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Next-Generation Interactive and Immersive Graphs: A Unity-Based Framework for Advanced Data Visualization

Master's Thesis

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Abstract

Over the past decades, data visualization has significantly evolved from traditional two-dimensional (2D) representation of text-based data towards immersive three-dimensional (3D) visualizations, leveraging emerging technologies such as Virtual Reality (VR). Within this advancement, social network graphs that represent entities as nodes and relationships as edges, essentially enabling connection analysis, have attracted particular interest for analyzing and understanding complex connections. Although research focusing on these graphs has concluded to numerous tools and applications, a framework that incorporates multiple smart techniques to improve user experience and be broadly applicable to different age and users' background groups, while utilizing an efficient and interactive approach of visually separating relationship types remains relatively limited. Various frameworks aim to enhance immersion and usability through selected user experience techniques, however, there remains a lack of an unified solution that combines a wide range of features including custom data import, multi-device support, diverse and intuitive interaction methods, and an interactive filtering mechanism designed to fit within the visualization environment.

This master's thesis proposes a Unity-based framework designed for immersive 3D and intuitive visualization of social network graphs, with broad applicability to desktop and VR devices, ensuring an enjoyable and engaging user experience. The framework integrates functionalities and intelligent techniques inspired by previous studies that aim to enhance information clarity and provide a user-friendly experience, distinctively employing the Fibonacci lattice layout algorithm, to evenly distribute nodes around in an imaginary sphere and reduce visual clutter in crowded networks. In addition, we propose an immersive filtering approach that incorporates color-coded 3D elements to represent different relationship types, allowing users to interactively reveal or hide specific connections within the network. This method offers a more intuitive and visually engaging alternative to distinguish different relationship types instead of traditional checkbox-based filtering panels. To assess the framework's effectiveness, a user study is conducted, where participants' accuracy and task completion time is assessed through specific use cases, followed by a questionnaire to gather insights into their overall experience, usability, and perception of this filtering technique.

Preface

This thesis would not be the same without the help of my supervisor Basak Oral, for whom I am very grateful that I have had her guidance from the very beginning and has given me motivation throughout the whole process. In addition, I would like to thank Richard van Tilborg for accepting to conduct my thesis through the company CoVince and providing me with this project, as well as Professor Alex Telea for his feedback and Professor Evanthia Dimara for agreeing to be a supervisor on my thesis.

I would like to deeply thank the members of my family who supported me from the moment I started my studies, who have done everything beyond their capabilities to assist me in this journey even if that meant sacrificing a part of themselves, always showing me love and support. I feel honored to be part of this family.

I immensely thank my treasure, my dog Azor, whom I consider my son and love unconditionally. Even without words, he always warms my heart and gives me purpose to keep going. My strength, most difficult goodbye but most cheerful hello.

I am deeply grateful to my boyfriend for standing by my side through even the toughest days, always offering support and willingly helping in any way. Thank you for brightening my gloomiest days and for your patience as we grow together.

Furthermore, I would like to thank my friends in Greece and the Netherlands, who always believed in me and cheered me up, providing me a home regardless the place. Your love has a huge impact on me and you are very dear to me.

Finally, I want to thank all the teachers throughout my life who have had an impact on me, who recognized my efforts and believed in my capabilities. Especially my piano teacher Maria Amanaki, who I consider a second mother and has raised me like a daughter from the age of 6, I can never thank her enough for shaping me through music.

Last but not least, I want to thank all the people and pets I have lost, your life and the love you expressed was guidance to me and I will always remember you. Until I meet you again.

Best,
Eva

Contents

List of Figures

List of Tables

Listings

Chapter 1

Introduction

The field of Immersive Data Visualization (IDV) has rapidly evolved in recent years, becoming a significant and impactful area of research. We define Immersive Data Visualization as the practice of representing data within interactive, three-dimensional (3D) virtual or augmented environments, typically accessed through devices like Virtual Reality (VR) headsets or Augmented Reality (AR) glasses. These environments provide users with a sense of presence and allow for naturalistic interactions, extending beyond traditional two-dimensional (2D) displays. Due to data continually growing in complexity and size, it was necessary to create the ability to effectively visualize large datasets; a crucial finding across various domains [18, 22]. Immersive visualization techniques provide users with the opportunity to observe, collaborate, and explore data while also enabling them to interpret it by identifying patterns, trends, and anomalies.

As a consequence of these advancements, there is a growing interest in incorporating techniques and features that facilitate collaboration within immersive systems. Numerous fields are employing technologies such as the VR, as **collaboration** has the recognizable value of sharing insights and discussions in data interpretation, ultimately accelerating users' learning curve [33]. Therefore, it improves analysis and fosters a more enjoyable and motivating experience, as users are increasingly eager to work together and communicate [33].

Initially, research in IDV was focused on traditional data visualization methods, which provided an innovative way of presenting information. These methods typically involve 2D representations displayed on flat screens, such as bar charts, line graphs, pie charts, scatter plots, and network diagrams often referred to as "graphs" in the context of nodes and edges. This was achieved by transitioning purely textual data representations to 2D graphs, an advancement that benefited analysts, researchers, and even students.

Immersive visualizations take this progress even further with modern techniques presenting graphs in a 3D space, offering a more engaging and dynamic user experience. By leveraging spatial awareness, depth perception, and interactive manipulation, users can explore complex datasets from multiple perspectives, offering a richer and more intuitive analytical experience. Instead of being confined to static charts or dashboards, these techniques allow users to physically navigate through data, making it easier to comprehend relationships that might otherwise be obscured in conventional formats.

Nowadays, immersive technologies have advanced by utilizing devices such as VR and AR, which are pushing the boundaries of data visualization even further. Significant research has been conducted in the fields of Human-Computer Interaction (HCI) and Immersive Analytics (IA), both playing a crucial role in evolving data visualization techniques. These technologies allow users to engage with data in a 3D space called a Virtual Environment (VE) while promoting collaboration, and therefore, users can engage with data in greater depth and clarity, enhancing their ability to identify trends, anomalies, and extract insights.

With this master's thesis, we aim to implement an **immersive data visualization framework, with a particular focus on visualizing social network graphs**. Social networks capture connections between nodes or entities, forming structures such as communities, hierarchies, or family trees. We focus on this type of graph because it supports a wide range of use cases and fields it can benefit, that align with the goals of the collaborating company **CoVince Innovations B.V.**[1]. Furthermore, the framework supports data representation on 2D displays (such as desktops), providing a 2.5D visualization, or 3D (Virtual or Augmented Reality) environments, enabling both individual and collaborative exploration of network datasets by importing data into the framework. As aforementioned, this work is conducted at the company CoVince, which provides access to all necessary resources and various functionalities derived from their already implemented framework. Specifically, these are:

1. The *Virtual Reality devices*, utilized for both the implementation and conducting the user study.

2. *Cross-Platform Compatibility* for VR and Desktop environments is implemented and available for use.

3. The *VR Interactions* and the *Movement for Desktop* inside the environment, providing intuitive user control with controller and ray-based input for the VR, and keyboard movement for the Desktop environment.

4. *Multi-User Support* is accessible, which provides a collaborative, multi-user environment with voice and video communication.

The significance of this approach lies in its versatility in various fields; the framework offers dataset import that follows a specific format, which can be processed and visualized within a virtual environment, regardless of the type of information it contains. Different domains can benefit from the visualizations as they prove to be helpful in the analysis and understanding of complex data. The employment of this approach visualizes data in an interactive and immersive manner, supporting complex data exploration, analysis of displayed information, and collaboration with others through an intuitive visual representation. Additionally, it introduces an immersive and interactive technique for separating relations between nodes or entities inside the dataset, which aims to reduce occlusion within the visualization, along with other techniques for intuitive exploration. To the best of our knowledge, even though existing frameworks are employing filtering mechanisms with gamification [23] or standard filtering panels [16], there are no other frameworks that incorporate a similar technique like this.

1.1 Research Questions

The development of this framework focuses on displaying *immersive data visualizations of social network graphs*. We aim to create a framework that prioritizes **user experience**, by utilizing user-friendly functionalities to enhance this experience while ensuring clear and comprehensive data representation. It enables the user's navigation in the virtual environment, which offers a sense of presence, and introduces a specific method for representing different relational connections between nodes or entities. Additionally, the framework emphasizes on its **broad applicability**, in addition to its built-in data import, allowing users to visualize personalized datasets from various fields. Finally, it fosters **collaboration** by allowing multiple users to coexist in the same shared environments and share insights, navigate, and explore data visualizations. A further explanation of these requirements is provided in Chapter 3.

This master's thesis aims to address the following research questions:

- RQ1: How does immersive visualization in a visually immersive 3D virtual environment using VR affect task completion time and accuracy compared to a standard 2D desktop display, on tasks regarding the exploration and navigation of social network graphs?

[1] https://covince.com/home/en

- RQ2: How does interactivity in 3D data visualization using VR impact user experience (user satisfaction, engagement) and data interpretation compared to a standard 2D desktop display, on tasks regarding the exploration and navigation of social network graphs?
- RQ3: How does the visual separation of relationship types in social network graph visualizations impact user experience in terms of information clarity, and how does it contribute to managing visual occlusion?

An experiment is conducted to answer these research questions, requiring participants to complete a set of predefined tasks. As detailed in Chapter 5, participants are divided into two groups to test the framework in a 2D (desktop display) or 3D setting (VR headset), following a between-subjects design, aiming to minimize learning effects and avoiding biased improvements in performance. To answer the first research question, we gather metrics regarding task performance, including accuracy and completion time.

To answer the second research question, the participants are presented with a standardized user experience questionnaire, the System Usability Scale (SUS) questionnaire [7], which is used to assess the system and includes 10 Likert scale questions [38] on a 5- point scale. Additionally, they have to answer a custom questionnaire to assess user experience, specifically engagement scores, immersion, and comprehension of the framework and the displayed data.

Finally, the third research question is answered by qualitative insights that are gathered through targeted questions in the custom questionnaire. Participants are asked to reflect on whether the visual separation of relationship types improved their ability to distinguish elements within the visualization and locate the information required to complete specific tasks.

