



Enhancing User Experience for Data Visualization in Three-Dimensional Immersive Space

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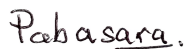
This dissertation is submitted to the University of Colombo School of Computing
In partial fulfillment of the requirements for the
Degree of Bachelor of Science Honours in Information Systems



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Declaration

I, H.M.P.S. Anjalika (2020/IS/004) hereby certify that this dissertation entitled Enhancing User Experience for Data Visualization in Three-Dimensional Immersive Space is entirely my own work and it has never been submitted nor is currently been submitted for any other degree.



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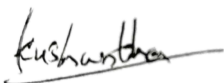


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Abstract

In the era of big data, effectively interpreting complex datasets is critical for decision-making across various fields. Many use data visualization formats, such as 2D techniques, to aid in this process. However, traditional 2D data visualization limits the ability to immerse oneself in the data and analyze large-scale, complex multidimensional data. To address this, virtual reality(VR) for data visualisation is identified as an alternative solution. While 3D visualization in VR offers a promising solution by enabling spatial and interactive data exploration, its potential is hindered by poor user experience (UX) design. This research introduces a UX-driven immersive 3D data visualization prototype to transform VR from a novel technology into a practical approach for data analysis.

We used the Design Science Research (DSR) approach over two development cycles. The first produced a basic VR prototype (VRVizX v1) to identify usability issues. The second (VRVizX v2) added enhancements like intuitive navigation, improved UI, feedback cues, and reset features. The final prototype was evaluated in a within-subjects comparative study with 30 users, comparing the VR system to a traditional 2D prototype. Users were evaluated using a Pre-Post test to assess the effectiveness of the system, in terms of accuracy and cognitive workload in understanding the data, using Meta Quest 2.

Our results indicated higher accuracy rates and significantly lower cognitive workload in VRVizX, as measured by the NASA Task Load Index (NASA TLX), including reduced mental demand ($p < 0.001$), effort, and frustration, along with higher perceived performance despite greater physical demand. Additionally, VRVizX received a higher System Usability Scale (SUS) score compared to the 2D system. Our qualitative evaluation suggests that effective UX design, including a clear and minimalistic user interface, multimodal feedback such as visual, auditory, and haptic cues, and support for trial and error through reset functionalities, can make VR visualization more effective than 2D approaches for analytical tasks.

While limited to one VR platform(Meta Quest 2) and scatterplot visualizations, this research provides strong evidence that UX-optimized VR data visualizations can overcome traditional 2D data visualization limitations. Future work should expand to diverse visualization types, dataset types(other than CSV), and to analyse multiple datasets at once to assess long-term usability across various user groups.

Keywords: Data visualization, Virtual Reality, User Experience, Immersive analytics, 3D interaction, Human-computer interaction.

Acknowledgement

It has been an incredible experience to complete research with the support, guidance, and generosity of many wonderful individuals. For everything, we sincerely thank each and every one for sacrificing their time, expertise, and encouragement to bring this work to fruition.

First and foremost, we would like to express our sincere and heartfelt gratitude to our supervisor, Dr. R.A.C. Ranasinghe, and co-supervisor, Dr. K.D. Sandaruwan, whose wisdom and encouragement guided us every step of this research. Their insightful feedback and strong belief in our work were invaluable. A special tribute goes to Dr. G.P. Lakraj from the University of Colombo's Department of Statistics, whose expertise in data science helped shape the analytical foundation of this research.

We are also deeply appreciative of all the participants who generously gave their time for our evaluations, including the team from OCTAVE at John Keells, whose real-world perspectives brought depth to our findings. We are indebted to Dr. Sumani Rajadurai for making this opportunity possible, and to Dr. Dilrukshi Gamage for her tireless coordination and support that made everything come together.

Finally, to our incredible team, this journey would not have been the same without our collaboration in brainstorming and sheer determination. Every challenge we faced became more of a smooth ride since we faced it together.

We acknowledge that no scholarly work stands alone; it is built upon the support of many. In tribute to the countless who contributed, directly or indirectly, we offer our deepest gratitude.

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List of Acronyms

2D	Two-Dimensional
3D	Three-Dimensional
AI	Artificial Intelligence
ANOVA	Analysis of Variance
API	Application Programming Interface
AR	Augmented Reality
CAVE	Cave Automatic Virtual Environment
CSV	Comma-Separated Values
DSR	Design Science Research
DSRM	Design Science Research Methodology
FOV	Field of View
GPU	Graphics Processing Unit
GUI	Graphical User Interface
HCI	Human-Computer Interaction
HMD	Head-Mounted Display
IA	Immersive Analytics
IT	Information Technology
KPI	Key Performance Indicator
MR	Mixed Reality
NASA-TLX	NASA Task Load Index
OS	Operating System
RAM	Random Access Memory

SDK Software Development Kits

SUS System Usability Scale

UCD User-Centered Design

UI User Interface

UX User Experience

VR Virtual Reality

WIMP Windows, Icons, Menus, Pointer

XR Extended Reality

Chapter 1

Introduction

In the era of big data, effectively interpreting complex datasets is critical for decision making across the vast number of fields where analyzing data is crucial for main functionalities. Traditional two-dimensional (2D) data visualizations, though widely used, often struggle to represent multidimensional relationships intuitively. Immersive three-dimensional (3D) visualization in virtual reality (VR) offers a transformative alternative, enabling users to explore data spatially and interactively. However, while VR unlocks new possibilities, its potential remains underutilized due to poor user experience (UX) design, including cluttered interfaces, limited interactivity, and inadequate feedback systems. This research proposes a UX-driven 3D immersive data visualization approach to enhance user comprehension and decision-making. Therefore, a combination of interaction design principles, multi-sensory feedback, and empirical evaluation aims to explore how VR can transcend technology's novelty and instead be developed as a practical tool for data analysis.

1.1 Problem Statement

There is a growing adoption of 3D immersive data visualization in VR; however, these systems mostly fail to develop an optimal UX to help the user with comprehension and decision-making. Currently, User-Centered Design (UCD) guidelines are not employed because the focus is only on technical implementation, such as rendering performance or spatial accuracy. Thus, many of the VR-visualization tools end up lacking being interactive, customizable, and providing feedback, leading to cognitive overload and compromised usability. Studies by Korecko et al. and Masud et al.[7][8] have demonstrated functional 3D visualization systems but have not thoroughly examined how their designs impact user comprehension or decision-making efficiency. Additionally, most frameworks lack multi-sensory feedback (haptic, auditory) and intuitive error recovery mechanisms that further diminish their real-world applicability.

This research seeks to address these gaps by developing and evaluating a UX-enhanced system for 3D immersive data visualization in VR by investigating:

- How UX guidelines can be systematically applied in VR-based data visualization.

- Whether enhanced UX leads to better comprehension and decision-making compared to traditional 2D visualizations.

The importance of this study lies in its potential to bridge the gap between technical VR capabilities and human-centered design, ensuring that 3D data visualization systems are not only functional but also intuitive, engaging, and effective for users. By integrating UX guidelines introduced by Vi et al.[9], this research aims to create a system that enhances usability and analytical efficiency in immersive analytics. The research approach involves:

- Identifying key UX challenges in current 3D visualization systems.
- Developing a prototype with improved interactivity, customization, and feedback mechanisms.
- Conducting empirical evaluations to measure its impact on user comprehension and decision-making abilities.

The findings will contribute to both academic research and practical VR development, offering actionable insights for designing more effective immersive data visualization tools.

1.2 Research Questions

1. How can UX be enhanced in 3D immersive data visualization?

- Hypothesis
 - The application of literature-documented VR design guidelines through a UX-optimized system will enhance usability metrics in 3D data visualizations relative to non-optimized data visualizations.

2. How does enhancing UX in 3D immersive spaces impact user comprehension and decision-making compared to 2D data visualization?

- Hypothesis
 - The UX-optimized system will produce enhanced comprehension and decision-making outcomes compared to traditional 2D visualization approaches.

1.3 Goals and Objectives

This research aims to enhance the UX in 3D data visualization within an immersive VR environment. The project seeks to enhance comprehension, decision-making, and engagement with complex datasets by integrating advanced 3D data visualization techniques and interactive dynamics. To accomplish this, the following objectives will be utilized,

1. Identifying UX guidelines needed for VR-based data visualization.

2. Design and develop an interactive 3D data visualization prototype for VR environments, incorporating the UX guidelines derived from immersive analytic research literature.
3. Evaluate the prototype’s impact on user comprehension and decision-making in 3D immersive data visualization.

1.4 Research Approach

Design Science Research (DSR)[1], as shown in Figure 1.1, is a systematic and iterative approach that aims to solve real-world problems by creating and evaluating innovative artifacts such as constructs, models, methods, or technological systems.

- The first step is **Problem Identification and Motivation**. Here, researchers define a specific problem, justifying its importance and reviewing existing literature to identify gaps. This phase ensures that research adheres to a meaningful challenge and lays the groundwork for solution development.
- Next, **Defining Objectives for a Solution** establishes clear, measurable goals from the problem analysis, defining what the artifact should achieve (improvement in efficiency, usability, or functionality), accompanied by stakeholder needs.
- The **Design and Development** phase then follows, where artifact conceptualization and construction take place, determining the architecture, features, and functionality using prototyping tools and iterative refinements to align with objectives.
- The **Demonstration** phase tests the artifact once an initial version is developed, within controlled or real-world settings, using methods such as case studies, simulations, or experiments to validate feasibility and effectiveness.
- The **Evaluation** phase, one of the most important in the entire development process, puts the artifact’s performance to the test against predefined goals using both quantitative metrics (for example, usability scores) and qualitative feedback (for example, user interviews) in determining the strengths and weaknesses of the artifact. After the evaluation, the cycle can iterate for Iterative Refinement, through which enhancement suggestions are analyzed through multiple cycles of feedback and testing until optimal performance is achieved.
- **Communication** mainly focuses on the dissemination of the findings to stakeholders, academic audiences, or industry practitioners via publications, presentations, or implementations, thereby ensuring that the knowledge generated reaches both practice and theory.

Throughout these phases, DSR emphasizes **rigor** (indicating that ground work is based on existing knowledge) and **relevance** (the need has arisen from solving real-world

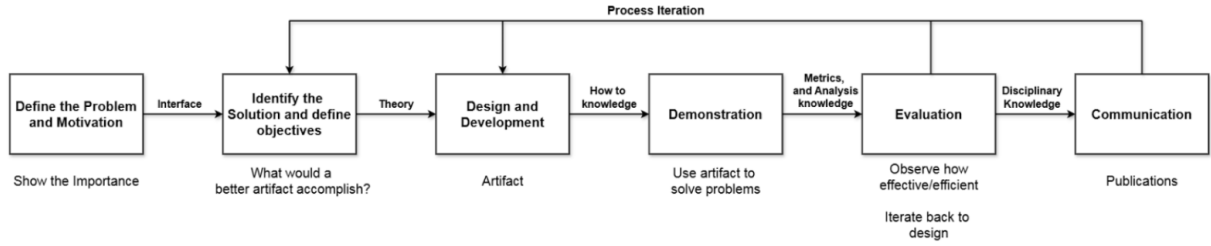


Figure 1.1: DSR process described by Brocke et al.[1]

problems), most often through frameworks such as Design Science Research Methodology (the DSRM model) or concurrent evaluation strategies to refine artifacts dynamically. Through this, DSR has been able to bridge the gap between research and real-world application through innovation across disciplines such as information systems, engineering, and sustainability by integrating user feedback with theoretical foundations.

1.5 Limitations, Scope and Assumptions

1.5.1 Limitations

This study incorporates several deliberate limitations to maintain research focus and feasibility:

1. **Visualization Scope** - The research is only focused on scatter plots visualization because they apply VR's 3D spatial capabilities by directly mapping variables to positional coordinates, are the most basic and widely recognized of all 3D chart types, thus allows to segregate the UX enhancements from visualization literacy effects, and also serve as a ideal setting for testing core interaction innovations (customization, navigation, and feedback systems) without added complication of multivariate representation. While this restricts generalizability into other chart types, it allows a more focused approach to understanding how UX guidelines apply to basic 3D visualization paradigms, and it is an essential first step before expanding to the more specialized formats.
2. **User Interaction Model** - The research focuses on individual UX, rather than collaborative or multi-user scenarios that might introduce additional complexity in interface design and user testing.
3. **Data Complexity** - To ensure controlled evaluation, the system accepts only one dataset at a time so that user understanding can be measured accurately, free of interfering factors presented by multiple simultaneous data sources.
4. **Performance Boundaries** - As this research is concerned with UX design rather than technical implementation, anything related to optimizing computational efficiency or other hardware-specific performance metrics does not lie within the domains of

this research, irrespective of the fact that the framework operates in a virtual reality environment.

These limitations were strategically implemented to enable focused development of UX guidelines, to facilitate controlled experimental conditions, to maintain manageable research boundaries, and to allow for thorough evaluation of core interaction concepts.

1.5.2 Scope

This research focuses on enhancing UX in data visualization within 3D immersive spaces, specifically targeting a VR environment. While previous studies explore 3D data visualization in VR, a noticeable gap remains in addressing the UX aspects of such systems, as discussed in Section 3.4. Therefore, this study aims to enhance UX and examine how these enhancements influence user comprehension and decision-making.

The study is limited to a sample of 30 university students enrolled in IT-related degree programs, aged between 18 and 34. Participants are required to have a solid understanding of data analysis. Industry professionals or individuals outside this demographic are not included within the scope of this research.

The research is conducted over 12 months, from May to April. This timeframe defines the extent of user testing, system iterations, and data analysis that can realistically be completed within the project duration.

This study follows a DSRM to guide the development and evaluation process. A mixed-methods approach is used to assess the system, combining both quantitative and qualitative data. The system is evaluated using task accuracy, completion time, semi-structured interviews, and standardized tools such as the NASA Task Load Index (NASA-TLX) and the System Usability Scale (SUS), which assess workload and usability.

The study focuses on VR headsets, specifically the Meta Quest 2 with hand controllers. The prototype is developed using Unity 3D and focuses on visualizing scatter plots, incorporating features such as basic plotting, outlier detection, and k-means clustering. Datasets used in the study are restricted to comma-separated values (CSV) file formats.

UX design guidelines are adapted from the work of Vi et al.[9], focusing on extended reality (XR) applications, and tailored to meet the study's goals. The prototype includes a minimalist interface, multisensory feedback (visual, auditory, and haptic), customization options, and trial-and-error mechanisms like reset. Navigation techniques such as walking and teleportation, along with interaction features like zoom, rotation, and panning, are also integrated, while ensuring user comfort through ergonomic positioning and smooth transitions.

1.5.3 Assumption

This study operates under four key assumptions that form the foundation of this research approach:

1. **Hardware Capabilities** - The research assumes that all test environments meet the minimum hardware requirements for optimal VR performance, including sufficient display resolution, refresh rates, and tracking accuracy. This ensures consistent performance across user tests and minimizes the impact of technical limitations on the UX evaluation results.
2. **Data Literacy** - The research assumes users can interpret 3D scatterplot encodings (axis variables, point color/size) without statistical training. This focuses evaluation on UX design rather than visualization fundamentals, as target users are familiar with basic data representation methods.
3. **Perceptual Consistency** - The research assumes participants with normal/corrected vision perceive visual properties (RGB colors, size scaling, depth cues) consistently. This standardization ensures all users experience the same visual feedback systems critical to the prototype evaluation.
4. **Task Relevance** - The analytical tasks (cluster identification, outlier detection, trend analysis) represent common scatterplot use cases in scientific and business domains. This assumption grounds this research’s findings in real-world applicability beyond controlled lab conditions.

1.6 Contribution

This research makes significant contributions to the field of Information Systems by advancing the understanding and implementation of user-centered design within immersive data visualization. Our work is distinguished by its integration of established UX guidelines by Vi et al. into the development of a system specifically tailored for 3D data visualization in virtual reality (VR) environments. Unlike previous studies that primarily focused on technical aspects of VR visualization, this research prioritizes the UX, particularly through the implementation of multi-sensory feedback systems, including auditory, visual, and haptic elements as well as user customization features. By doing so, our approach addresses a notable gap in current VR visualization research, which has often neglected holistic interaction design.

A second major contribution of this research is the provision of empirical evidence demonstrating the impact of enhanced UX design on user comprehension and decision-making in immersive environments. Through carefully designed user studies, we show that our UX-optimized VR system leads to measurable improvements over traditional 2D visualization methods. These findings not only support the value of user-centered design in data visualization but also provide a foundation for future research and development in the field.

Additionally, our work identifies and addresses critical gaps in existing VR visualization systems, particularly with respect to interactivity limitations. By pinpointing these

challenges and proposing practical solutions, our research not only advances academic knowledge in immersive analytics (IA) but also provides a model for how user-centered principles can be effectively applied in the design of immersive information environments.

Chapter 2

Background

2.1 Importance of Data Visualization

Data visualization is considered an important technique in rendering complex datasets into understandable, actionable insights for the direct recognition of patterns, trends, and outliers that may get hidden in raw data[10]. By presenting information visually, data visualization bridges the gap between the data complexity and human comprehension; therefore, it is a very crucial in areas driven by decision making based on gathered data, including business analytics, scientific research, healthcare, and education[11]. Medical practitioners working in healthcare routinely visualize medical imaging data, such as MRI and CT scans, for diagnostic purposes and treatment planning. Visualizing patient data over time can also help identify trends and improve patient outcomes[12]. Business Analysts use dashboards and charts to check Key Performance Indicators (KPIs) and market trends and formulate changes for implemented business strategies; for example, visualization of sales data can help determine underperforming areas to allocate resources efficiently[13]. In the same way, visualization tools in scientific research help researchers explore complex datasets like genomic data or climate models to generate insights and expand the frontiers of knowledge. For instance, visualizing protein structures in 3D can help researchers understand their functions and develop new drugs[14].

Beyond the analytical capabilities, data visualization helps in improving communication by rendering the information of complex datasets, making data more accessible and understandable. In education, teachers use visual aids such as charts and graphs to explain complex concepts to students; visual aids of historical data and scientific phenomena make learning engaging and productive[15]. In public policy, policymakers use visualizations to communicate the impact of proposed policies to stakeholders. Visualizing the effects of climate change can help raise awareness and drive action[16]. However, as datasets grow in size and complexity, traditional two-dimensional (2D) visualization methods face significant limitations, driving the search for advanced techniques for exploring and analyzing data, such as virtual reality (VR).

2.2 Challenges of 2D Data Visualizations

Although well-known and widely used, conventional 2D data visualization has limitations, particularly concerning multi-dimensional and large-scale datasets. One major challenge is the **limited spatial representation** of 2D visualizations; for instance, it is a struggle to represent spatial relationships in 2D scatter plots, bar charts, and even in heatmaps. Simply flattening or projecting 3D data into a 2D plane often leads to loss of context and misinterpretation[14]. This limitation is evident in geospatial analysis, wherein realistic interpretation of data depends largely on 3D models of the landscape or urban environment. This case is similar in molecular biology, as 2D visualization obscures important spatial relationships of protein structures, making it difficult to understand their functions and interactions[12]. **Cognitive overload** is another challenge, which occurs when presenting large or complex datasets in 2D. This overwhelms users, making it difficult to identify patterns or trends. 2D representations of multi-dimensional datasets often lead to overlapping data points, thereby hindering interpretation by users and causing confusion or erroneous assumptions[17].

In financial analysis, visualization of stock market data over time can be difficult due to the large volume of the data and the complex interrelationships between variables[13]. Additionally, 2D visualization doesn't provide **interactivity** to its users; they cannot rotate, zoom, or manipulate a data point in real-time, which restricts their ability to gain deeper insights[18]. This limitation is problematic in fields where dynamic exploration of complex datasets is essential for uncovering new insights, such as in scientific research. In engineering, visualizing 3D models of structures or machinery in 2D is problematic. This could hinder the detection of potential drawbacks and design optimization[14]. Thus, these limitations indicate that visualization techniques must advance to become sophisticated enough to continue being relevant as the complexity and the size of modern datasets continue to increase. Thus, VR promises to be an effective solution since it provides a platform that is spatially rich and interactive for data exploration.

2.3 VR as a Solution

VR is a transformative technology for data visualization, providing spatial and interactive facilities in contrast to traditional 2D methods. VR can be defined as an immersive, interactive computer-generated environment that simulates a physical presence in a virtual world[19]. Unlike 2D visualizations, VR enables users to explore data in 3D, thus making the environment more intuitive and engaging. Users traverse 3D data landscapes, manipulate data points in real time, and evaluate complex relationships from various perspectives[18]. In this way, an immersive experience sustains users' interest while enhancing their capability to explore and analyze data. Some unique VR characteristics make it suitable for data visualization. The first characteristic is the **immersion**, which provides a sense of presence, making the user feel as if they are interacting with data. Immersion increases

user engagement and allows for more intuitive exploration of the data[19]. The second characteristic of VR is its **intuitiveness**, which makes interaction with data a natural and effective way. Users within a VR space can manipulate data points using hand gestures or body movements, making interactions more natural[20]. Thirdly, **interactivity** enables dynamic and real-time interaction with data, such as rotation, zooming, and filtering. This makes VR an advanced method for data exploration and possibly revealing hidden insights[18]. For example, users can filter datasets by specific criteria or drill down into specific data points for a more focused view.

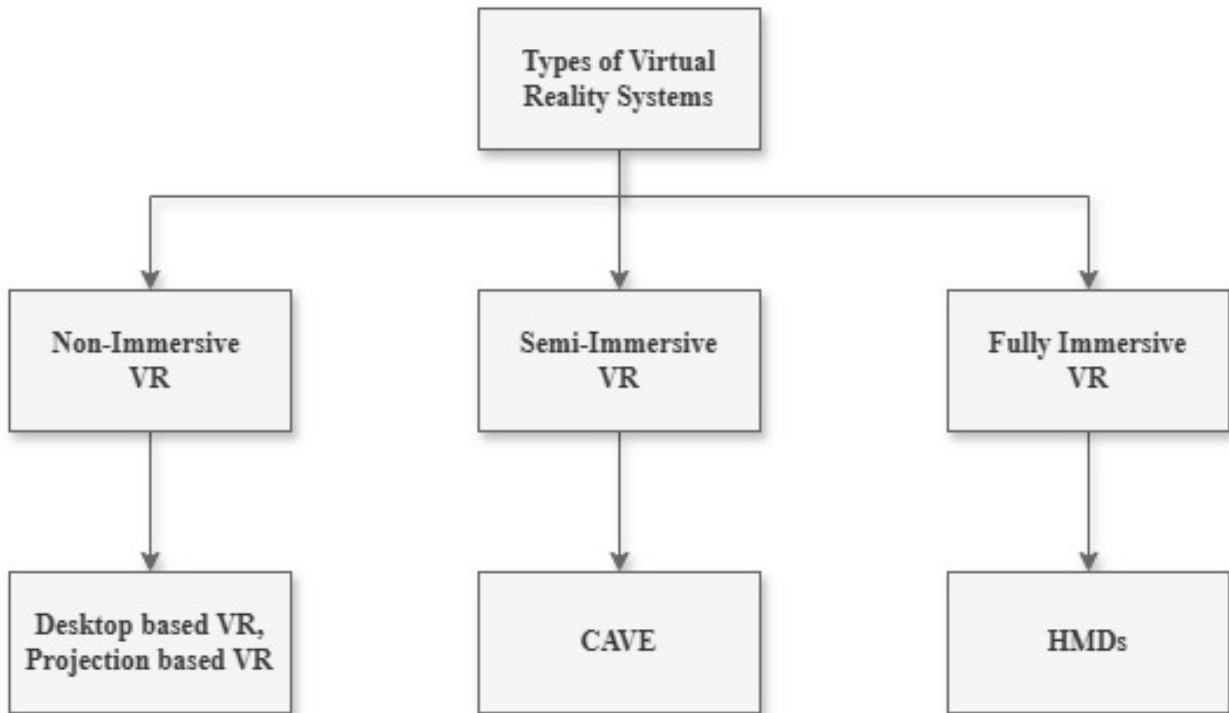


Figure 2.1: Types of Virtual Reality Systems

Different VR systems are available, as shown in Figure 2.1, and each has its strengths and weaknesses. **Head-Mounted Displays (HMDs)**, are the most common type of VR system. Oculus Quest 2 and HTC Vive Pro can be identified as common-use types of HMDs. These systems fully immerse a user in the environment by projecting 3D images directly onto the user's eyes, while simultaneously tracking the user's head and hand movements in real time[18]. Their portability, ease of use, and wide availability make HMDs the tools of choice in the majority of VR applications. **Cave Automatic Virtual Environment (CAVE)** systems (Figure 2.2) position multiple projection screens to create the immersive experience. Even though highly immersive, CAVEs can be expensive, require significant physical space, and are less portable than HMD setups[21]. CAVEs are usually the preferred choice in specialized environments such as research labs or training facilities, where a high level of immersion is a requirement. **Desktop-based VR systems** (Figure 2.3) use conventional monitors to present 3D visuals, usually in conjunction with input devices such as a mouse or a trackpad. These systems are inexpensive and accessible, but they lack the interactivity and immersion of HMDs and CAVEs[14]. Desktop-based VR is often used for applications

that place a primary concern on accessibility and cost, such as education or small-scale data analysis. **Projection-based VR systems** (Figure 2.4), which use large-screen or curved-surface projection to display 3D visuals using PowerWalls or Domes, offer high immersion but are less portable and expensive compared to HMD[21].



