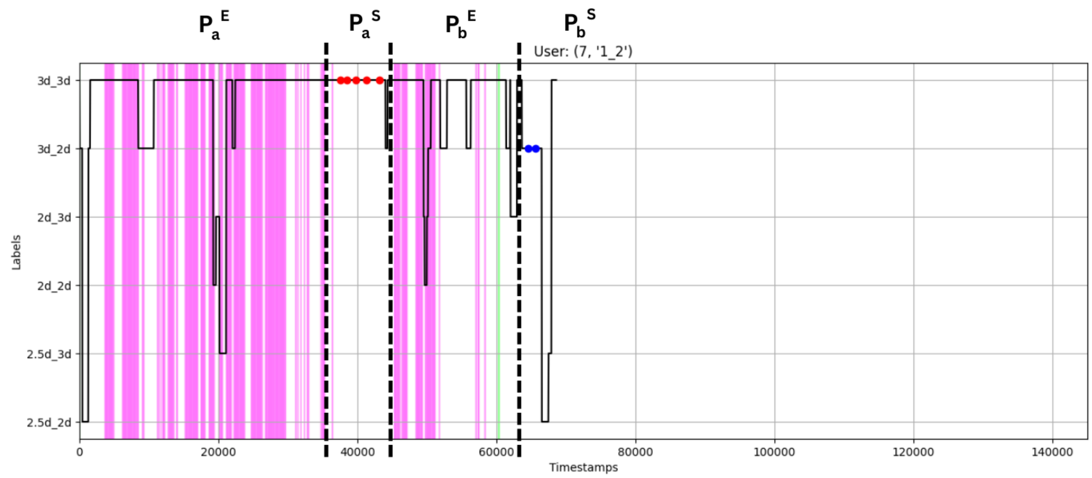
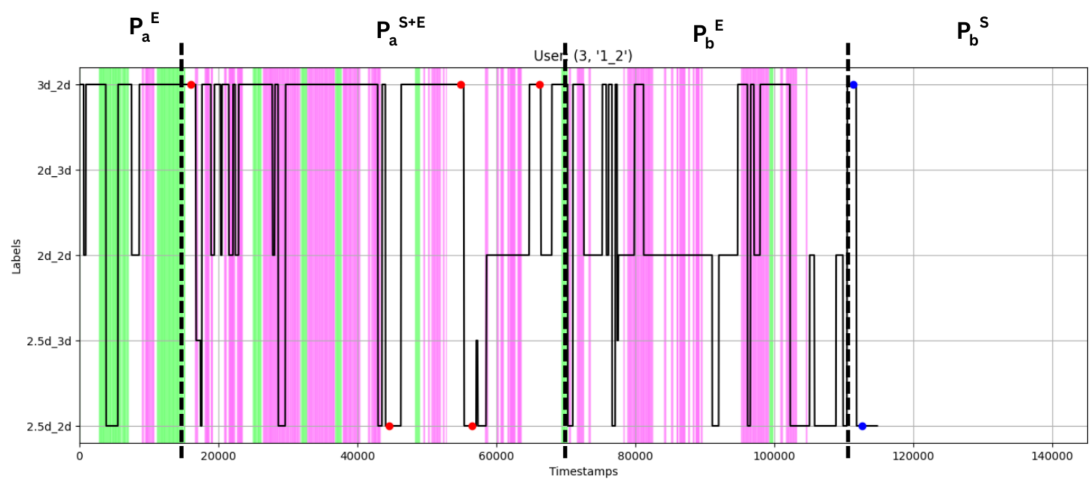



Figure 5.23: Exploration strategies followed by participants for the Elevation task. Each box represents an exploration phase and the size of each box represents the percentage of participants that employed the strategy.

Figure 5.24 makes it easier to understand the coding process described in Section 5.4.4 and also visualizes the exploration strategies on the AOI timeline that showcases the variations and diversities in different strategies.

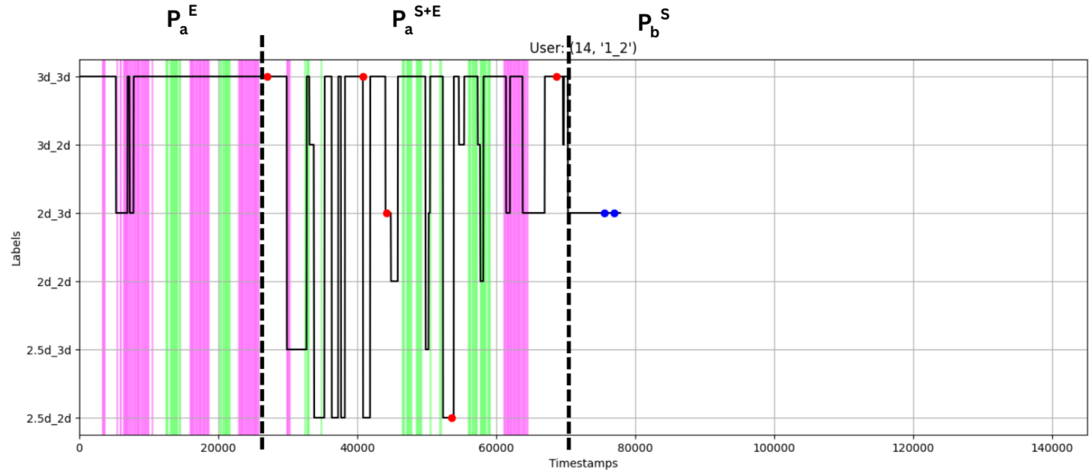



(a) **Exploration Strategy 1**: $P_a^E$ is when the participant explored the environment in the first phase of the task. $P_a^S$ is when the participant selected objects in the first phase of the task. $P_b^E$ is when the participant explored the environment in the second phase of the task. $P_b^S$ is when the participant selected objects in the second phase of the task.

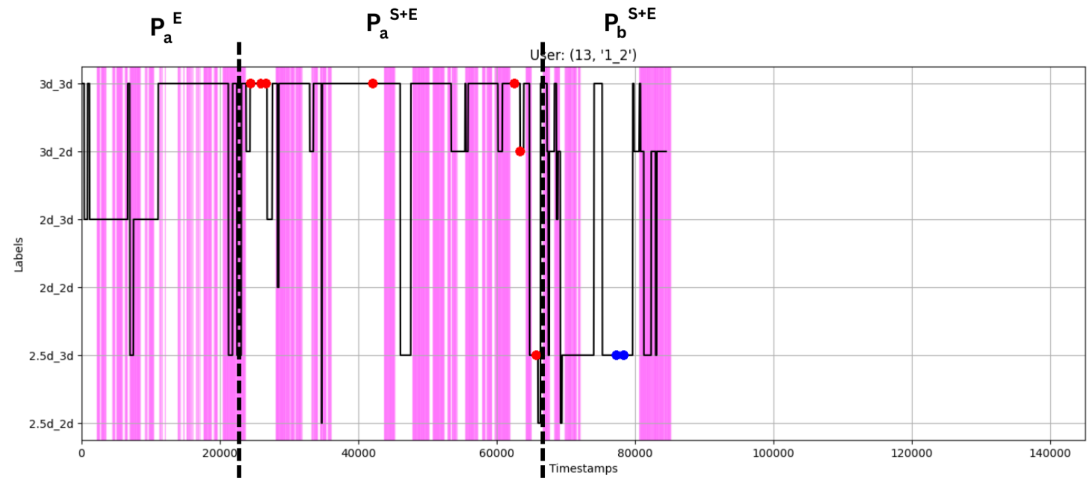



(b) **Exploration Strategy 2**: $P_a^E$ is when the participant explored the environment in the first phase of the task. $P_a^{S+E}$ is when the participant explored the environment and selected objects in the first phase of the task. $P_b^E$ is when the participant explored the environment in the second phase of the task. $P_b^S$ is when the participant selected objects in the second phase of the task.

Figure 5.24: Exploration Strategies given in Figure 5.23 visualized on AOI timelines.




(c) **Exploration Strategy 3**: $P_a^E$ is when the participant explored the environment in the first phase of the task. $P_a^{S+E}$ is when the participant explored the environment and selected objects in the first phase of the task. $P_b^S$ is when the participant selected objects in the second phase of the task.




(d) **Exploration Strategy 4**: $P_a^E$ is when the participant explored the environment in the first phase of the task. $P_a^{S+E}$ is when the participant explored the environment and selected objects in the first phase of the task. $P_b^{S+E}$ is when the participant explored the environment and selected objects in the second phase of the task.

Figure 5.24: Exploration Strategies given in Figure 5.23 visualized on AOI timelines (Part 2).

### Fixation Strategy

The results of the fixation strategy for the elevation task are provided in Table 5.25.

| Exploration phase \ Fixation | $A^3+R^3$ | $A^2+R^3$ | $A^3+R^{2.5}$ | $A^2+R^{2.5}$ | $A^3+R^2$ | $A^2+R^2$ | Erratic | Total Participants |
|---|---|---|---|---|---|---|---|---|
| $P_a^E$ | 50% | 40% | | | | | 10% | 20 |
| $P_a^S$ | 50% | 33% | | | | | 17% | 6 |
| $P_a^{E+S}$ | 35% | 50% | | | | | 7% | 14 |
| $P_b^E$ | 27% | 18% | | | | 9% | 45% | 11 |
| $P_b^S$ | 13% | 13% | | | 20% | 7% | 47% | 15 |
| $P_b^{E+S}$ | | | | | | | 100% | 4 |

Figure 5.25: Percentage of participants in different phases of the task that selected a particular view.

### Saccade or gaze-shift strategy

The results for the gaze-shift/saccade strategy for the elevation task are given in Table 5.26.

| Exploration phase \ Saccade | $A^3+R^3$ / $A^2+R^3$ | $A^3+R^3$ / $A^3+R^2$ | $A^3+R^3$ / $A^3+R^{2.5}$ | $A^3+R^3$ / $A^2+R^2$ | $A^2+R^3$ / $A^2+R^2$ | $A^2+R^3$ / $A^2+R^{2.5}$ | Total Participants |
|---|---|---|---|---|---|---|---|
| $P_a^E$ | 20% | 15% | | | 15% | | 20 |
| $P_a^S$ | 67% | | | | | 33% | 6 |
| $P_a^{E+S}$ | 50% | | | | | | 14 |
| $P_b^E$ | | | | | 27% | | 11 |
| $P_b^S$ | | 13% | | | 13% | | 15 |
| $P_b^{E+S}$ | 25% | | 25% | 25% | | 25% | 4 |

Figure 5.26: Percentage of participants in different phases of the task that employed one of the saccade strategies.

## 5.5.3 Viewpoint Task

Out of the 21 participants for whom eye-tracking data was accurately collected during Task 2, we analyzed a subset of 20 participants. The reason for excluding the remaining one individual from the analysis was their inconsistent task-solving strategies, which prevented us from categorizing them alongside the rest of the participants.