1.2 Proposed Framework

Previous studies often overlooked the importance of offering users the option to choose between displaying visualizations in 2D or 3D displays, causing limits to the wider adoption of visualization tools across different user groups, visualization environments, and domains. Moreover, to the best of our knowledge, there is no other data visualization framework that utilizes the Fibonacci Sphere algorithm [28] to distribute nodes around in the visualization, an algorithm that is considered highly effective for achieving uniform point distribution on an imaginary spherical surface. Furthermore, various existing frameworks are relying on traditional filtering panels rather than focusing on utilizing more immersive and 3D techniques to distinguishing different relationship types in social network graph visualizations.

In this master's thesis, we address those challenges by providing a range of features to make the interface more easily **accessible to users** by visualizing data in either 2.5D or 3D, accessible from standard computers and VR headsets, respectively, and custom data import. This ensures broader applicability and usability of the framework across a diverse range of users, in addition to the ability of importing custom datasets, enabling users to explore and visualize their own data from any domain. Furthermore, it utilizes the **Fibonacci Sphere algorithm** to evenly space out nodes in the 3D space, and an **interactive filtering approach** that utilizes 3D elements and colors to visually distinguish relationship types. These aim to tackle the challenges of occlusion and information overload, since the purpose of integrating them into the framework is to enhance clarity, interactivity and user experience. Finally, it supports multi-user collaboration, allowing multiple people to interact within the same shared environment simultaneously. This thesis focuses on interaction design and user experience for immersive social network graph visualization rather than algorithmic scalability. Therefore, the framework is scoped to visualizations of up to 50 nodes, allowing for effective evaluation of the aforementioned functionalities.

1.3 Structure of this Thesis

The research begins with Chapter 2, presenting a literature review of previous findings related to key topics that help build a strong framework, such as user behavior in immersive environments, various techniques of visualizing immersive data, and frameworks implemented in Desktop or VR environments that provide immersive visualizations. This review also showcases Unity's capabilities, a widely used Game Engine, highlighting its potential to create interactive and dynamic data visualizations other than creating games.

Following is Chapter 3, describing the design and methodology of the proposed framework. This includes a step-by-step process of designing and implementing the immersive visualization framework. It covers aspects such as the goals based on the research questions, the features and user requirements to provide a user-friendly experience, and the technological components of the hardware used.

In Chapter 4 we explain the implementation of the immersive visualization framework. This includes the actual design, tackling aspects such as algorithm implementation and integrated techniques, in addition to UX design choices to enhance user experience in immersive environments.

In Chapter 5, we describe the user study conducted to evaluate the framework's usability and effectiveness, aiming to answer the aforementioned research questions. The study design, participant demographics, tasks, and evaluation metrics are presented, aiming to assess factors such as immersion, efficiency, and user satisfaction. Moreover, we present and analyze the results of the user study, focusing to address each research question. This chapter discusses findings related to user performance, experience, and perception of the immersive filtering approach, aiming to find insights into the strengths and limitations of the proposed framework, by comparing the two groups; Desktop and VR.

Finally, Chapter 6 provides the discussion. It summarizes the main findings by comparing them with previous studies or existing frameworks, and outline potential directions for future work aimed at improving this framework and limitations of this study. Then, in Chapter 7 is the conclusion of this thesis by summarizing the outcomes of the previous chapters.

Chapter 2

Related Work

This chapter explores key elements that contribute to the development of our framework by analyzing insights drawn from a range of existing methods and research spanning several decades. We begin with Section 2.1, showcasing the evolution from 2D to 3D visualizations, deriving inspiration and insights from previous studies that leveraged technological advancements. Furthermore, Section 2.2 shows the importance of data visualization across various fields, as they benefit from its immersive features and its effectiveness in handling large datasets, and furthermore focuses on applications that utilize immersive data visualization for graphs.

Section 2.4 includes a discussion of key design principles for creating effective, user-friendly interfaces that facilitate features for an enhanced user experience, and finally the significance of using Unity 3D as the engine to develop our framework is discussed in Section 2.5, both for their use in Immersive Data Visualization (IDV). The insights gathered throughout those studies are taken as a guide as we incorporate them into our framework and advance upon them.

2.1 Advancing from 2D to 3D

Visualization techniques have evolved significantly within Human-Computer Interaction (HCI) research, progressing from traditional 2D methods, such as pie charts, histograms, tables, bars, and scatterplots [58], with basic interaction to immersive approaches integrating Virtual Reality (VR) and Augmented Reality (AR) for enhanced user engagement. This section aims to motivate the transition from 2D to immersive 3D data visualization by summarizing key findings from prior work. These insights highlight both the potential benefits of utilizing VR and 3D representations, such as improved data comprehension, memory retention, and interaction, as well as the challenges that must be addressed through thoughtful design. This foundation informs the design choices and the appropriate technologies utilized to assist in the implementation of this thesis' proposed immersive visualization framework.

InfoVis benefits from new technologies that focus on users' knowledge of the physical world and focus on providing easier identification and understanding of patterns for users, especially with alternative displays like Virtual Reality [44]. By leveraging VR and AR technologies, 3D spaces allow users to navigate complex, multidimensional datasets, enhancing depth perception, interactivity, and user engagement. Essentially, they allow users to intuitively navigate and interact within the environment, offering a sense of presence and freedom, in addition to a more comprehensive understanding of patterns and relationships, features that traditional 2D spaces struggle to convey. Furthermore, shared virtual environments enable collaborative data exploration, allowing multiple users to interact with visualizations simultaneously. These environments use design features such as avatars' colors, pointers, and the ability to manipulate the environment's elements (e.g., repositioning data graphs) to distinguish participants from one another [43, 53].

Various technologies such as projection technologies or immersive rooms, allowed users to physically navigate in the real world which corresponded to their movement in the virtual environment

[19, 25], however they were limited by their high costs and large size. Comparative studies demonstrate significant results on how display types affect perception, especially on the benefits of VR and 3D representations. Studies found that VR is an effective tool that utilizes our natural abilities to navigate, comprehend, and recall information, ultimately enhancing our understanding of data and its relationships. By depicting data in 3D space with stereoscopic depth perception, VR enables more natural spatial reasoning compared to abstract 2D screen representations, which has been shown to improve information recall, task performance, user confidence, and reduce errors when navigating and interpreting complex datasets [42, 36].

An important consideration in developing such frameworks is the integration of VR/AR technologies for data management and analysis in 3D (using filtering, grouping, linking [47]), and customizable parameters in VR environments (using different colors and scales of graph parameters [49]). These ultimately foster collaboration, high-level of user interaction and manipulation of data in real time. Based on the insights derived regarding the benefits of VR and 3D representations, we focus on those displays and plan to include functionalities that enhance the user experience.

However, displaying multidimensional data in 3D immersive environments presents challenges, as an additional dimension does not automatically guarantee better comprehension of represented data. Users may misinterpret data in 3D due to VR-induced distortions in distance perception, which are influenced by interface designs [3] and the user's familiarity with VR. Thoughtful design choices and appropriate techniques are therefore essential to reduce misinterpretation. While benefits like natural interaction, spatial memory, and enhanced engagement are evident, issues such as cognitive load, motion sickness, fatigue, and interface complexity persist. Nevertheless, immersive visualizations build on 2D techniques by introducing interaction methods that attempt to mitigate issues similar to this.

2.2 Applications using Immersive Data Visualization

An increasing number of fields are adapting and embracing technological advancements, making interactive and immersive data representation a growing area of interest for large datasets. Immersive data visualization (IDV) tools are being developed across diverse domains, from accounting to assist in decision support by providing analysis on large and complex datasets [35], to biology and geology, where VR enables representation of complex structures and environments in 3D [69, 22]. Domain-specific applications have demonstrated the effectiveness of interactive analysis compared to non-interactive and static visualizations, increasing users' confidence in their data exploration skills. Furthermore, task-specific visualizations and interaction modes provide an advanced user experience, such as small multiples or spatial map layouts in immersive environments, that support focused analytical tasks through tailored manipulative visuals and interactive designs in VR/AR environments [46, 54].

A wide range of additional fields benefit from immersive data visualizations, particularly considering the scale of modern datasets, the advantages of spatial memory and interaction within virtual environments, and collaborative capabilities. Examples include ontology [34, 50], semantic data [8, 24, 27], healthcare [59], and education [33, 68]. This broad applicability across domains underscores the need for flexible, multi-purpose frameworks that support custom data import and cross-domain visualization, which is a key motivation for the framework proposed in this thesis.

Given this diverse pool of immersive visualization applications, the following review focuses on a selected subset of existing frameworks that directly inform our design. Rather than surveying all graph visualization systems, we focus on frameworks chosen for their innovative interaction techniques, cross-platform support, collaborative features, or approaches to handling complex relational data. By analyzing these systems, we identify their core functionalities, distinguishing features, interaction techniques, and design choices, that act as an inspiration to this thesis and guide our framework's development.

One notable example is **IATK** (An Immersive Analytics Toolkit), a data visualization toolkit that creates data graphs in immersive environments in desktop and VR environments [16]. This toolkit stands out for its cross-platform flexibility and its exploration, as it aims to support users in navigating large and complex datasets by introducing innovative interaction techniques. It offers multiple functionalities, including details on demand to retrieve values of selected information, animated transitions, and importing CSV files as datasets to be visualized. Multidimensional data representations have gained particular interest in the development of immersive systems. **ImAxes** being one of them, contributes to this field with a framework that visualizes data based on the proximity and orientation of the axes in VR [17].

Another impressive toolkit is called **Flow**[1], which offers an immersive, multi-user virtual environment for 3D data visualization using any type of device, especially VR and AR, thus supporting cross-platform collaboration. It focuses on enhancing spatial awareness and providing an engaging and immersive experience for all participants, due to its capability of representing data in three dimensions, and allowing for real-time observation and exploration of the virtual environment. Additionally, **Noda**[2] addresses the limitations of exploring and representing data in 2D by introducing a 3D virtual environment designed for intuitively interacting and manipulating immersive social network graph visualizations. It is designed specifically for VR, and it supports real-time collaboration among users, enabling multiple participants to interact within the same virtual space, share insights, and modify visualizations dynamically.