Figure 2.2: CAVE VR system[2]

The advantages of HMDs are considerably higher compared to other virtual systems used for data visualization. The **portability** of HMDs is one of their significant advantages. Unlike CAVE systems or projection-based setups, which need large, fixed installations, HMDs are lightweight and easy to set up, making them ideal for a wide range of environments. HMDs can be used in facilities like offices, classrooms, or even at home, since no special equipment or infrastructure is needed. Due to this reason, HMDs are extremely adaptive and versatile in applicability. Their applicability thus runs through different areas such as education, healthcare, and business[18]. Another key advantage is their **affordability**. HMDs are much more affordable than CAVEs and projection-based systems, requiring only a minimum amount of investment as compared. Cost-effectiveness drives the widespread adoption of HMDs and makes advanced data visualization within the reach of an ever-expanding audience, including small businesses, schools, and individual researchers[18].

The **immersive experience** offered by HMDs is another significant factor that



Figure 2.3: Desktop-based VR system[3]

differentiates them. HMDs create a sense of presence, which gives users the impression that they are interacting with the data. This kind of immersion encourages user involvement while allowing exploration to be more intuitive. Users can “walk through” a 3D scatter plot and “touch” data points, which is more engaging and memorable[19]. Comparisons between the **field of view (FOV)** of HMDs and desktop-based systems will provide superiority to the HMDs’ FOV because it further enhances the sense of immersion. For example, the Meta Quest 2 has a field of view around 90-100 degrees, whereas desktop-based systems offer much more limited FOV. Consequently, this wider FOV allows users to immerse themselves more in data because they can see more of the virtual environment at once[19]. Furthermore, **advanced tracking systems**, including inside-out tracking or external sensors, accurately track the real-time head and hand movements of the users. This **tracking accuracy** enables precise interactions with data, enhancing the overall UX; with hand gestures, users can manipulate the data points, rotate 3D models, or zoom in on specific details with great precision[18]. Modern HMDs, including the HTC Vive Pro 2, offer features such as **high resolution (up to 5K)** coupled with **low latency (less than 20ms)** to ensure the experiences are smooth and immersive. These are critical to provide realistic and engaging data visualizations because they minimize visual artifacts, thus making interaction feel natural and instantly responsive[18].



Figure 2.4: Projection-based VR system[4]

2.4 The Need for Enhanced UX Guidelines in VR Data Visualization

Despite the advantages of HMDs, designing effective VR data visualization systems requires addressing unique UX challenges. Most traditional 2D UX principles, such as User-Centered Design (UCD) and Fitts's Law, have limitations when it comes to addressing the spatial and immersive dynamics associated with data. **UCD** focuses on the system designs for users based on needs and preferences and is effective for data visualizations in a 2D plane, but becomes incompetent against embodied interactions and spatial awareness required in VR[22]. Users interact with data in 3D space when it comes to VR, thus needing depth, perspective, and spatial relationship design, which are elements not considered in traditional 2D frameworks[18]. In much the same manner, **Fitts's Law**, which predicts the time taken for a target area to be reached in 2D interfaces, could be adapted for use with 3D environments where depth perception and motion sickness become significant factors[23]. In particular, 2D interfaces have flat targets located on a single plane, while in VR, targets exist in 3D space, requiring users to account for depth when interacting with them. This adds complexity that Fitts's Law does not address[18]. Additionally, rapid movements in VR can cause motion sickness, which is not an issue in 2D interfaces. This means that designers will have to strike a balance between the speed of interaction with user comfort, an aspect that Fitts's Law does not consider[23].

The inability to accommodate the **affordances** present in VR is another limitation of 2D UX guidelines. In 2D interfaces, affordances are the perceived actions that a user can

undertake within a system and are often indicated by visual cues such as buttons, sliders, and handles[23]. When considering VR, affordances must also incorporate some semblance of a 3D interaction and physical movement. Therefore, while 2D affordances may include flat buttons or sliders, they may not fit into a 3D environment. Instead, VR requires affordances that take into account the natural behaviors of a human being: grabbing, pushing, or pulling on virtual objects[18]. Moreover, 2D interfaces do not provide much in terms of **haptic feedback**, which is critical for supporting intuitive interactions in a VR space. Without such feedback, users might struggle to understand how to interact with virtual objects, thereby causing frustration and mistaken assumptions[23]. Likewise, the **feedback and feedforward principles** of 2D interfaces certainly are not enough for VR applications. In 2D, feedback is often limited to visual or auditory feedback, such as highlighting a button when it is clicked. Yet in VR, feedback must extend to multi-sensory signals, including haptic feedback, or spatial audio to propel user understanding and engagement[19]. In particular, haptic feedback may enhance user perception of "feeling" data points or interactions, thus being more intuitive and immersive[24].

Therefore, 2D UX principles have their limitations in enhancing UX for VR data visualization. Motion sickness, cognitive overload, and spatial disorientation arise as new challenges in VR that the conventional 2D design principles do not address, necessitating the formulation of XR-oriented UX principles. One such principle is that reducing **motion sickness** involves minimizing the latency of operations and giving stable reference points. When the latency between user motion and display rendering is high enough, discomfort interferes with the user's experience; hence, a VR system must optimize rendering and tracking to minimize latency[24]. Motion sickness can also be alleviated by incorporating static elements such as a horizon line or fixed objects that add to the frame of reference[19]. **Cognitive overload**, which occurs when users are flooded with too much information, can be tackled through layered information presentation and spatial organization. Allowing users to explore information on their own through layering will reduce cognitive overload on the user[18]. Enhancing presentation clarity through organizing data in a 3D environment, such as grouping related data points in clusters or layers, helps relate complex relationships[14].

Enhancing **spatial understanding** is another critical aspect of VR data visualization. Spatial relations are difficult to represent clearly with 2D data interfaces, especially when it comes to multi-dimensional datasets; it is, however, possible for a user to gain such an understanding when interacting with a 3D version in a VR environment because it allows exploration of the data. Examples include rotating, zooming, and manipulating data points to help users gain deeper insights[19]. The natural interaction carried out by gestures or body movement further enhances spatial understanding by aligning with natural human behaviors[20]. Also, **multi-sensory feedback approach** ensures immersive and effective VR data visualization systems. Whereas in 2D interfaces, feedback comprises visual or auditory cues, which can limit the ability to convey complex information. Multi-sensory feedback in VR, on the contrary, helps with providing an immersive experience and enhances

the user's understanding and engagement, which includes feedback such as haptic feedback and spatial audio. For example, haptics offer a "feeling" of the data points or interaction, which makes it more natural[24]. Spatial audio acts as a guide for users to locate and interact with data points in the virtual world, thus enhancing immersion and usability[18].

This research attempts to enhance user experience with data visualization within VR environments by leveraging the unique characteristics of VR and applying VR-specific UX guidelines to address these challenges. This research aims to critically analyze the 2D UX guidelines that limit their incorporation in VR and then extend a new methodology to designing and evaluating such immersive data visualization systems that are intuitive, engaging, and effective. The following Literature Review segment will contain a comprehensive analysis of existing research on data visualization, VR technologies, and UX design guidelines. It will highlight gaps in these current narratives and provide the theoretical foundation for this study, thus guiding the development of a system with VR-specific UX guidelines for immersive data visualization.

Chapter 3

Literature Review

3.1 Introduction

Data has become the primary tool for decision-making across various sectors, enabling organizations to understand their customers, refine products and services, and identify areas for improvement. As Donalek et al.[25] note, large and complex datasets are only useful if value can be obtained from them. The authors also emphasized that visualization is an essential bridge between raw data and human understanding, as it helps one to comprehend and explore.

Data visualization has undergone significant evolution in the past and is now an essential component of academia and business. According to Gidey and Awono[26], visualization has gained prominence in recent decades due to the increasing size and complexity of data. Visualization helps in making decisions but does not substitute critical thinking; it helps in the ability to understand and work with data. According to Nguyen et al.[27], Users need a good visualization tool that will enable them to gain insights from the data. This encompasses spotting trends, patterns, and anomalies, which are vital for deriving useful insights.

In this review, we will explore the advantages of three-dimensional (3D) visualizations as compared to two-dimensional (2D) visualizations, summarize user experience (UX) guidelines for Extended Reality (XR) applications, review the literature on 3D data visualization, and identify gaps in current research.

3.2 Comparison of 2D and 3D Visualization

2D visualizations have been used largely in education and business because of their familiarity and simplicity. However, as datasets become more complex, especially with multidimensional data, traditional 2D methods cannot capture fine-grained relationships well. Zhang et al.[28] state that traditional visualization and interaction methods depend on 2D graphical user interfaces (GUI) and follow the WIMP (Windows, Icons, Menus, Pointer) design model. However, these methods face limitations in flexibility, scalability, cost-effectiveness, and interactivity, especially when used in large-scale or complex datasets.

VR is another option available, it is more intuitive and immersive by nature. Carlo et al.[29] describe VR as a computer-generated 3D space that may be rendered on flat screens, room-based systems, or head-mounted displays (HMDs). They continue to explain that the greatest advantage of VR is that it can impose stereoscopic depth, allowing the user to view objects within the virtual world and thus creating the illusion of reality. This immersive experience is increased further by the sense of "presence". This allows the users to feel as if they are physically present in the virtual world. Sense of presence is shaped by aspects like the field of view (FOV), the field of regard, and display size, which together contribute to more natural, real-world responses from the users[29][27].

Carlo et al.[29] conducted a comparative study on how individuals search for information in natural scenes on 2D screens versus in VR. The study revealed that participants had a higher accuracy in VR than in 2D displays, and on average, the participants completed the tasks 28.62% faster in VR. The authors mention that participants preferred VR because of the depth perception, clearer visuals, and immersive experience, which the 2D displays fail to provide. The results indicate that VR is a promising tool for 3D data visualization, which can help in increasing user comprehension and decision-making.

Anderson et al.[30] explored in a study whether VR enhances the visualization of complex weather data compared to a 2D desktop environment. They conducted the study using three setups: a desktop-based application with an Xbox One Controller interface, a VR application using an Xbox One Controller, and another VR application using the Leap Motion interface. Due to the low sample size, the study did not achieve statistically significant accuracy or task completion time differences. Nevertheless, participants preferred the VR experience, stating that it allowed for better comprehension of the data and made the interaction more engaging. In particular, VR with the controller was rated the most effective. These findings suggest that VR has the potential to enhance the effectiveness of users' interaction with and understanding of complex data than 2D.

Millais et al.[31] compared two data visualizations based on VR, "Be The Data" and "Parallel Planes", to their 2D versions, to examine their influence on workload and generation of insight. Although VR did not significantly change the overall workload, it required more physical movement. Participants reported reduced cognitive workload, higher levels of satisfaction, and improved accuracy in their insights. These findings suggest that VR can improve engagement and the accuracy of interpreting data and can be used as an effective approach to explore intricate data sets.

Although 2D visualizations are popular because of their simplicity, they fall short when working with complex, multi-dimensional data. VR, however, provides benefits such as better depth perception, increased engagement, and improved user understanding. The next section will cover key UX guidelines for developing successful XR applications with HMDs.

3.3 User Experience Guidelines for HMD-based Extended Reality Applications

3.3.1 Design Considerations for XR Applications

Vi et al.[9] point out that XR requires a new set of UX guidelines because the existing guidelines for 2D applications fail to address the unique concerns of 3D spatial environments. To address these concerns, they developed dedicated UX guidelines with a focus on wearable HMD-based XR applications. Vi et al.[9] stress that the 3D spatial environment should be considered while designing XR applications. They note that placing interactive elements, for example, buttons and sliders, within the user’s FOV reduces redundant movement. It is also important not to clutter the interfaces, as it can overwhelm users and make navigation harder. These principles are especially relevant in designing VR 3D data visualizations, where users need to move through complicated data while keeping track of the spatial surroundings.

Moreover, Vi et al.[9] explain that XR applications should offer flexible settings and interaction options. Issues such as disorientation and motion sickness can affect how users interact with the system. In 3D data visualization, enabling users to customize the environment according to their preferences can significantly enhance usability and overall experience. For example, providing multiple navigation methods, such as walking or teleportation, allows users to select the most comfortable option, thereby reducing potential discomfort during interactions.

One of the main guidelines pointed out by Vi et al.[9] is to prioritize user comfort when designing XR applications. Placing interactive objects in VR should be done in a way that users can interact with them without exerting themselves. It is also important to avoid activities that involve excessive physical movement or repetitive actions, as these can lead to user fatigue. This is especially important in data visualizations, in which the users may need to deal with large datasets over a prolonged period.

The next guideline addressed is the need for a minimalist user interface (UI). Vi et al.[9] state that there is no universal UI design applicable to all XR applications. Therefore, they propose that the interfaces should be minimalist and tailored to fit the specific hardware capabilities of the HMD. In 3D data visualization, this means that data should be presented in a straightforward and uncluttered manner, avoiding information overload while providing users with the necessary tools to interact with and manipulate the data comfortably.

According to Vi et al.[9], it is also important to give users continuous haptic, visual, and auditory feedback while in the XR experience. This helps users navigate and interact within the virtual world without overwhelming them. Providing consistent feedback to users is also important as it helps them to track their progress and to see how their choices affect the application. According to Zhang et al.[28], intuitive interaction techniques, along with timely feedback, enable users to browse and modify data in ways that clearly show the results of their actions.

Vi et al.[9] emphasize the need to map XR interactions to real-world information and mental models in a way that they are familiar and intuitive. Zooming and rotating, for example, should be effortless and intuitive for the user. They also recommend including features that support trial and error, like undo, redo, and reset functionality, so users can experiment with the application without the hesitation of creating irreversible mistakes.

3.3.2 Interaction Methods: Controllers vs. Gesture-based Interfaces

In VR, the users typically engage with the environment through the use of controllers or gestural inputs. Controllers enable users to navigate within the virtual environment, as well as select and grab objects through buttons and motion sensors. The utilization of hand-tracking technology in gesture-based interactions enables the user to engage with the virtual environment through hand gestures.

While hand-tracking may appear to be a more natural input method, research[30][32] has shown that it results in poorer performance and is perceived as less user-friendly compared to using controllers. In a study by Anderson et al.[30], it was discovered that hand-tracking devices such as Leap Motion were inaccurate and took several tries to function correctly. They also say that users were required to hold their hands in an elevated position for an extended period, leading to fatigue. The study demonstrated that the participants favored the controller for tasks demanding precision, such as pointing, grasping small objects, or placing objects within the virtual environment.

Additionally, Johnson et al.[32] discovered that participants gave hand-tracking poorer ratings for performance and naturalness. When hand-tracking was utilized in place of controllers, the participants felt less in control and found it difficult to complete the tasks. These studies demonstrate that, particularly for higher-precision tasks, controller-based interactions are more useful and effective than gesture-based interactions.

In summary, effective user experiences in HMD-based XR applications rely on the right design considerations and interaction methods that can strengthen users' understanding and decision-making. Although gesture-based interfaces show potential, controller-based methods remain the most precise and reliable. The following section reviews previous research on 3D data visualization and examines how well the existing frameworks align with these UX principles.

3.4 Evaluation of Existing 3D Data Visualization Systems

The main goal of data visualization, whether in traditional 2D formats or immersive environments like VR and AR, is to help users identify patterns and trends that lead to deeper understanding and informed decision-making. As we have already discussed the shortcomings of 2D settings for data visualization, this section analyzes 3D data visualization

systems, discussing their strengths and weaknesses in facilitating user understanding and decision-making.

Millais et al.[31] studied VR-based visualizations like "Be The Data" and "Parallel Planes", which supported features like hovering and brushing. Although VR made users more engaged than 2D visualizations, they realized that individuals still mapped their views into 2D-like representations and generated fewer deeper insights in VR. This limitation, even estimated on a small dataset, would likely be enhanced with more complex data. The issue could be attributed to the failure to apply user experience design guidelines, like trial-and-error and diversified feedback mechanisms. The application relied solely on visual feedback and walking-based navigation, which limited the overall user experience.

Yassien et al.[33] implemented the VR/AR system CDVVAR to display datasets in the form of bar charts, pie charts, and scatter plots. Data manipulation features, including graph scaling, selection of step sizes for numeric axes, and category criteria filtering, were implemented in this system, which would have promoted user comprehension. However, they fall short in other facets of the UX. They found that VR was more effective than augmented reality (AR) for engagement, navigation, and identification of data points. To optimize the tool further, reducing visual noise, optimizing trial-and-error features, and providing more feedback systems apart from visual, i.e., pinging, would be useful.

NDMVR is a browser-based VR application created by Korecko et al.[7] to visualize histograms. While they provide features like navigation, scrolling along the x and y axes, and supporting panes to guide the user, they do not discuss how these interactions can enhance UX or facilitate data comprehension. Additionally, no user study has been conducted to examine the efficacy of the tool in decision-making, especially with complex datasets.

Wei et al.[34] proposed a VR data visualization system with static, dynamic, and interactive data visualizations. Static visualizations do not allow any user interaction, and dynamic visualizations provide basic animations, like data transitioning from initial to final values. Interactive visualizations emphasize user interaction but are limited to basic actions, i.e., pressing buttons to see different states of the data. In addition, the use of random, high-contrast colors can reduce accessibility when there is no option to personalize the experience. Individuals prefer interactive and dynamic information over static, according to their studies, valuing greater interactivity. We hypothesize that better user experience and decision-making are achievable with increased interactivity, personalization, and adherence to UX standards.

Masud et al.[8] addressed the need for an interactive 3D data visualization system with filtering, grouping, and linking functionality. The system, however, only supports two-variable visualizations in pie charts and bar charts. This raises the question of why users would switch from traditional 2D displays to VR if the experience offers little added value. While the system is centered on interactivity, its functionality is quite limited and only includes a simple menu for selecting charts and attributes, with no other interactive features. Even with a relatively small dataset of 173 rows, the interface becomes cluttered, raising

concerns about how the application would perform with a complex dataset. Furthermore, no user studies have been conducted, so it is unclear how the system affects user comprehension and decision-making. This study serves as a prime example of the problems that could occur if the UX principles were not followed.

Dongyun et al.[35] explored how three 3D interaction techniques, "Teleportation", "Walking", and "Grab", affect spatial memory in 3D visualizations. "Teleportation" enables users to move instantly by pointing a controller at a location, offering speed but reducing their sense of connection to the environment. Users can physically navigate the environment by "Walking", which aligns with how people move in the real world. However, "Walking" necessitates a wider physical space free of obstructions. "Grab" allows users to rotate objects around the y-axis for more controlled interactions. The study results indicated that "Walking" had the greatest impact on spatial memory, followed by "Grab", and finally "Teleportation". While "Teleportation" was thought to be the most user-friendly, it was also shown that "Walking" resulted in quicker interaction times than "Grab". However, the study was only conducted on small side-viewed 3D scatterplots and did not specify how the navigation techniques function when implemented on larger data sets. Our research aims to incorporate these techniques while addressing the limitation of using small, hand-sized plots. As summarized in Table 3.1, we present the strengths of these existing systems and the limitations that are addressed through our research process.

In theory, 3D data visualization in VR has the potential to enhance decision-making due to its intuitive and immersive nature. However, as Wagner et al.[36] pointed out, 3D data visualization faces challenges such as complexity in navigation, perspective distortion, foreshortening, and occlusion. These issues can undermine effectiveness if not properly addressed. While existing systems suggest that 3D data visualization can enhance user engagement, they still face challenges with interactivity and user experience design, which are crucial for improving comprehension and decision-making. The next section discusses the research gaps in existing 3D data visualization systems that this study aims to address.

3.5 Research Gap

This literature review highlights the gaps in current research on 3D data visualization in VR. Studies by Korecko et al.[7] and Masud et al.[8] are focused on the development of 3D visualization systems but fall short of explaining the effect of their systems on user comprehension and decision-making. Several systems, including those developed by Millais et al.[31], Korecko et al.[7], Wei et al.[34], and Yassien et al.[33], are lacking in terms of interactivity and customization. These features are required to address the different user preferences and increase usability.

Another significant limitation is the lack of trial-and-error mechanisms. Since VR is still relatively new to most users, mistakes are inevitable. However, none of the studies we reviewed include mechanisms that would let users reverse errors with ease, making interactions more natural and intuitive. In addition, most frameworks only rely on visual

cues, missing out on the potential of using auditory and haptic feedback that can further enhance user engagement and understanding. The system developed by Masud et al.[8] exhibits usability issues due to overly cluttered interfaces, which can further complicate the understanding of the data. Another problem is that the systems have only been tested on small datasets. While they work well with small datasets, their efficacy with complex datasets is unknown, as is the impact of scalability on user comprehension and decision-making.

Although Dongyun et al.[35] have examined the effect of Walking, Teleportation, and Grab interactions on spatial working memory, they only tested them with small 3D plots. This limitation reduces the relevance of their findings, as visualizations are typically larger, as demonstrated in the studies by Millais et al.[31] and Korecko et al.[7]. Therefore, it is important to understand how these navigation techniques contribute to user comprehension in larger visualizations. The main goal of the research is to enhance the UX for data visualization in 3D immersive spaces, addressing the current limitations. We have developed a 3D data visualization system in VR that is both intuitive and immersive, by following the UX guidelines discussed in Section 3.3.1. We will conclude by investigating whether enhancing the user experience can result in improved understanding and decision-making, thereby bridging the gaps in existing research.

Table 3.1: Summary of VR Visualization Research: Strengths and Limitations

Research	Strengths	Limitations
Millais et al.[31]	<p>Engaging VR experience (“Be The Data”, “Parallel Planes”).</p> <p>Features like hovering and brushing improve interactivity.</p>	<p>Users still preferred analyzing data in 2D</p> <p>Few deep insights generated.</p> <p>Lacked UX principles like trial-and-error and multi-sensory feedback.</p>
Yassien et al.[33] – CDVVAR	<p>Multiple chart types (bar, pie, scatter).</p> <p>Data manipulation (scaling, filtering).</p> <p>VR is better than AR for navigation and engagement</p>	<p>Visual noise not reduced.</p> <p>Lacked trial-and-error design.</p> <p>Only visual feedback used.</p>
Korecko et al.[7] – NDMVR	<p>Browser-based VR tool.</p> <p>Supports scrolling/navigation with guide panes.</p>	<p>No user study.</p> <p>UX and data comprehension not addressed.</p>
Wei et al.[34]	<p>Offers static, dynamic, and interactive visualizations.</p> <p>Users preferred dynamic/interactive formats.</p>	<p>Limited interactivity (just pressing buttons).</p> <p>Poor accessibility due to random color use.</p> <p>No personalization.</p>
Masud et al.[8]	<p>Includes filtering, grouping, and linking features.</p> <p>Focused on interactivity.</p>	<p>Only supports two-variable visualizations.</p> <p>Limited functionality.</p> <p>Cluttered interface.</p> <p>No user study.</p>
Dongyun et al.[35]	<p>Explores 3D navigation methods (Teleport, Walk, Grab).</p> <p>Walking improved spatial memory and speed.</p>	<p>Only small scatterplots tested.</p> <p>Navigation with large datasets is unexplored.</p>

Chapter 4

Methodology

4.1 Research Approach

As introduced in Section 1.4, this study adopts the Design Science Research (DSR) methodology. This section explains why DSR is appropriate for this research and how it guided the research process.

Teperi et al.[37] explain that DSR is an iterative and creative approach that focuses on solving problems through the development of innovative solutions. It focuses on the solution with a strong emphasis on understanding the users and their needs. Instead of only presenting theoretical explanations, DSR encourages the design of practical artefacts that can improve existing systems or create entirely new solutions. The process is both structured and flexible, making it ideal for research that involves designing, building, and feasibly evaluating prototypes.

This research focuses on developing a virtual reality (VR) based prototype to enhance user experience (UX) in three-dimensional (3D) data visualization within immersive environments. While UX guidelines, such as those adopted from the study by Vi et al.[9], provide a foundational basis, it is equally important to understand how users interact with and perceive the prototype. By incorporating user feedback and refining the system through iterative development, the DSR approach ensures that the solution evolves to better meet user needs over time. This approach offers not only a framework for building the prototype but also a structured and meaningful way to validate its usefulness and usability.

The following sections include the iterative process carried out during the study, describing how the system was improved and evaluated in each cycle based on user feedback and observations.

4.2 Problem Identification

As outlined in Section 3.4, several VR-based systems have been developed to visualize data in 3D environments. However, as discussed in Section 3.5, many of these systems fall short in addressing UX. Some interfaces are cluttered and overwhelming, while others lack essential features such as interactivity, trial-and-error flexibility, or customization options. In addition,

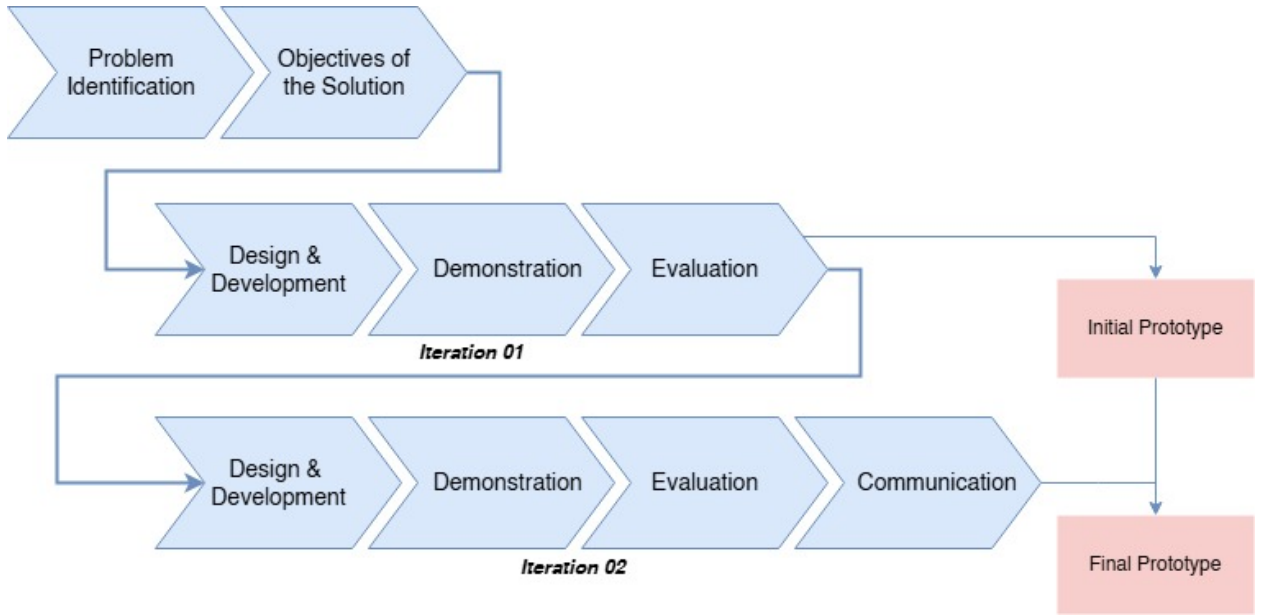


Figure 4.1: Design Science Research Methodology (DSRM) Flow

a number of these systems have not conducted user studies or have only been tested with small datasets, raising concerns about their effectiveness with larger, complex datasets. This research aims to bridge these gaps by developing a system that not only supports 3D data visualization but also prioritizes UX. Based on this identified gap, the research is guided by the following questions:

1. How can UX be enhanced in 3D immersive data visualization?
2. How does enhancing UX in 3D immersive spaces impact user comprehension and decision-making compared to 2D data visualization?