**Exploration Strategy**

In the process of solving the given task, participants demonstrated diverse approaches, revealing four predominant strategies. The sequence of exploration, along with the percentages of participants who followed that strategy, is outlined in the Figure 5.27:

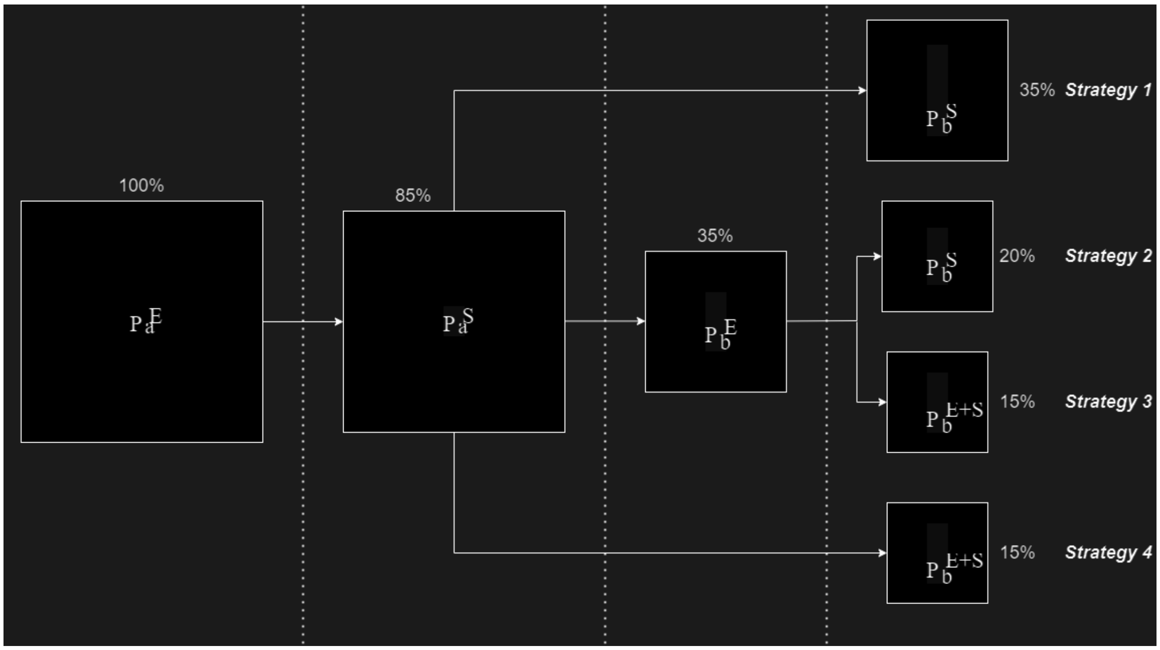
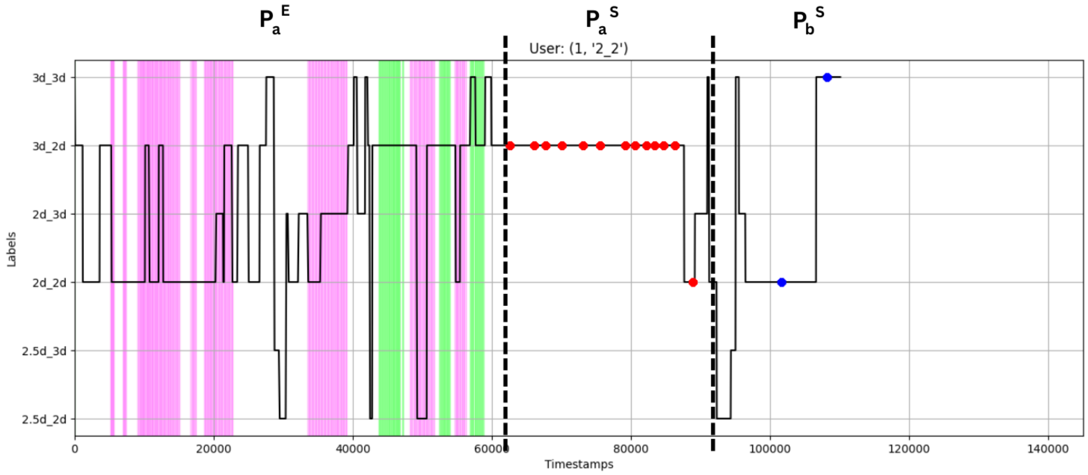
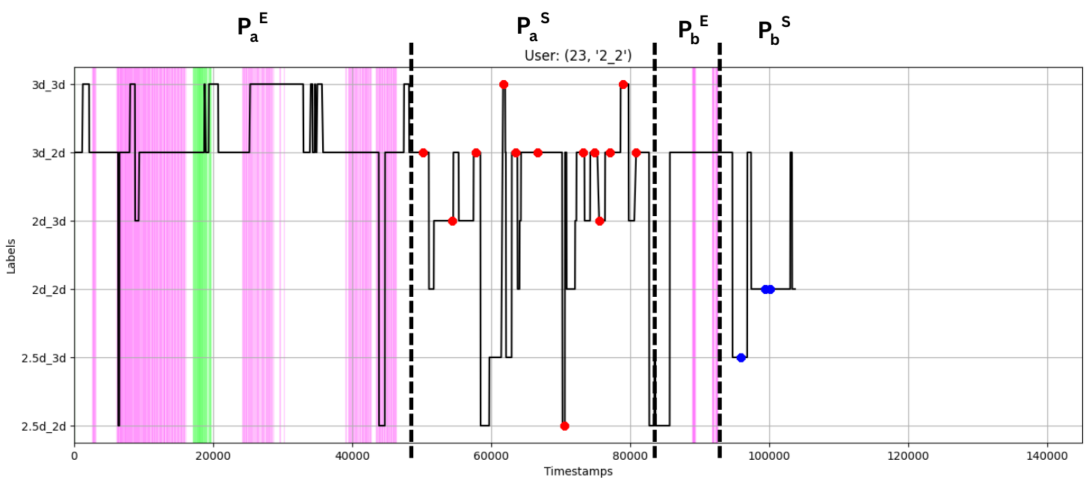



Figure 5.27: Exploration strategies followed by participants for the Viewpoint task. Each box represents an exploration phase and the size of each box represents the percentage of participants that employed the strategy.

Figure 5.28 makes it easier to understand the coding process described in Section 5.4.4 and also visualizes the exploration strategies on the AOI timeline that showcases the variations and diversities in different strategies.

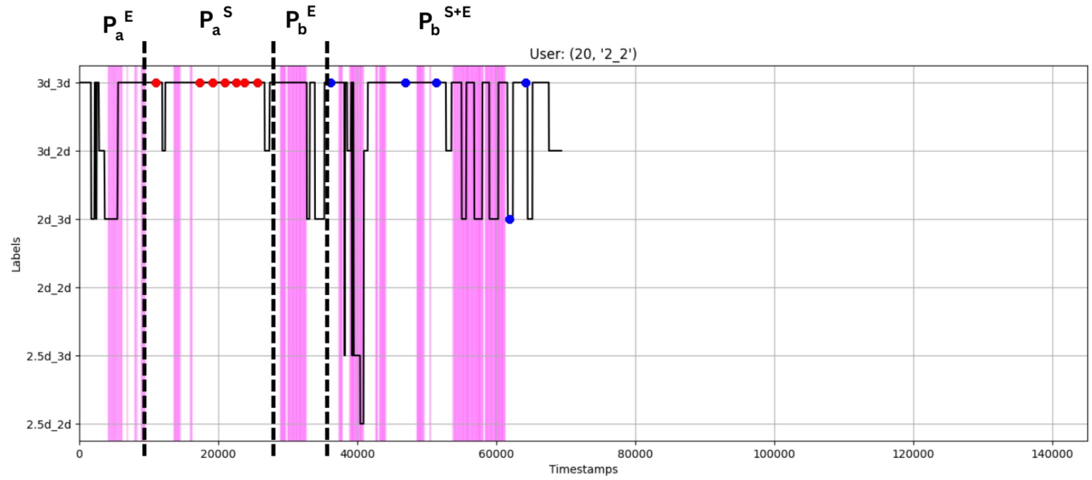



(a) **Exploration Strategy 1**: $P_a^E$ is when the participant explored the environment in the first phase of the task. $P_a^S$ is when the participant selected objects in the first phase of the task. $P_b^S$ is when the participant selected objects in the second phase of the task.

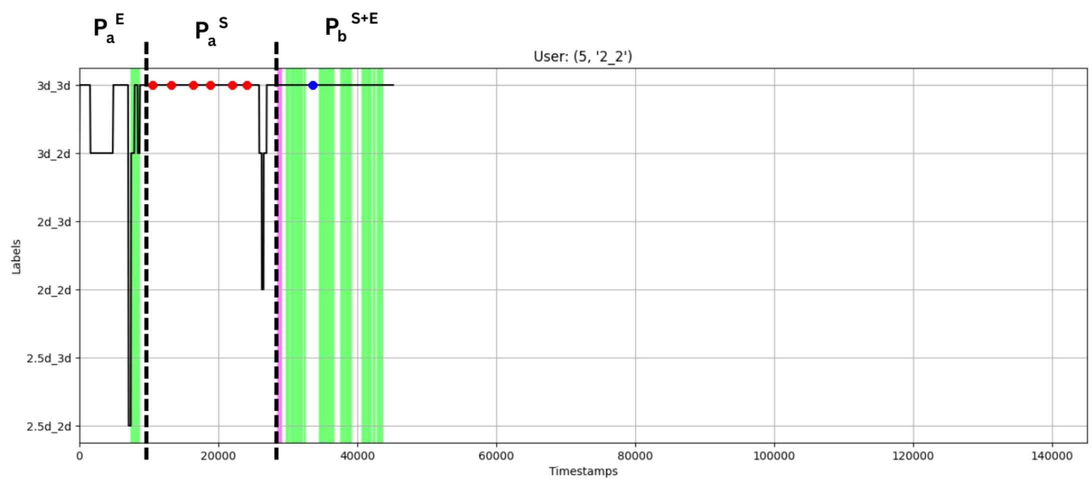



(b) **Exploration Strategy 2**: $P_a^E$ is when the participant explored the environment in the first phase of the task. $P_a^S$ is when the participant selected objects in the first phase of the task. $P_b^E$ is when the participant explored the environment in the second phase of the task. $P_b^S$ is when the participant selected objects in the second phase of the task.

Figure 5.28: Exploration Strategies given in Figure 5.27 visualized on AOI timelines.




(c) **Exploration Strategy 3**: $P_a^E$ is when the participant explored the environment in the first phase of the task. $P_a^S$ is when the participant selected objects in the first phase of the task. $P_b^E$ is when the participant explored the environment in the second phase of the task. $P_b^{S+E}$ is when the participant explored the environment and selected objects in the second phase of the task.




(d) **Exploration Strategy 4**: $P_a^E$ is when the participant explored the environment in the first phase of the task. $P_a^S$ is when the participant selected objects in the first phase of the task. $P_b^{S+E}$ is when the participant explored the environment and selected objects in the second phase of the task.

Figure 5.28: Exploration Strategies given in Figure 5.27 visualized on AOI timelines (Part 2).

### Fixation Strategy

The results of the fixation strategy for the viewpoint task are given in Table 5.29

| Exploration phase \ Fixation | $A^3 + R^3$ | $A^2 + R^3$ | $A^3 + R^{2.5}$ | $A^2 + R^{2.5}$ | $A^3 + R^2$ | $A^2 + R^2$ | Erratic | Total Participants |
|---|---|---|---|---|---|---|---|---|
| $P_a^E$ | 55% | 40% | | | | | 5% | 20 |
| $P_a^S$ | 41% | 41% | 6% | 6% | | | 6% | 17 |
| $P_a^{E+S}$ | 67% | 33% | | | | | | 3 |
| $P_b^E$ | 33% | 44% | | | | | 22% | 9 |
| $P_b^S$ | 23% | 15% | | | | | 62% | 13 |
| $P_b^{E+S}$ | 50% | | | 17% | 17% | | 17% | 6 |

Figure 5.29: Percentage of participants in different phases of the task that selected a particular view.

## Gaze-shift/Saccade strategy

The results for the gaze-shift/saccade strategy for the elevation task are given in Table 5.30

| Exploration phase \ Saccade | $A^3+R^3$ / $A^2+R^3$ | $A^3+R^3$ / $A^3+R^2$ | $A^3+R^3$ / $A^2+R^2$ | $A^3+R^3$ / $A^3+R^{2.5}$ | $A^2+R^3$ / $A^3+R^{2.5}$ | $A^2+R^3$ / $A^2+R^2$ | $A^2+R^3$ / $A^2+R^{2.5}$ | Erratic | Total Participants |
|---|---|---|---|---|---|---|---|---|---|
| $P_a^E$ | 25% | 15% | | | | 30% | | | 20 |
| $P_a^S$ | 29% | | | 12% | 12% | | 33% | | 17 |
| $P_a^{E+S}$ | 33% | | | 33% | | | | 33% | 3 |
| $P_b^E$ | 12% | | 12% | | | 25% | 12% | | 9 |
| $P_b^S$ | 12% | | | | | | 15% | | 13 |
| $P_b^{E+S}$ | | 33% | | | | | | | 6 |

Figure 5.30: Percentage of participants in different phases of the task that employed one of the saccade strategies.

# Chapter 6

# Discussion

In this chapter, we interpret what we have learned from our findings. We start by examining the results obtained from the quantitative phase and then do the same for the qualitative phase. We then address the limitations and further research of our study. Finally, we present a set of spatial visualization design recommendations for GIS systems that aim to enhance their effectiveness.

## 6.1 Quantitative Phase

In this section, we first discuss our findings about the complexity of the task i.e., the number of distractors. Then we discuss our findings about the dimension of the attribute space. Finally, we discuss our findings about the reference space. Here, we refer to both statistical and practical significance to discuss the impact of factors on quantitative results.