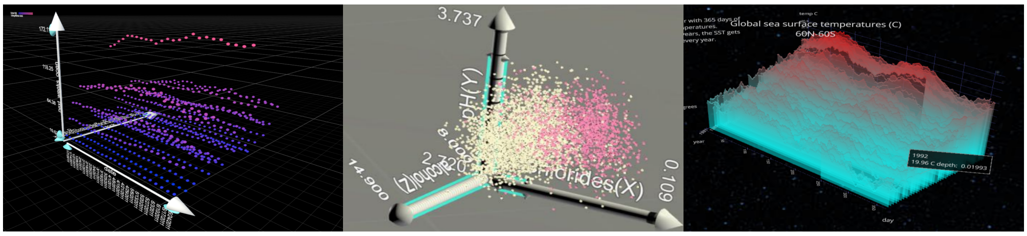
Finally, several applications utilize 2D data visualization (in desktop environments) to present their data, and the selected frameworks are included as a baseline for interaction techniques that remain effective when translated to immersive environments. For instance, **The Linked Open Data Cloud**[3] presents a diagram of social network graphs, where each node contains information about a specific domain. By hovering over a node, the user can observe its immediate connections. Similarly, in the study by Viégas et al. [63] network graphs were developed based on connections found in emails, such as recipients and CC'd contacts, and in the social network framework **Vizster** [31] they provided functionalities such as connectivity exploration, visual search, and analysis based on friends' relationships between groups of people, using the Spring Embedder algorithm. Other related applications are **GUESS** [1], **UCINET** [6], and **JUNG**[4].

2.3 Graph Visualization Systems

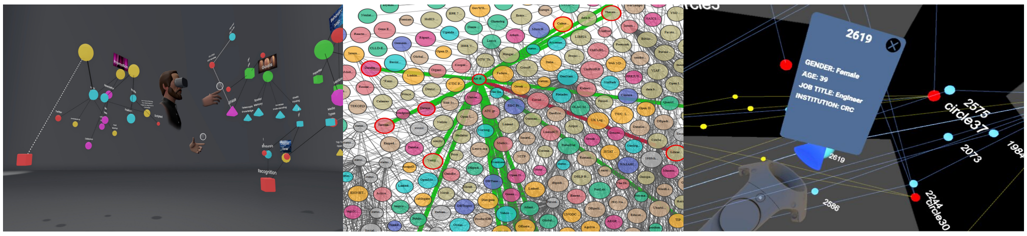
Following the previous section highlighting various systems, we narrow our focus to immersive systems designed for graph visualization, a specialized area of IDV systems. This focus aligns with the primary objective of this thesis: the representation of social network graphs in immersive environments in an effective and intuitive visualization. Social network graphs are a specific type of graph where nodes represent people or organizations and edges capture social relationships. This section examines graph visualization systems broadly, and we focus on the features and functionalities of graph visualization applications, and does not seek to provide a comprehensive overview of all existing systems, but rather to extract key insights and techniques.

GraphVR is an immersive 3D-focused framework developed in Unreal Engine, designed to enable natural and intuitive interaction with graphs in VR [10]. It addresses challenges like occlusion and information overload by incorporating a menu on top of the in-system controller with various functionalities, such as manipulation, rotation, and scaling of graphs. Similarly, **Gephi** is an open-source software tool for desktop environments, aiming to display large network graphs in real time [4], utilizing their implemented Force Atlas algorithm able to achieve high speed and stability (i.e. the ability to ensure that nodes gradually settle into steady positions without oscillating, resulting in a clear and readable final layout) for over 20.000 nodes. Both applications facilitate personalized node design as all nodes are customizable, where colors and sizes can be altered. **Tulip**[5] is a powerful desktop graph visualization framework providing extensive

[1] https://flowimmersive.com/
[2] https://store.steampowered.com/app/578060/Noda/
[3] https://lod-cloud.net/
[4] https://jung.sourceforge.net/
[5] https://tulip.labri.fr/site/



(a) IATK (b) ImAxes (c) Flow



(d) Noda (e) The Linked Open Data Cloud (f) VRige

Figure 2.1: The figures showcase some of the discussed frameworks, their functionality and appearance.

customization capabilities and a comprehensive API for developers [2].

Multiple applications focus on efficiently representing their dense information in immersive environments, utilizing techniques such as colors, sizes, and labels for distinction. One such tool is proposed by Sorger [57], in which the user can explore large dynamic graphs, overview and analyze nodes' details and connections. **NodeTrix** is another framework [32] provided in desktop and VR, that combines node-link diagrams with adjacency matrix representations, allowing users to switch between visualizing sparse parts of a graph as node-link layouts and dense subgraphs as matrices, facilitating more effective exploration of different network structures.

Additionally, **VRige** is a visualization system developed in Unity for VR, designed to facilitate user interaction and navigation while providing graph manipulation capabilities [23]. It enhances the ability to identify links and compare information within a network of people, along with a feature to address occlusion caused by excessive on-screen data; a filter cube that enables dataset filtering based on specific criteria, allowing the user to focus on the graph rather than the user interface, thus encouraging exploration of the dataset. An equivalent approach is followed in **Graph2VR** [39], which features a circular menu displaying a submenu with various options in VR. Both frameworks yielded positive results, with participants favoring their functionalities for simplifying the observation of relationships between nodes within the graph. Some example figures are shown in Figure 2.1, demonstrating an overview of some of the mentioned frameworks.

2.4 Design Principles for IDV

With the widespread adoption of head-mounted displays (VR/AR), researchers are increasingly focusing on certain key design aspects of virtual environments to enhance immersion and user engagement, specifically in IDV. According to the FIVE framework [56], the authors pinpoint several definitions as guiding principles in the development process. **Immersion** refers to a computer system's capability to create a vivid and surrounding illusion for the user while enhancing the user's self-representation of their virtual body—the feeling of being present in the virtual environment. **Presence** regards the user's perception of being physically inside the virtual environment, being conscious of their surroundings, and identifying their virtual body. Additionally, **matching** describes the synchronization of the user's real-world movements and behaviors with those in the virtual environment, thus reinforcing the sense of being seamlessly connected.

Moreover, aside from the senses while being inside the virtual environment, it is important to consider that user experience outlines all different aspects of how users perceive an application, playing a crucial role in the design, especially when proposing new techniques or innovative frameworks aiming to improve user interactions and avoid frustration. **User experience** extends beyond basic functionality, focusing on enriching models and improving quality, to develop a more holistic approach [30]. Therefore, it ensures efficiency, but also meaningful and engaging interactions that enhance the overall experience. **Emotion and affect** are essential components for creating an enjoyable experience, as they provide insight into how users perceive the emotional impact of technology. The focus is primarily on fostering positive emotions, such as joy, fun, and pride, while mitigating frustration and dissatisfaction. Ultimately, effective user experience design integrates these components into an interactive system to form a cohesive, meaningful, and engaging experience.

Post-WIMP(Windows, Icons, Menus, Pointers) User Interfaces followed similar approaches to ensure the creation of user-friendly, simplistic, and intuitive interfaces [61]. These interfaces aim to be easy to learn and remember for beginners, and highly productive for expert users, and it is crucial to focus on the task and not the interface, thus without the need for constant instruction or guidance. They incorporate different types of interactions and techniques, such as speech, gestures, or even haptic feedback devices to sense and send information, marking menus that exploit muscle memory, and the use of 3D widgets instead of 2D. Another study by Cordeil et al. [18] explored how **Immersive Analytics** aim to use multi-sensory interfaces to enhance user immersion while promoting collaboration. By deploying new technologies, these systems focus on creating engaging and immersive user experiences. The authors emphasize that collaboration is a crucial factor in data visualization applications, alongside user experience. Additionally, they highlight the benefits of immersive analytics, such as that multiagency technology offers diverse stimuli, which makes visualizations an interactive activity rather than a static view, and the combination of large displays can enhance collaboration and immersion.

When establishing a harmonious and thoughtfully designed experience, it is essential to provide users with the ability to perform specific **interaction mechanisms**, as effective visual representations of large datasets are crucial for a better understanding [55]. Because visual occlusion can occur in 3D visualizations, the system must provide mechanisms that help users comprehend their position and orientation when interacting with objects, enabling them to create clearer views of the displayed information while maintaining a sense of interaction freedom. These mechanisms follow *Shneiderman's Visual Information Seeking Mantra* [55] and include: **overview of the information**, **zooming in or out on items of interest** (which helps maintain the sense of position and context), **filtering out irrelevant elements** (displaying only content of interest), **details on demand** (allowing users to select items for more information), **relate** (view relationships among items), **history** (the ability to retrace steps with actions such as undo and replay), and **extract** (exporting or saving data).

2.5 Importance of Unity3D for IDV

The Unity3D game engine was originally developed for game development, utilizing an easy-to-learn C# programming language and offering an extensive library that makes it accessible to both beginners and experienced developers. Over time, Unity3D has expanded beyond gaming, in various fields with unique applications such as VR, AR, cross-platform applications [64], and even the representation of geographical information [65]. Its high-performance render engine, physics, advanced visuals, etc., showcase its various capabilities that extend beyond the typical game development purpose.

Furthermore, researchers have shown particular interest in this game engine and its capabilities, especially for immersive data visualization. Its ability to manage large datasets and efficiently visualize them, along with its online server facilitating real-time collaboration among multiple users, makes it an invaluable tool. It has extended applications; for instance, representing DNA/RNA sequences and structures [69], visualizing landscapes for geologists by utilizing custom visualization browsers [22], employing APIs and dictionaries to assist in reconstructing 3D representations [47], supporting AR/VR development and providing tools for interactive immersion [3, 36], and visualizing large datasets in an immersive and interactive experience [16, 17, 49].