4.3 Objectives of the Solution

1. Identifying UX guidelines needed for VR-based data visualization.
2. Design and develop a 3D data visualization prototype for VR environments by identifying and applying UX guidelines derived from immersive analytics (IA) literature.
3. Evaluate the prototype's impact on user comprehension and decision-making in 3D immersive data visualization.

4.4 Iteration 01

4.4.1 Design and Development

The first task was to review the existing literature relevant to UX guidelines for XR applications, including VR, Augmented Reality (AR), and Mixed Reality (MR). However,

not all of these guidelines directly applied to our research, as we focused on VR-based data visualization. Therefore, we critically examined and selected guidelines most relevant to immersive VR environments and adapted them to meet the requirements of 3D data visualization.

The design guidelines we selected were adapted from a study by Vi et al.[9] and tailored for VR data visualization:

1. **Organize the Spatial Environment to Maximize Efficiency:** Data points and axes should be positioned within the user's natural field of view (FOV), minimizing unnecessary head or body movement during exploration.
2. **Create Flexible Interactions and Environments:** Users should be able to customize elements of the visualization, such as repositioning axes or adjusting the size and color of data points.
3. **Prioritize User Comfort:** Interface elements should be arranged in ergonomic zones, and smooth transitions should be used to reduce discomfort or motion sickness during navigation and exploration.
4. **Keep It Simple: Do Not Overwhelm the User:** Clear and minimal visuals should be used for axes and legends, with toggles to hide or reveal additional data layers, avoiding excessive on-screen text or icons.
5. **Use Cues to Help Users Throughout Their Experience:** Visual, auditory, and haptic cues should be used to enhance user engagement during visualization.
6. **Build Upon Real-World Knowledge:** Realistic lighting and shading techniques should be used to improve depth perception, and interactions should feel intuitive through familiar spatial cues.
7. **Provide Feedback and Consistency:** Haptic feedback should be included for selecting or interacting with data points, and consistent visual styles should be ensured for interactive elements.
8. **Allow for Trial and Error:** Users should be encouraged to explore freely by resetting the visualization or selecting a new chart type without the fear of making irreversible mistakes.
9. **Allow Users to Feel in Control of the Experience:** Actions should be easily reset, and user actions, such as rotating or scaling the scatterplot, should respond smoothly and predictably.

Based on these guidelines, we initiated the design for the prototype, VRVizX v1, using the Unity Engine version 2022.3.37f1. However, we have carried out the full implementation of these guidelines in the second iteration. In this initial version, we implemented a simple 3D scatter plot with basic interactive menu options.

The core features included:

- Axis selection - users can select different dimensions of the dataset for the X, Y, and Z axes.
- K-means clustering - segments data points into meaningful clusters.
- Outlier selection - highlights data points that are significantly different from others.

In terms of navigation and interaction:

- Users could explore the virtual space by walking or using teleportation within the environment.
- The zoom feature was incorporated to allow users to interact more closely with the data points.
- Haptic feedback was incorporated when hovering over a data point. Visual cues such as detail-on-demand (e.g., displaying coordinates when a data point is selected) were also included.

This VRVizX v1 served as a foundation to explore preliminary ideas related to usability and interactivity in VR-based 3D data visualization.

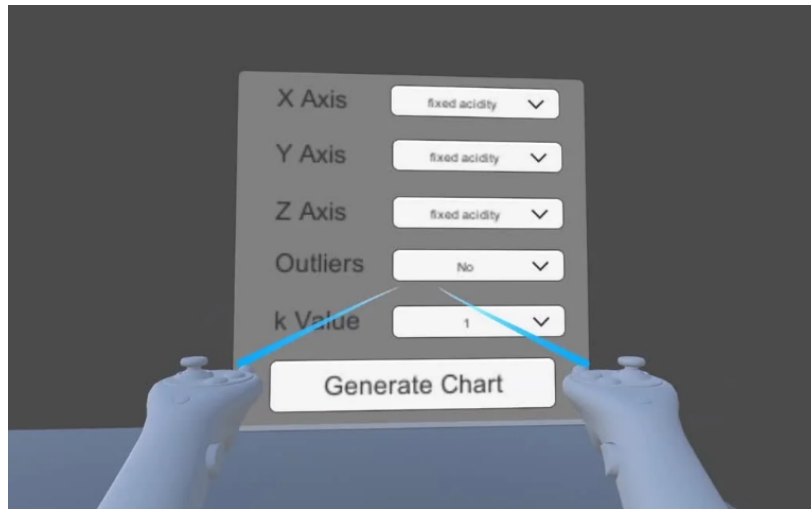


Figure 4.2: Menu in the Initial Prototype

4.4.2 Demonstration

We conducted two sets of evaluations with VRVizX v1. The first was a user study involving seventeen second-year students from the University of Colombo School of Computing. The goal of this study was to understand how the system was performing in terms of usability and UX.

A fixed dataset named Red Wine Quality[38] was used in this user study to ensure consistency across all the participants. The dataset originates from red variants of the

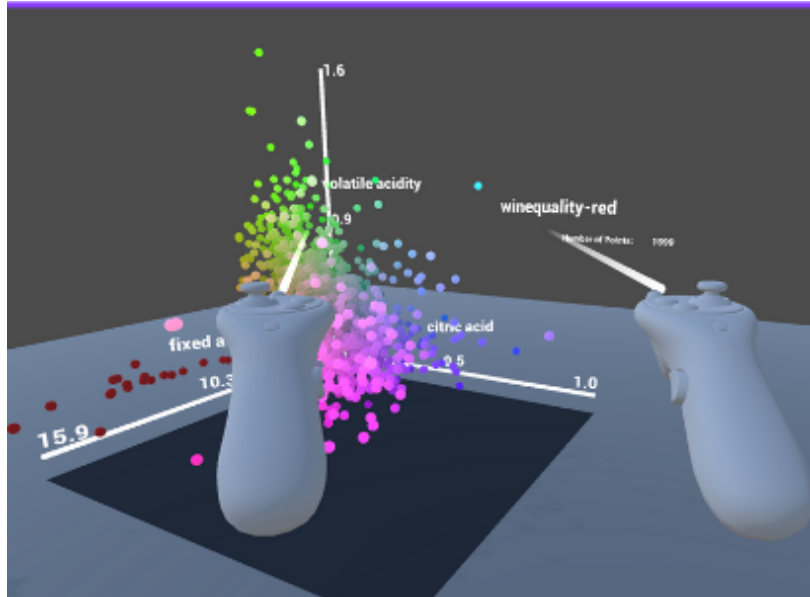


Figure 4.3: Scatterplot with Outliers in the Initial Prototype

Portuguese Vinho Verde wine and contains 1,599 rows with 12 attributes. These attributes are categorized into 11 physicochemical input variables and 1 output variable, which represents the quality score of the wine on a scale of 0 to 10. The input variables include: fixed acidity, volatile acidity, citric acid, residual sugar, chlorides, free sulfur dioxide, total sulfur dioxide, density, pH, sulphates, and alcohol.

Before participants began exploring the system, each of them was given a brief introduction to the dataset and instructed on how to operate the VR controllers. This included guidance on how to navigate the virtual space (e.g., walking and zooming), how to use the menu to select axes, number of clusters, and outliers, and how to display details on demand for individual data points.

Once the introduction was complete, participants were allowed to freely explore the application for an unlimited amount of time, allowing them to interact at their own pace and become familiar. Subsequently, participants were presented with a comparative 3D scatterplot rendered on a 2D computer screen, developed using the Matplotlib library. This allowed for a direct comparison between VRVizX v1 and traditional 2D data visualization. Finally, the participants were asked to fill out a questionnaire focused on capturing their background, prior experience with VR and data visualization tools, and feedback on their interaction with the system.

Next, VRVizX v1 was demonstrated using the same dataset to employees at OCTAVE, the Data and Advanced Analytics Division of the John Keells Group. This study was focused on collecting qualitative feedback through direct interaction and discussion. The participants provided valuable insights from an industry perspective, especially concerning the practical applicability of immersive VR-based data visualizations in real-world business environments.

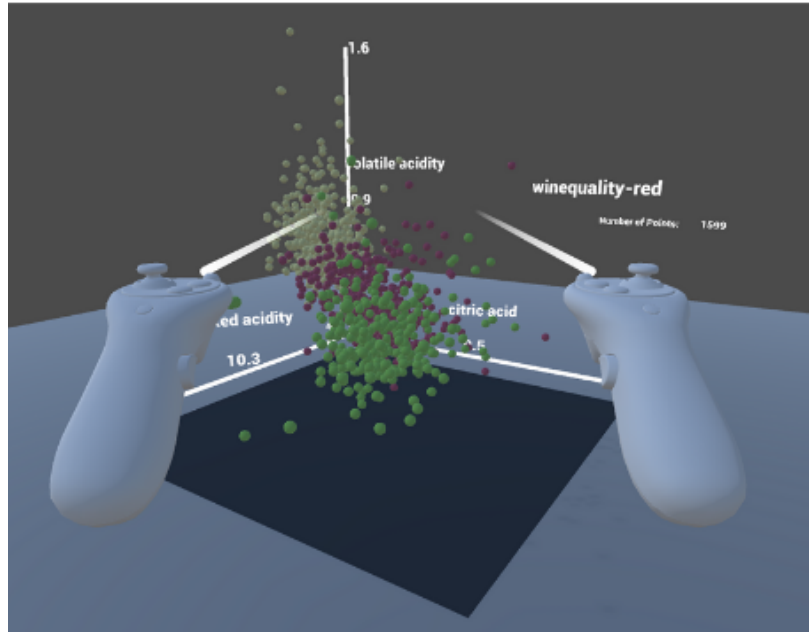


Figure 4.4: Scatter Plot with clusters in the Initial Prototype

4.4.3 Evaluation

The key findings related to both user studies will be discussed in this section. In the first user study, we found out that:

- 82.3% of participants found overlapping clusters easier to distinguish in VR compared to 2D visualizations.
- 92.3% of participants found cluster density more identifiable in VR compared to 2D visualizations.
- 76.5% of participants had no prior experience with VR. Some discomfort was noted by a few users, particularly related to headset weight and eye strain, though many did not report significant issues.
- 64.7% found the gesture-based interactions smooth and responsive, though some noted that they took time to get used to.
- 64.7% found the application easy to navigate, especially with the provided instructions. Some users found it complicated due to a lack of prior experience.
- 70.58% rated the prototype positively (7-10), while 23.5% found it average (4-6), and 5.9% rated it poorly (1-3).
- 94.1% expressed a high likelihood of using the tool for future data analysis tasks.
- 88.2% of participants found the 3D immersive environment more engaging than the 2D visualization.

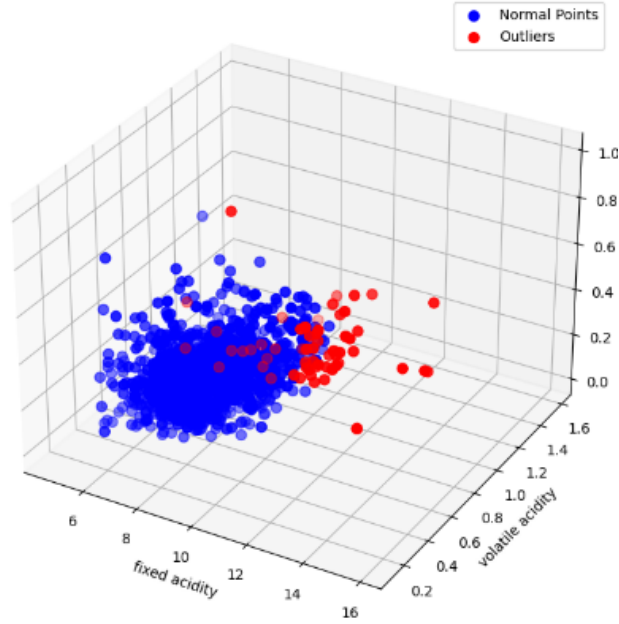


Figure 4.5: Scatter Plot with outliers in the 2D Plane

- 61.5% of participants agreed that VR makes it easier to intuitively identify outliers compared to 2D visualization.

Findings from the second user study with the Octave employees:

- The user interface (UI) of VRVizX was not clear enough, with several participants describing it as blurry, which highlighted a significant usability issue.
- The haptic feedback (vibration) was considered excessive by several participants.
- Some participants reported that the Zoom feature was not smooth enough.

These findings showed that while the prototype was appreciated, it was not at a satisfactory level, and it fell short in addressing several important UX related issues. These will be used to refine the prototype and shape the second iteration.

4.5 Iteration 02

4.5.1 Design and Development

Based on the findings from the first iteration, the prototype was refined to develop VRVizX v2, which contains many improvements focused on enhancing the overall UX in 3D data visualization.

In the first iteration, we identified numerous significant usability issues. The UI appeared blurry and was difficult to understand, the zoom feature lacked smoothness, and the haptic feedback was too strong and distracting. The second iteration focused on addressing these concerns while introducing additional factors aimed at enhancing the overall UX. The enhancements included in VRVizX v2 are as follows:

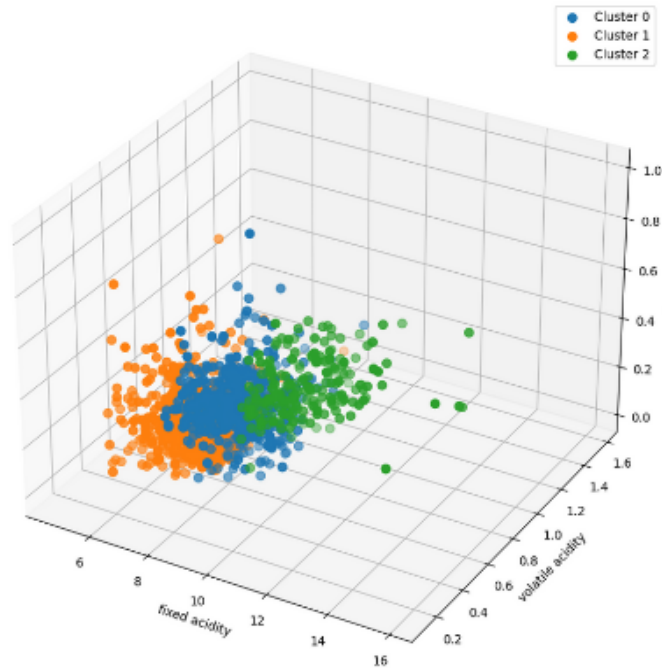


Figure 4.6: Scatter Plot with clusters in the 2D Plane

- Improved Navigation and Interaction:
 - Smoother zooming mechanism.
 - Supports panning and rotation controls, including X and Y axis rotation.
- User Interface Enhancements:
 - Minimalistic layout to reduce visual clutter and enhance comprehension.
 - Clearer axis labels and menu options.
 - Realistic lighting and shading to improve depth perception.
- Feedback Mechanisms:
 - Visual tooltips and detail-on-demand for selected data points.
 - Visual indication when a data point is selected (e.g., color change)
 - Error messages and confirmation prompts.
 - Auditory cues were integrated into UI interactions.
 - Fine-tuned the haptic feedback.
- Customization Options:
 - Customization options such as changing the size and color of data points, as well as setting specific colors for outliers.
- User Control Options:
 - Reset options to support trial-and-error

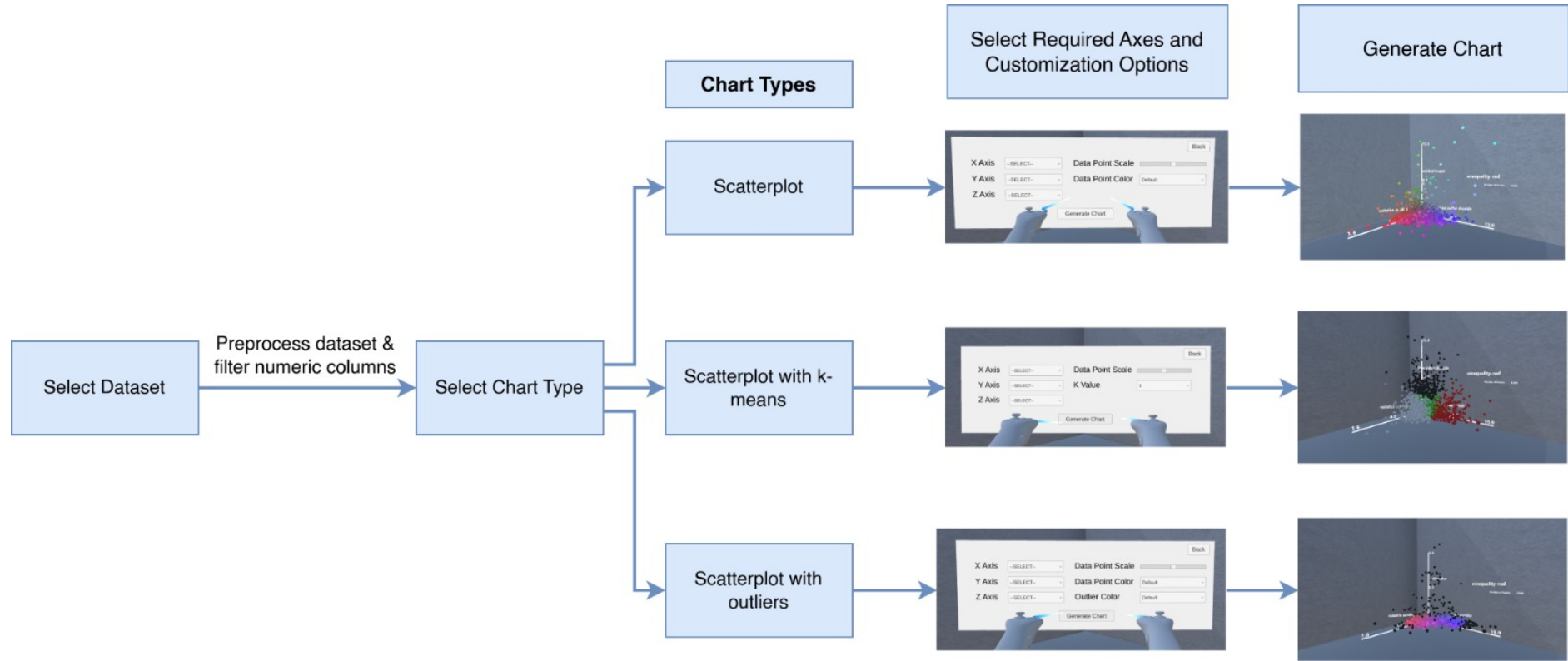


Figure 4.7: Flow of the VRVizX v2 Prototype

These improvements were made based on the feedback from the user studies conducted in the first iteration and the UX principles for XR applications. Detailed implementation information of the prototype is provided in Chapter 5: Implementation. The next step is to evaluate whether these changes effectively enhanced the UX, user comprehension, and decision making.

4.5.2 Demonstration

To evaluate the final prototype, VRVizX v2, a comparative user study was conducted with 30 students from the University of Colombo School of Computing, aged between 18 and 34. All participants were pursuing a degree in Information Technology (IT), consisting of 18 males and 12 females, with 26 students in their fourth year and 4 in their third year of study. The study was conducted in a physical space measuring 3 by 3 meters to ensure the safety of the participants. Figure 4.8 illustrates the flow of the study, from onboarding to task completion. The study followed a within-subject design, where each participant used both systems: VRVizX v2 and a 2D data visualization tool.

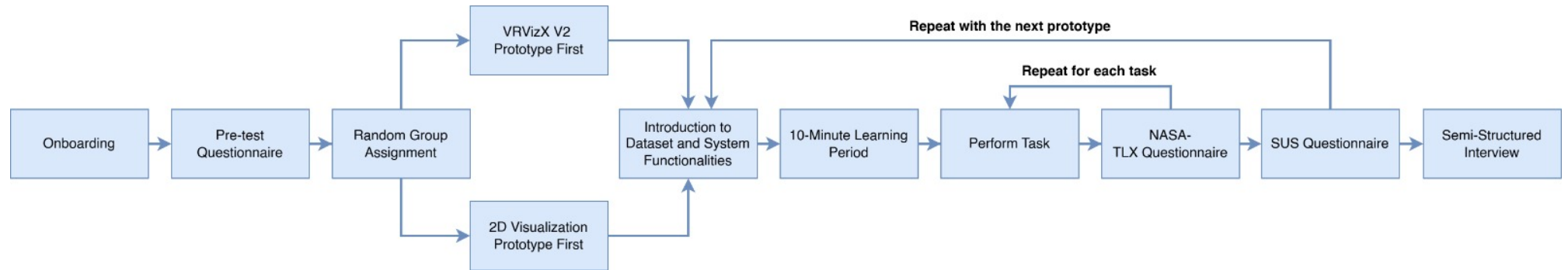


Figure 4.8: Flow of the user study in iteration 02

1. During the onboarding phase, an overview of the research was provided to the participants.
2. Next, they were required to complete a pre-test questionnaire, which explained the purpose of the study and ensured their privacy and rights. This step was mandatory before they took part in the study. The questionnaire is included in Appendix B. The results revealed that:

- All participants had a background in data analysis. Every participant had prior experience with spreadsheets such as Excel, while most were also familiar with tools such as Power BI, Matplotlib, Tableau, and QlikView. A smaller group had used tools like Plotly and RapidMiner.
- 76.7% of the participants had never used any 3D data visualization tools before.
- 76.7% of the participants had never used VR for data visualization.
- 50% of the participants had previously interacted with 3D visualizations on the web.

These results suggest that while participants were generally experienced in data analysis, their exposure to immersive or 3D visualization technologies was limited.

3. To ensure fairness in the comparative study, participants were randomly and equally assigned to two groups. One group interacted with the VRVizX v2 system first, followed by the 2D system, while the other group experienced the 2D system first and then the VR system.
4. After completing the pre-test questionnaire, participants were given a detailed description of the dataset, Red Wine Quality[38], which was also used in the previous user study during iteration 1. Participants were then introduced to the functionalities of both systems and instructed on how to interact with them.
 - The 2D system was developed using Jupyter Notebook with the Matplotlib library and included functionalities to select the chart type, such as the scatter plot with outliers (Figure 4.9) and the scatter plot with K-means clustering (Figure 4.10), along with the X, Y, and Z axes, and a reset option.
 - The participants interacted with the 2D system using the laptop trackpad, and to interact with the VRVizX v2 system, Meta Quest 2 controllers were used.
 - Both systems were operated on a laptop equipped with an AMD Ryzen™ 5 5600H processor, 16GB of DDR4 RAM (3200 MHz), an NVIDIA GeForce RTX™ 3050 GPU (4GB GDDR6), and Windows 11 Home (64-bit).
 - The user study consisted of three tasks, described in detail in Appendix C:
 - Task 1 involved identifying the data point that is farthest from the rest of the dataset.

- Task 2 required participants to determine the correlation between variables based on a given view.
 - Task 3 focused on identifying the cluster to which a new data point belongs.
5. Following the system descriptions, participants were given 15 minutes to familiarize themselves with each system.
 6. While the participants performed each task, completion time and accuracy (based on predefined correct answers) were measured.
 7. After completing each task, participants filled out the NASA Task Load Index (NASA-TLX) questionnaire, which measures subjective workload. The NASA-TLX evaluates workload across six sub-dimensions: mental demand, physical demand, temporal demand, performance, effort, and frustration. This was done after each task, resulting in three NASA-TLX responses per system. The NASA-TLX questionnaire is included in Appendix D.
 8. After completing all three tasks in one system, participants filled out the System Usability Scale (SUS) to evaluate overall usability. The SUS questionnaire is included in Appendix E. They then repeated the same process for the other system.
 9. A semi-structured interview was conducted to collect qualitative feedback on participants' experiences with both the 2D and 3D systems. The interview focused on their experiences with the systems and the tasks, the usefulness and usability of specific features, interaction methods, customization options, and navigation techniques. While participants were free to express their thoughts openly, the interview was guided by a set of questions provided in Appendix F.

After completing the user study for all the participants, the collected data was analyzed to evaluate the usability, efficiency, and UX of VRVizX v2 compared to the 2D data visualization system.

4.5.3 Evaluation

The results of the user study are presented and analyzed in Chapter 6: Results and Evaluation

4.5.4 Communication

Insights and user feedback gathered during the study are further discussed in Chapter 7: Discussion.