### 6.1.1 Distractors

In Section 5.3.1, we posited hypotheses for both the simple tasks, suggesting that time would increase with an increase in the number of distractors (H1 and H7). Our experimental results strongly accept both H1 (Height task) and H7 (Distance task), with $D_5$ being the quickest followed by $D_{15}$, and then $D_{25}$ in both the tasks. Additionally, we also hypothesized that the accuracy for the Height Task would remain unaffected (H2 - Height task), whereas for the Distance Task accuracy would increase (H8 - Distance task) with an increase in the number of distractors. Our experimental results strongly reject H2 and strongly accept H8, with $D_5$ being most accurate followed by $D_{15}$, and then $D_{25}$ in both the tasks.

Our results about the increase in time align with the findings of Cockburn et al. [16] where participants were asked to retrieve pages in increasing density of the dataset in a document management system. They found that the mean task completion time for retrieval tasks was significantly different with an increase in the density of the dataset, where participants had to contend with more "clutter".

Moreover, the rise in time from $D_{15}$ to $D_{25}$ is less prominent than the increase in time from $D_{15}$ to $D_5$ for both tasks. Furthermore, the time taken to solve the Height task is between 4.92 to 10.09 seconds, whereas the time taken to solve the Distance task is between 9.17 to 16.17 seconds.

On the other hand, the decline in accuracy from $D_{25}$ to $D_{15}$ is less prominent than the decrease in accuracy from $D_{15}$ to $D_5$ in the Height task. In contrast, for the Distance task, both decreases in accuracy from $D_{25}$ to $D_{15}$ and from $D_{15}$ to $D_5$ are similar. Furthermore, the accuracy of the Height task is between 74.31% to 91.67%, whereas the accuracy for the Distance task is between 36.11% to 62.04%.

Since our results show that the outcomes are consistent across both tasks we can say that the effect of the number of distractors on user performance is consistent and not task-dependent. Furthermore, our results emphasize that an increased number of distractors increases the time required and decreases accuracy significantly, indicating an influence on cognitive load during task-solving.

### 6.1.2 Attribute Space

In Section 5.3.1, we posited hypotheses for both simple tasks that the time taken will be similar for both $A^3$ than $A^2$ (H3 and H9). Our experimental results weakly accept H3 (Height task), with a 16.98% increase in the time taken for $A^3$ compared to $A^2$. However, H9 (Distance task) was strongly accepted, with a minimal 0.18% difference favoring $A^3$. Additionally, we hypothesized that the accuracy for these tasks would be similar for $A^3$ and $A^2$ (H4 and H10). Our experimental results strongly support both H4 (Height task) and H10 (Distance task), showcasing similar accuracy between $A^3$ and $A^2$, with a slight advantage for $A^3$.

These findings align with Seipel et al.'s [60] experiment, where participants were asked to estimate the ratio of two different spatial distance measurements and relative ranking among potential candidates in $A^3$ and $A^2$ settings. Their study concluded that accuracy and time were similar between $A^3$ and $A^2$. However their study was conducted in a $R^2$ setting for $A^2$ and $R^{2.5}$ setting for $A^3$ and were not compared in the same reference space.

Moreover, the time required to complete the Height task in $A^3$ is slightly greater than in $A^2$, with durations of 8.47 seconds and 7.24 seconds, respectively. Conversely, the time taken to complete the Distance task is similar in both $A^3$ and $A^2$, with durations of 12.96 seconds and 12.93 seconds, respectively.

On the other hand, the accuracy is comparable in both the task between both $A^3$ and $A^2$ with accuracy for Height task being 82.72% and 81.64% respectively, and Distance task being 49.38% and 48.92% respectively.

Since our outcome on time taken varies slightly across tasks, we can conclude that the impact of dimensionality of attribute space on time taken may be task-dependent but not significantly. On the other hand, our outcome on accuracy is consistent in both tasks, thus we can conclude that the impact of dimensionality of attribute space on accuracy is not task-dependent. Furthermore, our results emphasize that the dimensionality of the attribute space may not have a significant influence on the cognitive load, as the time taken was slightly more for $A^3$ as compared to $A^2$, whereas the accuracy remained similar for both $A^3$ and $A^2$ scenarios.

### 6.1.3 Reference Space

In Section 5.3.1, we posited hypotheses for both simple tasks that the time taken will not be affected by the dimension of the terrain and will be similar for $R^3$, $R^{2.5}$, and $R^2$ (H5 and H11). Our experimental results weakly accept H5 (Height task) and H11 (Distance task), with strong support between $R^3$ and $R^2$ for the Distance task. Time taken for the Height task was the least for $R^2$ followed by $R^{2.5}$, and then $R^3$, whereas for the Distance task time taken was comparable for $R^3$ and $R^2$ and was more than the time taken for $R^{2.5}$. Additionally, we also hypothesized for both simple tasks that the accuracy will be similar for $R^2$ and $R^{2.5}$ and will be greater than that of $R^3$ (H6 and H12). Our experimental results partially accept both H6 (Height task) and H12 (Distance task), with the accuracy of $R^3$ and $R^{2.5}$ being comparable and significantly less than that of $R^2$ in both tasks.

These findings partially align with Seipel et al's [59] experiment where participants evaluated height differences among bars in geographic positions and evaluated the distances between the bars. Their results show that there was no significant difference in time taken, with a slightly greater time for $R^3$. However, the accuracy for $R^2$ and

$R^{2.5}$ were comparable and significantly greater than that of $R^3$.

Moreover, the decrease in time from $R^{2.5}$ to $R^2$ is less prominent than the decrease in time from $R^3$ to $R^{2.5}$ for Height tasks. For the Distance task, the time taken is similar between $R^3$ and $R^2$ and is more than the time taken for $R^{2.5}$. Furthermore, the time taken to solve the Height task is between 6.98 to 8.81 seconds, whereas the time taken to solve the Distance task is between 12.31 to 13.29 seconds.

On the other hand, the accuracy for $R^3$ and $R^{2.5}$ is similar and less than the accuracy of $R^2$ for both tasks. Furthermore, the accuracy for the Height task is between 79.86% to 86.34%, whereas the accuracy for the Distance task is between 44.68& and 56.84%.

Since our outcome on time taken varies slightly across tasks, we can conclude that the impact of dimensionality of reference space on time taken may be task-dependent. On the other hand, our outcome on accuracy is consistent in both tasks, thus we can conclude that the impact of dimensionality of reference space on accuracy is not task-dependent. Furthermore, our results emphasize that the dimensionality of the reference space may influence cognitive load, as the time taken was slightly more for $R^3$ as compared to $R^2$, and also the accuracy was significantly less for $R^3$ and $R^{2.5}$ as compared to $R^2$.

## 6.2 Qualitative Phase

In this section, we first talk about our findings about the fixation analysis. We then talk about our findings about gaze shifts/saccade.

### 6.2.1 Fixation analysis

As observed in both Table 5.26 and 5.30, throughout all exploration phases, the $R^3$ terrain consistently emerged as the most favored view. The choice between $A^3$ or $A^2$ views could potentially depend on the screen position, given that during each exploration phase, 50% or more of the participants opted for the $R^3$ view positioned at the top-middle of the screen. Moreover, The use of 3D does not align with the findings from Section 6.1.3 of our study, where we found that a $R^3$ view took more time and was less accurate compared to other views. The motivation behind opting for a $R^3$ view may stem from various factors including:

- According to the findings of Lei et al. [41], $R^3$ view had a prolonged and focused browsing as compared to $R^2$ view. The extended fixation time of $R^3$ view allowed users to acquire more detailed information about the environment and thus enhance the overall understanding. Moreover, Tory et al. [67] in their findings stated that in a combined 3D/2D display, participants utilized 3D view significantly more than 2D view.

- A more appealing and aesthetic effect of 3D might have lead participants to engage in $R^3$ more than a $R^2$ or $R^{2.5}$ view [52, 26, 71, 16].
- $R^3$ view was always centrally placed. This decision was based on the findings of Tory et al. [67] which stated that the eye-gaze patterns were not significantly altered whether the $R^3$ view was positioned centrally or off to the side. However, there was a significant difference in error analysis, indicating that a $R^3$ view in the center may reduce the number of serious errors compared to $R^3$ views placed off to the side.
- The Elevation task required participants to select bars based on their elevation on the terrain. For this, a $R^3$ terrain view was the only option as the other views lacked terrain height information i.e., they were flat and photo-realistic and did not contain contour lines. The use of 3D maps in the Viewpoint task remains unaffected by their usage in the Elevation task. This is because of the usage of a Latin Square methodology for task sequencing. Specifically, half of the participants (12) started with the Viewpoint task, thus ensuring an absence of bias in map usage.

Additionally, in the second phase of both tasks ($P_b$), a noticeable increase in erratic behavior was observed in the Elevation task where participants deviated from fixating on a single view to solve the task. On the other hand, in the Viewpoint task, erratic behavior did not increase significantly, and participants preferred sticking to $R^3$ view. This showed that participants were more comfortable using $R^3$ to find the tallest bar in the Viewpoint task than finding the distance in the Elevation task. Furthermore, in the Elevation task, 9% of participants in $P_b^E$ and 27% in $P_b^S$ favored the $R^2$ view, as illustrated in Table 5.25. Interestingly, none of the participants showed a preference for $R^{2.5}$. In the Viewpoint task, 12% of participants opted for one of the $R^{2.5}$ views during $P_a^S$, while 17% utilized $A^2$+$R^{2.5}$, and an equal percentage chose $A^3$+$R^2$ in $P_b^{E+S}$. Surprisingly, none of the participants selected $A^2$+$R^2$ (top-down view) during the Viewpoint task. These findings suggest that, apart from the preference for $R^3$, the choice of other reference space types may be task-dependent.

### 6.2.2 Gaze-shift/Saccade Analysis

As observed in both Table 5.26 and 5.30, gaze shifts during both tasks predominantly involved the use of a $R^3$ view. This consistency in the choice of viewpoint aligns with the fixation analysis in Section 6.2.1, which also highlighted the use of $R^3$. These findings do not align with the findings of the Quantitative phase in Section 6.1.3 of our study where we found that a $R^3$ view took more time and was less accurate compared to other views.

Another interesting observation is the notable difference in the number of different gaze shifts between the Viewpoint and Elevation tasks throughout all phases of exploration. Specifically, the Viewpoint task consistently had a significantly higher number of shifts, except during phase $P_b^{e+S}$, where the Elevation task surpassed the Viewpoint task in the count of gaze shifts by 3. A reason for this could be the nature of the tasks themselves. The Viewpoint task necessitated comparisons between multiple viewpoints and demanded an overall understanding of the environment, potentially favoring the use of combination views [26, 68]. Thus, the frequency of gaze shifts might be dependent on the complexity and specific requirements of the task, suggesting a task-dependent nature in gaze-shift patterns.

Lastly, in both tasks, gaze shifts were observed during the selection phase between $R^3$ and $R^{2.5}$ views in $P_a$. This might be because $R^{2.5}$ looks similar to $R^3$ view and also provides less occlusion [58]. In contrast, during the exploration phase, shifts occurred between $R^3$ and $R^2$ views which align with the findings of Convertino et al. [18] that state that orthogonal views were observed to assist users in patter recognition and focusing attention on spatial relationships. During $P_b$ no such patterns were observed. This observation further highlights shifts in saccade patterns during different phases of the task. Additionally, there was no specific pattern observed in the dimensionality of attribute space during gaze-shifts and aligns with our findings from Section 6.1.2 of our study as it states that the dimensionality of the attribute space may not have a significant impact on the cognitive load of the participant during task solving.

## 6.3 Limitations and Further Research

In this section, we list limitations that might have affected the findings of our study and discuss future research directions. These are as follows:

- Due to time constraints, the experiment could only include a limited number of tasks. Conducting the same experiment with a greater number of or different sets of tasks might provide a clearer understanding of whether the dimensionality of the presentation space is task-dependent or not. Further research can include additional tasks that could offer a better perspective on the generalizability of the findings across different types of cognitive activities.

- The time constraints in the length of the study limited the exploration of whether camera angles influence how users perceive data in different dimensions. Increasing the number of repetitions in the experiment could have provided the opportunity to systematically investigate the impact of various camera angles on participants' perceptions. Further research can include incorporating higher difficulty levels as it will help in determining a threshold where time and accuracy no longer exhibit a significant change, providing a better understanding of the relationship between the complexity of the task and performance metrics. It can also include investigations of whether camera angles have an impact on user performance.

- The time constraint in the length of the study limited the number of quantitative tasks to only 2. Expanding the number of tasks in the experiment could have offered a clearer understanding of whether accuracy and task completion time in various dimensional views are task-dependent. Further research can explore whether specific views prove more effective for particular tasks.