2.6 Our Approach

In this thesis, we develop a framework that builds on existing systems by integrating proven visualization and interface design strategies into an immersive and accessible framework. The framework is deliberately scoped to social network graphs of up to 50 nodes, prioritizing the evaluation of immersive interaction techniques and user experience over large-scale data processing. Although it does not introduce a new layout algorithm, it employs the Fibonacci Sphere algorithm to evenly distribute nodes around an imaginary sphere [28], ensuring even distribution. While existing frameworks utilize algorithms such as the Spring Embedder [31] or Force Atlas [4] that focus on performance, the Fibonacci Sphere approach prioritizes uniform spatial distribution in 3D space, which, to the best of our knowledge, has not been employed in prior visualization frameworks.

Additionally, as demonstrated in Table 2.1, only a small number of frameworks integrates cross-device accessibility to support both 2D and 3D devices. Therefore, this framework provides a comprehensive combination of functionalities such as this, and the introduction of a filtering approach of isolating different relationship types and visualizing them individually, aiming to reduce occlusion in social network graph visualizations. It further supports collaboration by enabling access across diverse platforms and user groups, while allowing data import for personalized visualizations across various domains.

The framework adopts the conventional node-link representation for social networks [51], where each item (i.e., entity) in the dataset corresponds to a vertex (i.e., node) in the visualization, and each relationship is represented as an edge (i.e., link) connecting two vertices. Further details on the functionalities and framework implementation are discussed in Chapter 3. A comprehensive comparison of the discussed frameworks, including our approach, along with their capabilities and features, is presented in Table 2.1.

Tool/ Frame-work	Displays supported (2D/3D)	Immersive Visualizations	Intended Purpose	Features / Functionalities
IATK	2D and 3D	Data graphs, animated transitions, filtering	Data exploration and manipulation of large datasets	Data import, brushing and linking, details on demand, animated transitions
ImAxes	3D	Multidimensional dataset visualization based on axes placement	Visualizing, interacting, and manipulating multidimensional datasets	6DOF manipulation, hand interactions for positioning and orientation
Flow	3D	Real-time 3D data graph exploration	Multi-user, real-time, spatially aware data exploration	Data import, cross-platform collaboration, VR/AR support, multi-user interaction
Noda	3D	Social network graphs in VR	Visualizing and interacting with immersive social network graphs	Data import, real-time collaboration, real-time visualization customization, interaction in VR
Gephi	2D	Social network graphs in 2D	Real-time large network graph visualization	Data import, customizable nodes, force-directed layout, interactive zoom, and pan
The Linked Open Data Cloud	2D	Social network graphs with node connections	Visualization of domain-specific social network data	Hover interactions to explore node connections
GraphVR	3D	Social network graphs in 3D	Immersive interaction with social network graphs in VR	Controller menu for manipulation, rotation, scale of graph elements
NodeTrix	2D and 3D	Social network graphs, node grouping	Analyzing dynamic network graphs	Data import, customizable nodes, node grouping, node manipulation functionalities
VRige	3D	Social network graphs in VR	Interaction with dynamic networks and filtering in VR	Filter cube for dataset filtering, manipulation, and navigation
Graph2VR	3D	Social network graphs in VR	Immersive exploration of linked data graphs	Database import, circular menu, interaction with graph elements
Our approach	2D and 3D	Social network graphs in desktop or VR	Immersive exploration of social network graphs, with functionalities for easy observation and analysis of relationships	Data import, real-time collaboration, hover interaction to observe connections, techniques for data observation and separation of relations

Table 2.1: Comparative summary of some existing immersive data visualization tools and the approach that will be implemented in this master's thesis. The 2D display on the second column is considered the Desktop version, and 3D is the VR. A detailed overview of the functionalities and the development of our framework (mentioned in the last table row) can be found in Chapter 3.

Chapter 3

Framework Design

This chapter outlines the practical aspects and implementation details of the proposed framework, providing a clearer perspective on the development process and overall vision of this master's thesis. Specifically, it introduces the approach, including the goals and scope of the study, the features and user requirements that the framework aims to support, and the technologies employed provided by the company. The chapter concludes with a demonstration of the file structure required for dataset import.

In this thesis, a framework is developed that focuses on representing social network graphs effectively and clearly, with functionalities that support an immersive and interactive experience. Based on a specific file structure, the user is able to import, visualize their own dataset and navigate it in the virtual world either in a 2D or 3D display setting (desktop or VR). This framework aims to provide visual representations with features and interactions that enhance the user experience, improving the feeling of presence in the virtual world. The aim is to create a framework that is widely accessible to various user groups by providing those functionalities, but also due to the ability to visualize datasets of any field with the only requirement to follow a specific file structure.

3.1 Goal

For ease of reference, we state the key objectives of this study, which correspond to the research questions introduced in the Introduction (Section 1.1):

- The potential difference in completion time and accuracy of participants while using our immersive framework in 3D with a Virtual Reality headset in comparison to our framework in the standard desktop 2D display setting.
- The potential difference that immersive data visualizations may have on user experience and interpretation of displayed data when represented on the Virtual Reality device (in 3D) compared to the traditional 2D display on the desktop.
- The extent to which visual separation of relationship types support clarity and reduce visual occlusion in the graph.

These objectives are addressed through a controlled user study (described in Section 5.1), where we collect data using defined metrics and questionnaires. The analysis of this data provides insights to answer our research questions.

3.2 Scope

To maintain manageable complexity within the constraints of this master's thesis, the framework is scoped to visualizations of up to 50 nodes. This deliberate limitation allows for focused evaluation of the proposed interaction techniques and functionalities of the framework, rather than algorithmic scalability. While the Fibonacci Sphere algorithm is theoretically extensible to larger datasets, the scope for this thesis will be limited to this specific number of nodes to ensure effective testing, user interaction, and visualization without excessive occlusion. Extending to larger datasets, to visualize them in the virtual environment and handle them accordingly to avoid occlusion, would require additional implementation efforts that fall outside the research focus of this thesis and is considered future work.

3.3 User Requirements

Based on the research insights and analysis in Chapter 2 and in collaboration with CoVince Innovations B.V., we identified the following user requirements **(R)**:

R1: Accessibility across devices, users of diverse expertise and domains. The framework must be accessible to a broad range of user groups, across both 2D (i.e., desktop) and 3D (i.e., VR) displays for people to easily access it depending on the devices available to them. Furthermore, it must incorporate a custom data import system that adapts to diverse application domains, to increase flexibility and adaptability for various professional or educational use cases.

R2: Smart user techniques and designs. Users need reliable methods to explore nodes within the visualization, along with clear visual feedback to understand the current state of the visualization. This requires implementing proven interaction techniques and providing visual cues that support navigation and comprehension of the network structure, such as color-coding and interactive highlighting.

R3: Co-existence of multiple users in the same virtual space. The framework should enable multiple users to simultaneously explore the same visualization, with visual mechanisms to distinguish between participants. While this is a desirable functionality, it is treated as a secondary priority given the focus of this thesis on individual user experience.

3.4 Features

To address these requirements, the framework implements the following features **(F)**:

F1: Dual-Mode Visualization (2D/3D display) - addresses R1. The framework offers the flexibility to display the dataset in either 2D or 3D displays, with the 2D option visualizing in a standard desktop and the 3D utilizing VR to enhance immersion within the virtual environment. Users are able to explore and interact with the data from a broader accessibility across different devices and user preferences.

F2: Custom Data Import - addresses R1. It provides import and processing of custom datasets, following a predefined file format (Listing 3.1). For the import of the file, our framework incorporates the company's functionality of uploading the dataset immediately to their application, and the processing takes place with the use of the **JsonUtility Method for Unity**[1]. This method gets the file as an input and create a JSON representation to derive information from it.

F3: User Interaction and Design - addresses R2. Following established graph visualization practices, the framework color-codes edges (i.e. the connections) based on the color of the relationship type to distinguish between different relationship categories. Furthermore, it includes the functionality of highlighting nodes, entities, and their relationships by hovering over them. This is achieved by using the **Quick Outline Unity Package**[2] which creates a solid outline to any object, and the **Line Renderer Unity Component**[3] which draws lines in the 3D space. Finally, this study evaluates a relationship filtering approach where different relationship types are represented as 3D color-coded, oval-shaped, selectable elements in the visualization, and the user can isolate and display one of those. For example, in a dataset with 'Colleague,' 'Family,' and 'Friends' connections, users see three color-coded oval elements, and by clicking on one filters the

[1] https://docs.unity3d.com/6000.0/Documentation/ScriptReference/JsonUtility.html
[2] https://assetstore.unity.com/packages/tools/particles-effects/quick-outline
[3] https://docs.unity3d.com/6000.0/Documentation/ScriptReference/LineRenderer.html

visualization to display only nodes connected by that relationship type and their corresponding edges, hiding all others. This technique aims to reduce visual clutter, potentially improving users' ability to explore information within specific relationship types.

The VR interaction uses ray-casting for node selection, which involves casting a ray from the controller to an interactive object. While alternative techniques exist (e.g. Filter: ability to hide elements between the user and a object while keeping those behind it visible), the Ray technique was chosen for this thesis as the preferred approach for its high efficiency, low physical demand, and positive user perception [37], as well as its consistency with the CoVince application's existing interaction design.

F4: Collaborative Exploration - addresses R3. The framework enables multiple users to simultaneously explore visualizations in a shared VR environment, with visual differentiation through personalized avatars and uniquely colored selection rays. This functionality leverages the existing collaborative infrastructure of the CoVince application.

Given the scope of this master's thesis, the user study focuses on evaluating individual user experience through features **F1, F2, and F3**. While the framework includes multi-user support **(F4)**, evaluating collaborative features would require a different study design with multi-participant scenarios, and is therefore identified as future work.

3.5 Technologies

The user study employed two display conditions, the desktop (2D) and VR (3D). Desktop participants completed the study either remotely on their own computers/laptop or in-person on the experimenter's laptop, on a designated location. VR participants were tested in-person at the company facilities using a Meta Quest 3 headset that was supplied by CoVince.