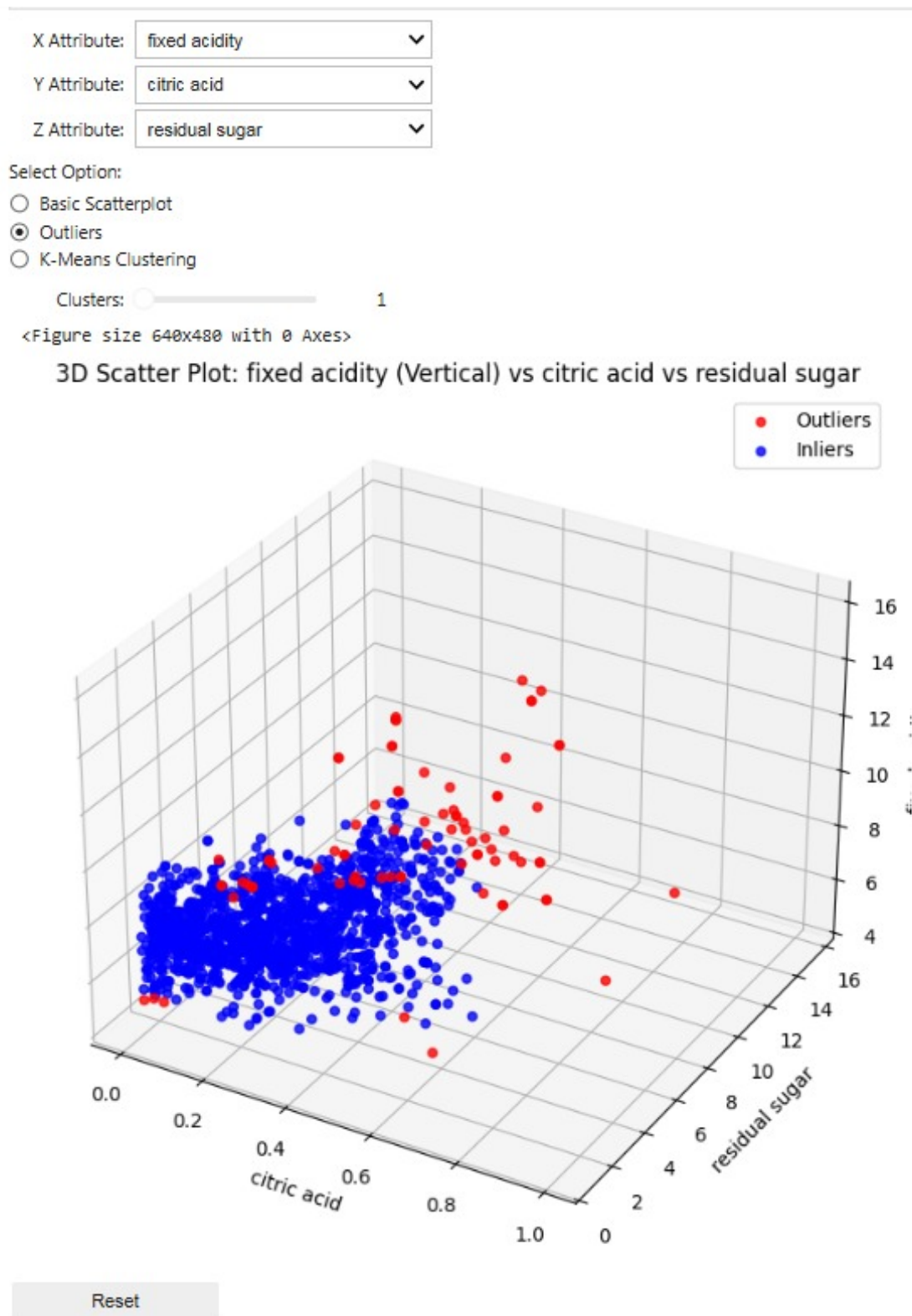


Figure 4.9: 2D data visualization system displaying a scatterplot with outliers

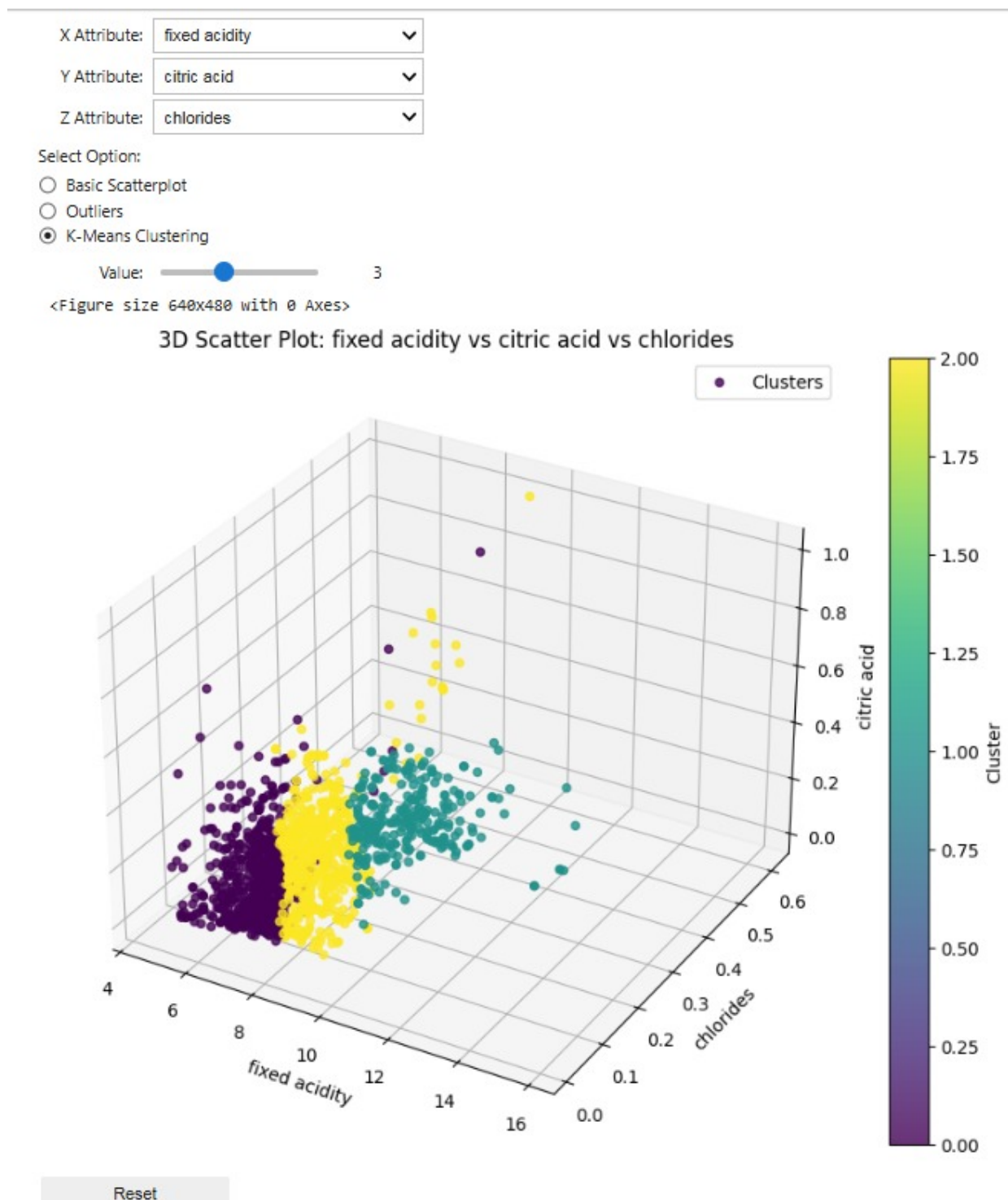


Figure 4.10: 2D data visualization system displaying a scatterplot with clusters

Chapter 5

Implementation

5.1 Introduction

This chapter focuses on the technical implementation of the VRVizX prototype, which aims to enhance user engagement and comprehension by leveraging the intuitive and immersive nature of virtual reality (VR). It provides a seamless workflow that begins with uploading a dataset and ends with interactive three-dimensional (3D) visualizations. The prototype follows a modular architecture to support scalability and flexibility for future enhancements. It is built using the Unity Engine and relies on its extended reality (XR) development tools for controller-based interactions, haptic feedback, and spatialized user interface (UI) elements to deliver a user-centric experience.

5.2 System Architecture

The prototype follows a modular, component-based architecture with distinct components responsible for tasks such as input handling, data processing, visualization, and scene management. These components interact with each other through well-defined interfaces, which allows for future enhancements such as adding new types of visualizations or supporting additional VR hardware. This architecture ensures a clear separation of concerns between components, enables independent testing and debugging, and promotes the reusability of components.

Figure 5.1 presents the architecture of the VRVizX prototype. The description of each component within the architecture is described below:

- **VR Controller Input Module:** It captures raw input signals from Meta Quest 2 controllers and translates them into high-level commands such as "select," "zoom," and "rotate". Then these are passed to the interaction engine.
- **Interaction Module:** This is the core logic layer that interprets user commands and triggers the appropriate actions in the 3D space. For example, it manages object selection, scatterplot manipulation, and tooltip generation in the VRVizX.

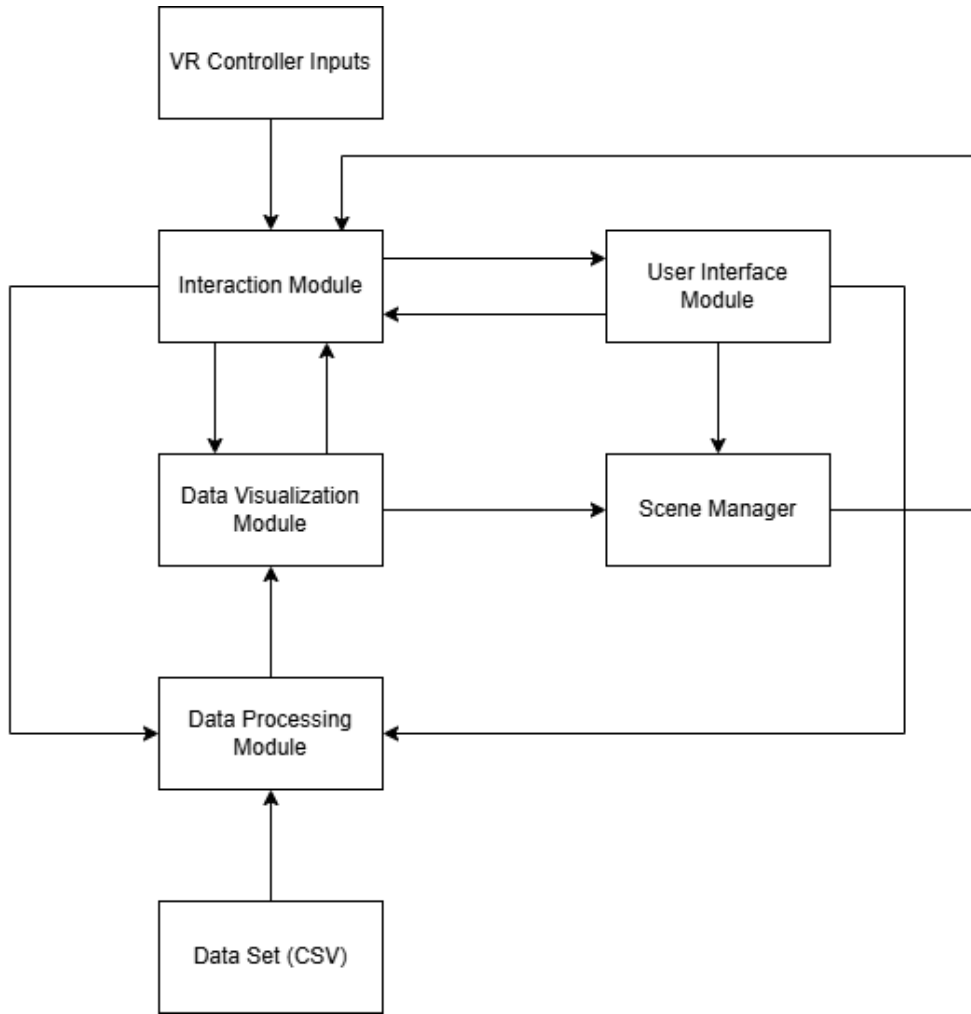


Figure 5.1: Architecture of the VRVizX Prototype

- **UI Module:** Handles all the visual elements presented to the user. This includes dataset upload dialogs, chart type selection menus, axis assignment interfaces, and customization controls such as color, scale, and clustering parameters (e.g., K-value for K-means). It displays validation messages and delivers auditory cues to enhance interaction feedback.
- **The Scene Manager:** Handles transitions between different scenes in VRVizX. These transitions are managed asynchronously to reduce performance bottlenecks and ensure a smooth user experience (UX). It also maintains the persistence of user selections and loaded data across scenes. The main scenes in VRVizX include:
 - **Start Scene:** Launch interface with basic navigation.
 - **Upload Scene:** Dataset upload and preprocessing.
 - **Chart Configuration Scene:** Chart type and axis selection.
 - **Visualization Scene:** 3D chart display and interaction.
- **Data Processing Module:** This is responsible for preprocessing the selected datasets before visualization. It parses the comma-separated values (CSV) file, validates the

structure, detects numerical attributes, and handles missing values.

- **Data Visualization Module:** It generates the selected visualization based on the selected X, Y, and Z axes, data point color and size, and K-value. The visualization is displayed in a 3D space where users can navigate to specific areas of the data. It dynamically adjusts the size, orientation, and interactivity of the visualization based on user input and the position of the VR headset.

5.3 Development Tools and Technology Stack

5.3.1 Unity Game Engine

Unity (version 2022.3.37f1 LTS) was chosen as the development platform for VRVizX after considering both technical requirements and practical constraints. Since the aim was to build an interactive 3D data visualization prototype for VR, performance and XR support were key priorities. Unity’s mature XR ecosystem and support for a wide range of VR headsets made it a strong fit for the project.

Another advantage of Unity is its use of C#, which provides a solid object-oriented programming environment. This allowed for clear structuring of interaction logic, modular UI components, and scalable architecture that evolved through multiple development iterations.

Unity also proved reliable in terms of performance. The ability to render complex 3D scenes without frame rate drops was essential to prevent VR discomfort. In addition, Unity’s built-in features for scene management, UI layout, and visual optimization enabled responsive and immersive interfaces throughout the user workflow. The active Unity developer community and extensive documentation further supported development efficiency.

To support rapid development and interactive VR capabilities, the following Unity features and built-in tools were utilized:

- Built-in 3D primitives (e.g., cubes, planes, spheres) and default materials were used for constructing early prototypes and representing data in 3D space.
- Lighting and rendering tools such as real-time shadows, and reflection probes were used to balance visual clarity with runtime performance.
- Unity’s UI layout system (via world-space canvases) was used to position VR interfaces naturally within the scene.

All core interaction logic, such as zooming, rotating, details-on-demand, tooltips, reset view options, and camera control was implemented using custom C# scripts. These scripts extended Unity’s component-based model to manage user input, control interaction states, and deliver responsive feedback within the VR environment.

5.3.2 Tools and Libraries

The following Software Development Kits (SDKs) and Unity packages were used to develop the VRVizX prototype:

- **Oculus XR Plugin:** Provides native support for Oculus devices, handling both headset and controller tracking.
- **OpenXR Plugin:** Ensures hardware-agnostic VR development by supporting multiple headset types under a unified application programming interface (API).
- **XR Interaction Toolkit:** Enables common VR interactions such as raycasting, grabbing, teleporting, and UI interaction.
- **XR Device Simulator:** Enables development and testing without requiring a physical headset by emulating VR inputs.
- **Unity Input System:** Offers flexible input handling, supporting a range of input devices including keyboard, mouse, and XR controllers.
- **TextMeshPro and Unity UI System:** Used for creating high-resolution text and interactive UI elements in a 3D environment.

In addition to that, the implementation logic and UI behaviour were done using C# because of its seamless integration with the Unity development environment.

5.4 System Flow

5.4.1 Start Scene

When the user enters the system, they are presented with a simple 3D interface with a “Start” button as shown in Figure 5.2. When they click on the button, the scene transitions to the data visualization environment, where the user will be required to upload a dataset. This transition is managed by the Scene Manager.

5.4.2 Dataset Upload and Preprocessing

Once the user uploads the desired dataset in CSV format, as shown in Figure 5.3, the Data Processing Module performs the following tasks to prepare the dataset for visualization:

1. The system parses the file to ensure structural validity.
2. It identifies numerical columns, as scatterplots require numerical data for plotting.
3. Missing values are handled through mean imputation.
4. The processed dataset is stored in memory, making it accessible for visualization tasks.

To improve system transparency, visual cues are included to communicate the success or failure of the upload process.



Figure 5.2: UI of the Start scene

5.4.3 Chart Type and Axis Selection

The VRVizX prototype has three visualization types:

1. Basic 3D Scatterplot
2. 3D Scatterplot with Outlier Highlighting
3. 3D Scatterplot with K-Means Clustering

Based on the selected visualization type (Figure 5.4), the system presents a corresponding menu, as shown in Figures 5.5, 5.6, and 5.7.

This menu allows users to assign data attributes to the X, Y, and Z axes and customize visual properties such as data point size and color. For the second visualization type, additional options are provided to define the color used for outliers, while the third type includes a parameter for specifying the number of clusters.

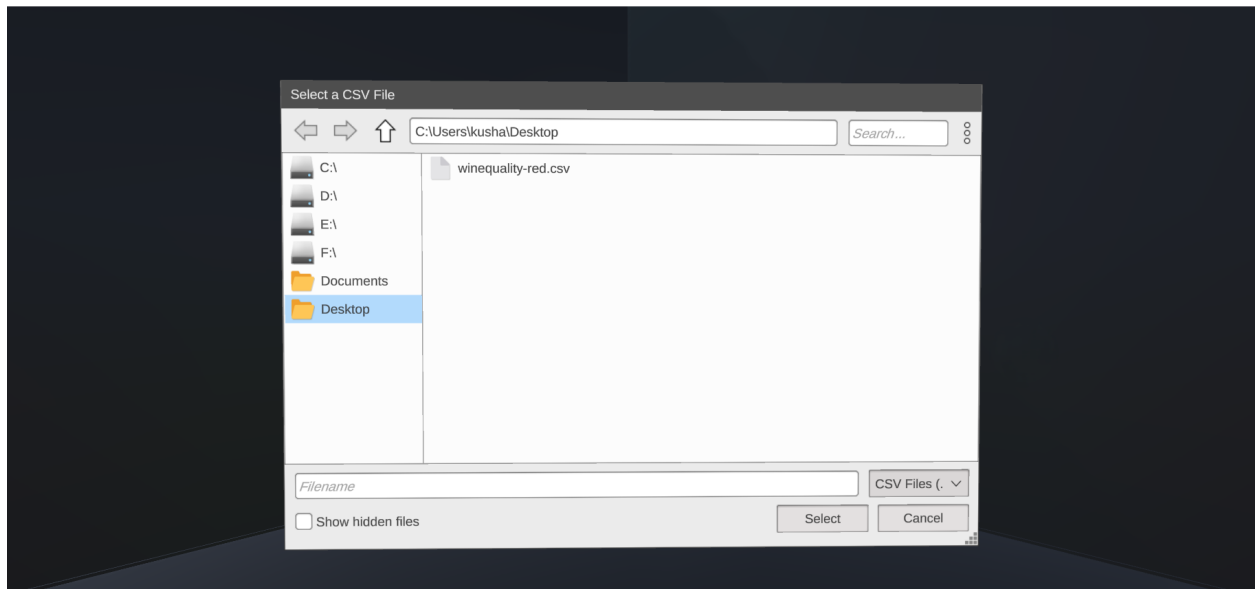


Figure 5.3: UI for dataset selection

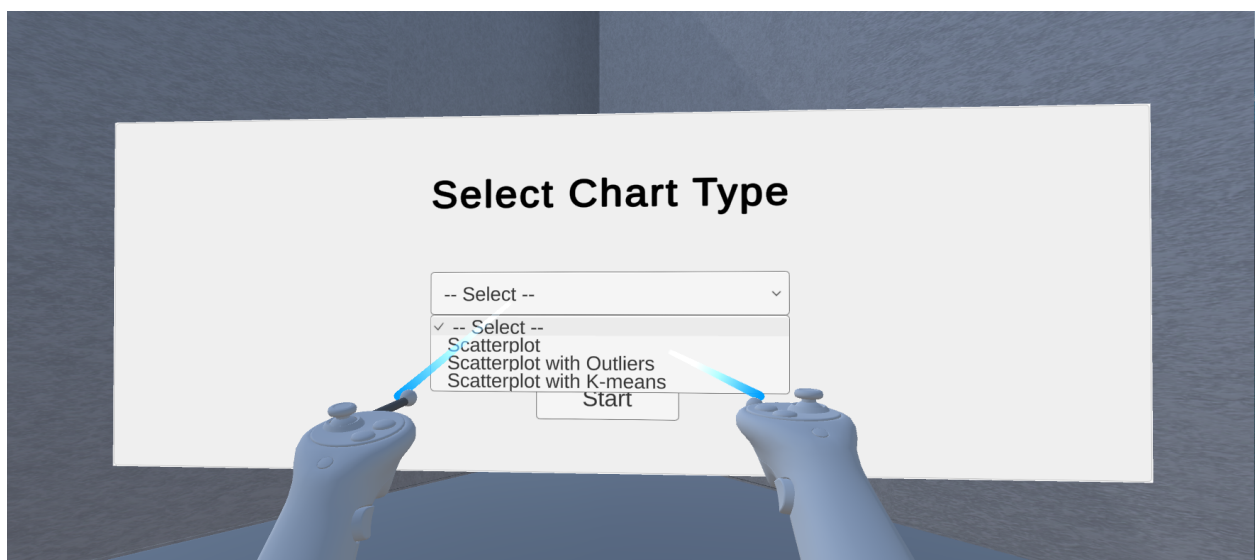


Figure 5.4: Menu for selecting the visualization type

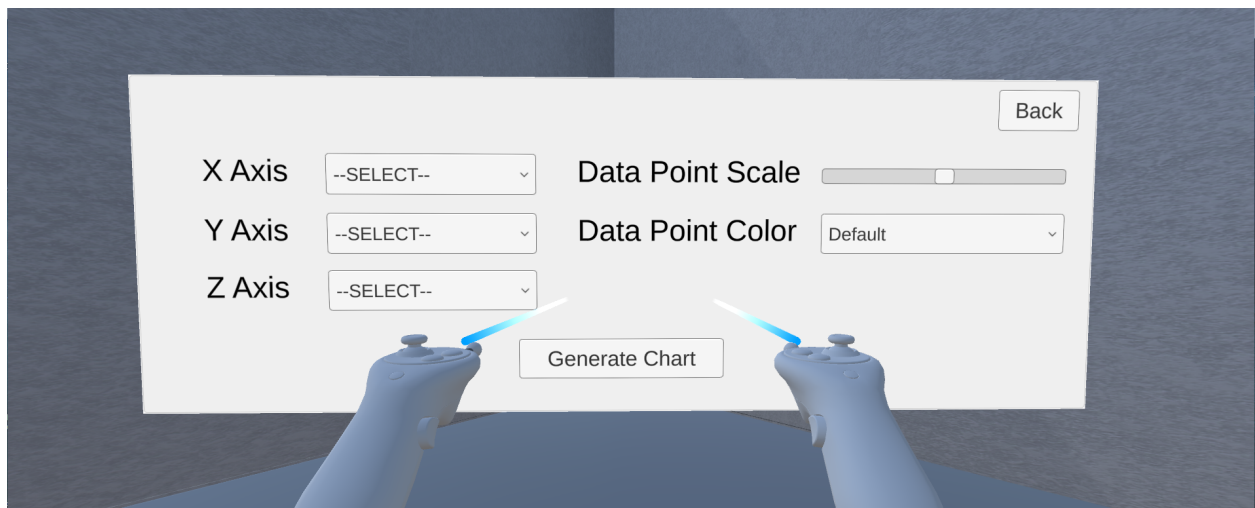


Figure 5.5: Menu for the basic scatterplot

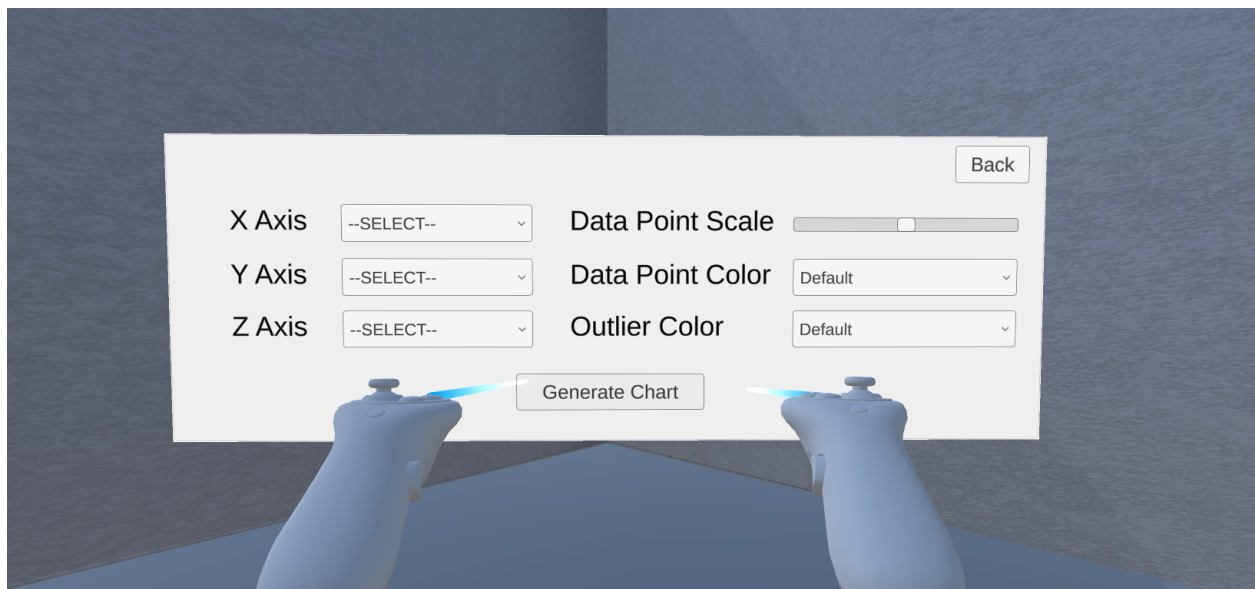


Figure 5.6: Menu for the scatterplot with outliers

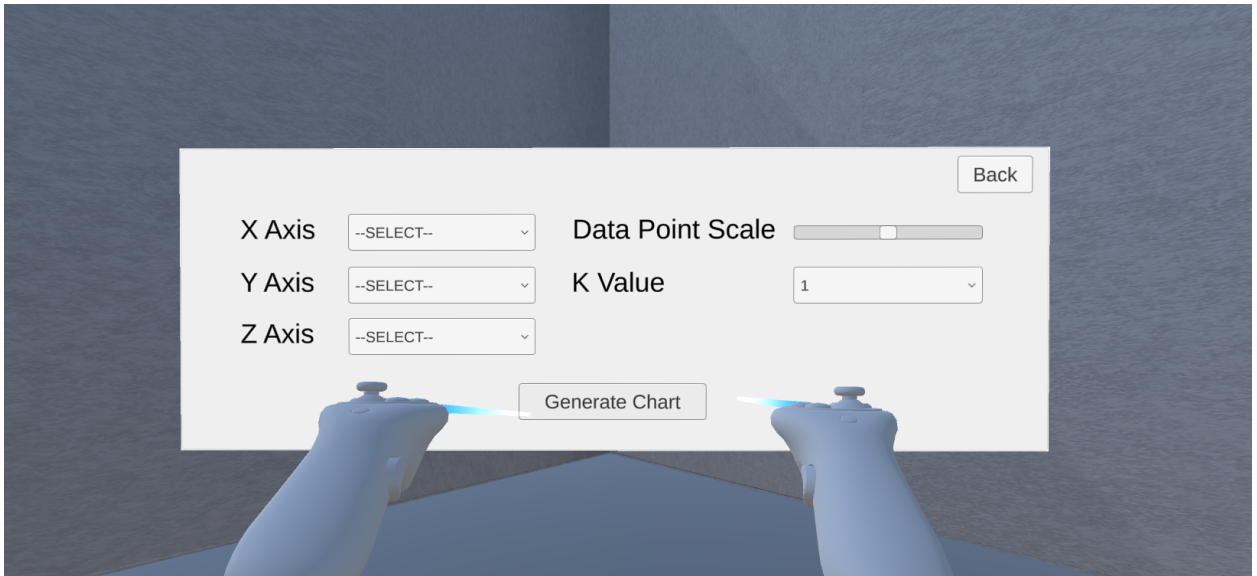


Figure 5.7: Menu for the scatterplot with K-means clustering

5.4.4 Visualization and Interaction

Once the user clicks the “Generate Chart” button after selecting the axes and customization options, the system uses the Data Visualization Module to render the chart in a virtual 3D environment, as shown in Figures 5.8, 5.9, and 5.10. The chart is scaled and positioned relative to the user’s viewpoint. It supports real-time interaction through zooming, rotation, and panning, allowing the user to comprehend the data from multiple perspectives. Clicking on individual data points reveals tooltips that display the corresponding coordinate values. The next section will cover interaction techniques in detail.