- Increasing the number of participants in the experiment would have allowed for a larger dataset, enabling a more robust analysis of the findings. A larger sample size would enhance the generalizability and reliability of the research results.

- The blurring of the terrain texture on flat surfaces could have potentially influenced the results. Visual clarity and detail play a role in perception and decision-making, and any distortion in the texture might impact participants' responses and behavior during the experiment. Future research can conduct a comparative study on different textures of maps, and compare if change in texture leads to a difference in user performance.

- Limiting the experiment to a forestry domain may have introduced a specific bias in the outcomes, as different environments or scenarios could yield different results. Future research can expand our research scope by conducting a study on diverse sets of data from various domains and on different tasks. This approach will contribute to a better understanding of the subject matter and enable us to draw a more general conclusion.

- Distance task had significantly less accuracy as compared to the Height task. The task design for the Distance task only took into account the distance between objects. One potential explanation for reduced accuracy could be attributed to the angle formed between object pairs and the impact of depth perception on distance perception. To address this, future research could investigate user performance by examining the distances about the angle between object pairs. Additionally, the camera positions could also be used to alter the angle from which users perceive the data and could provide valuable insights into understanding and improving distance judgment.

- Width and height are the two monocular depth cues that are used by the observers to perceive depth within an environment. In this study, 2D scaling was implemented to enlarge the width of bars situated farther back, thus eliminating the monocular depth cue of width and focusing solely on height as the determining factor. However, this approach may have introduced a bias in the findings as both width and height are used as monocular depth cues [10]. Future research could investigate whether keeping the monocular depth cue of width influences user performance.

## 6.4 Design Recommendations

In this section, we list a set of design recommendations that could enhance the efficiency of geo-visualization representations in GIS systems based on our findings. The recommendations are as follows:

- Our findings in Section 6.1.1 suggest that the complexity of the task has a significant impact on the cognitive load of the participant while solving tasks.

Tasks with the least complexity i.e., the least number of distractors on screen had the highest user performance in both the tasks according to our findings in Section 5.3.4. Moreover, user performance decreased significantly at each increasing level of difficulty (in terms of complexity). Thus, we propose that the visualization in the system should be simplified by abstracting the data. To enhance data simplification, Shneiderman's [61] seven abstract tasks for users- overview, zoom, filter, details-on-demand, relate, history, and abstract, should be employed in the system. This will help make the data clearer and easier to understand.

- Our findings in Section 6.1.2 suggest that the dimension of attribute space may not have a significant impact on the cognitive load. It may have a slight impact on the task completion time based on the type of task but will not affect the accuracy of the task. Moreover, through our findings in section 6.2.1 and 6.2.2, we also concluded that participants did not have a preference for a specific view based on the dimension of the attribute space. Thus, we propose that both dimensions - $A^3$ and $A^2$ can be employed to design a visualization system. However, based on the type of task, it may have a small but negligible impact on task completion time.

- Although our findings in Section 6.1.3 identified $R^3$ as the least efficient view, participants demonstrated a preference for using it to solve complex tasks as discussed in Section 6.2.1. Our findings also align with previous literature that states that a $R^3$ view may provide a more appealing and aesthetic effect that leads participants to engage in it more than any other view type [52, 26, 71, 16]. Based on these findings, we propose that the primary view of the system employs a $R^3$ view. A secondary view can be accompanied along with the $R^3$ view in the form of either a $R^{2.5}$ or $R^2$ view, a choice that could be task-dependent as discussed in Section 6.2.2. Providing $R^2$ view will help during exploration phases as the orthogonal view will provide users with a new perspective and also help users to pay attention to spatial relationships. Additionally, our findings in Sections 6.1.2 and 6.1.3 consistently show that the $A^2 + R^2$ view achieves the highest accuracy. This may be because the two dimensions of this space are orthogonal to the line of sight, facilitating rapid eye movement between patterns. In contrast, in a 3D space, depth cues and occlusion limit the amount of visible information on the screen, reducing the capacity to convey information effectively [73]. Providing a 2D overview map alongside the 3D environment enables users to understand the relative layout and distances between objects [73]. Therefore, it is recommended to present this view as a secondary orthogonal perspective. On the other hand, a $R^{2.5}$ view will provide a perspective of the terrain with less occlusion and can help users during the selection phases. Furthermore, having a secondary view will provide multiple perspectives of the information and users will have the option to use both views in combination which might mitigate the shortcomings associated with a pure $R^3$ view and also enhance exploratory view analysis of spatial data that could potentially offer new possibilities to evaluate landscapes [12]. A combined view could also outperform the performance of a pure $R^2$ view [69] which was found to be the most accurate view in both tasks according to our findings in Section 5.3.4.

The type of navigation controls can also affect the efficiency of problem-solving. For instance, according to Ware and Plumlee [73], the visual working memory has a capacity to store 3 simple items/patterns. If users have to compare 3 or fewer patterns, zooming navigation proves to be the most efficient. However, if the comparison is for more than 3 patterns, having multiple windows for navigation proves is more efficient because users can have rapid eye movements back and forth and do not have to store the information in the visual working memory.

# Chapter 7

# Conclusion

Advancements in technology have made it possible to use 3D in GIS technologies and have evolved it from using just 2D maps. This has raised a debate in the field of information visualization regarding the usage of 3D versus 2D. Some argue that 2D is better for detailed analysis, precise navigation, and orientations, while others argue that 3D is better for overall understanding, shape understanding, and facilitating navigation. The varying strengths observed for these two dimensions also suggest that combining these views could improve overall user performance by mitigating the shortcomings of individual views.

To compare 3D and 2D dimensions we initially introduced a systematization to categorize the presentation space of the visualization, comprising of an attribute space (data) and reference space (terrain). This systematization is an expansion to the foundation laid by Dubel et al. [21]. Our expansion involves refining the 2D reference space defined by Dubel et al. by further categorizing it into a 2.5D and 2D space. This categorization is based on the type of camera employed, with 2.5D employing a perspective camera and 2D employing an orthographic camera. The resulting systematization offers a framework for the comparative analysis of different dimensions.

We developed a system named MultiDim using Unity which included all views outlined in our systematization along with a mosaic view that consisted of all views on a single screen. To ensure coherence, we synchronized the camera and user interactions across all views, facilitating synchronized data interpretation. Additionally, the system integrated an eye tracker that allowed us to monitor participants' eye movements throughout task-solving. This eye-tracking functionality provided insights into participants' interactions with the system and offered vital information about their focal points during task execution.

We conducted a user study consisting of a quantitative part and a qualitative part, involving 24 participants (10 male, 14 female), and presented the results. The quantitative part aimed to compare participant efficiency at completing different, relatively simple tasks and dimensions of attribute and reference space. The findings revealed the user performance of participants under various conditions and highlighted differences between dimensions in terms of accuracy and task completion time. On the other hand, the qualitative study relied on eye tracker data and highlighted different strategies that participants employed while solving more complex tasks. This study revealed the user preferences and gaze patterns of participants while solving the tasks.

Our findings indicate that the complexity of a task, determined by the number of distractors and the dimension of the reference space, significantly affects user performance. Interestingly, the dimension of the attribute space does not have a significant impact on user performance. Additionally, eye-tracking data revealed that users show a preference for 3D reference space views when dealing with complex tasks, and their choice of using a secondary view depends on the nature of the task.

Lastly, our study opens up possibilities for future research, suggesting comparisons between different dimensions, such as camera angle, terrain texture, various domains, and tasks. Furthermore, we propose ways to enhance Geographic Information Systems (GIS) by recommending specific dimensional views that are suitable for task-solving, based on the insights gained from our study.