3.6 Entity Relationship Structure

This framework follows a specific structure for the represented data, which uses a three-level hierarchical graph model to represent social networks:

- **Main Entity**: The higher-level organizational unit. It is connected only to entities which showcase part of this organization. Also referred to as the "Central Entity", as it always appears in the center of the visualization
- **Entities**: The in-between level, which includes connections with other entities and individual nodes.
- **Nodes**: Individual people within the network. Nodes connect to entities (indicating affiliation) and to other nodes (indicating relationships).

The visual representation of this model is in Figure 3.1. We utilize edges to showcase a connection between entities and/or nodes, however, we represent the relationship types - between entities and nodes, or between nodes - as a separate interactive object. Each relationship has a specific type, including "Work", "Colleagues", "Employees" (professional connections), "Family" (familial connections), and "Friend" (personal connections). To illustrate this model and provide an example illustration, we use a campus containing different companies, where the Main Entity is the "Campus", Entities are "Companies" within the campus, and Nodes are "Employees" of those companies. However, this model can represent any three-level organizational network, we use this campus/company example throughout the thesis for consistency.

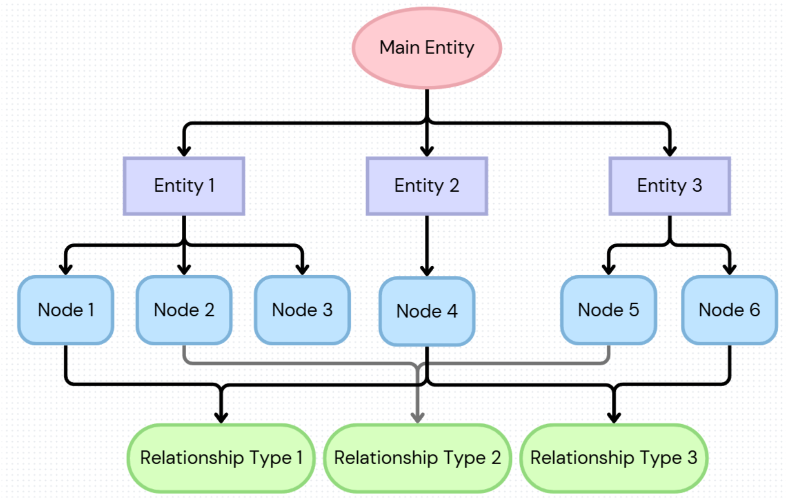


Figure 3.1: Three-level hierarchical data model showing relationships between main entity, entities, and nodes.

3.7 File structure

This thesis focuses on visualizing data, rather than processing specific data structures for visualization purposes. To enable the framework to process diverse datasets, all datasets imported into the framework must adhere to a predefined JSON schema that separates entities (e.g., organizations) from individual nodes (e.g., employees). As demonstrated in Listing 3.1, the required file structure for this thesis, Each element includes a unique ID, name, additional data attributes, and a list of typed relationships specifying the target entity/node ID and relationship type (e.g. "Work", "Family", or "Friend"). The distinction between different relationship types is essential because we assign each relationship type a distinct color for visual differentiation, following standard graph visualization practices. The Main Entity is not included in the file structure, however it is prompted to the user at the launch of the framework.

```
{
  "RelationTypes": [
  "string",
  "string",
  ...
  ],
  "Entities": [
  {
    "id": "string",
    "name": "string",
    "data": [
    {
      "datatype": "string | int | list | image | etc.",
      "dataname": "LOGO | NAME | ROLE | etc.",
      "datavalue": "corresponding value"
    },
    ...
    ],
    "relations": [
    {
      "source": "string (node ID)",
      "target": "string (node/entity ID)",
      "type": "Work | Friend | OtherRelationType"
    }
    ]
  },
  ...
  ],
  "Nodes": [
  {
    "id": "string",
    "name": "string",
    "data": [
    {
      "datatype": "string | int | list | image | etc.",
      "dataname": "LOGO | FULLNAME | ROLE | etc.",
      "datavalue": "corresponding value"
    },
    ...
    ],
    "relations": [
    {
      "source": "string (node ID)",
      "target": "string (node/entity ID)",
      "type": "Work | Friend | OtherRelationType"
    }
    ]
  },
  ...
  ]
}
```

Listing 3.1: Grammar of the JSON Dataset

Chapter 4

Interactive Visualization Design

This section presents the implementation details of the framework, focusing on the selection of algorithms, techniques employed to enhance user experience, and the overall design decisions that guided the development process.

4.1 Implementation

4.1.1 Node Distribution

A significant component of this proposed framework addresses the issue of visual occlusion, to support **F3** and **R2** as detailed in Chapter 3. The initial approach in the prototype involved randomly positioning nodes within a predefined 3D space around the central entity or node. However, this led to visual occlusion due to the unstructured and uncontrolled placement of the nodes. To mitigate this, we employ the **Fibonacci Sphere** algorithm [28], which generates an imaginary sphere centered around a specified position. Each node is distributed across the surface of this sphere, maintaining a uniform distance from both the center and one another, based on a predefined radius.

One of the primary advantages of this approach is its ability to distribute points uniformly and efficiently across a spherical surface. It aims to maintain clarity and spatial balance among nodes, making it suitable for visualizing small to medium-sized social network graphs[1]. This results in a visually balanced and evenly spaced distribution of points, which is beneficial in interactive 3D environments where clear spatial organization and real-time responsiveness are crucial factors for an enhanced user experience. The detailed steps of this distribution approach are outlined in Algorithm 1.

Considering that the framework supports full 3D exploration, the algorithm facilitates an initial clear visualization of multiple nodes. As users shift their viewpoint, previously obscured nodes become visible from alternative viewing angles, maintaining clarity within the virtual environment. As discussed in Section 3.2, the framework is designed to support up to 50 nodes, and a visual representation of this configuration is presented in Figure 4.1 shows the even distribution achieved by this algorithm.

4.1.2 Exploration through Progressive Filtering

In this master's thesis, we employ the Fibonacci Sphere algorithm within the framework's visualization, which operates through progressive filtering. This allows users to explore the network hierarchically without displaying all elements simultaneously. Figure 4.2 illustrates the following sequence of user interactions, where each step corresponds to one figure (a-d), using the example described in Section 3.6. Users begin with the main entity at the center (center entity) with all

[1] https://extremelearning.com.au/

Algorithm 1 Fibonacci Sphere Node Distribution

Require: sphere radius r, number of nodes n, center vector position $\vec{C}$
Ensure: list of 3D positions *positions*

```
positions ← empty list
U⃗_world ← (0, 1, 0)                                  ▷ World up vector
R ← rotation from U⃗_world to U⃗_cam

for i = 0 to n − 1 do
    φ ← arccos(1 − 2(i + 0.5)/n)                     ▷ The 0.5 helps distribute the points evenly
    θ ← π(1 + √5) · (i + 0.5)

    O⃗_u ← (sin(φ) · cos(θ), sin(φ) · sin(θ), cos(φ))  ▷ O⃗_u(unrotated): Un-rotated offset vector
    O⃗_r ← R · O⃗_u          ▷ O⃗_r(rotated): Apply rotation to align sphere with camera's height
    P⃗ ← C⃗ + r · O⃗_r
    append P⃗ to positions
end for
return positions
```

$$\vec{U}_{world} \leftarrow (0,1,0), \quad R \leftarrow \text{rotation from } \vec{U}_{world} \text{ to } \vec{U}_{cam}$$

$$\phi \leftarrow \arccos\left(1 - \frac{2(i+0.5)}{n}\right), \quad \theta \leftarrow \pi(1+\sqrt{5}) \cdot (i+0.5)$$

$$\vec{O}_u \leftarrow \begin{pmatrix} \sin(\phi) \cdot \cos(\theta), \\ \sin(\phi) \cdot \sin(\theta), \\ \cos(\phi) \end{pmatrix}, \quad \vec{O}_r \leftarrow R \cdot \vec{O}_u, \quad \vec{P} \leftarrow \vec{C} + r \cdot \vec{O}_r$$

connected entities distributed on an imaginary sphere around it (Subfigure 4.2a). When a user clicks an entity -in this case, the "Blockbuster LLC"-, it becomes the new center of the visualization and displays 3D oval-shaped elements representing available relationship types (Subfigure 4.2b). Upon selecting a relationship type -in this example, the "Employee"-, only nodes connected via that relationship are shown, distributed around the focal entity (Subfigure 4.2c). Then, clicking a node makes it the new focal point and again displays the available relationship types (Subfigure 4.2d).

This progressive focus approach maintains even spatial distribution at each interaction level while allowing users to explore specific subgraphs. Finally, detailed information about a node or entity (e.g., name, age, hobbies) can be accessed through an information button displayed on the corresponding node or entity. This button is visible only for the node or entity that is currently positioned at the center of the visualization, as demonstrated in Subfigure 4.2e.

4.1.3 Tracing Scene Changes

Prior research highlights several key elements that contribute to ensuring an optimal user experience. In particular, an important feature for supporting usability and handling user errors is a **history mechanism**, as outlined in Section 2.4. User errors such as accidental interactions or incorrect navigation are common in exploratory environments, especially those involving complex data and crowded visualizations. Additionally, users may wish to revisit previous states to reassess their choices or explore alternate paths.

To address this need, the framework implements a step-tracing functionality that allows users to navigate backward through their interaction history. This is achieved via a "Back" button positioned on the upper-left side of the screen on the desktop setting, or initiated by clicking the "R3" or "L3" button on the VR controllers in the VR setting. Each visualization of current active GameObjects within the scene is encapsulated in states, ensuring that the prior visualization is accurately restored, and the button retrieves the last recorded state.