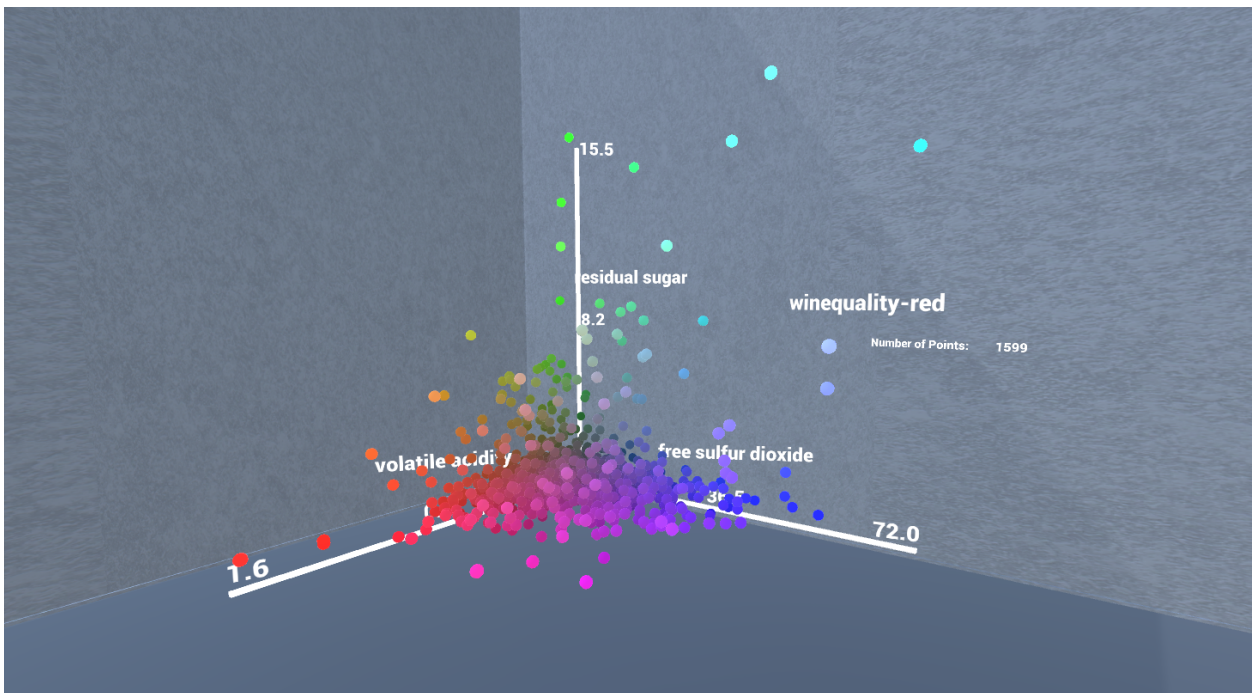


Figure 5.8: Basic Scatter Plot visualization

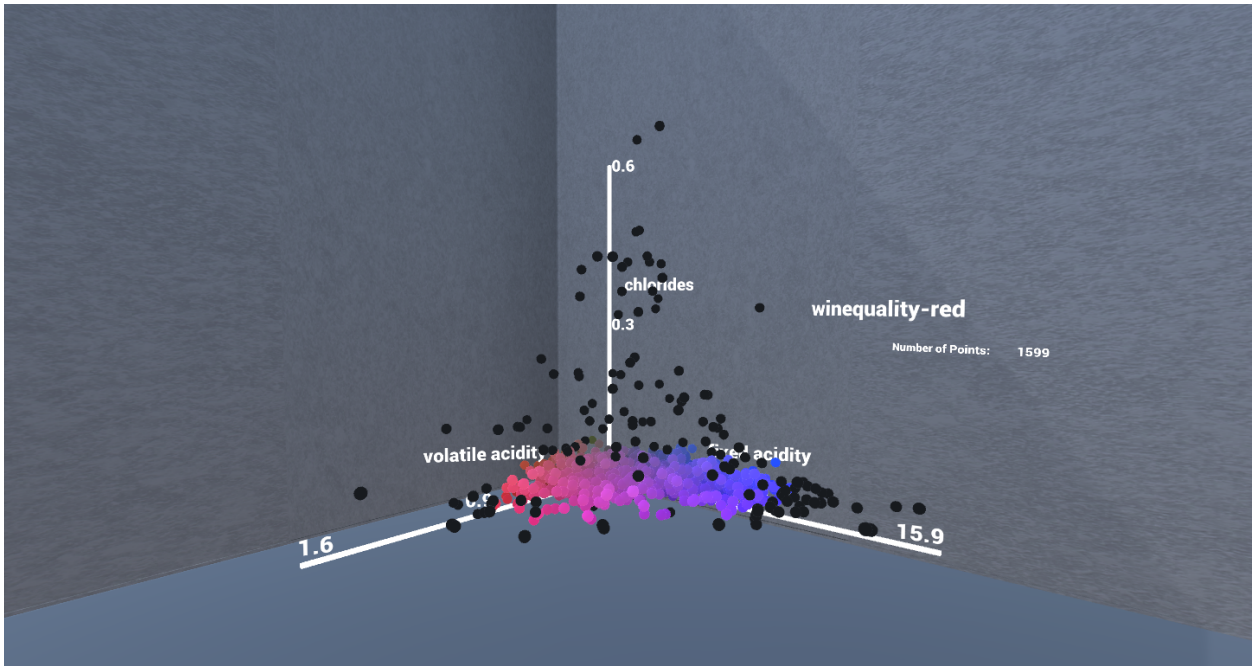


Figure 5.9: Scatter plot with outliers visualization

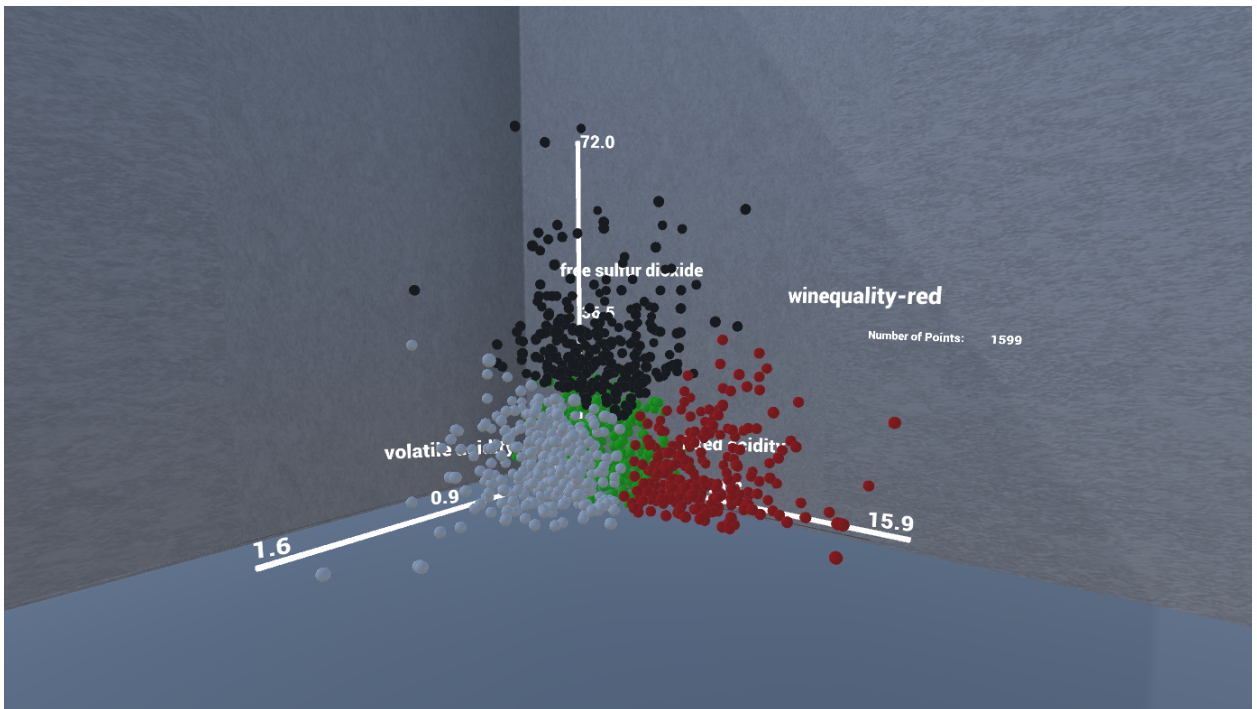


Figure 5.10: Scatter plot with K-means clustering visualization

5.5 Interaction Techniques

5.5.1 Features in VRVizX

The VRVizX system offers several interactive features that enable users to interact with the data visualization efficiently. These features enhance navigation and provide detailed insights into the data. The main interaction techniques are:

- **Select:** Users can point at and select data points using VR controllers. Upon selection, tooltips appear with relevant details, and subtle haptic feedback is triggered to confirm interaction.
- **Zoom:** Users can zoom in and out of the visualization using button combinations.
- **Rotation:** Enables users to orbit around the data using controller input, offering multiple perspectives. The scatterplot can be rotated around different axes by using the controller, enabling users to view the data from various angles and gain better insights.
- **Pan (Walk-through):** Allows users to pan across the dataset using two main methods: physically walking within the defined VR boundary or using teleportation. This freedom of navigation offers both immersive and efficient traversal through the data.
- **Visualize:** Triggers the rendering of the selected chart type with specified parameters.
- **Details on Demand:** When a data point is selected, detailed information such as attribute values is displayed on a floating panel without cluttering the interface, as shown in Figure 5.11.
- **Back Navigation:** Returns users to previous menus or the home scene.
- **Reset:** Reverts the view to its original state after zooming or rotating.

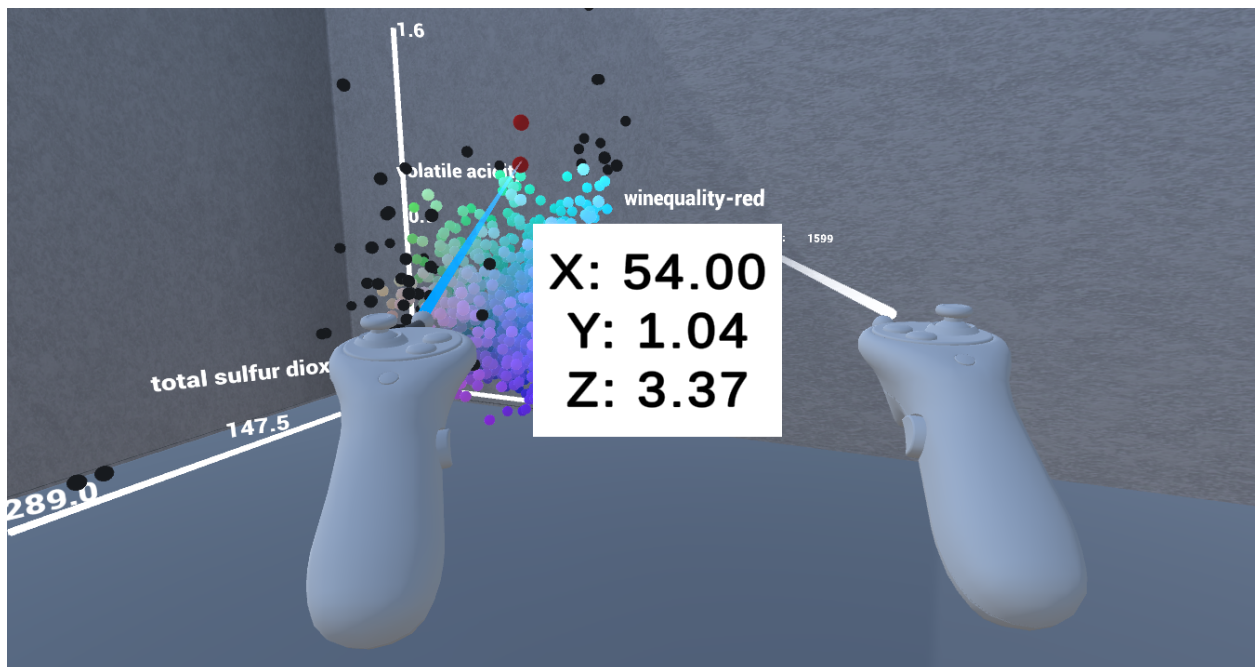


Figure 5.11: Displaying a tooltip by clicking over a data point to reveal its coordinate values.

5.5.2 Controller Mapping

Each function in VRVizX is mapped to specific controller buttons using Unity’s Input System and XR Interaction Toolkit. These mappings were designed to feel intuitive and comfortable, with careful attention to ergonomic use on Meta Quest controllers. Custom mappings were tested to ensure that all functions were working correctly across different controller inputs.

Table 5.1 below presents the mapping between controller inputs and their corresponding functions. The layout of the Meta Quest 2 controller buttons is shown in Figure 5.12.

Controller	Function
Left Controller Joystick	Virtually walk within the scene
Right Controller Joystick	Teleport and rotate the view
Grip Buttons	Retrieve data of selected data points
Trigger Buttons	Interact with UI menus
X Button	Reset the chart to its initial state
A Button	Open the chart generation menu
Left Grip + Left Joystick	Zoom in/out on the chart
Right Grip + Right Joystick	Rotate the chart

Table 5.1: VR Controller to function mapping

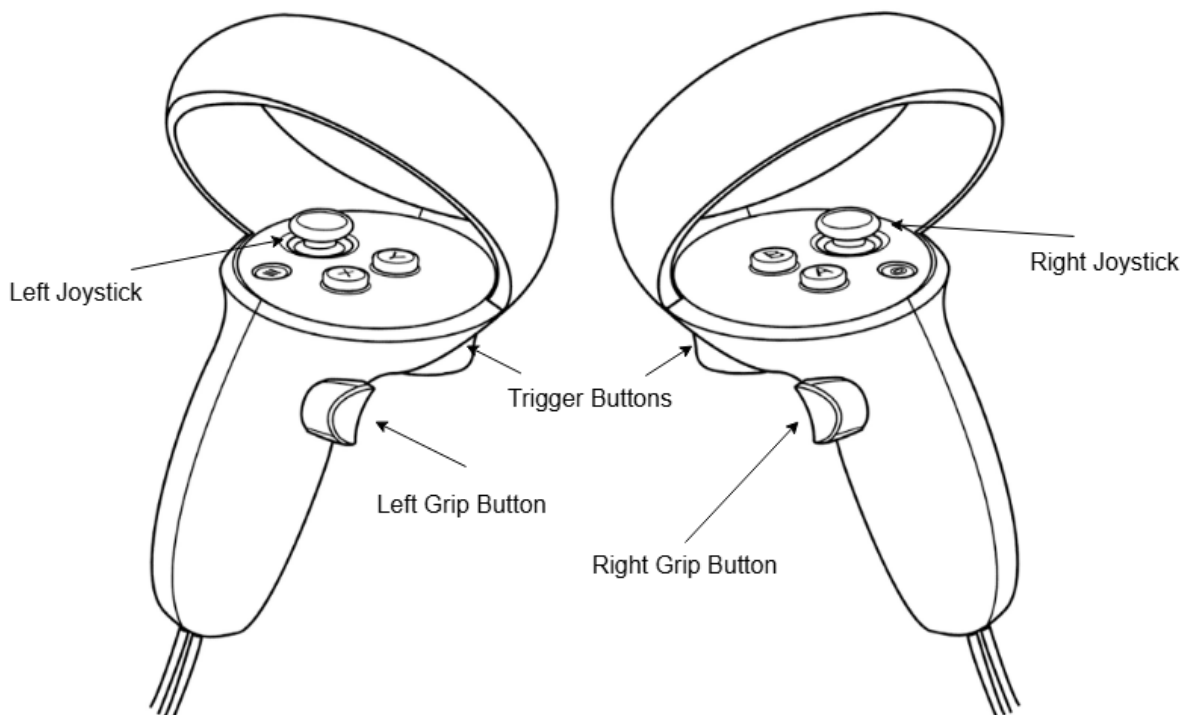


Figure 5.12: Meta Quest 2 controllers

5.5.3 Multimodal Feedback

One of the key UX guidelines for XR applications is the inclusion of multi-modal feedback, an important element that helps increase user engagement and awareness. VRVizX includes

feedback mechanisms such as:

- **Haptic Feedback:** Users receive tactile feedback through controller vibrations when hovering over or selecting a data point.
- **Auditory Cues:** Confirmation sounds are played upon successful interactions, such as interacting with UIs.
- **Visual Cues:**
 - **Tooltips:** These appear dynamically when clicking on data points, displaying the coordinates of the data point.
 - **Visual Highlights:** Selected data points and active UI elements are highlighted using color changes or outlines to guide user attention.
 - **Confirmation Prompts:** Critical actions (e.g., resetting the view) trigger confirmation prompts to prevent accidental commands, as shown in Figure 5.14.
 - **Error Messages:** Clear and concise error messages are displayed for actions such as invalid CSV files or missing axis selections, as shown in Figure 5.13.
 - **Consistent Visual Styles:** VRVizX follows a unified design theme across menus, charts, and prompts, contributing to a seamless UX.

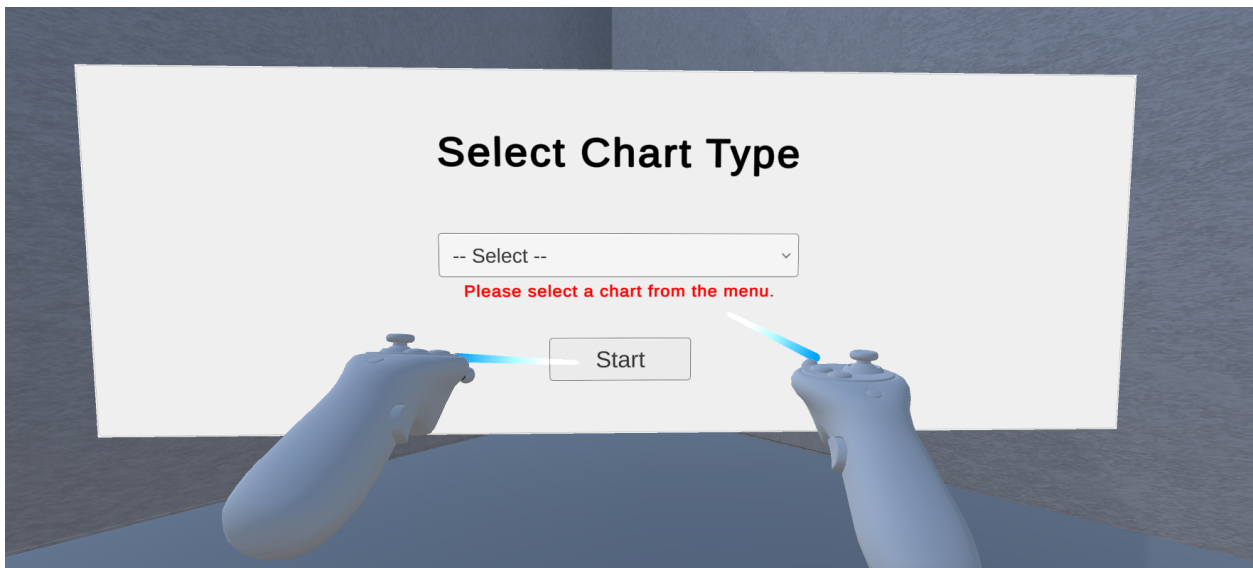


Figure 5.13: Error message displayed when the user fails to select a visualization type

5.5.4 UI Customization

Customization plays a vital role in enhancing UX, particularly in immersive environments like VR, where user control over the interface directly impacts engagement and usability. VRVizX supports several customization options, including:

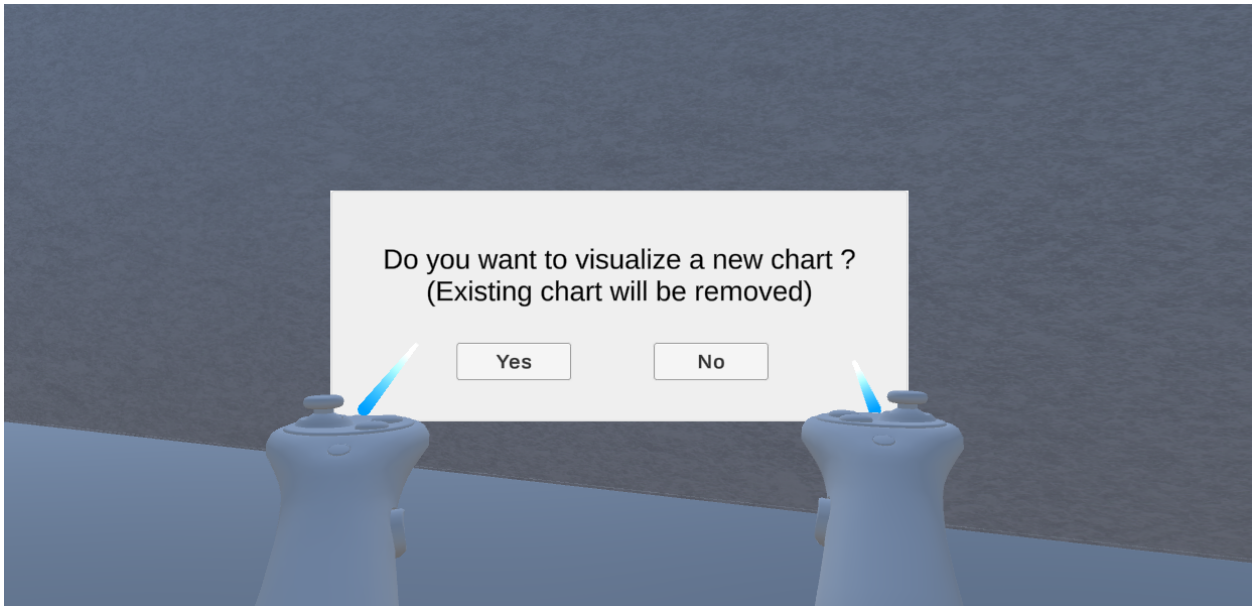


Figure 5.14: Confirmation message when the reset button is clicked

- Data point scale and color: VRVizX allows users to customize the size and color of data points to enhance visual clarity, especially in complex datasets. Additionally, users can adjust the color of outliers, making it easier to differentiate them from the main data distribution and aiding in anomaly detection.
- Axis selection: Once the visualization type is selected, the user can select any three numerical attributes to visualize. This allows the users to easily explore how different attributes are related to each other from different perspectives.
- Smooth Transitions: Zooming, rotating, and transitioning between scenes are designed to be smooth, reducing motion sickness and increasing usability.
- Minimalistic Design: The interface avoids excessive visual clutter, providing only essential elements to maintain focus on the data.