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# Appendix A

# Additional Information

## A.1 Elevation task

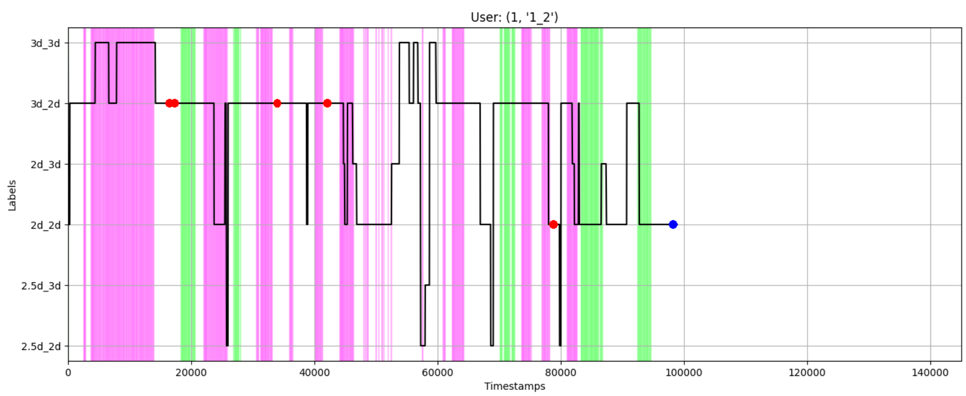


Figure A.1: Participant 1

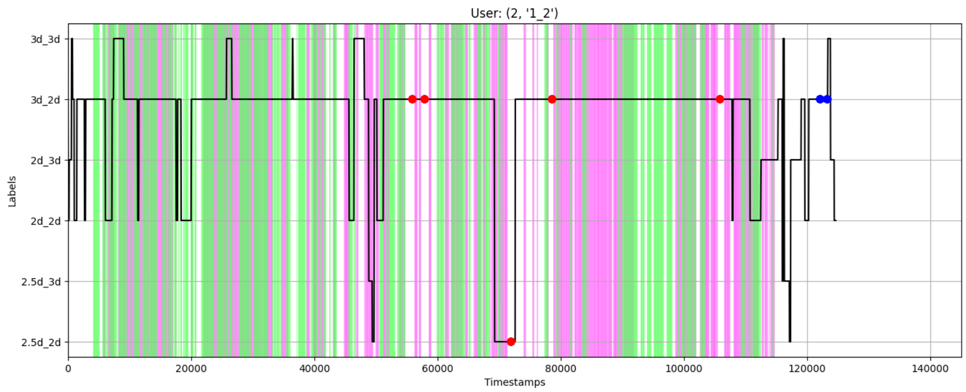


Figure A.2: Participant 2

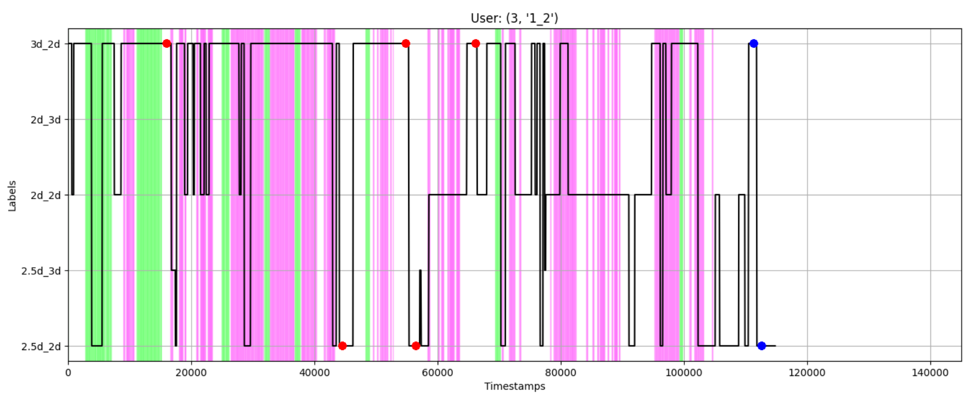


Figure A.3: Participant 3

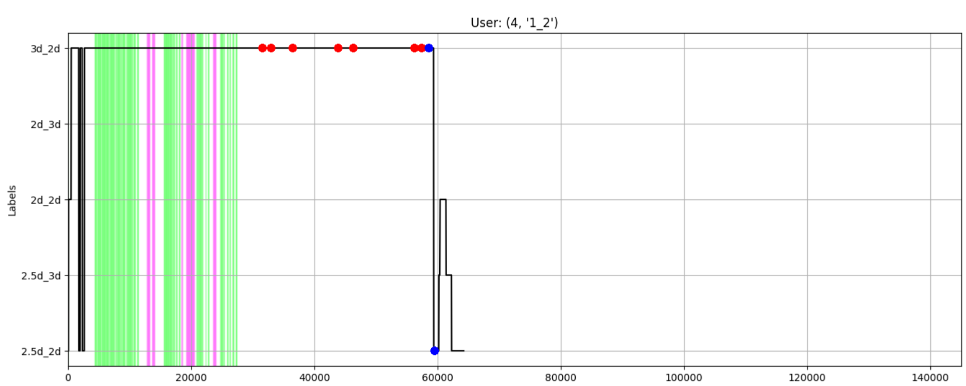


Figure A.4: Participant 4

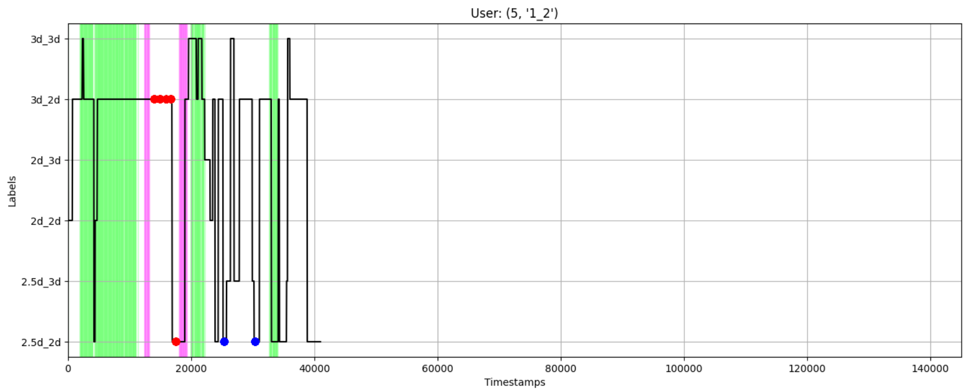


Figure A.5: Participant 5

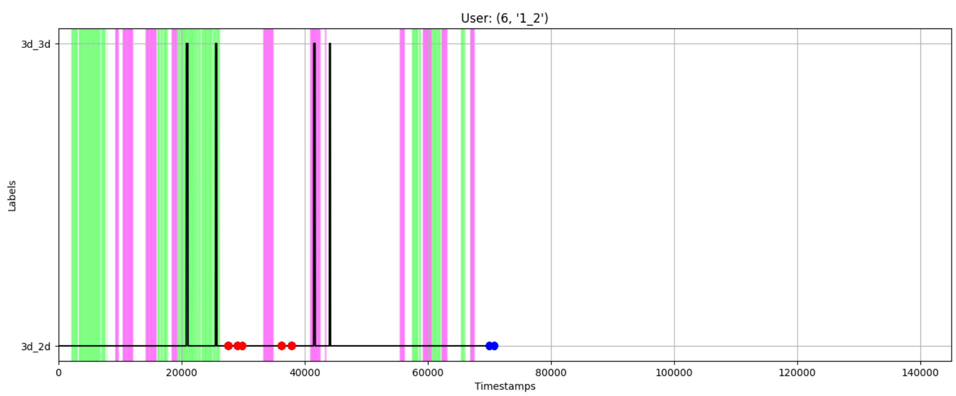


Figure A.6: Participant 6

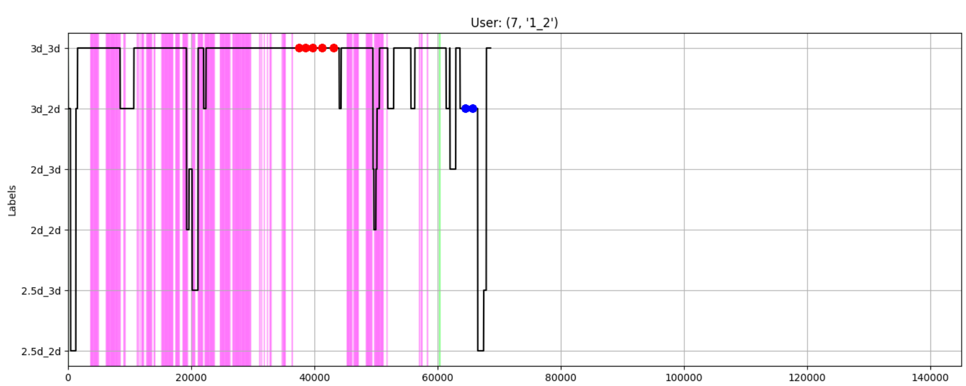


Figure A.7: Participant 7

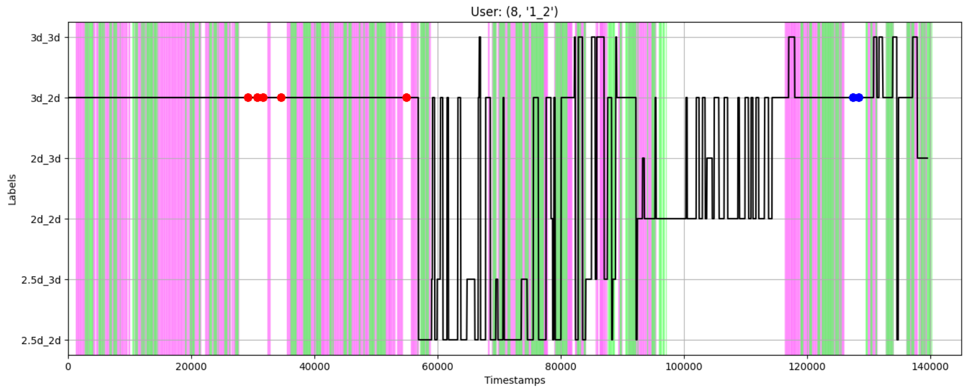


Figure A.8: Participant 8

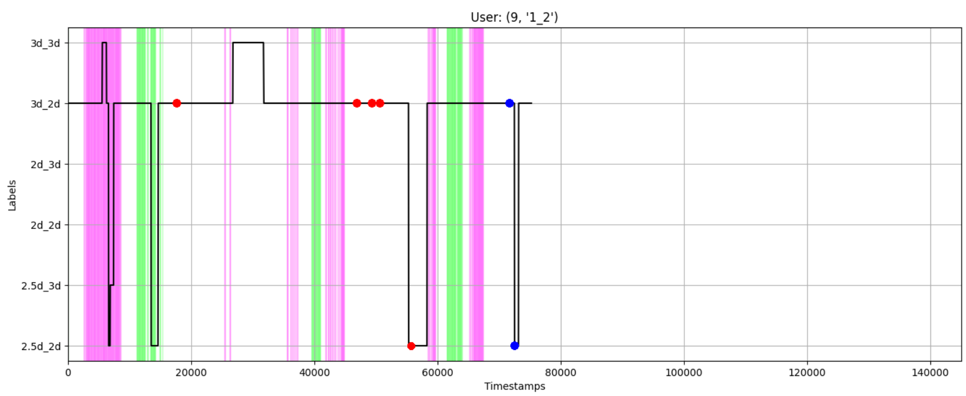


Figure A.9: Participant 9

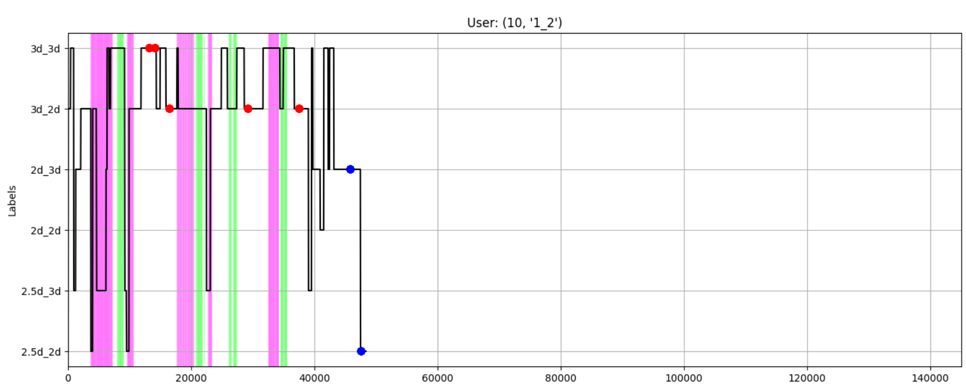