This feature enhances both usability and user confidence by providing the ability to retrace their previous exploration steps, including navigation paths and interaction actions. This enables

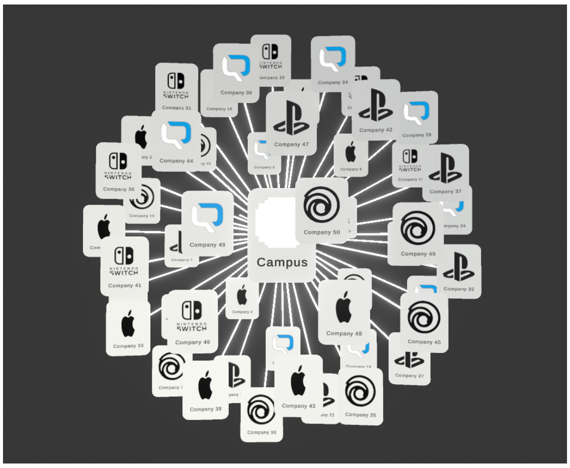


Figure 4.1: The visual representation of the Fibonacci Sphere algorithm, which creates an imaginary sphere around the center entity "Campus".

users to explore alternative visualization paths without losing progress or needing to start over. Instead of saving every movement, the framework records key interaction states, such as selecting a node or entity, or filtering by a specific relationship type, thereby providing greater flexibility in cognitively demanding and immersive 3D environments.

4.1.4 Navigation Controls

Ensuring an enhanced user experience was vital for this framework, as the user has to feel comfortable in exploring the visualization and also accessing the functionalities. Therefore, the navigation inside the 3D environment was implemented using two different approaches: one for the desktop version and one for the VR version. The framework supports Dual-Mode Visualization (**F1**), allowing users to choose between those two settings depending on their preferred experience.

Setting up the desktop version

In the desktop version, we implemented the movement and rotation controls as follows; vertical movement, the utilization of the y-axis for ascending and descending within the visualization, is controlled using the **E and Q keys**, while horizontal navigation is managed using the **W, A, S, and D keys**. Camera rotation is handled via the **mouse**: by clicking and holding the mouse button, users can drag the view in the desired direction. This results in a smooth, continuous rotation of the camera, which is generally preferred for desktop environments.

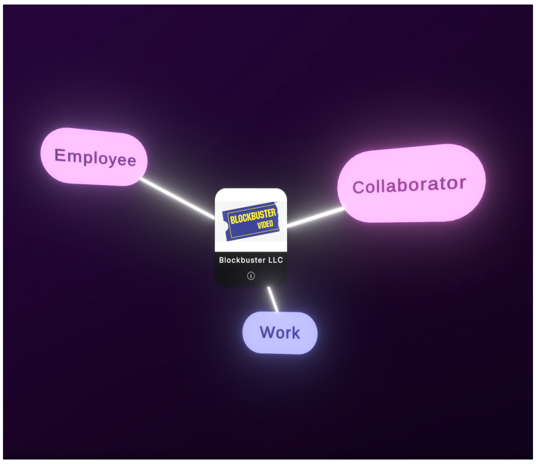
Setting up the VR version

The VR version utilizes both the left and right controllers. To explain the various button functionalities, we will refer to the naming conventions shown in Figure 4.3 (this image is derived from the EON-XR documentation page[2]). Starting with the right controller, the **joystick R1** allows the user to navigate within the 3D environment in all axis directions. **Button R2 and L2** enables the selection of objects, such as nodes or interface elements like the "open information panel" or "close" button. Furthermore, **button R3 and L3** serves as the "back" function, to visit previous visualizations (i.e., history tracking). This choice was made to enhance intuitiveness, as static on-screen buttons can be less effective in VR environments.

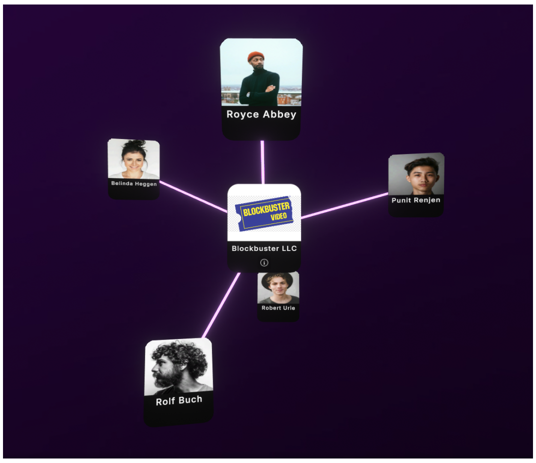
Finally, on the left controller, **joystick L1** is responsible for rotating the camera. While the desktop version supports smooth camera rotation, we implement snap rotation in VR to mitigate

[2] https://docs.eon-xr.com/HTML/HMD/controllers.html

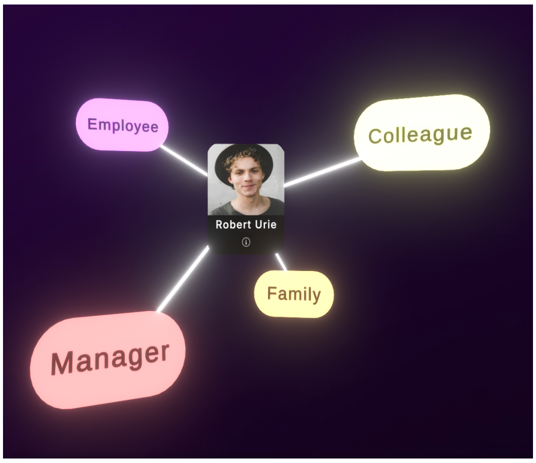
(a)



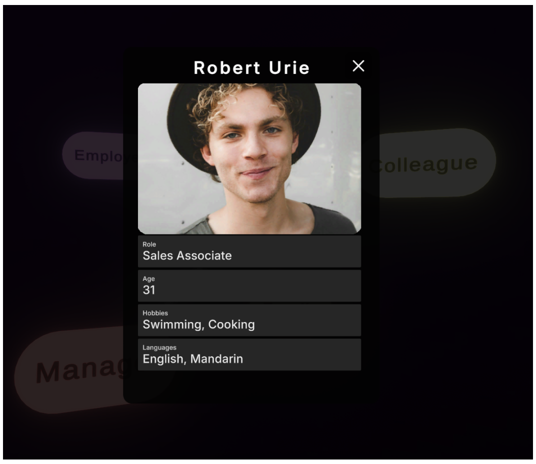
(b)



(c)



(d)



(e)

Figure 4.2: Sequence of user interactions within the visualization framework; Subfigure (a) the main entity positioned at the center, surrounded by connected entities, (b) selected entity becomes the new center entity, and its associated nodes are arranged around it, (c) selecting a node reveals the available relationship types, and (d) choosing a relationship type displays only connected nodes of this relationship, and (e) the information panel is activated via the button on the center node.

motion sickness [14]. VR sickness occurs when there is a mismatch between what visual movement and physical acceleration, which can cause nausea and discomfort[3]. Snap rotation addresses this by rotating the view in discrete steps rather than continuously, reducing prolonged visual motion and the associated discomfort.

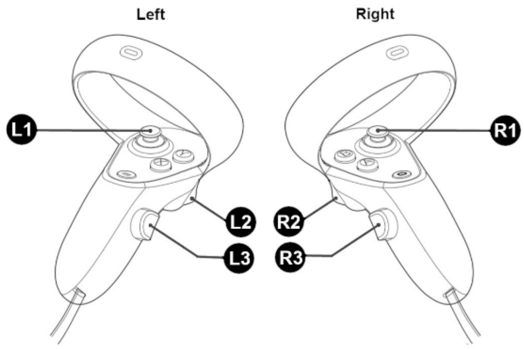


Figure 4.3: The VR left and right controllers with their according names for the buttons, for description purposes.

4.2 User Experience Enhancing Techniques

This section outlines the design choices aimed at enhancing the user experience and ensuring a visually appealing visualization. Drawing inspiration from the FIVE framework [56], these choices are intended to strengthen users' sense of immersion and presence in the virtual environment while fostering an enjoyable experience that evokes only positive emotions. The focus is on promoting ease of use, clarity, and engagement while minimizing frustration and dissatisfaction.

4.2.1 Visual Effects

The occlusion of nodes in 3D environments is often inevitable and can be challenging for the visibility of nodes or connections in social network graphs. To address this issue and enhance the visual clarity of entities or nodes and their relationships, a custom material was created using Unity's Standard Shader with emission properties to simulate a glow effect. This technique surrounds the object with a soft, luminous light, aiming to increase its perceptual prominence.

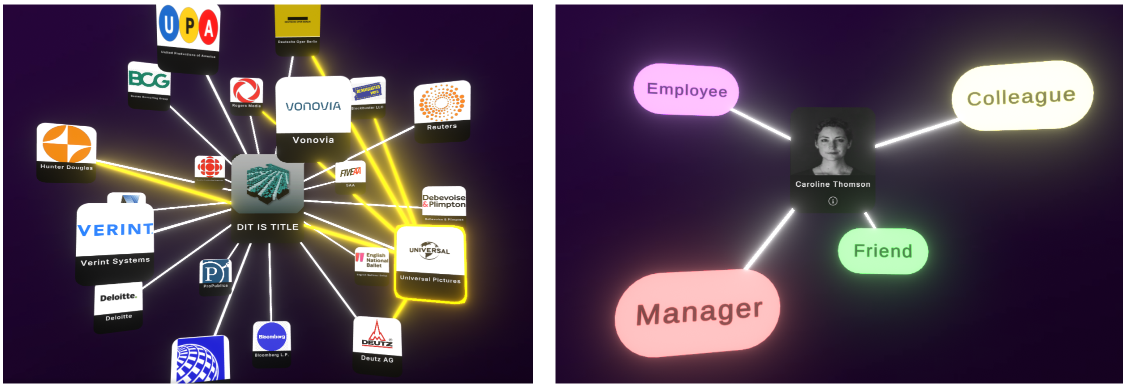
The initial version utilized a simple yellow Line Renderer to depict connections between nodes. However, this approach lacked visual prominence, particularly when multiple nodes and edges overlapped. On the contrary, the glowing effect serves as a visual highlight, drawing user attention more effectively because of the use of visual cues involving color and luminance compared to other methods like shape or size transformations [20]. An example of this effect can be seen in Figure 4.4.