5.5.5 Ergonomic Design

Ergonomics plays an important role in the design of XR applications, as poor interaction design can lead to user fatigue and discomfort. VRVizX was developed with careful attention to ergonomic principles to ensure a comfortable and intuitive experience.

- UI Positioning: Menus and interactive panels are placed within the user's natural field of view (FOV) to reduce neck and eye strain. These elements dynamically adjust based on the user's orientation to ensure accessibility without necessitating excessive head movement.
- Predictable Controls: The behavior of all interactive elements remains consistent throughout the application. For example, rotating the scatterplot always responds proportionally to joystick input.

- **Depth Perception:** Realistic lighting and shading are incorporated to enhance depth cues in the scatterplot, allowing users to perceive the spatial distribution of data more effectively.
- **Reset Options:** Users can reset the scatterplot view at any time, returning the zoom level and rotation to default, thus providing a reliable fallback.
- **Gestural Comfort:** Common actions are mapped to simple and low-effort gestures, minimizing physical strain and ensuring a smooth experience during prolonged sessions.

Despite following ergonomic practices in the system, certain physical discomforts remain beyond its control. Issues with VR hardware, such as fatigue from prolonged standing and the weight of HMDs, can affect the duration and the experience.

5.6 Challenges and Solutions

During the implementation phase of VRVizX, several technical challenges were encountered and addressed:

- Traditional 2D UI components did not translate well into immersive 3D environments. To maintain usability, UI elements were converted into world-space canvases and dynamically positioned relative to the user's height and viewing direction.
- Limited resources and guidance for VR application development made design decisions more challenging, necessitating extensive experimentation and user testing.
- Preserving user data and application state during scene transitions was challenging. To address this, singleton managers and serialized data structures were used to maintain state information across scenes.
- Haptic feedback was fine-tuned through several iterations, resulting in medium-strength vibrations during hover and selection. This improved interactivity without causing discomfort.

Chapter 6

Results and Evaluation

6.1 Overview

This chapter focuses on evaluating the results of the final prototype, VRVizX v2. The user study involved 30 participants and followed a within-subject design, where each participant tried both the two-dimensional (2D) data visualization prototype and the immersive three-dimensional (3D) data visualization prototype, VRVizX v2.

- Participants were assigned three tasks per prototype.
- After completing each task, they were asked to complete the NASA Task Load Index (NASA-TLX) questionnaire to assess their perceived workload.
- Upon completing all three tasks for a prototype, participants completed the System Usability Scale (SUS) to evaluate overall usability.
- Accuracy and completion time for each task were recorded for both prototypes to assess their effectiveness in supporting user comprehension and decision-making.

According to Sawyer[39], Analysis of Variance (ANOVA) is a statistical test used to identify statistically significant differences between the means of multiple groups. It is applied when a continuous dependent variable is influenced by one or more independent variables. In this study, ANOVA was utilized to assess the significant differences in participants' perceived workload, usability, task accuracy, and task completion time between the 2D data visualization prototype and the immersive virtual reality (VR) prototype, VRVizX.

6.2 Perceived Workload (NASA-TLX)

The NASA-TLX is a subjective assessment tool for evaluating perceived mental workload during task performance. It captures the cognitive and physical effort required from participants by measuring six dimensions:

1. Mental Demand – The amount of mental and cognitive activity involved, such as thinking, deciding, or calculating (1 = Low, 5 = High).

2. Physical Demand – The level and intensity of physical activity required to complete the task (1 = Low, 5 = High).
3. Temporal Demand – The degree of time pressure the user feels while completing the task (1 = Low, 5 = High).
4. Effort – The amount of effort the participant must exert to achieve the desired level of performance (1 = Low, 5 = High).
5. Performance – The user’s perceived success in accomplishing the task (1 = Failure, 5 = Perfect).
6. Frustration Level – The extent to which the user feels irritated, stressed, or content and relaxed during the task (1 = Low, 5 = High).

These dimensions are combined to calculate an overall workload score. In this study, NASA-TLX was used to assess the perceived workload between the 2D data visualization tool and VRVizX across three tasks, using a scale of 1 to 5.

We found no statistically significant difference in the overall perceived workload between the 2D prototype ($M = 2.73$) and VRVizX ($M = 2.68$), with a p-value of 0.685 when considering average NASA-TLX scores across all tasks and all six dimensions. Additionally, task-wise analysis of overall workload scores also revealed no significant differences between the two environments (Task 1: p-value = 0.631, Task 2: p-value = 0.086, Task 3: p-value = 0.920). These results suggest that users perceived a similar level of workload in both 2D and VR systems, regardless of the specific task performed.

However, notable differences were observed in several NASA-TLX subscales, including mental demand, physical demand, performance, effort, and frustration, when comparing the 2D and VR environments. These differences appeared both within each task and across all tasks.

6.2.1 NASA-TLX Subscale Analysis Within Each Task

This section focuses on the analysis of NASA-TLX subscales (mental demand, physical demand, temporal demand, performance, effort, frustration) within each task. It compares the perceived workload between the 2D and VR environments for each specific task. Table 6.1 below summarizes the ANOVA results, focusing on the p-values for each subscale across the three tasks to indicate whether the differences between the environments were statistically significant. Further details on the specific tasks can be found in Appendix C.

Figure 6.1 shows the average scores reported by participants in each subscale across the three tasks for both 2D and VR environments. Table 6.1 highlights whether the differences are statistically significant, while the bar charts help identify the direction of those differences, such as whether 2D or VR was perceived as more demanding in each dimension.

Subscale	Task 1	Task 2	Task 3
Mental Demand	0.069	0.001	0.296
Physical Demand	< 0.001	0.115	0.004
Temporal Demand	0.793	0.878	0.818
Performance	< 0.001	< 0.001	0.033
Effort	0.127	0.007	0.217
Frustration	0.011	< 0.001	0.037

Table 6.1: P-value for each task across NASA-TLX dimensions for 2D vs 3D

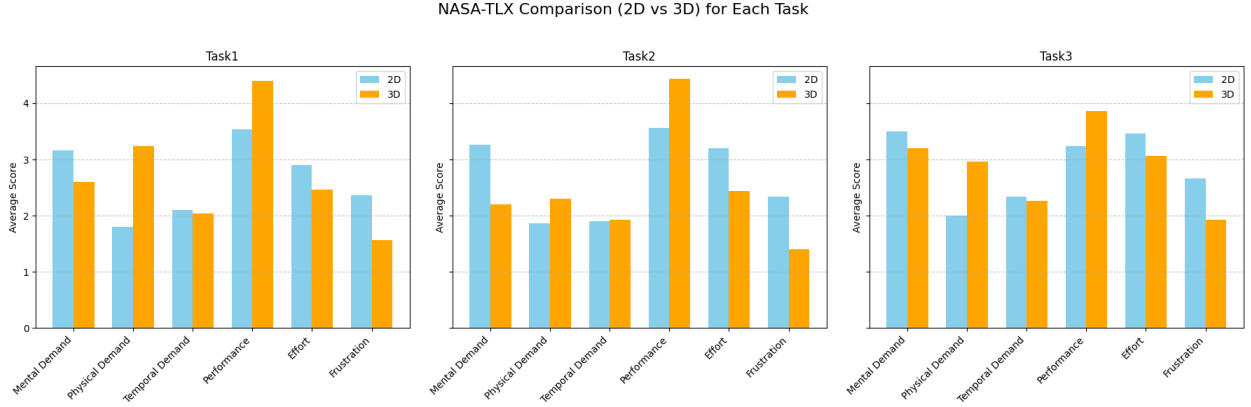


Figure 6.1: Average NASA-TLX scores for each task in 2D and VR environments

The analysis of the NASA-TLX results revealed several key findings regarding the perceived workload in the 2D and VR environments across the tasks. Mental demand showed a significant difference in Task 2, with 2D being perceived as more mentally demanding than VR. However, no significant differences were found in Task 1 and Task 3.

It was observed that significant differences in physical demand were found in Task 1 and Task 3, with VR being perceived as requiring more physical effort than 2D, while no significant difference was observed in Task 2.

There were no significant differences in temporal demand across any of the tasks, indicating that participants did not experience greater time pressure in either environment.

In terms of performance, all three tasks exhibited significant differences, with VR yielding a higher mean score, suggesting that participants felt more successful in completing the tasks in the VR environment. As noted in Appendix D, a higher score on the NASA-TLX scale represents better performance, with 5 indicating 'perfect' and 1 indicating 'failure'.

A significant difference in effort was observed only in Task 2, where participants felt that VR required less effort compared to 2D. In both Task 1 and Task 3, no significant differences were found.

Finally, for frustration, significant differences were found across all tasks where VR was associated with lower frustration levels, indicating that participants felt less frustrated in the VR environment than in the 2D environment.

6.2.2 NASA-TLX Subscale Analysis Across All Tasks

In this section, the focus shifts to the overall analysis of the NASA-TLX subscales across all tasks. It examines the perceived workload across the three tasks, comparing the workload in 2D and VR environments for each NASA-TLX subscale.

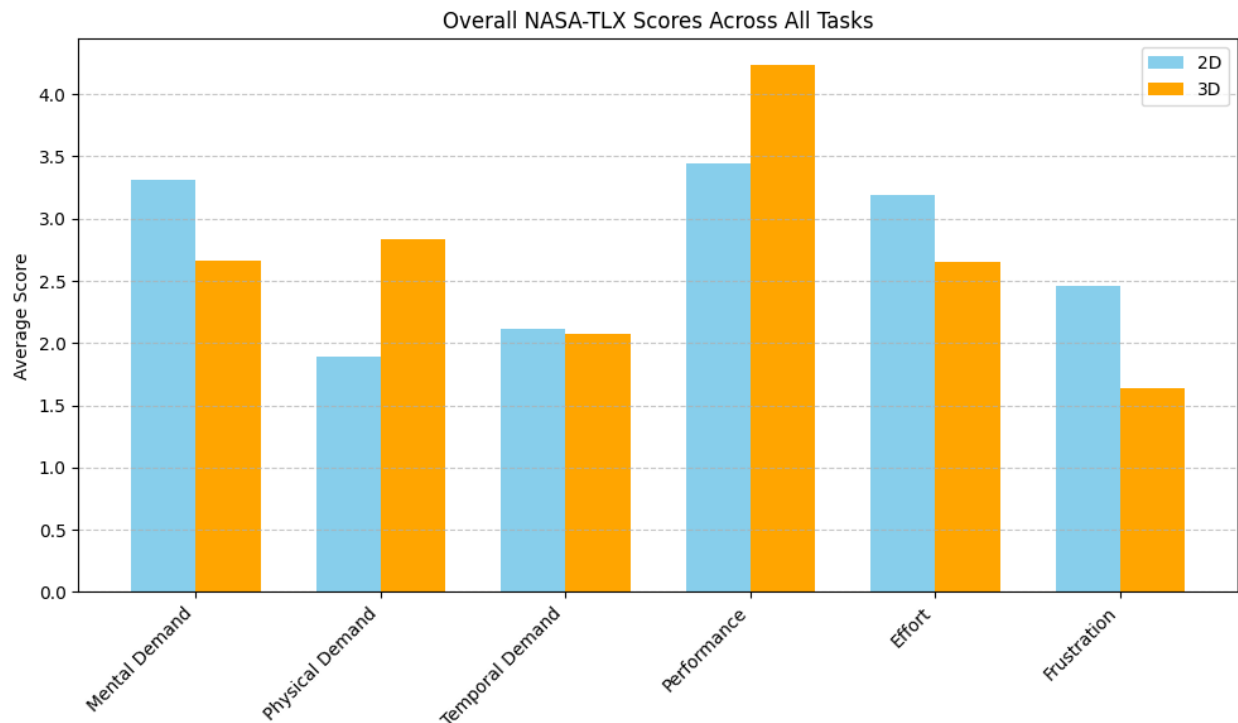


Figure 6.2: Average NASA-TLX scores for all tasks in 2D and VR environments

Subscale	P-value for all tasks
Mental Demand	< 0.001
Physical Demand	< 0.001
Temporal Demand	0.447
Performance	< 0.001
Effort	0.002
Frustration	< 0.001

Table 6.2: P-value for all tasks across NASA-TLX dimensions for 2D vs 3D

As shown in Table 6.2, significant differences were observed in mental demand, physical demand, performance, effort, and frustration when comparing the 2D and 3D environments across all tasks. As shown in Figure 6.2, VR was perceived as less mentally demanding, requiring less effort, and leading to lower frustration levels compared to 2D. Additionally, participants reported a higher success rate and overall performance in the VR environment. However, physical demand was higher in VR than in 2D, indicating that VR tasks required more physical effort.

6.3 System Usability Evaluation (SUS)

The SUS is a commonly used tool for evaluating the overall usability of a system. It consists of a 10-item questionnaire, with responses measured on a scale from 1 to 5, and the resulting score ranges from 0 to 100. Higher scores indicate better perceived usability. In this study, the SUS was used to evaluate the usability of the 2D and VRVizX systems. As noted in the study by Aang Subiyakto et al.[40], odd-numbered questions (1, 3, 5, 7, and 9) are positively worded, while even-numbered questions (2, 4, 6, 8, and 10) are negatively worded. The full list of questions can be found in Appendix E.

To calculate the SUS score for each participant, the responses to odd-numbered questions were adjusted by subtracting 1 from the user's response. In contrast, the responses to even-numbered questions were adjusted by subtracting the user's response from 5. After calculating the individual scores for each question, the total score for each participant was computed by summing the adjusted scores. The total score was then normalized by multiplying it by 2.5, resulting in a final score ranging from 0 to 100.

This procedure was applied to all 30 participants in both the 2D and VRVizX systems. Finally, the mean SUS score was calculated for each system to provide an overall measure of usability. The tables below, Table 6.3 and Table 6.4, show the SUS score calculation for the 3D and 2D systems, respectively.

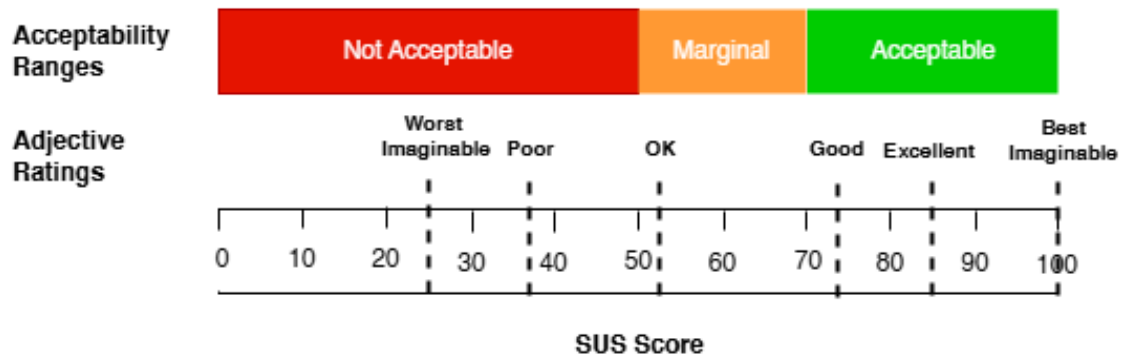


Figure 6.3: SUS scores based on the adjective rating scale. Adapted from Bangor et al.[5]

The results are as follows:

- **Results from Tables 6.3 and 6.4:**

- The average SUS score for the **VRVizX system** is **77.4**.
- The average SUS score for the **2D system** is **53.8**.

- **Interpretation from Table 6.5:**

- The **VRVizX system** is graded **B+** (77.2–78.8).
- The **2D system** falls into the **D** range (51.7–62.6).

Table 6.3: SUS Results for 3D Visualization

	Q1	Q2	Q3	Q4	Q5	Q6	Q7	Q8	Q9	Q10	Σ	$\Sigma*2.5$
R1	4.0	2.0	4.0	2.0	5.0	1.0	5.0	2.0	4.0	3.0	32.0	80.0
R2	4.0	2.0	2.0	2.0	4.0	2.0	5.0	2.0	4.0	2.0	29.0	72.5
R3	5.0	2.0	4.0	2.0	4.0	1.0	5.0	1.0	5.0	1.0	36.0	90.0
R4	4.0	2.0	3.0	4.0	4.0	1.0	5.0	3.0	2.0	3.0	25.0	62.5
R5	5.0	1.0	4.0	4.0	5.0	2.0	5.0	1.0	4.0	2.0	33.0	82.5
R6	5.0	2.0	4.0	2.0	5.0	1.0	5.0	2.0	5.0	2.0	35.0	87.5
R7	3.0	1.0	4.0	3.0	4.0	1.0	3.0	3.0	3.0	2.0	27.0	67.5
R8	4.0	2.0	5.0	5.0	5.0	1.0	4.0	2.0	4.0	2.0	30.0	75.0
R9	5.0	1.0	4.0	2.0	5.0	1.0	4.0	1.0	4.0	1.0	36.0	90.0
R10	4.0	2.0	4.0	3.0	4.0	1.0	4.0	1.0	4.0	2.0	31.0	77.5
R11	5.0	2.0	5.0	2.0	5.0	2.0	4.0	2.0	5.0	3.0	33.0	82.5
R12	3.0	4.0	3.0	3.0	4.0	2.0	4.0	3.0	3.0	2.0	23.0	57.5
R13	4.0	1.0	4.0	1.0	3.0	3.0	4.0	2.0	3.0	2.0	29.0	72.5
R14	5.0	1.0	4.0	2.0	5.0	1.0	5.0	1.0	4.0	4.0	34.0	85.0
R15	5.0	1.0	5.0	1.0	5.0	1.0	5.0	2.0	4.0	2.0	37.0	92.5
R16	2.0	4.0	4.0	5.0	4.0	2.0	2.0	4.0	5.0	1.0	21.0	52.5
R17	4.0	1.0	5.0	3.0	4.0	1.0	5.0	1.0	4.0	2.0	34.0	85.0
R18	3.0	1.0	5.0	1.0	3.0	1.0	5.0	1.0	4.0	3.0	33.0	82.5
R19	4.0	3.0	4.0	2.0	4.0	1.0	5.0	2.0	4.0	2.0	31.0	77.5
R20	5.0	1.0	4.0	4.0	3.0	2.0	3.0	1.0	5.0	2.0	30.0	75.0
R21	4.0	1.0	5.0	1.0	5.0	1.0	5.0	1.0	5.0	4.0	36.0	90.0
R22	5.0	2.0	5.0	2.0	5.0	1.0	4.0	1.0	4.0	2.0	35.0	87.5
R23	4.0	1.0	5.0	1.0	4.0	3.0	3.0	1.0	4.0	4.0	30.0	75.0
R24	5.0	3.0	4.0	3.0	4.0	2.0	4.0	2.0	4.0	4.0	27.0	67.5
R25	4.0	1.0	5.0	1.0	5.0	1.0	5.0	1.0	4.0	1.0	38.0	95.0
R26	5.0	1.0	2.0	5.0	5.0	1.0	5.0	2.0	3.0	1.0	30.0	75.0
R27	4.0	2.0	3.0	2.0	4.0	2.0	3.0	2.0	4.0	2.0	28.0	70.0
R28	4.0	1.0	4.0	4.0	5.0	1.0	3.0	1.0	4.0	2.0	31.0	77.5
R29	4.0	3.0	3.0	4.0	5.0	1.0	5.0	2.0	4.0	4.0	27.0	67.5
R30	3.0	1.0	3.0	4.0	4.0	1.0	5.0	2.0	3.0	2.0	28.0	70.0
Σ											929.0	2322.5
Mean												77.416667

Table 6.4: SUS Results for 2D Visualization

	Q1	Q2	Q3	Q4	Q5	Q6	Q7	Q8	Q9	Q10	Σ	$\Sigma*2.5$
R1	1.0	4.0	2.0	4.0	2.0	1.0	4.0	4.0	2.0	4.0	14.0	35.0
R2	2.0	3.0	2.0	1.0	4.0	2.0	2.0	4.0	2.0	2.0	20.0	50.0
R3	1.0	3.0	2.0	4.0	1.0	2.0	2.0	2.0	2.0	2.0	15.0	37.5
R4	2.0	5.0	1.0	3.0	2.0	2.0	1.0	5.0	1.0	5.0	7.0	17.5
R5	2.0	4.0	2.0	3.0	4.0	2.0	1.0	3.0	2.0	5.0	14.0	35.0
R6	1.0	3.0	2.0	5.0	4.0	4.0	5.0	4.0	2.0	3.0	15.0	37.5
R7	5.0	1.0	5.0	2.0	4.0	1.0	4.0	1.0	5.0	2.0	36.0	90.0
R8	1.0	5.0	1.0	5.0	2.0	5.0	1.0	5.0	1.0	4.0	2.0	5.0
R9	2.0	4.0	2.0	4.0	5.0	3.0	4.0	5.0	3.0	1.0	19.0	47.5
R10	3.0	1.0	4.0	1.0	4.0	1.0	5.0	1.0	4.0	2.0	34.0	85.0
R11	2.0	4.0	3.0	2.0	3.0	4.0	2.0	4.0	3.0	3.0	16.0	40.0
R12	2.0	3.0	3.0	3.0	3.0	3.0	4.0	3.0	3.0	4.0	19.0	47.5
R13	3.0	1.0	3.0	1.0	3.0	2.0	4.0	2.0	2.0	1.0	28.0	70.0
R14	5.0	1.0	4.0	4.0	5.0	1.0	5.0	5.0	4.0	3.0	29.0	72.5
R15	2.0	4.0	4.0	1.0	2.0	3.0	3.0	2.0	3.0	2.0	22.0	55.0
R16	4.0	3.0	4.0	4.0	4.0	5.0	4.0	1.0	4.0	2.0	25.0	62.5
R17	3.0	2.0	4.0	2.0	4.0	2.0	4.0	2.0	4.0	2.0	29.0	72.5
R18	2.0	4.0	1.0	1.0	4.0	3.0	2.0	4.0	2.0	4.0	15.0	37.5
R19	3.0	1.0	3.0	1.0	4.0	2.0	4.0	3.0	4.0	1.0	30.0	75.0
R20	1.0	1.0	1.0	2.0	3.0	3.0	3.0	3.0	3.0	2.0	20.0	50.0
R21	3.0	2.0	2.0	2.0	4.0	2.0	4.0	3.0	4.0	3.0	25.0	62.5
R22	3.0	2.0	2.0	1.0	2.0	2.0	5.0	2.0	5.0	1.0	29.0	72.5
R23	1.0	4.0	2.0	1.0	1.0	2.0	4.0	5.0	2.0	1.0	17.0	42.5
R24	1.0	4.0	1.0	3.0	2.0	4.0	1.0	5.0	2.0	2.0	9.0	22.5
R25	4.0	3.0	2.0	2.0	3.0	4.0	2.0	3.0	3.0	2.0	20.0	50.0
R26	2.0	3.0	2.0	1.0	2.0	2.0	4.0	4.0	3.0	2.0	21.0	52.5
R27	4.0	3.0	4.0	1.0	4.0	2.0	3.0	2.0	3.0	2.0	28.0	70.0
R28	2.0	1.0	4.0	1.0	4.0	2.0	2.0	1.0	3.0	1.0	29.0	72.5
R29	3.0	4.0	2.0	1.0	4.0	1.0	3.0	4.0	2.0	1.0	23.0	57.5
R30	3.0	1.0	5.0	1.0	3.0	1.0	5.0	1.0	4.0	1.0	35.0	87.5
Σ											645.0	1612.5
Mean												53.75

SUS Score Range	Grade	Percentile Range
84.1 - 100	A+	96 - 100
80.8 - 84.0	A	90 - 95
78.9 - 80.7	A-	85 - 89
77.2 - 78.8	B+	80 - 84
74.1 - 77.1	B	70 - 79
72.6 - 74.0	B-	65 - 69
71.1 - 72.5	C+	60 - 64
65.0 - 71.0	C	41 - 59
62.7 - 64.9	C-	35 - 40
51.7 - 62.6	D	15 - 34
0.0 - 51.6	F	0 - 14

Table 6.5: Curved Grading Scale Interpretation of SUS Scores (Adapted from Sauro and Lewis[6])

- **SUS Acceptability Scale (Figure 6.3):**

- The **VRVizX system** is categorized within the "**Acceptable**" range (71.1–100).
- The **2D system** is positioned within the "**Marginal**" range (51.7–71).

- **Adjective Rating Interpretation (Figure 6.3 and Sauro[41]):**

- The **VRVizX system** falls into the "**Good**" range (71.1–80.7).
- The **2D system** falls into the "**OK**" range (51.7–71).

The results indicate that the VRVizX system was generally found to be usable, with an average SUS score of 77.4, which suggests a good user experience. In contrast, a considerably lower SUS score of 53.8 was recorded for the 2D system, indicating that its usability is significantly lower and requires substantial improvements. It can be concluded that the VRVizX system was perceived as more effective and user-friendly compared to the 2D version. However, despite the better performance of the VRVizX system, it has not yet reached the highest usability classifications, such as "Excellent" or "Best Imaginable", leaving room for further refinements in the user experience (UX).

To identify whether there was a statistically significant difference in usability between the VRVizX and 2D systems, a one-way ANOVA was conducted on the SUS scores. The results revealed a significant difference between the two groups ($p < 0.001$), indicating that the observed difference in usability was statistically meaningful.