Figure A.10: Participant 10

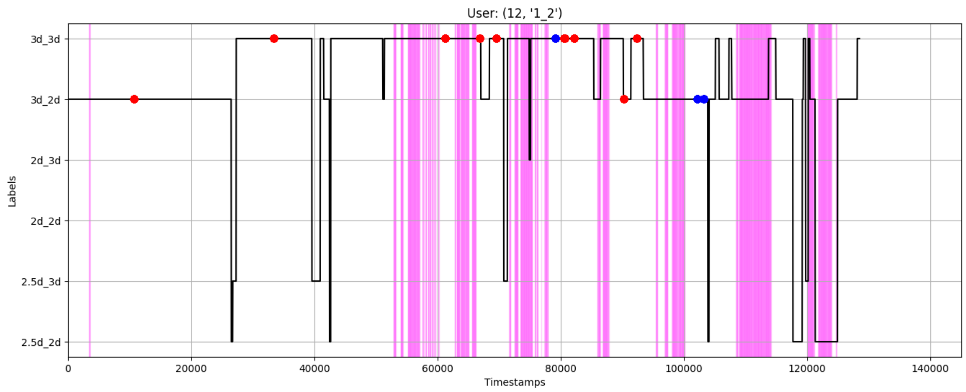


Figure A.11: Participant 12

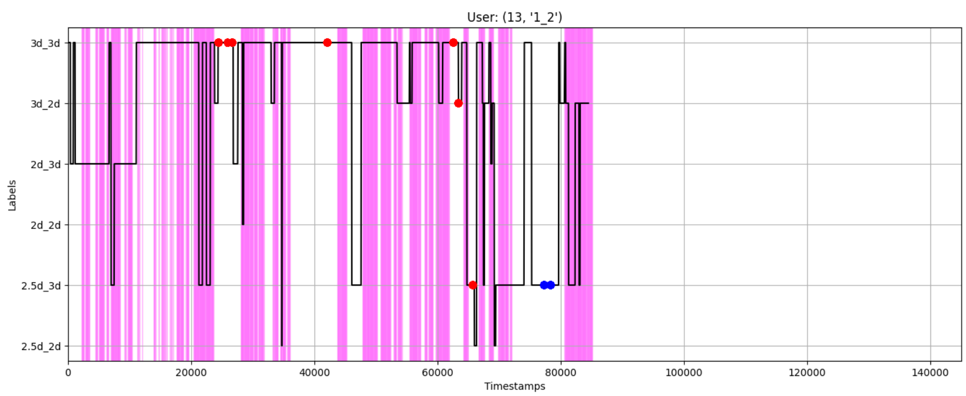


Figure A.12: Participant 13

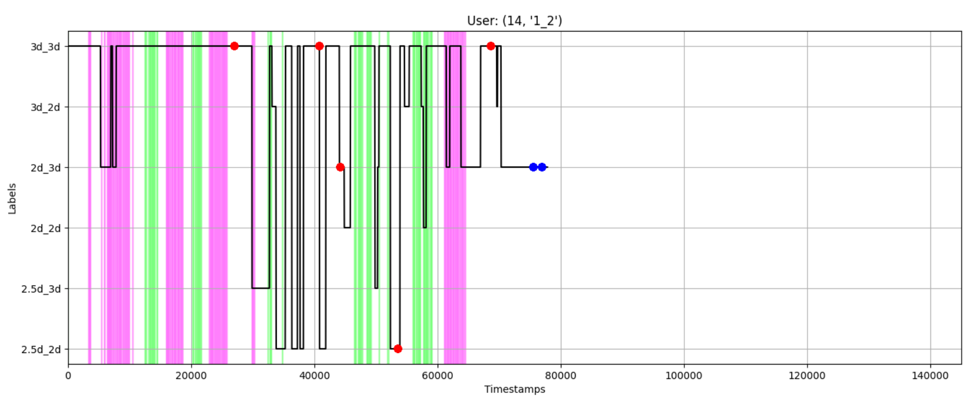


Figure A.13: Participant 14

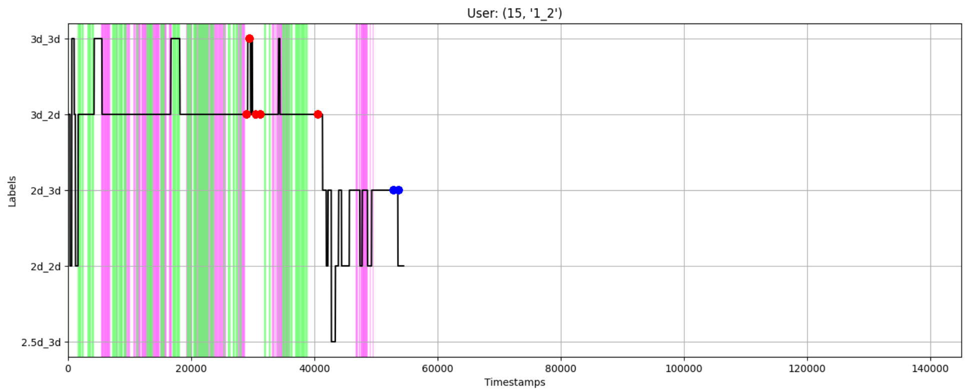


Figure A.14: Participant 15

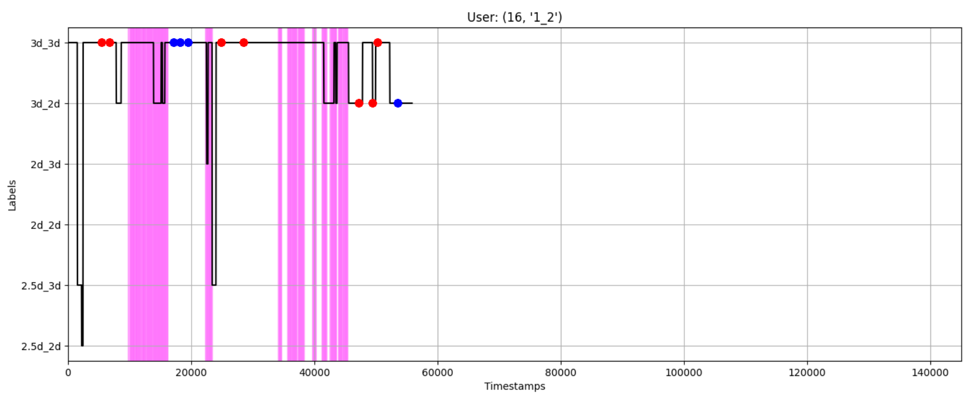


Figure A.15: Participant 16

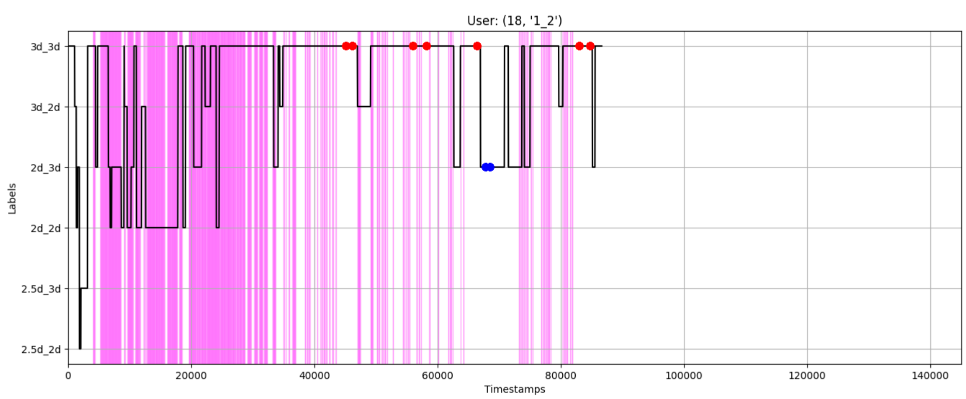


Figure A.16: Participant 18

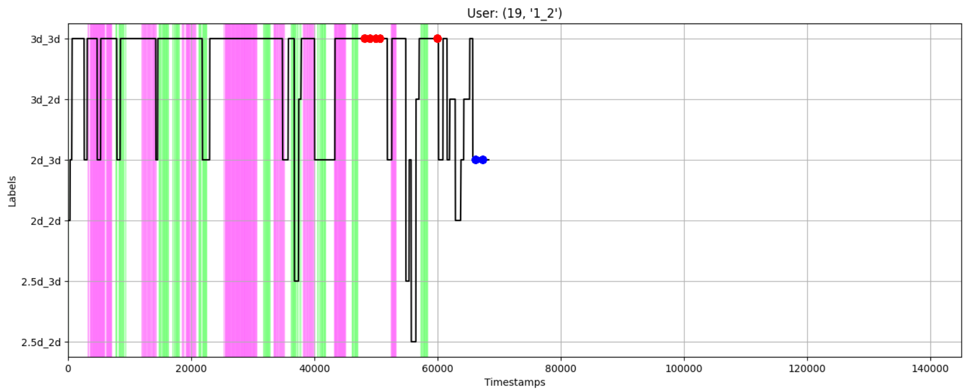


Figure A.17: Participant 19

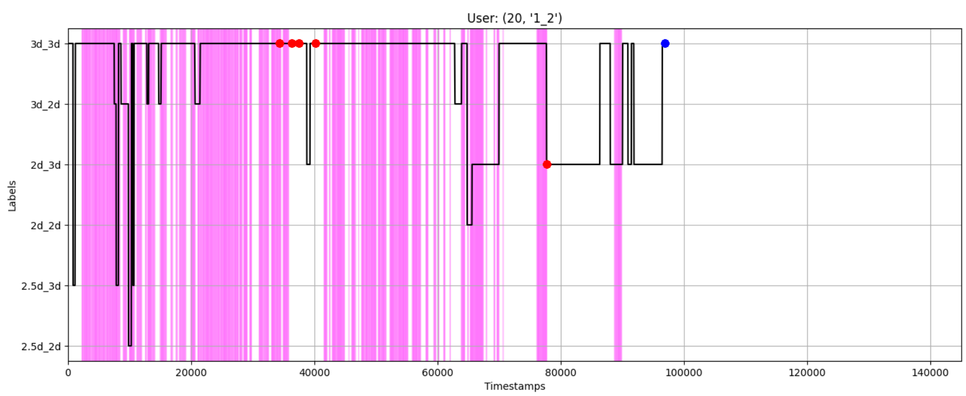


Figure A.18: Participant 20

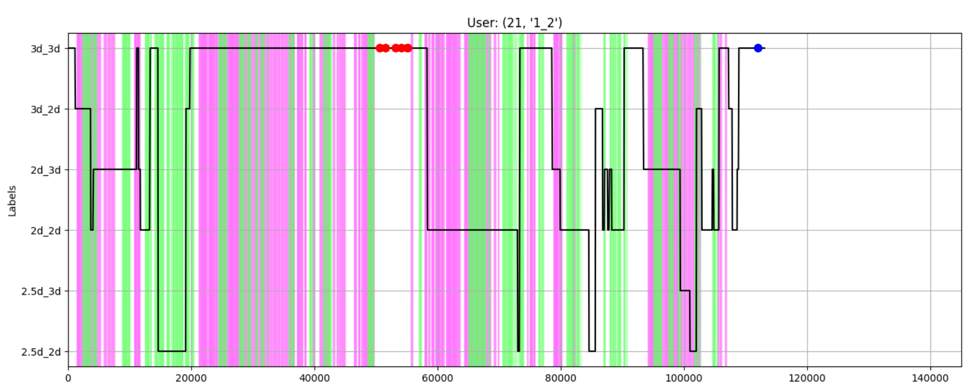


Figure A.19: Participant 21

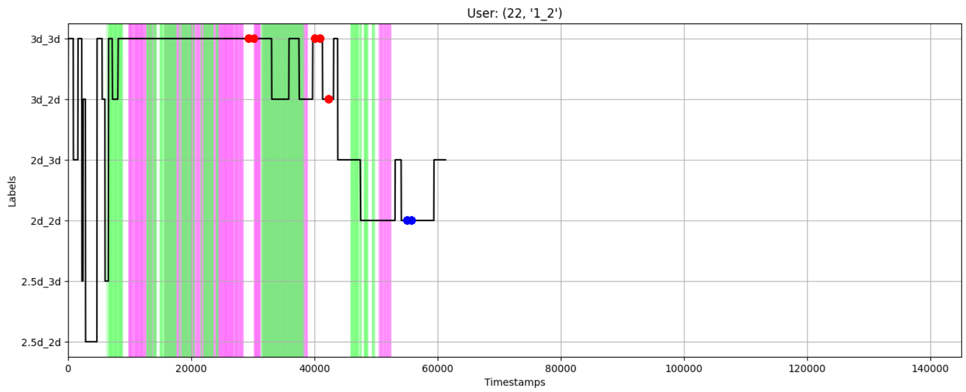


Figure A.20: Participant 22

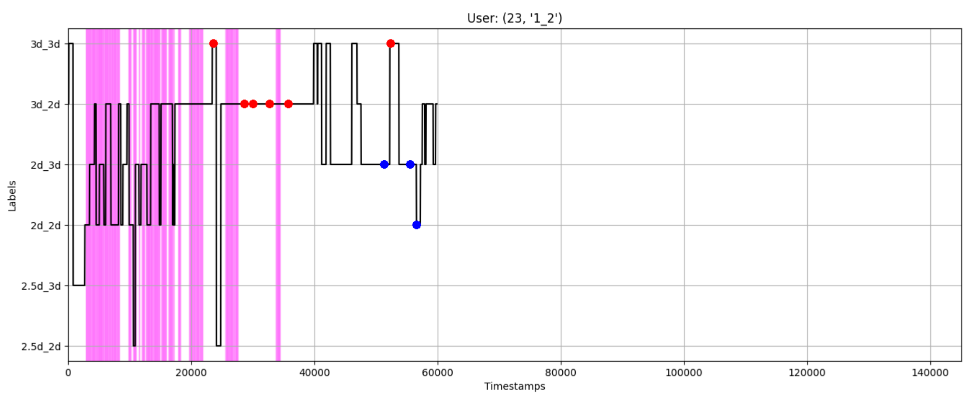


Figure A.21: Participant 23