This effect enhances the material by emitting light in its assigned color, creating a subtle "bleeding" of the color around the object. In the initial prototype, the background color was a faint blue, which occasionally created visual confusion when multiple bright colors were present simultaneously. Therefore, to reduce this issue and improve overall clarity, the background was adjusted to a deep purple which is consistent to other applications in the company's platform, allowing the glow effect to appear more luminous and visually distinct, particularly for vivid relation-type colors.

While this effect works well in desktop versions, it presented performance challenges in the VR environment, leading to frame drops and noticeable latency. These issues were likely related to

[3] https://developers.meta.com/horizon/design/locomotion-user-preferences/

technical limitations on the VR integration within the company's platform, and due to the limited timeframe of this master's thesis, they could not be fully resolved. To mitigate this issue, we chose to include this feature exclusively in the desktop version, excluding it from the VR implementation for user comfort and performance stability.



(a) (b)

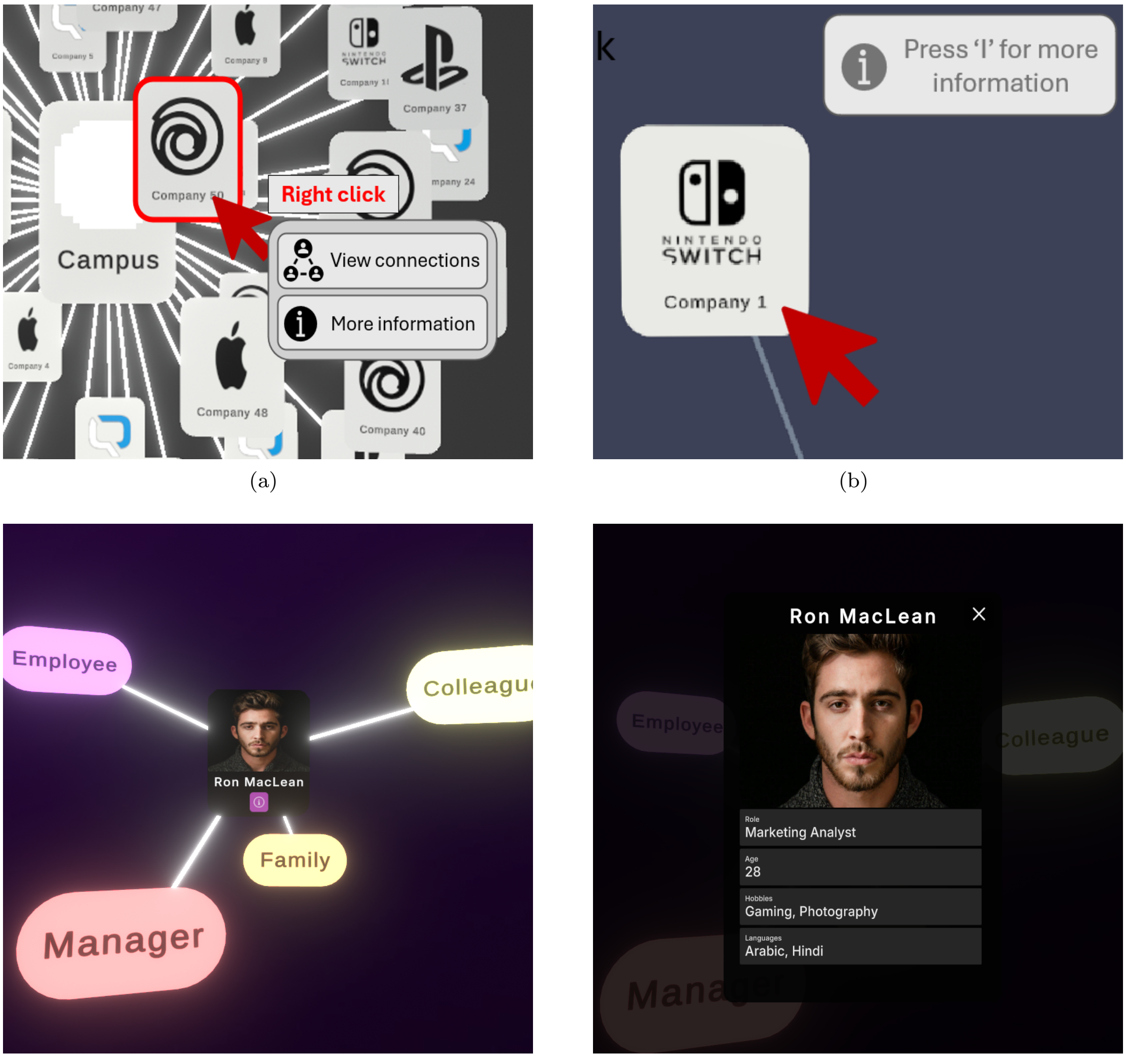
Figure 4.4: The glowing effect on two different scenarios; Subfigure (a) shows the connections between entities and (b) shows the relation types on a demonstration dataset.

4.2.2 Viewing Data Approach

The proposed framework provides the functionality of accessing information (e.g. name, role, hobbies) about the central entity or node displayed in the visualization; the current entity or node positioned in the center of the visualization. To implement this feature in an intuitive and cognitively light manner, three possible interaction methods were considered. The first method involved displaying an options menu either by right-clicking on a node in the desktop version or by pressing a designated button on the VR controller in the VR version. This menu would appear in any scene, whether it displayed all node connections or only relation-type connections. The second method enabled users to access a node's data panel by pressing a designated keyboard (or controller) key, but only after selecting the desired entity or node and while in the relation-type connections scene. Finally, the third approach was to include a button at the bottom section of the entity or node to open the data panel.

The first approach mirrors the traditional menu behavior, in which users right-click on the desktop, or press one of the VR controller buttons to reveal a menu. Specifically, this menu allows the user to choose between viewing detailed information about a node or switching to a view that highlights its connections, with each option presented separately for clarity. Alternatively, the second approach relies on a keyboard shortcut in the desktop version (or a designated VR controller button in the VR setting), where pressing the *I* key on the desktop (or *B* button in VR) opens the data panel. In this case, a small icon is shown in the upper-right corner of the screen to indicate which key to press. The final approach utilizes a button that appears on the bottom center of the node, which is activated only on the main entity, and on click activates the information panel. All prototype approaches are shown in Figure 4.5.

After evaluating all three methods, we selected the third approach for implementation, as it offers the most natural and user-friendly interaction. The first option, which relied on an interactive options menu, presented several usability concerns regarding potential user overwhelm, particularly in cluttered visualizations where misclicks, visual clutter, and cognitive load are common, therefore reducing immersion. This risk is amplified in VR, where raycasting can make precise selection difficult, and while enabling menus with the click of a button or right-click are familiar on desktop, they are non-standard and reduce immersion in VR.



(a) (b) (c) (d)

Figure 4.5: Prototypes of the three different approaches to show the data panel; Subfigure (a) shows the options menu, (b) shows the information icon, (c) shows the panel's activation button (the purple icon of information on hover), and (d) shows the data panel itself that appears from any of those approaches.

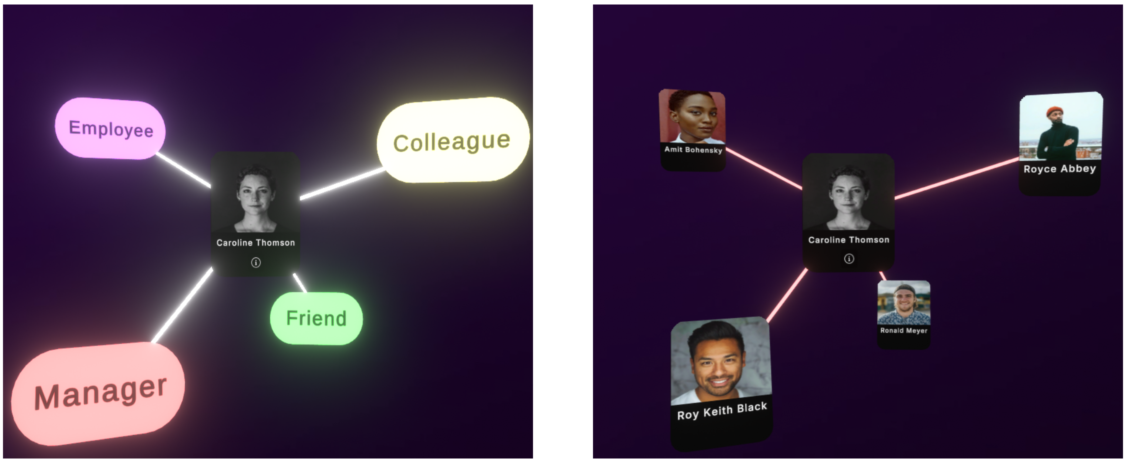
The second technique, triggering the data panel via a keyboard key or VR controller button, offered a clearer interaction. However, it relies on an on-screen icon to guide users on which button to press for the interaction, which can fall outside the field of view, especially on different screen sizes. This approach is particularly problematic in VR, as the icon remains fixed on the screen display and does not move naturally with the user's head, which can reduce the sense of immersion, increase eye strain, or even cause discomfort.

The third method resolves these limitations by placing the activation button directly on top of the entity or node's 3D element that is positioned in the center of the visualization. This ensures visibility as it follows the camera's position, and interaction is intuitive and user-friendly; users hover with a mouse or raycast in VR which showcases a different color of the button (indicating its interactivity), then click on it to open the data panel. This method preserves immersion, reduces cognitive load, and avoids interaction errors. It also minimizes visual clutter, making it the most effective, immersive, and user-centric design choice among the options considered.

4.2.3 Visual Separation of Relationship Types

This framework introduces a distinctive filtering mechanism designed to provide an immersive and interactive experience, aiming to enhance both user satisfaction and the sense of presence within the visualization. Our approach aims to overcome the conventional filtering panel where all options are typically presented in a static list of checkboxes, and replaces it with a visual, object-based representation of relationship types. This filtering mechanism forms the foundation of the progressive exploration workflow described in Section 4.1.2, where users navigate the network hierarchically.