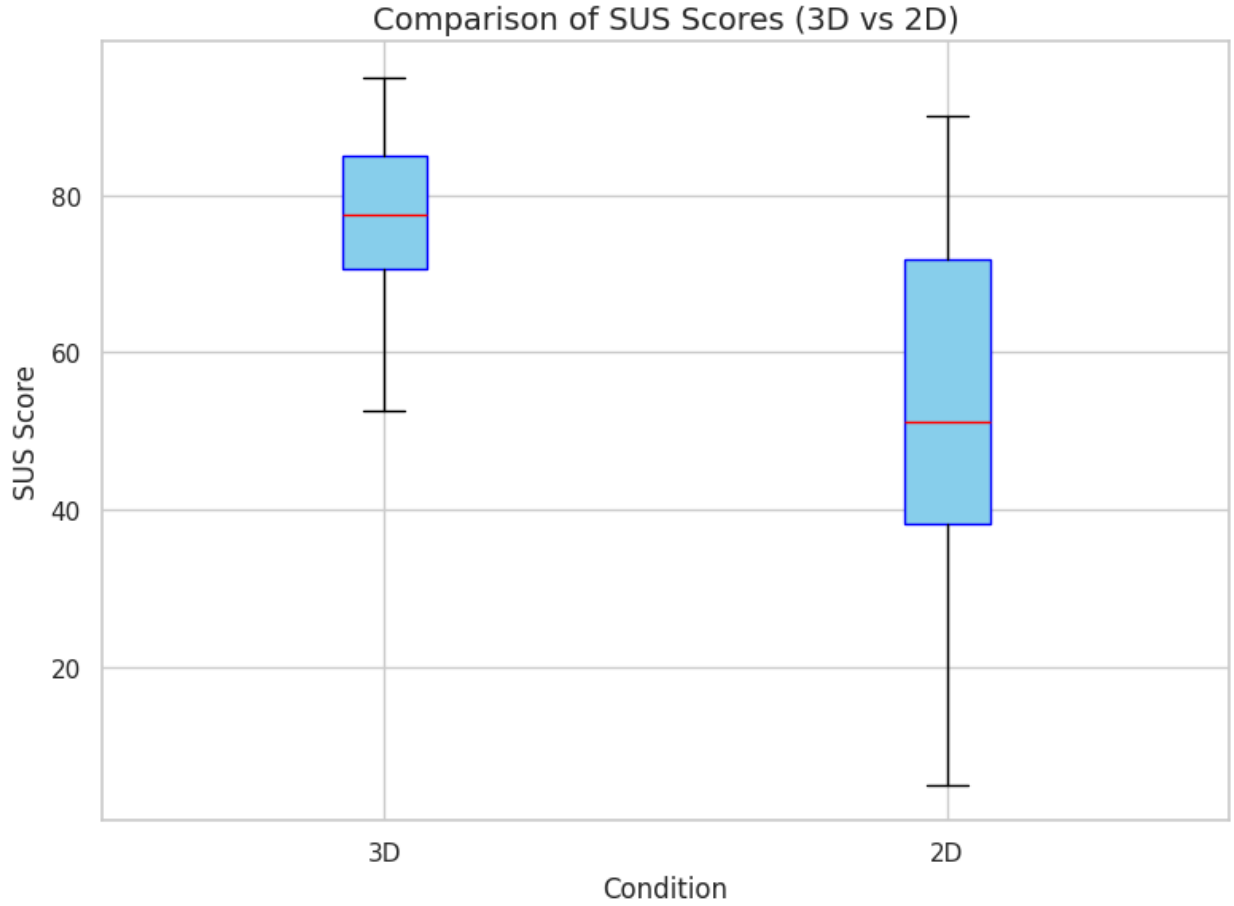


Figure 6.4: Box plot comparison of SUS scores for the VRVizX and 2D systems

6.4 Task Accuracy

The accuracy of participants in completing each task was evaluated for both the 2D and VRVizX (3D) systems to assess how well they were able to comprehend and accurately respond to the visualizations. Since the correct answers were predefined, a one-way ANOVA was conducted to analyze the accuracy data. Table 6.5 presents the total number of correct responses for each task in the 2D and VRVizX systems.

Task	2D System	VRVizX
Task 1	8/30	23/30
Task 2	19/30	30/30
Task 3	4/30	22/30

Table 6.6: Number of correct responses per task for the 2D system and VRVizX (3D).

Based on Figure 6.5, Task 1, which required participants to identify the point farthest from the rest, revealed a statistically significant difference in accuracy between the 2D system and VRVizX (3D), with $p < 0.001$. While only 26.67% of participants answered correctly in the 2D environment, the accuracy increased to 76.67% in VRVizX.

Task 2, which required participants to determine the type of correlation between variables, also showed a statistically significant difference in accuracy between the two

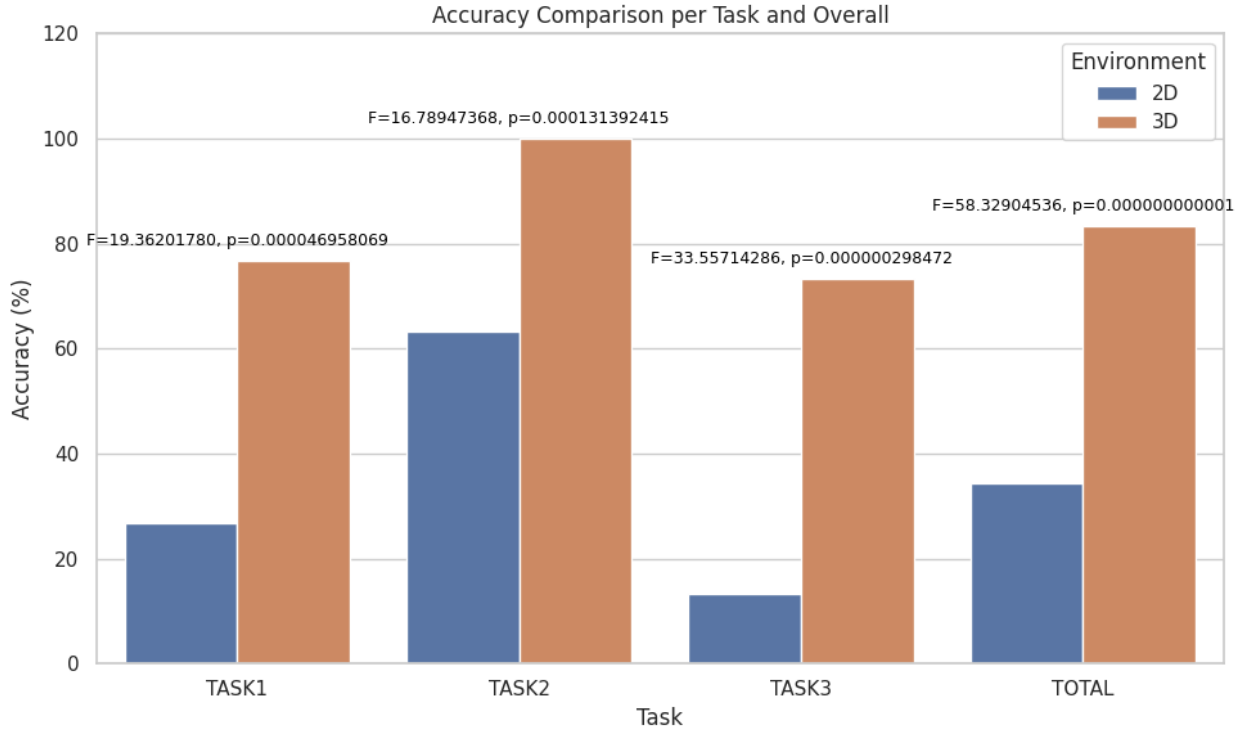


Figure 6.5: Task accuracy comparison between the 2D system and VRVizX (3D), showing the percentage of correct responses for each task and overall performance.

systems ($p < 0.001$). In the VRVizX (3D) environment, all participants (100%) answered correctly, whereas the 2D system achieved an accuracy of only 63.33%.

In Task 3, which involved identifying the correct cluster for a new data point, there was a significant difference in performance between the two systems ($p < 0.001$). Participants using VRVizX (3D) achieved an accuracy of 73.33%, whereas only 13.33% of participants in the 2D system answered correctly.

Overall, the results across all tasks showed a significant difference ($p < 0.001$), indicating that all three tasks were performed better in the 3D environment. This suggests that when dealing with complex datasets involving three variables, the VRVizX (3D) system outperforms the 2D system. This improvement may be attributed to the depth perception present in the VRVizX (3D) system, which was lacking in the 2D system. The findings suggest that the VRVizX (3D) system enhances users' understanding and decision-making, particularly for tasks where spatial awareness is crucial.

6.5 Task Completion Time

The time taken to complete each task was also analyzed in both environments. Figure 6.6 shows the average completion times for each task and the overall average time across all three tasks, for both the 2D system and VRVizX (3D). This includes the time taken for all responses, regardless of whether they were correct or incorrect.

The average time taken to complete each task varied between the 2D and VRVizX (3D) systems. For Task 1, the average completion time was slightly higher in the 3D environment

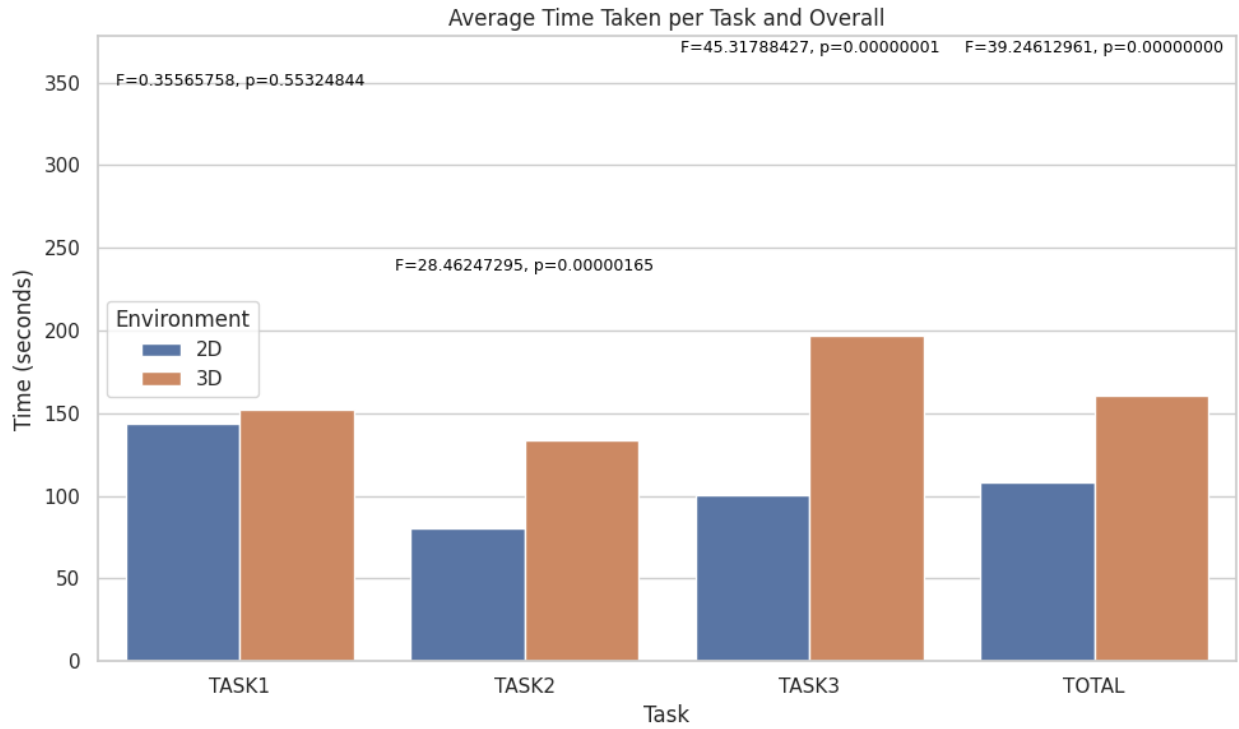


Figure 6.6: Comparison of average completion times per task and overall between the 2D system and VRVizX (3D), including all responses

compared to the 2D system, though the difference was not statistically significant ($p = 0.5532$).

Participants took significantly longer to complete Task 2 and Task 3 in VRVizX (3D). For Task 2, the average time was 133.57 seconds in VRVizX (3D) compared to 80.30 seconds in 2D. For Task 3, it was 196.83 seconds in VRVizX (3D) and 100.18 seconds in 2D. Both differences were statistically significant ($p < 0.001$).

When examining the overall task completion time, the average in the VRVizX (3D) was 160.84 seconds, compared to 108.08 seconds in the 2D system, with the difference being statistically significant ($p < 0.001$). However, as this includes both correct and incorrect responses, the time differences may not fully reflect task efficiency. To determine whether the increased time in VRVizX (3D) is due to higher accuracy or the nature of the environment, we analyzed completion times by considering only the correct responses.

We calculated the average completion time for each task based on the number of correct answers in both the 2D and VRVizX (3D) systems. Figure 6.7 displays the time taken for each task, considering only the correct responses, for both the 2D and 3D systems.

In Task 1, the average time taken was 181.12 seconds in the 2D system, compared to 155.78 seconds in the VRVizX (3D) system. Despite participants taking longer to complete the task in 2D, the difference was not statistically significant ($p = 0.3463$).

In Task 2, however, there was a statistically significant difference, with the average time in 2D being 82.32 seconds and in VRVizX (3D) it was 133.57 seconds ($p < 0.001$). Similarly, in Task 3, a statistically significant difference was observed, where the average time was 89.00 seconds in 2D, compared to 211.32 seconds in VRVizX (3D) ($p < 0.005$).

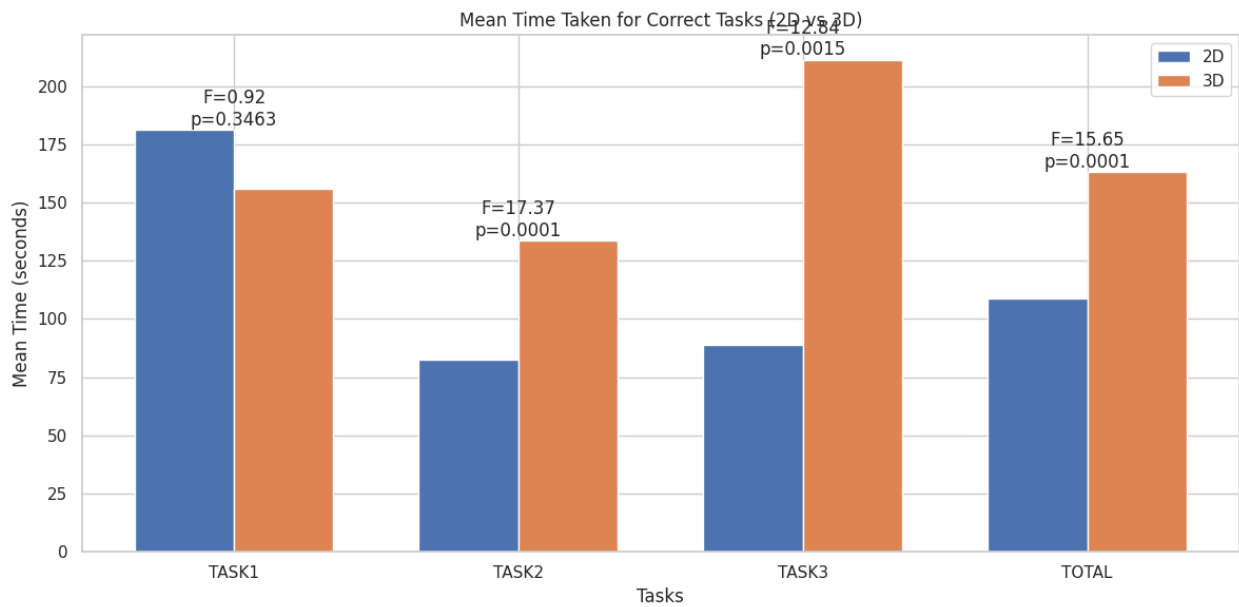


Figure 6.7: Time taken to complete each task, considering only correct responses, for both the 2D and 3D systems.

When considering the overall task completion times, a statistically significant difference was also observed between the 2D and 3D systems, with the average time being 108.68 seconds in 2D and 163.19 seconds in VRVizX (3D) ($p < 0.001$). This reflects the previous results, where both correct and incorrect responses were included. When examining the time taken to complete tasks, including only correct responses, VRVizX (3D) required more time than the 2D system, with this difference remaining statistically significant.

While some participants mentioned the novelty and enjoyment of the experience, others highlighted an initial learning curve when adapting to the VR controls. These factors may have contributed to the increased time spent on tasks.

Participants shared mixed views regarding task completion durations in both the 2D and 3D environments. For instance:

”Took a little bit of time to adapt to the controllers. When completing the tasks, I don’t think there is any difference.”

”In 2D, it’s very hard and time-consuming to complete a task because of the lack of interactivity. In the 3D model, I felt the unfamiliarity at the beginning since I’m new to VR technology, but got familiar with time and was able to complete the task quickly.”

While 3D environments may initially pose usability challenges, they also offer an engaging experience that can encourage deeper exploration. This exploratory behavior, along with the unfamiliarity with VR, may help explain the longer completion times observed in the 3D system.

6.6 Findings from Semi-Structured Interviews

After completing the SUS questionnaire, participants took part in a semi-structured interview lasting approximately 5 to 10 minutes. The structure of the interview is provided in Appendix F. During this session, they were asked about several key themes, including their overall experience with the systems, ease of navigation, interaction mechanisms, use of the reset feature, and the effectiveness of haptic, auditory, and visual cues. Participants were also invited to share their system preference (2D vs. VRVizX), thoughts on customization and potential improvements, and any physical discomfort they experienced while using VR.

6.6.1 Overall Experience

Several participants noted that the 3D system enabled a better understanding of data, particularly in identifying outliers and clusters. One participant stated, “In 3D, I could clearly see the outliers and other patterns,” while another emphasized, “I could walk around the data and see relationships from different angles.” This spatial awareness allowed users to explore datasets from multiple perspectives, which is not possible in the 2D system.

The 3D environment also appeared to improve task performance. Users reported higher accuracy and faster completion times, especially for more complex tasks such as clustering. As one participant mentioned, “When completing the 3rd task, in the 3D environment, I was able to rotate and walk around the scatterplot to find the right answer.”

With regards to the user engagement, many participants found the 3D experience more interactive and enjoyable. The immersive nature of the tool was frequently praised: “The 3D environment felt more accurate and was also fun to use so I took time to explore it.” Similarly, another user remarked, “Compared to the 2D visualization, the 3D one was interactive and more engaging.”

Despite the overall satisfaction, some participants reported an initial learning curve when using the VR system. The novelty of head-mounted displays (HMDs) and unfamiliar controller functions were cited as early challenges. “There should be some initial exposure to the HMD-based VR platform... the controller buttons and their functions were confusing at first,” one participant explained. Others shared similar experiences, noting that while the beginning felt overwhelming, they became more comfortable over time: “Initially, it felt a bit difficult, but as I got used to the system, it became more comfortable.”

Participants also offered critical feedback on the user interface (UI) and the system’s suitability for non-technical users. While VRVizX was considered intuitive after users became familiar with it, the need for onboarding support was frequently mentioned. One participant stated, “Technical support is a must before starting the tasks in the 3D system for new users.”

In contrast, the 2D system was described as easier to use initially, due to its familiarity and simplicity. However, participants reported difficulty in extracting meaningful insights, especially for spatially complex tasks. “In 2D, it’s difficult to get a proper 3D perspective, so some data points are not clear,” one participant noted. Another commented, “I struggled to

identify clusters, and even simple tasks were difficult to complete.” Some users did appreciate the speed and clarity of the 2D system for basic tasks: “Sometimes I missed the simplicity of 2D. The 3D took more effort to navigate, while 2D let me click and analyze faster.”

While some participants appreciated the simplicity and speed of the 2D system, the majority preferred VRVizX for its immersive environment, improved data exploration, and greater engagement, despite the initial learning curve needed to become familiar with the system.

6.6.2 Reset Feature

Participants considered the reset feature highly beneficial, especially when they felt disoriented while navigating or interacting with the VR environment. Several users found it useful when they zoomed in too far or rotated the chart excessively, as the reset function allowed them to return to the default view with a single action. A participant mentioned, “Very helpful when I got lost in the data. One click and I was back to the default view,” while another shared, “It was useful because VR is new to me, and when I made mistakes like rotating too much, it was easy to reset the chart.”

However, some participants suggested improvements to the reset function, such as adding an undo feature that would allow them to return to the previous state rather than just resetting to the default. One participant explained, “It would be even better if I could go back just one step instead of all the way, just like an undo feature.” Despite these suggestions, the reset feature was seen as a valuable feature for improving the UX in a 3D data visualization system.

6.6.3 Minimalist UI

A key UX guideline for extended reality (XR) applications is to maintain a minimalist interface, particularly in VR environments where unfamiliarity can cause user anxiety. To assess this, participants were asked about the clarity and simplicity of the VRVizX interface. Many described the design as clean, uncluttered, and easy to navigate. One participant stated, “The menus were not cluttered at all; I was able to select options from the menu very easily.” Another referred to the interface as “minimalist and simple.”

The screen layout made it easier for participants to concentrate on the visualization without distraction. As one participant noted, “The screen layout was clean and simple. Nothing got in the way of seeing the data.” Another commented, “All the interfaces worked well; I was able to focus on the data without being distracted by UIs.”

While some participants found the charts visually dense, this was attributed to the complexity of the data rather than the interface. One participant remarked, “The chart was overwhelming at a glance, but that is how it is with complex datasets.” The zoom feature helped address this issue, enabling users to explore specific regions of interest. As another mentioned, “Having the zoom feature, I was able to focus on certain areas, it was helpful.”

Most participants viewed the UI as simple and minimalist. While a few mentioned the initial complexity of the visualizations, they did not see this as a drawback of the interface design but rather as a characteristic of the complex datasets.

6.6.4 Navigation Techniques

Kim et al.[42] stated that navigation is a key aspect of VR applications, enabling users to explore and orient themselves within the virtual space. Navigation techniques, such as walking and teleportation, shape how users explore the environment. These techniques impact their ability to interact with the data and their overall experience.

Many participants found teleportation useful for covering large distances efficiently. One participant shared, “I liked teleportation. It felt natural, especially when I had to move between different parts of the graph.” Another participant mentioned, “Jumping between clusters of data using teleportation worked perfectly. It saved me time moving around.” On the other hand, some users preferred walking, particularly in larger spaces, as it felt more immersive. One participant noted, “Walking felt natural and good because there was a spacious room, or else teleportation would be a better option.”

Many participants appreciated having multiple navigation techniques, as they could move in ways that suited their comfort and the available physical space. As one participant said, “Having different ways to move around was good. I could choose what worked best for me.”

Providing two navigation options proves to be more effective, allowing users to choose the method that best suits their VR experience and the physical space they are in. Teleportation is a great choice when physical space is limited or when a quick move to a specific location is needed with a single action.

6.6.5 Auditory, Visual, and Haptic Cues

Multimodal feedback is an important UX feature for XR applications, as noted by Vi et al.[9]. It enhances users’ engagement and interaction with the system. The combination of auditory, visual, and haptic cues contributes to a more immersive and responsive experience.

Auditory feedback, such as sounds triggered during selection, was found to help confirm system responses. As noted by one participant, “The sound when selecting things was helpful. It let me know the system recognized my action.” The integration of sound and vibration was also positively received, though a desire for adjustable volume levels was expressed by some participants.

Participants found visual cues to be helpful and clear. Features like highlighted hovered data points, boundary warnings, and on-screen messages provided clear guidance and improved understanding. One participant stated, “The messages, like error and confirmation messages, were helpful. It guided me when I missed something.” These cues were also valued for confirming actions, preventing mistakes, and aiding users in navigating the 3D environment. The tooltip feature was noted as particularly beneficial, as participants appreciated its utility for efficiently identifying clusters or comparing values. One participant

remarked, “I used it quite a bit. It was good for checking values quickly without needing to look back at the axes, and the font size and the font itself were clear and neat.” However, some participants recommended improvements, such as the option to pin or reposition tooltips to avoid obstructing other data.

Haptic feedback received mixed reactions from participants. While many found the vibrations engaging and helpful for interaction, others felt that it was initially distracting, especially in areas with densely packed data where multiple vibrations occurred rapidly. Over time, most users adapted to the feedback, with several noting that it enhanced their sense of immersion. One participant explained, “In the beginning, I couldn’t understand the vibration I felt, but after I got familiar with the system, this feature was very helpful, especially when identifying a particular data point.” However, some participants reported that the vibrations were too intense at times or caused confusion, particularly when multiple selections were made unintentionally.

The use of visual, auditory, and haptic cues was found to be effective in enhancing data exploration and user engagement. However, improvements could be made, such as offering customizable settings to adjust sound volume and vibration intensity, as well as the ability to pin or reposition tooltips.

6.6.6 Customization Options for Charts

Participants regarded the ability to customize data point appearance as a valuable feature that enhanced the overall data exploration experience. For instance, enlarging data points helped some users identify correlations more easily in Task 2. One participant shared, “Making the data points larger made it easier.”

Color customization for outliers was also appreciated, as it improved visual clarity. As one user noted, “I used the color customization for outliers to make them stand out more.” Participants also suggested additional options, such as adjusting opacity, to help view overlapping data points more effectively.

The customization process itself was described as simple and user-friendly. One participant mentioned, “It took only a few steps to make changes.” Overall, the ability to adjust the visual properties of data points helped users focus on key insights, such as spotting outliers, and contributed to clearer data interpretation.

6.6.7 Physical Discomfort in VR

Since VR was unfamiliar to many participants, we aimed to check whether they experienced any discomfort while using the system. A range of responses was reported. Several participants reported no physical discomfort, while others experienced specific issues. Discomfort related to wearing glasses was frequently mentioned, with comments such as, “I wear glasses, so my eyes started to hurt after a while,” and “It was hard to use the HMD because of the spectacles.”

Some participants reported mild symptoms, including watery eyes, headaches, and shortness of breath. In some cases, discomfort was not felt during use but occurred shortly after removing the headset, such as light headaches. One participant also mentioned that a loose headset contributed to their discomfort.