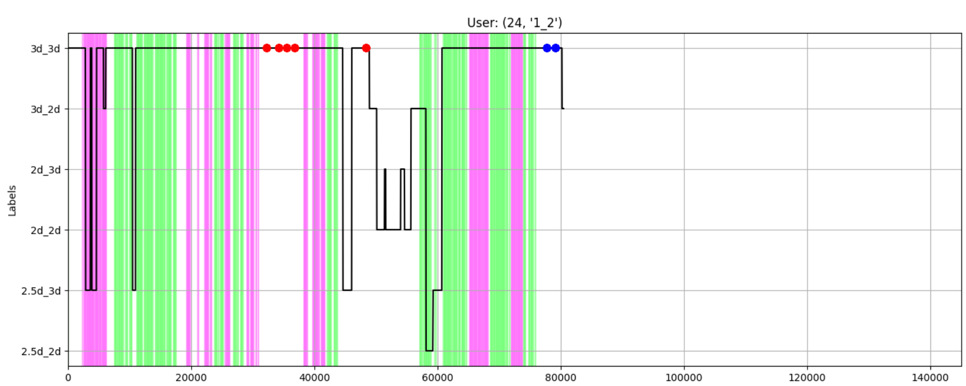


Figure A.22: Participant 24

## A.2 Viewpoint Task

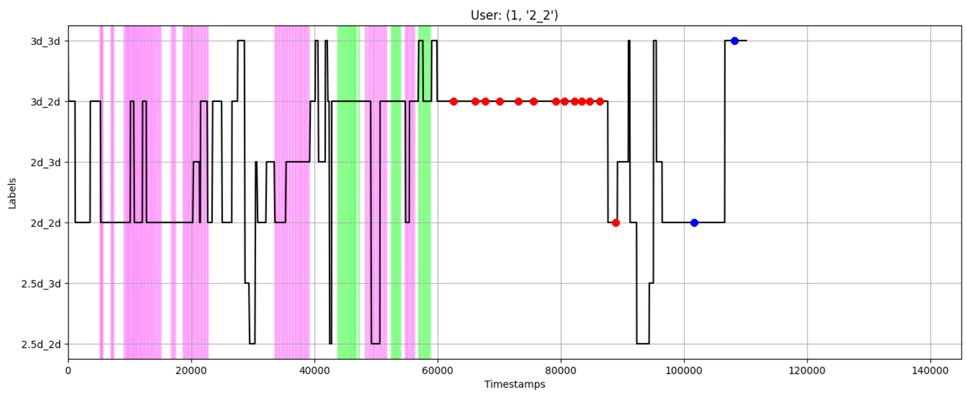


Figure A.23: Participant 1

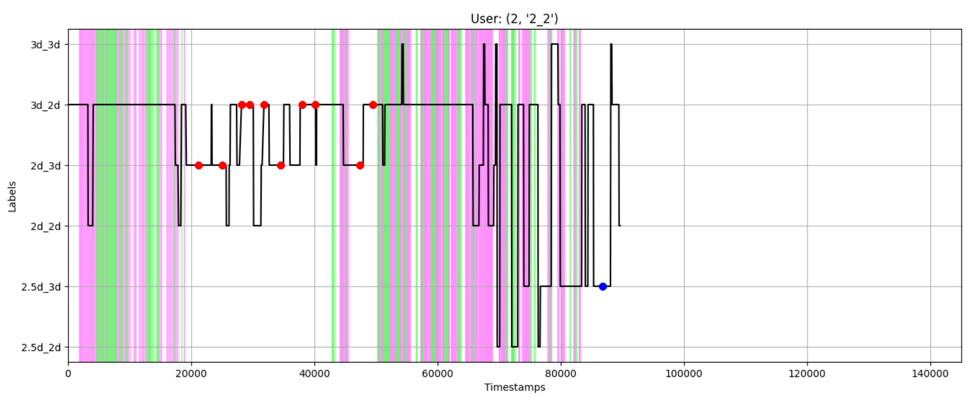


Figure A.24: Participant 2

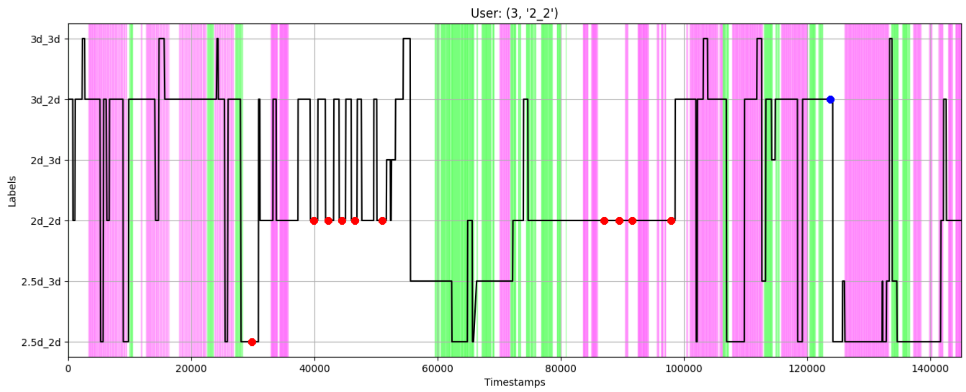


Figure A.25: Participant 3

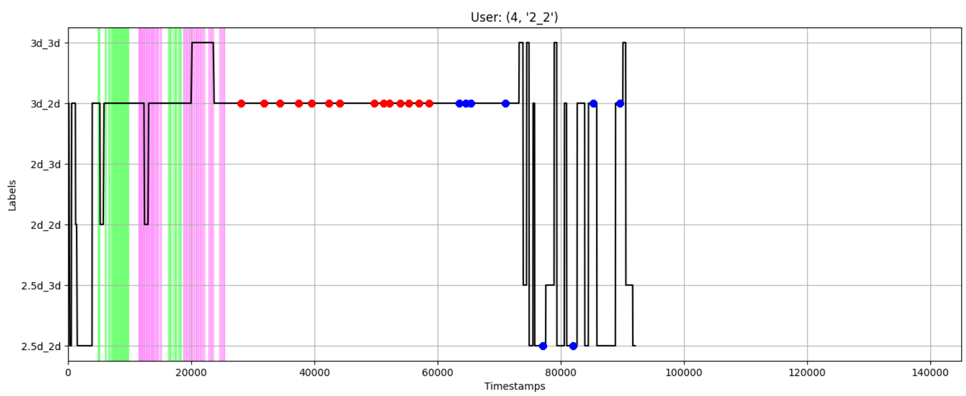


Figure A.26: Participant 4

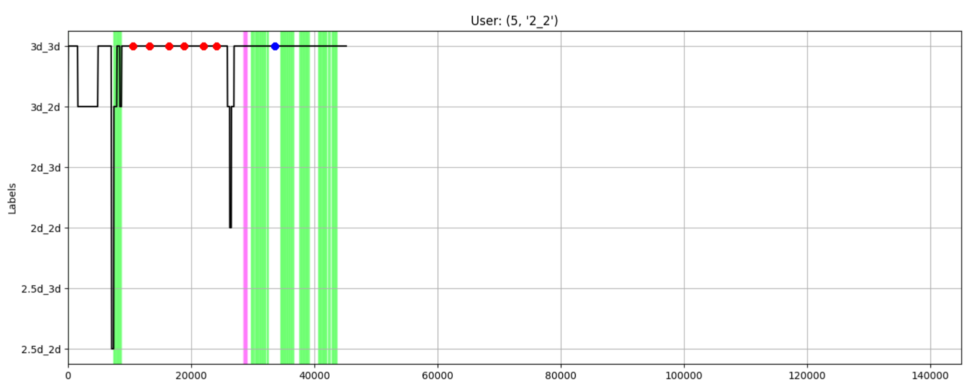


Figure A.27: Participant 5

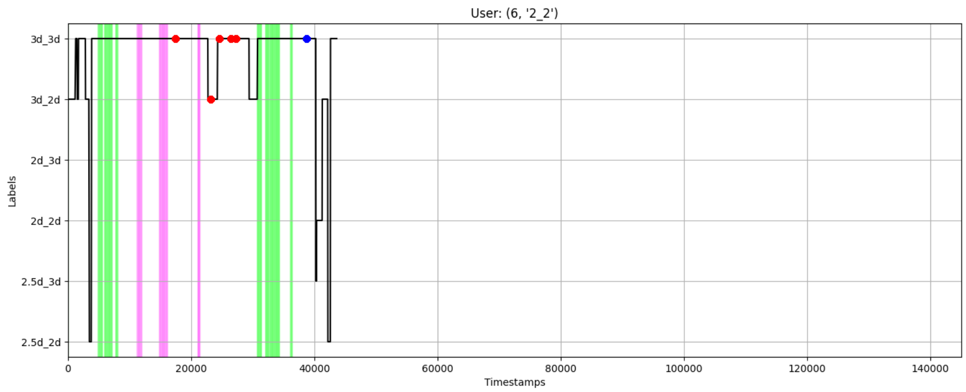


Figure A.28: Participant 6

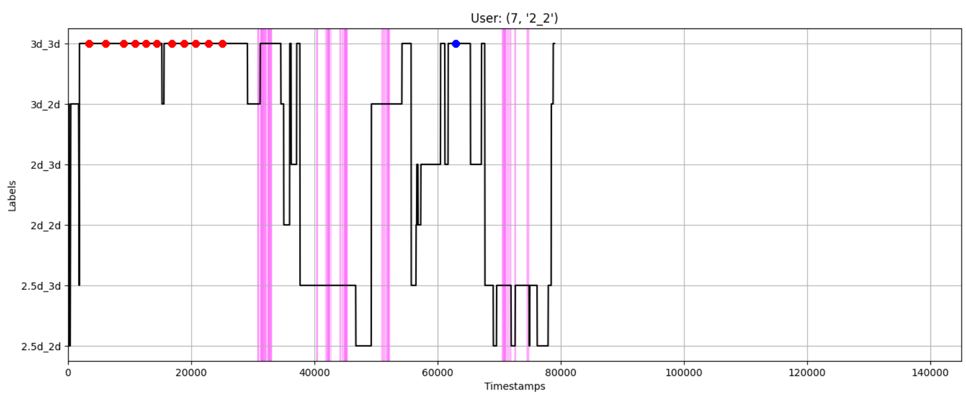


Figure A.29: Participant 7

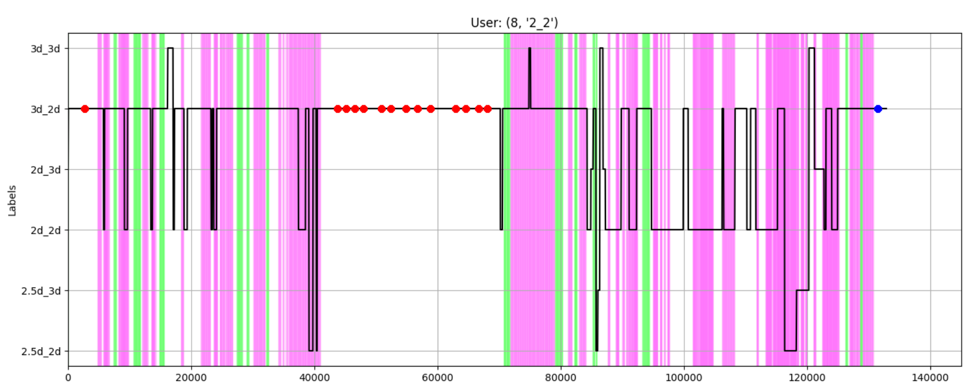


Figure A.30: Participant 8

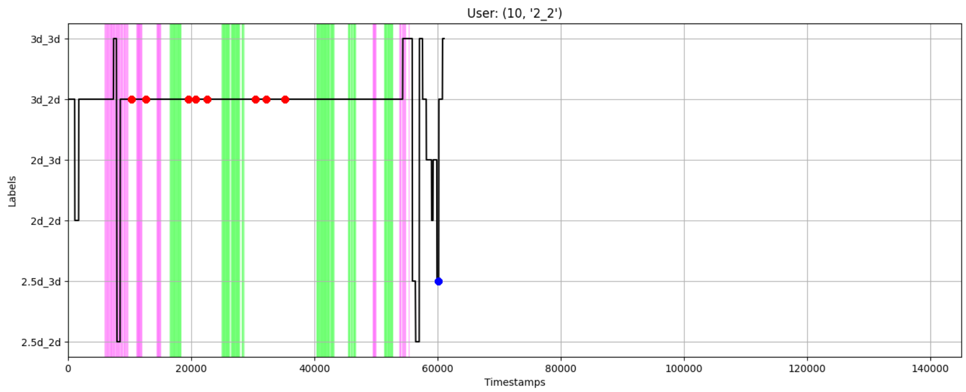


Figure A.31: Participant 10

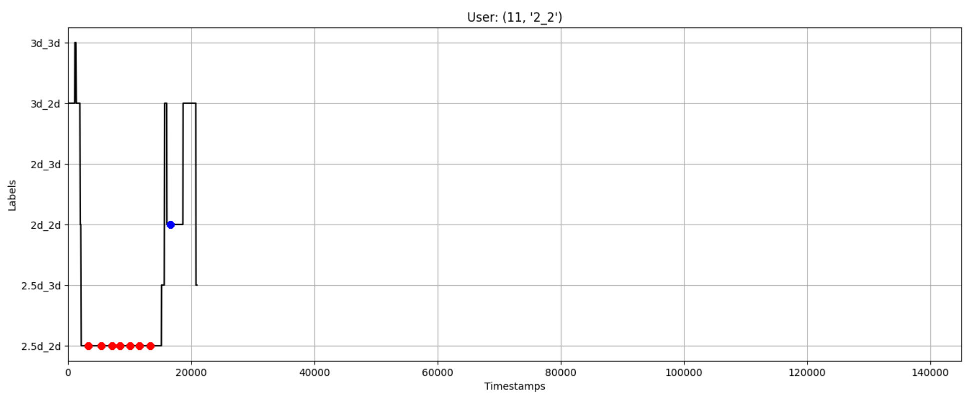


Figure A.32: Participant 11

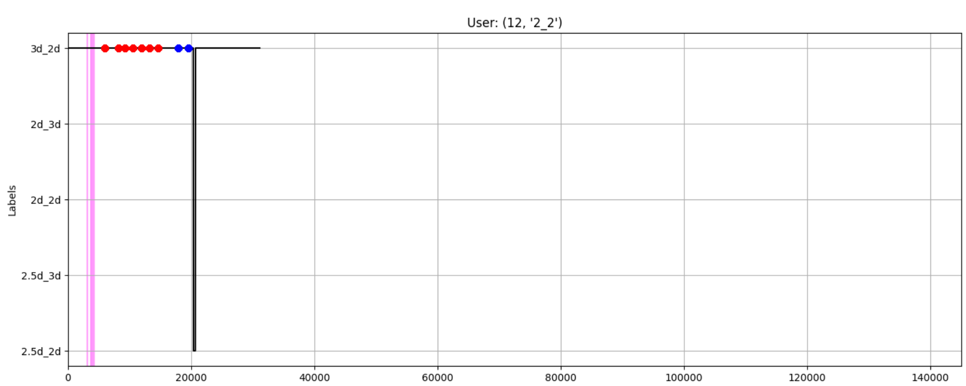


Figure A.33: Participant 12

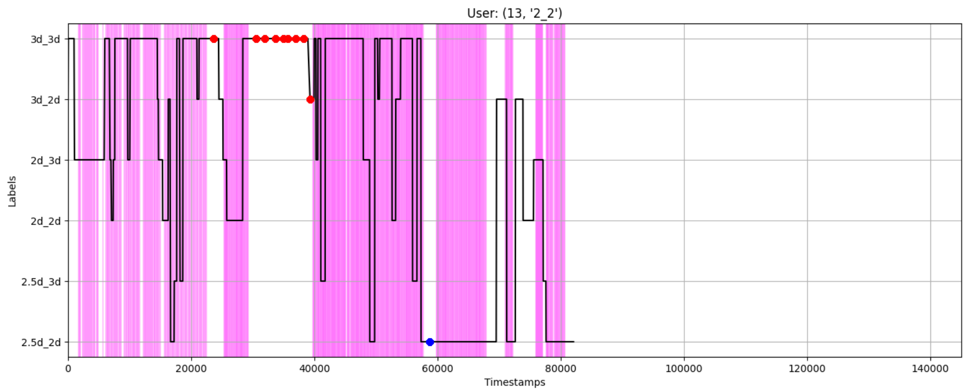


Figure A.34: Participant 13

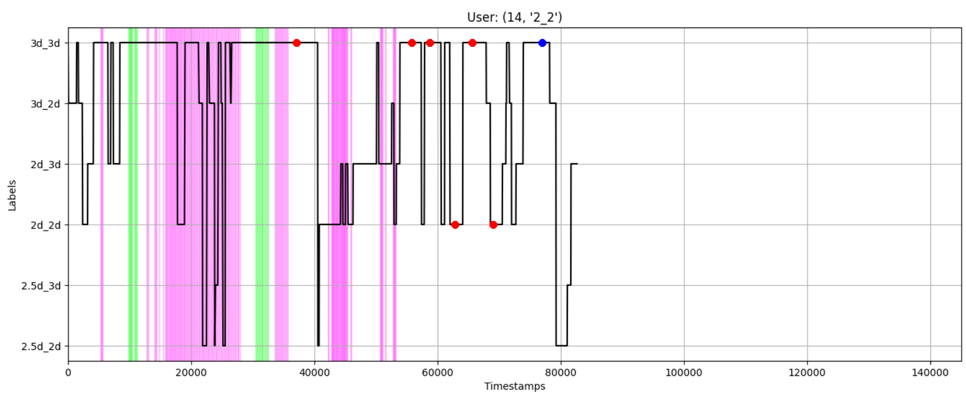


Figure A.35: Participant 14

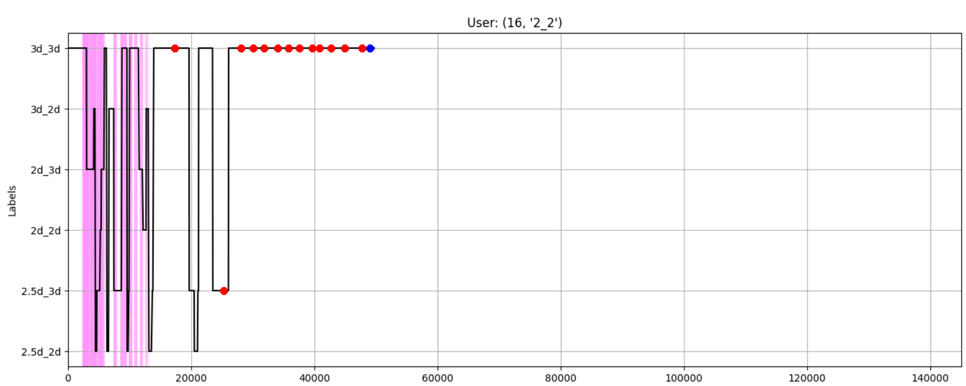


Figure A.36: Participant 16

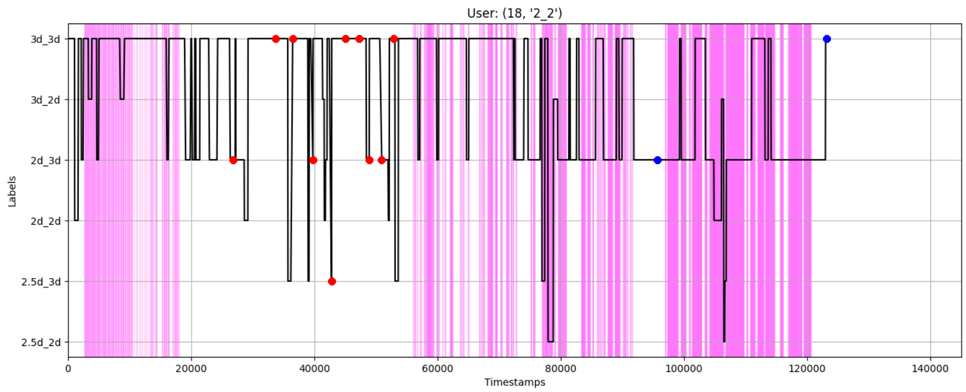


Figure A.37: Participant 18

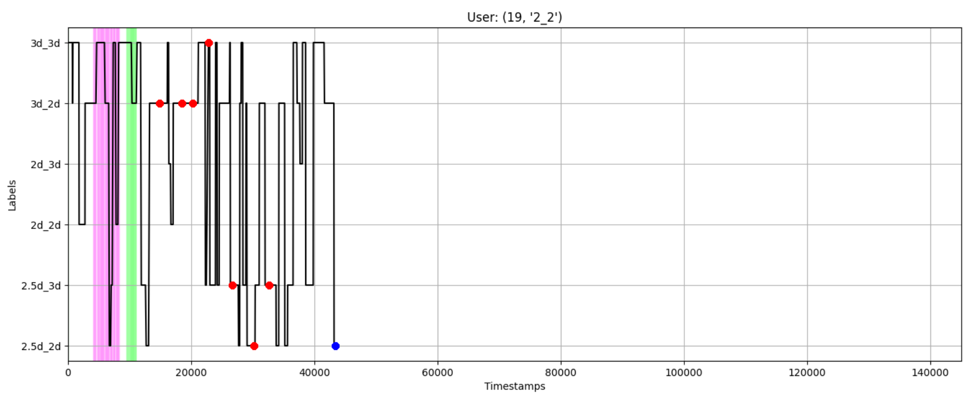


Figure A.38: Participant 19

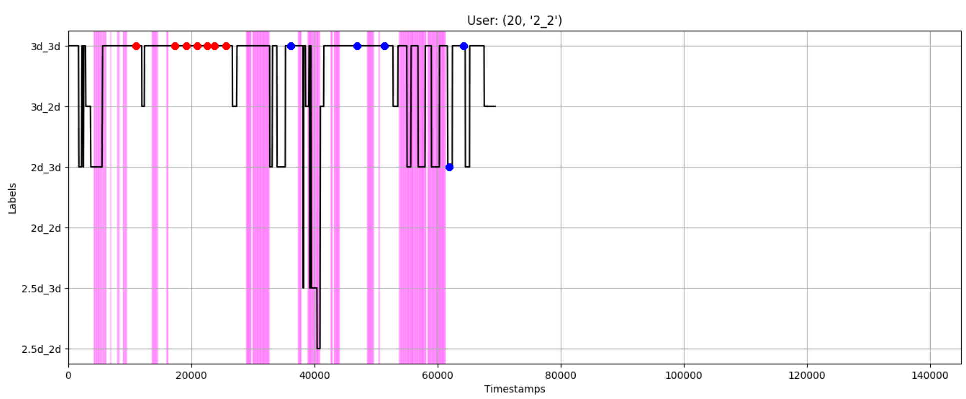


Figure A.39: Participant 20

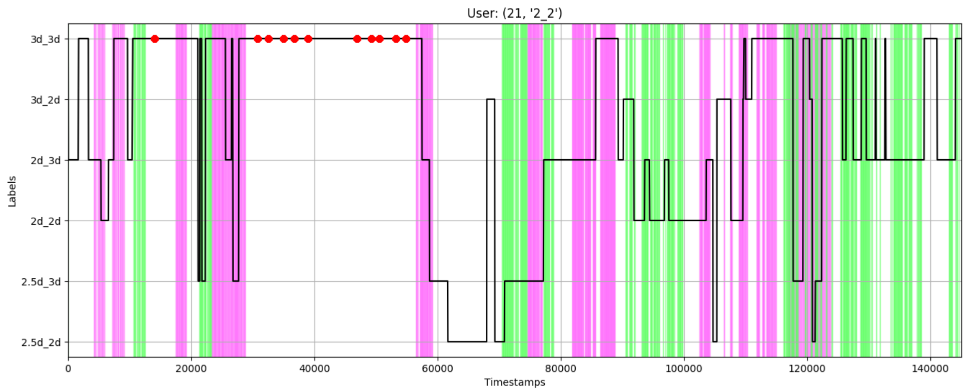


Figure A.40: Participant 21

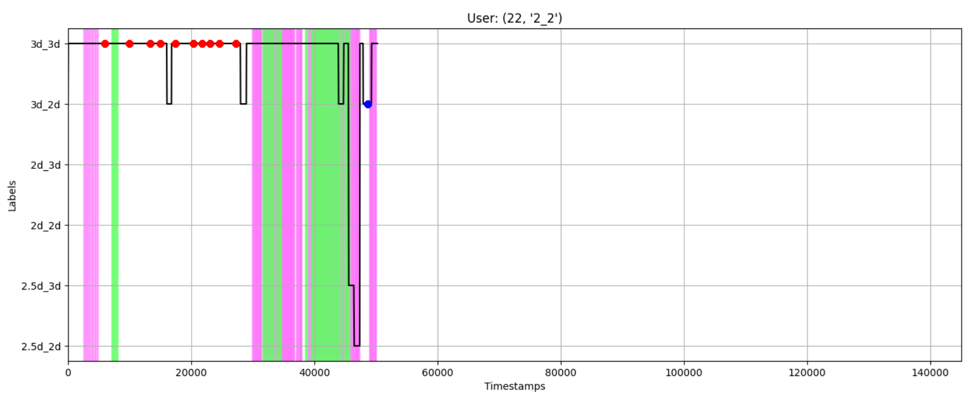


Figure A.41: Participant 22

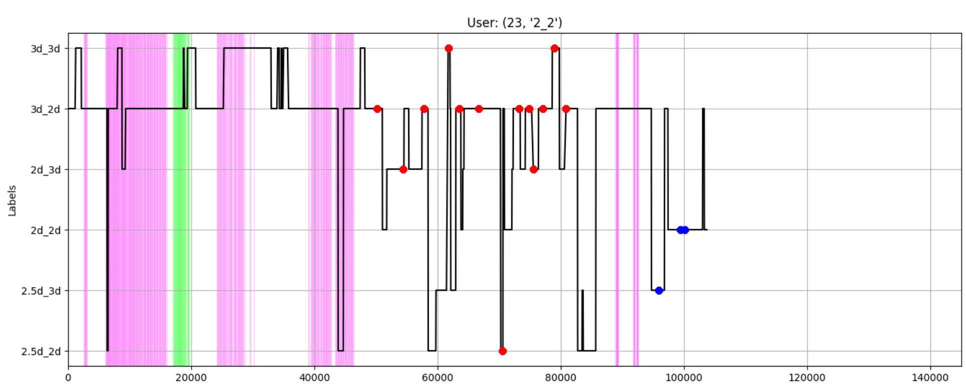


Figure A.42: Participant 23

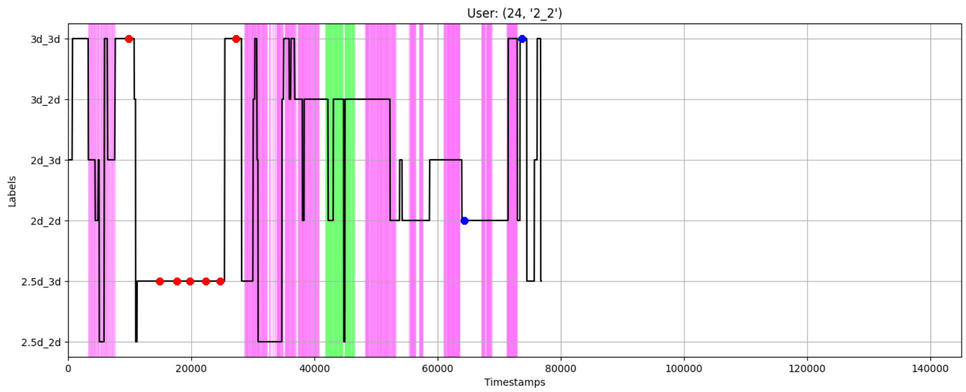


Figure A.43: Participant 24