Although some participants had prior experience with VR and reported no issues, it was evident that HMDs introduced a range of physical discomfort, particularly for those who wore spectacles.

6.6.8 System Preferences

Many participants expressed a strong preference for VRVizX, highlighting its interactivity, clarity, and depth perception. The 3D environment helped users better understand spatial relationships between data points and provided improved insights into cluster distribution and the overall spread of the data. Several users noted that the engagement and visualization experience felt significantly richer in 3D, with one stating that it was easier to "figure out relationships".

For Task 1, several participants preferred the 2D system, noting its simplicity and ease of use for non-spatial analysis. However, others found VRVizX more effective due to its interactive features, particularly the ability to rotate and zoom. One participant shared, "3D is better because the interactive features and outlier comparison are easier in the 3D setup," while another noted, "For tasks 1 and 2, accuracy-wise, I prefer the 3D system because I was able to observe data points and clusters closely, rather than just assuming, as in the 2D tool."

For Task 2, many participants leaned toward the 2D system, likely due to their familiarity with traditional plots for detecting correlations. One participant shared, "When finding the correlation, I prefer 2D." Another noted, "For the 2nd task, I felt that the 2D system is better." However, one participant felt that there was "no significant difference in terms of the effort" between the 2D system and VRVizX for this task.

For Task 3, there was a strong preference for the 3D system. Most participants found that the ability to navigate, rotate, and explore the scatterplot made it much easier to locate clusters and understand spatial relationships. One participant noted, "It would be nearly impossible to find the correct data points in 2D," while another emphasized, "3D was definitely easier, especially for complex tasks like finding clusters." Features like tooltips and the ability to perceive depth were also highlighted as beneficial, with one user commenting, "For the 3rd task, I use the tooltip in the 3D system to identify the relevant cluster."

While 3D was praised for its interactivity and depth, some users felt it might not be ideal for long analysis sessions. They preferred 2D for smaller datasets, urgent tasks, or daily use, citing comfort and familiarity, such as with tools like Matplotlib. However, they were open to using the 3D system for more complex or exploratory tasks. Some users acknowledged that the 3D tool took longer but found it more enjoyable and effective for detailed exploration.

6.6.9 Suggestions for Improving VRVizX

While VRVizX was described by many as interactive, immersive, and enjoyable, participants also identified several areas for improvement. One common suggestion was to introduce more customization options, such as the ability to adjust brightness, sound, and vibration levels. Others wanted more visual control over data points, including opacity adjustments to better handle overlapping points. Navigation controls were also a point of concern. One participant found the rotation speed too fast and noted that the camera movement was uncomfortable at times. To improve navigation and orientation, it was suggested that directions and controller functions be displayed within the user's field of view (FOV). Additionally, some participants mentioned the difficulty of remembering controller functions and proposed that these be shown on-screen.

Tooltip behavior was another minor issue, as participants noted that multiple tooltips would appear simultaneously when moving the pointer quickly. They suggested that limiting the display to one tooltip at a time would make it easier to focus on specific data points. Finally, participants suggested that when dealing with large clusters of data, it would be helpful to have tools that allow for visual separation of the clusters. This would make it easier to interpret the data, especially when the clusters overlap.

Chapter 7

Discussion

7.1 Research Findings

This research systematically evaluated the effectiveness of a user experience (UX)-optimized system for virtual reality (VR)-based data visualization through two iterative prototypes, VRVizX v1 and v2, comparing their performance against traditional two-dimensional (2D) methods. The findings demonstrate both the potential and challenges of data analytics in VR, offering empirical evidence for the benefits of UX-optimized VR environments while identifying areas requiring further refinement.

The initial evaluation of VRVizX v1 revealed strong user engagement with the three-dimensional (3D) visualization system, with 88.2% of participants reporting high engagement compared to conventional 2D visualization. Spatial perception was identified as a clear advantage, as 82.3% found overlapping clusters more distinguishable in VR, and 92.3% could better identify cluster density. These quantitative findings were grounded by users' qualitative feedback, where the majority of participants described the experience as "intuitive" for recognizing spatial relationships that were hidden in 2D data visualization. However, this first iteration also exposed significant usability concerns that affect these positive results. Industry professionals from Octave - the data analytics division of John Keels Group, provided particularly valuable critiques, with multiple individuals describing the interface as "blurry", the interaction techniques, such as the zoom feature, lacked smoothness, and vibration as excessive. These observations presented the need for immediate interface refinements.

The evaluation of VRVizX v2 compared to a traditional 2D visualization method revealed several key findings across multiple dimensions of UX and analytical performance. The NASA Task Load Index (NASA-TLX) workload assessment provided detailed insights into cognitive and physical demands, showing that while the overall workload scores between VRVizX (M=2.68) and 2D (M=2.73) systems were not significantly different (p-value=0.685), important differences were identified when examining specific cognitive dimensions including mental demand, physical demand, performance, effort, and frustration. The VRVizX demonstrated reduced mental demand, particularly for the correlation analysis task (Task 2, p-value=0.001), where participants reported needing less cognitive effort

compared to the 2D condition. Across all three analytical tasks, users experienced consistently lower frustration levels when working in VRVizX, along with higher performance ratings, suggesting high user confidence in their analytical outcomes. However, these cognitive benefits were accompanied by increased physical demand in the VRVizX for Tasks 1 and 3. The reason could be the use of hand controllers and the physical navigation required in the immersive environment.

System usability, as measured by the SUS scale, showed VRVizX v2 achieving a score of 77.4, which falls within the "Good" range and represents a significant improvement over the 2D system's score of 53.8 ("OK" range). This 43.86% relative advantage in usability scores reflects the effectiveness of the UX optimizations implemented in the VRVizX prototype. The evaluation of task accuracy demonstrates VRVizX's significant advantages for spatial data analysis. In the outlier detection task (Task 1), participants achieved 76.67% accuracy in VR compared to just 26.67% in 2D, representing nearly a threefold (2.87 times greater) improvement. The cluster identification task (Task 3) showed an even more significant difference, with 73.33% accuracy in VR versus 13.33% in 2D (a 5.5-fold increase). Most remarkably, the correlation analysis task (Task 2) resulted in perfect accuracy (100%) in the VRVizX, compared to 63.33% in the 2D system. These results provide strong evidence that VRVizX's spatial representation capabilities offer fundamental advantages for certain types of analytical work, particularly those requiring 3D reasoning and pattern recognition.

Analysis of mean times of task completion durations revealed important temporal patterns that must be considered alongside the accuracy results. Overall, VRVizX's tasks required approximately 48.81% more mean time to complete than the 2D tasks (160.84s vs 108.08s in 2D), with this difference being mostly identified in complex spatial tasks. The correlation identification task (Task 2) and cluster identification task (Task 3) showed the highest mean time differences, taking 133.57s in VRVizX compared to 80.30s in 2D for Task 2 and 196.83s in VRVizX compared to 100.18s in 2D for Task 3. When examining only correct responses, for Task 2 (133.57s versus 82.32s in 2D) and Task 3 (211.32s versus 89s in 2D), VRVizX maintained these longer mean time durations despite its accuracy advantage. This pattern suggests that the additional completion duration in VRVizX may be because of new VR users and higher engagement that leads to deeper data exploration rather than interface inefficiency. This is an interpretation supported by participants' comments from the semi-structured interview, which describes a deeper investigation of data relationships in the VRVizX v2.

The semi-structured interview provided valuable qualitative feedback confirming the quantitative feedback. Participants consistently expressed the superior spatial comprehension offered by VRVizX, with users describing the ability to physically "walk around data" as fundamentally transformative for understanding complex 3D relationships. The teleportation feature was also praised for its usefulness in exploring data while reducing time waste. The majority of users confirmed that VRVizX successfully implemented minimalist interfaces critical for VR applications. Participant feedback described the

interface as "clean," "uncluttered," and "simple to navigate," which enabled clear data focus. While some noted initial visual density in the scatterplot, they attributed this to dataset complexity rather than interface design. Participants found that the Zoom and rotation functionalities helped reduce complexity by allowing them to focus on specific regions. The multimodal feedback system received generally positive feedback. Visual cues like highlighted data points and tooltips were appreciated, with a majority of users specifically noting their effectiveness. Some participants reported that multiple tooltips appearing simultaneously could create visual clutter during rapid movements. The auditory feedback system was described as helpful but occasionally overwhelming to some users, who suggested volume customization options. Haptic feedback generated the most varied responses. While most users found the controller vibrations useful for confirming selections, some described the intensity as distracting during use, particularly when analyzing dense data clusters where multiple haptic triggers occurred quickly. Several participants recommended implementing adjustable vibration strength settings to accommodate different user preferences and task requirements.

The majority of participants praised the VRVizX as significantly more engaging than traditional 2D methods. There were some reports of physical discomfort from users. Complaints were received about eye strain and fatigue during longer analytical sessions. The learning curve associated with controller use was identified as a notable factor, but the majority reported adapting to the interface within the testing session duration. Preferences between the VRVizX and 2D were based on the given task, with some of the participants favoring conventional 2D approaches for simple tasks such as correlation analysis (Task 2) due to speed advantages, while they preferred the VRVizX for complex spatial tasks such as cluster identification (Task 3). This qualitative feedback improved the understanding of the UX dimensions that quantitative metrics alone cannot fully capture.

7.2 Critical Reflection

The findings of this research provide evidence that a carefully designed UX-optimized system can significantly enhance the effectiveness of VR-based data visualization systems. By comparing VRVizX v2 against a traditional 2D method, these results not only validate the proposed system but also contribute meaningful empirical data to the ongoing discussion about the role of VR in professional data analysis.

The first research question, concerning how UX can be enhanced in 3D immersive data visualization, is thoroughly addressed by the research's findings. The significant improvement in system usability scores (77.4 for VRVizX v2 versus 53.8 for the 2D system) with 43.86% relative advantage demonstrates that the application of UX principles based on the research literature can overcome many of the challenges mentioned in section 3.6 Research Gap. These findings provide an empirically proven system for the work of Vi et al.[9] by showing how their general extended reality (XR) design guidelines can be successfully adapted for a practical data visualization system. Observed lower mental demand, effort,

frustration levels and higher performance in the VRVizX v2 compared to the traditional 2D visualization, particularly for complex analytical tasks, suggests that well-designed immersive environments can make challenging cognitive work feel more manageable, which leads to the conclusion that the adopted UX guidelines are suitable to enhance the UX.

Regarding the second research question about the impact on user comprehension and decision-making, the research provides evidence that the UX-optimized VRVizX v2 prototype offers advantages over a conventional 2D method for analytical tasks. The significant improvement in accuracy for spatial reasoning tasks, ranging from nearly three to over five times higher in VRVizX, strongly supports the hypothesis that VRVizX enhances user comprehension and decision-making. These high accuracy rates are important because they suggest that the UX-optimized VR visualization is not only more engaging but also helps users to perform analytical tasks accurately with higher comprehension. The perfect accuracy (100% accuracy) achieved in VRVizX for correlation analysis (Task 2) suggests that some analytical tasks may be fundamentally better suited to be analyzed using immersive visualization approaches. Despite these high accuracy records, the VRVizX comparatively demonstrates a longer completion time. This can be attributed to the users' novelty to the VR and deep data exploration from users.

The research findings confirm and significantly extend previous understanding of VR data visualization. While observed cognitive benefits align with the general understanding of VR for data analytics, VRVizX v2 demonstrated significantly higher improvements in analytical accuracy and usability than prior visualization-specific studies had achieved. These enhanced outcomes suggest that previous mixed results in VR data visualization research may have resulted from focusing primarily on technical capabilities rather than the UX. This interpretation is strengthened by participants' strong performance when completing tasks within the VRVizX v2, despite being new to VR tools. The success VRVizX v2 prototype provides empirical evidence that VR's potential for data visualization can only be achieved through careful consideration of both technological and human factors.

7.3 Limitations

While this research offers valuable insights into VR-based data visualization with enhanced UX, its scope limits the generalizability of the conclusions. The results cannot be generalized across different hardware platforms because research was conducted exclusively on the Meta Quest 2, meaning the evaluation cannot assess how visualization quality or UX might differ on other types of VR headsets, mixed reality (MR) devices, or future hardware with advanced ergonomics. While performance issues such as frame drops were not especially studied in this research, they could have caused additional challenges to the analytical process.

The research focuses on UX design rather than technical improvement, which means it cannot evaluate system performance under more demanding conditions. The results cannot represent how the prototype would behave with real-time data streams or enterprise-level computational requirements. Similarly, the adopted single-session user study design did

not evaluate long-term usability patterns. The research cannot determine whether user performance would improve with much longer practice, how physical discomfort might occur over hours of professional use, or how spatial awareness develops with repeated exposure to VRVizX.

Because of the choice of a controlled dataset (wine quality metrics[38]), the research did not evaluate its applicability to specialized domains such as geospatial, molecular, or time-series visualizations. While this measured perceived workload using NASA-TLX, it couldn't capture deeper cognitive differences between VR and 2D visualization. For example, it did not evaluate how the brain processes spatial information differently in VR versus traditional displays (neural correlates of spatial reasoning), differences in long-term memory retention, or how collaboration dynamics might affect when multiple users work together in the VRVizX.

The study was conducted without evaluating alternative controller mappings across different user groups. This limitation means the evaluation didn't assess whether different button layouts might improve accessibility or efficiency, how left-handed users or those with motor impairments might interact with the system, or whether customizable controls could better serve varied skill levels. Additionally, the participant pool of the 2nd iteration consisted only of university students with an IT background with limited VR experience. While this provided insights into novice-user adaptation, the results may not reflect the needs of professionals or frequent VR users, who might exhibit different interaction patterns or tolerance for VR. The limited spread of the age of the participants and the educational background of the participants further limits the generalizability of the findings.

7.4 Recommendations

Based on the research findings and participant feedback, several key recommendations were identified to improve the design and implementation of the VRVizX prototype. The feedback techniques should be carefully changed to enhance rather than disrupt the analytical process. Haptic and auditory cues need balanced intensity settings, while tooltips should be limited to one active display at a time to prevent visual overload during fast pointer movements. These adjustments would maintain engagement while reducing cognitive strain.

The system should offer customization options to address diverse user needs and preferences. This includes adjustable visual elements like brightness and data-point opacity, along with interaction settings for haptic intensity and sound volume. Implementing robust undo/redo functionality would encourage exploratory analysis by allowing users to reverse actions easily. Such flexibility is particularly important in VR environments where trial-and-error learning is common. Brief hand controller-mapping reminders displayed in the user's field of view could reduce the learning curve for new VR users. These features are especially useful in time-consuming analytical sessions where fatigue may affect spatial understanding.

The interaction model should be enhanced to support dynamic data exploration.

Real-time cluster separation tools for exploring more complex datasets would enable deeper data exploration. From a hardware perspective, HMD manufacturers should focus on ergonomic improvements to facilitate extended use. Weight reduction, better weight distribution, and adjustable optics for glasses wearers would significantly improve comfort during lengthy analysis sessions. These physical considerations are just as critical as software design in creating viable professional tools. Future evaluations should adapt more diverse testing conditions to validate these recommendations. Studies with diverse user demographics (including non-technical users) would provide deeper insights into real-world applicability. By addressing both technical and human perspectives, the VRVizX prototype can realize its full potential as a next-generation analytical system.

Chapter 8

Conclusion

This research is conducted to answer two core questions: How can user experience (UX) be enhanced in three-dimensional (3D) immersive data visualization? and How does enhancing UX in virtual reality (VR) impact comprehension and decision-making compared to 2D methods? The research successfully addressed its primary goals and objectives, which focused on addressing these questions by systematically enhancing the UX in 3D data visualization within an immersive VR environment. The first objective, which is identifying UX guidelines for VR-based visualization, was achieved by adapting UX guidelines from Vi et al.[9].

The second objective, design and develop an interactive 3D data visualization prototype, was realized through iterative development, and incorporating key design principles with thoughtful controller mappings. Key design principles includes core interaction features (Select, Zoom, Rotation, Pan, Tooltips, Back Navigation and Reset), multi-modal feedback (haptic, auditory, and visual) to increase user engagement and awareness, minimalist interfaces with customization to prevent visual clutter and cognitive load, and ergonomic interaction design to minimize user discomfort.

The third objective, evaluating the prototype's impact, was met through empirical studies. The evaluation results demonstrate that a UX-optimized VR framework (VRVizX) significantly improves analytical accuracy for spatially complex tasks, achieving 2.87 to 5.5 times higher accuracy than 2D systems while maintaining 'Good' usability based on the System Usability Scale (SUS) score of 77.4. Notably, NASA Task Load Index (NASA-TLX) results revealed that VRVizX reduced mental demand, effort, and frustration levels across all tasks, despite requiring greater physical demand. While task completion times were 48.8% longer in VRVizX compared to 2D, this difference reflected deeper data exploration and the system's engaging nature rather than interface inefficiency, as evidenced by users' qualitative feedback and significantly higher accuracy rates.

Reflecting on the research process, the iterative Design Science Research (DSR) methodology proved effective in balancing technical innovation with human-centered design. The early prototype exposed significant usability issues that guided refinements in the later iterations. While the research evaluation based on university students and a controlled dataset limits the generalization, this constraint provided valuable insights into novice-user

adaptation, a critical demographic for VR adoption.

This research provides a foundation for several future directions in immersive data visualization studies. This system could be expanded to support a broader range of visualizations to evaluate its generalizability, other than scatterplots. Future iterations could support additional dataset formats beyond comma-separated values (CSV) and incorporate advanced view manipulation features like dynamic filtering and annotations. Since the prototype currently only allows one dataset at a time, future iterations could introduce multiple datasets at once to visualize. Additionally, collaborative VR environments could be implemented, enabling real-time, multi-user interaction with shared datasets, an essential step toward practical workplace applications.

To enhance real-world practical applicability, the system should be evaluated with more diverse user groups (domain experts, non-technical users, and individuals with various accessibility needs) and expanded to include advanced features to save visualizations, add session notes (via voice or controller input), and reproducible analysis workflows. Longitudinal studies could assess how user performance, comfort, and adoption rates change over extended use, addressing current limitations in session length and physical discomfort. Testing of controller mappings with diverse user groups could further refine interaction design. Also, an Artificial intelligence (AI) based predictive analysis method can be introduced to get more effective insights from data.

Finally, domain-specific evaluations in fields such as healthcare imaging, financial analytics, and scientific simulations would help tailor UX guidelines to specialized use cases, ensuring the system meets real-world analytical needs across disciplines. These advancements would solidify this system's versatile role for data exploration and decision-making.

This research contributes a validated UX-optimized system that bridges VR's technical capabilities with practical usability demands. By demonstrating that intuitive design, not just technological advancements, drives analytical success in VR, research shifts the focus in immersive VR analytics from novelty to utility.

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Appendices

Appendix A

User Questionnaire for Iteration 01

Below is the full list of questions used to collect participant feedback during the demo session.

do you have any prior experience in working with Virtual reality environment? *

☐ No

☐ Yes

Do you have experience working with data visualizations or data analysis tools? *

☐ Yes

☐ No

If yes, which tools have you used before (e.g., Excel, Tableau, Power BI)?

Your answer _____

Do you experience motion sickness or discomfort when using VR? Were there any physical challenges (e.g., weight of the headset, discomfort during extended use)? *

Your answer _____

How did you find the gesture-based interactions (e.g., zooming, rotating)? Were they smooth and responsive? *

1



2



3



4



5



Was the application easy to understand and navigate? *

1



2



3



4



5



Are overlapping clusters are more easily distinguished in VR than 2D visualizations ? *

- ☐ Yes
- ☐ No
- ☐ May Be

Did the immersive 3D environment make data exploration more engaging compared to 2D alternatives? *

- ☐ Yes
- ☐ No
- ☐ May Be

Is the cluster density more identifiable in VR than 2D visualizations ?

- ☐ Yes
- ☐ No
- ☐ May Be

Were the outliers clearly visible in the VR than the 2D visualization?

- ☐ Yes
- ☐ No
- ☐ May be

Rate your overall satisfaction with the app on a scale of 1 to 10. *

1	2	3	4	5	6	7	8	9	10
<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

How likely are you to use this application for data analysis in the future (1 - Not likely, 10 - Very likely)? *

1	2	3	4	5	6	7	8	9	10
<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

Appendix B

Pre-test Questionnaire for User Study in Iteration 02

Pretest Questionnaire for VRVizX Study

Thank you for participating in this study on enhancing the user experience in 3D immersive data visualization. This research focuses on improving user experience in 3D immersive data visualization compared to traditional 2D data visualization.

This pretest questionnaire aims to gather background information on your experience with data visualization.

Your Rights as a Participant:

1. Your participation in this study is entirely voluntary.
2. You may choose to withdraw at any time without giving a reason.
3. All the information you provide will be kept confidential and will only be used for research purposes.
4. Your identity will not be revealed in any reports or publications resulting from this study.
5. You have the right to ask questions about the study at any time.

By continuing, you confirm that you understand the purpose of this study and voluntarily agree to participate.

Do you consent to participate in this study? *

- ☐ Yes, I agree to participate.
- ☐ No, I do not agree to participate.

Next

Clear form

User ID (Given by the Researcher) *

Your answer

Select your age range *

- ☐ Under 18
- ☐ 18–24
- ☐ 25–34
- ☐ 35–44
- ☐ 45–54
- ☐ 55+

What is your highest level of education? *

- ☐ Ordinary Level (O/L)
- ☐ Advanced Level (A/L)
- ☐ Currently pursuing a Bachelor's degree
- ☐ Bachelor's degree completed
- ☐ Master's degree
- ☐ PhD
- ☐ Other: _____

Which 2D data visualization tools have you used before? *(Select all that apply)* *

- ☐ Matplotlib
- ☐ Tableau
- ☐ Power BI
- ☐ Excel Charts
- ☐ D3.js
- ☐ QlikView
- ☐ Other: _____

Rate your experience with data visualization tools *

- ☐ Never used
- ☐ Rarely (Less than once a month)
- ☐ Occasionally (A few times a month)
- ☐ Frequently (Weekly)
- ☐ Expert (Daily use)

Have you used any 3D data visualization tools before? *

- ☐ Yes
- ☐ No

Have you interacted with 3D data visualizations on the web? *

- ☐ Yes
- ☐ No

Have you ever used VR for data visualization? *

- ☐ Yes
- ☐ No

[Back](#)

[Submit](#)

[Clear form](#)

Appendix C

List of User Tasks for User Study in Iteration 2

Task 1: Find the data point that is farthest from the rest of the dataset.

Steps:

- Select the scatterplot with outliers.
- Select the following attributes:
 - X-axis: Volatile Acidity
 - Y-axis: Citric Acid
 - Z-axis: Fixed Acidity
- Adjust the view to display the Y-Z plane.
- Ask the participant to select the farthest data point and report its coordinates.

Task 2: Identify the type of correlation (positive, negative, or none) between selected variables.

Steps:

- Select the scatterplot without outliers or K-means clustering.
- Select the following attributes:
 - X-axis: Density
 - Y-axis: pH
 - Z-axis: Sulphates
- View the relationship using the X-Y axes.
- Ask the participant to determine and report the type of correlation.

Task 3: Given a new data point, determine which of the three clusters it belongs to.

Steps:

- Select the scatterplot with K-means clustering.
- Select the following attributes:
 - X-axis: Residual Sugar
 - Y-axis: Chlorides
 - Z-axis: Free Sulfur Dioxide
- Select the number of clusters as 03.
- Provide the coordinates of a new data point ($X = 3.20$, $Y = 0.13$, $Z = 17.00$)
- Ask the participant to identify which cluster the new point belongs to.

Appendix D

NASA-TLX Questionnaire

⋮

How mentally demanding was the task? *

	1	2	3	4	5	
Very low	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	Very high

How physically demanding was the task? *

	1	2	3	4	5	
Very low	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	Very high

How hurried or rushed was the pace of the task? *

	1	2	3	4	5	
Very low	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	Very high

How successful were you in accomplishing what you were asked to do? *

	1	2	3	4	5	
Failure	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	Perfect

...

How hard did you have to work to accomplish your level of performance? *

	1	2	3	4	5	
Very low	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	Very high

How insecure, discouraged, irritated, stressed, or annoyed were you? *

	1	2	3	4	5	
Very low	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	Very high

Appendix E

System Usability Scale (SUS) Questionnaire

System Usability Scale

© Digital Equipment Corporation, 1986.

	Strongly disagree						Strongly agree
1. I think that I would like to use this system frequently	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>		
	1	2	3	4	5		
2. I found the system unnecessarily complex	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>		
	1	2	3	4	5		
3. I thought the system was easy to use	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>		
	1	2	3	4	5		
4. I think that I would need the support of a technical person to be able to use this system	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>		
	1	2	3	4	5		
5. I found the various functions in this system were well integrated	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>		
	1	2	3	4	5		
6. I thought there was too much inconsistency in this system	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>		
	1	2	3	4	5		
7. I would imagine that most people would learn to use this system very quickly	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>		
	1	2	3	4	5		
8. I found the system very cumbersome to use	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>		
	1	2	3	4	5		
9. I felt very confident using the system	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>		
	1	2	3	4	5		
10. I needed to learn a lot of things before I could get going with this system	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>		
	1	2	3	4	5		

Appendix F

Semi-Structured Interview Guide

1. How was your overall experience with the tasks?
2. How was your overall experience with the systems?
3. What would you change or improve about VRVizX?
4. Were you able to identify patterns (e.g., clusters, outliers) more easily in 2D or 3D?
5. Was it easier to determine correlations in 3D than in 2D? Why or why not?
6. Which interaction method did you prefer in 3D, zoom, or rotation? why?
7. Did cues such as tooltips (visual), haptics, or auditory feedback help you interpret the data?
8. Did you find the reset feature useful? Why or why not?
9. Which navigation technique did you prefer: walk or teleport?
10. Did you use the customization options (e.g., data point size, color of outliers and data points)? If so, did you find them useful?