In this design, each relationship type is displayed as a 3D interactive oval object within the environment. When the user selects one of these objects, only the connecting nodes corresponding to the chosen relationship type are displayed, while others are temporarily hidden. Figure 4.6 illustrates this functionality: Subfigure (a) shows the current centralized node ("Caroline Thomson") connected through four relationship types ("Employee", "Colleague", "Manager", and "Friend"), each highlighted with a different and distinct color to make it visually distinguishable. Subfigure (b) demonstrates the filtering process, where the user selects the "Manager" relationship type, and only the nodes of this specific connection appear on the visualization. The filtering effect is reinforced by the consistent use of color, ensuring that the visual identity of each relationship type is maintained throughout the interaction, from the object itself to the connection lines of this specific relationship.



(a) (b)

Figure 4.6: The visual separation of the relationship types as shown in an example scenario in Subfigure (a), which shows the four different relationship types that this node has (i.e. "Employee", "Colleague", "Manager", "Friend"), and then (b) shows when the user has clicked on a specific relationship type, in this case "Manager", revealing the four individual people connected to the node through this specific relationship.

A crucial benefit of this filtering approach is its ability to reduce visual clutter by dynamically hiding irrelevant information, thereby allowing the user to focus on the subset of information most relevant to their current exploration. In addition, it places filtering actions directly within the 3D visualization rather than separate 2D UI panels, aiming to provide an interactive and engaging process, that more closely aligns with the immersive goals of the framework. By incorporating filtering directly into the visualization space with an object-based technique, users experience an interaction that is intuitive, exploratory, and immersive. Ultimately, even though the scope of this thesis is limited to a small dataset, this method aims to provide an intuitive interaction model for exploring relations within social network graph structures, with reduced clutter and overwhelm.

4.2.4 Interface Tasks

Based on a previous study that focuses on providing interface tasks in their framework to create a consistent and smooth user experience [55], we incorporate similar tasks into our framework. These tasks were carefully designed to provide functionalities that are intuitive, easily accessible, and aimed at reducing potential frustration or dissatisfaction. These include:

- **Overview and details-on-demand**: accessible via an information button on the bottom part of the node, that displays data about the current central entity or node(the one displayed in the middle of the visualization). An example of this can be found in Subfigure (c) of 4.5.
- **Zooming in and out**: controlled through the VR controllers by moving either one of the joysticks up and down (VR setting) or keyboard commands ("W" and "S") on desktop (Desktop setting).
- **Filtering**: enabled through the approach of visually filtering relationship types, as described in Section 4.2.3.
- **Relate**: supported by a hover function that highlights a node's connections to others.
- **History**: provided through a "Back" button (Desktop version) or "R3"/"L3" button (VR version) that allows users to revisit previous visualizations.

One additional interface task mentioned in this study was the ability to extract visualizations, such as exporting or saving data. This feature was not implemented in the current framework, as it was not essential to complete this study, but it is identified as future work since this functionality can be highly beneficial for professionals working with data visualizations, allowing them to export the visual representation they are currently viewing.

4.2.5 Smooth Animations

Achieving a sense of immersion in the framework required a significant aspect to be considered: the smooth transition from one screen to another. Animations play a vital role in creating a more pleasant and intuitive user experience by helping users better perceive and understand changes occurring with each click on the screen. Incorporating smooth transitions, such as gradual appearance and disappearance of interface elements, not only enhances engagement but also positively impacts cognitive processes like decision-making, particularly when compared to abrupt visual changes [13, 29].

Therefore, the framework integrates fade-in and fade-out animations for visual elements that appear in response to user interaction, and different visualization elements must appear. Furthermore, since the user can freely navigate and rotate the camera within the virtual environment, the visual elements are dynamically positioned relative to the current camera orientation. This ensures that new content is smoothly repositioned in front of the user, maintaining immersion and spatial coherence.

4.2.6 Sound Effects on Interactions

Sound effects significantly enhance user experience by increasing user engagement, satisfaction, and the feeling of presence within the application, while also enhancing the application's flow. Specifically, auditory feedback during interaction not only improves task performance but also helps users retain their attention and remain immersed in the experience [52, 9]. Moreover, consistent and context-relevant sounds support faster familiarization, as users begin to anticipate and associate specific sounds with certain actions, reinforcing intuitive use [41]. Therefore, the auditory feedback is essential for designing intuitive and engaging user interfaces.

Based on these insights, we integrated sound effects into three key user interactions: clicking on a node, opening and closing the data panel, and pressing the "Back" button ("R3"/"L3" on VR) to revisit previous visualizations. Each sound was carefully selected to align with the nature of the interaction. Clicking a node triggers a sharp, responsive sound that suggests the appearance of new content. Opening the data panel plays an ascending, swift tone, while closing it uses a descending variation, reinforcing the directional action. The "Back" button on desktop (or "R3"/"L3" on VR) is accompanied by a subtle "whoosh", evoking the sense of moving backward. These auditory cues aim to enhance the user experience by increasing immersion and reinforcing interaction feedback naturally and intuitively.

4.3 Details of the Dataset

4.3.1 Dataset Import

The initial design incorporated an introductory User Interface (UI), where the user is prompted to import a folder containing the dataset in JSON format, along with a separate folder containing images used in the application. Upon clicking the *Upload Folder* button, a file explorer window pops up - enabled via the imported package described in the Features Section 3.4. By pressing *Next*, the user advances to a panel with an input field, where they specify what type of data is being represented.

However, we decided to adopt an alternative approach that better aligns with the company's other applications. Since the proposed framework is part of the company's platform, users are first presented with a configuration page when launching it. On this page, they are prompted to select which dataset they wish to visualize, either by uploading a custom dataset that follows the specific data structure described in Listing 3.1 or by choosing from the predefined options available within the application. This feature accommodates the framework's feature **F2**, as described in Section 3.4, with an indicative overview shown in Figure 4.7.

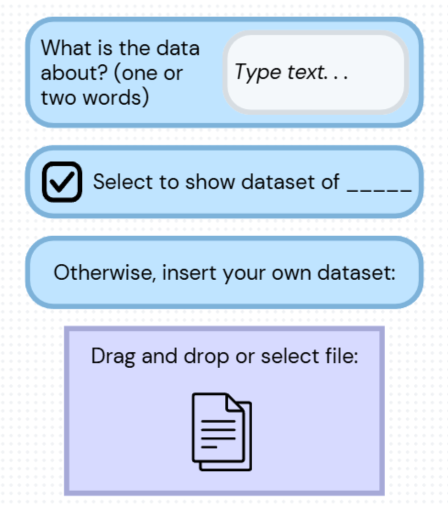


Figure 4.7: Overview of the company's application page after launching the framework, to either select or upload a dataset.

4.3.2 Dataset Generation

Initially, the agreement of collaborating with CoVince Innovations B.V. included with providing access to a dataset to conduct the user study. However, due to the presence of classified information that could not be disclosed to participants outside the organization, I opted to generate a custom dataset for the study. Specifically, part of the initial data was sourced from the DBpedia[4] knowledge base, which contains publicly available information about organizations (referred to here as companies) and their members (referred to as employees). The dataset used in this study is accessible via the following link. The SPARQL query used to retrieve this dataset is shown in Algorithm 2, and was executed using the SPARQL Query Formatting interface[5].

Once the dataset was retrieved in JSON format, it was reformatted to comply with the structure outlined in Listing 3.1. As the DBpedia data did not contain enough explicit connection links between entities or nodes to create evaluation scenarios for the user study, the connections were manually created to align with the use cases presented to participants. While not all entities or nodes within the visualization contain task-relevant information, they were included as placeholders to enhance immersion and foster a sense of presence in the system. Although the framework is capable of supporting up to 50 nodes, due to the last-minute change in data availability, the final dataset used in the study consisted of 20 nodes.

Since the dataset only provided textual data in JSON, corresponding visual assets were sourced to enhance realism. Company logos were obtained from the official websites of the actual companies listed. For employee profile pictures, Unsplash[6] was used, a platform offering high-quality, freely usable images for personal and commercial purposes. These images were assigned to fictional employees to simulate a realistic dataset. As such, all elements of this self-generated dataset are imaginary and were created solely to support individual performance evaluation during the user study, without any reliance on real-world personal data.

Algorithm 2 SPARQL Query: Company and Employee Roles

Require: RDF dataset with DBpedia ontology
Ensure: List of companies, employees, and optional roles

```
PREFIX dbo: <http://dbpedia.org/ontology/>
PREFIX rdfs: <http://www.w3.org/2000/01/rdf-schema#>

SELECT ?company ?companyLabel ?person ?personLabel ?role
WHERE {
    ?company a dbo:Company .
    ?company rdfs:label ?companyLabel .
    ?person dbo:employer ?company .
    ?person rdfs:label ?personLabel .
    OPTIONAL { ?person dbo:position ?role }
    FILTER (lang(?companyLabel) = "en")
    FILTER (lang(?personLabel) = "en")
}
LIMIT 20
```

[4] https://www.dbpedia.org/
[5] https://dbpedia.org/sparql
[6] https://unsplash.com/

Chapter 5

Framework Evaluation

In this chapter, an overview of the user study including the procedure to conduct it, the use cases and the aim of the evaluation is described in Section 5.1. Then, the participants and some demographics results are detailed in Section 5.2, and finally the findings based on the conducted user study, including the separate evaluation of each research question are demonstrated in Section 5.3.

This thesis proposes a framework for effective data visualization, allowing users to either import custom datasets or select from data available within the company's application, while applying techniques and mechanisms aimed at enhancing user experience in addition to a distinctive filtering approach. To assess whether the framework successfully addressed the three research questions related to user experience, task completion time, accuracy, and comprehension of the proposed filtering technique (outlined in Section 1.1), we conducted a user study using custom questionnaires and tasks.

The following sections present the study's findings; however, it is worth noting that the VR group faced certain disadvantages due to a less seamless integration compared to the Desktop group. Participants in the VR condition encountered bugs, and the glowing effect was not implemented in the VR environment. Although the framework supports collaborative exploration as a functionality, this aspect was not assessed in the current study because the dataset did not include scenarios where collaboration would significantly improve the results over individual exploration. As collaboration was considered a secondary objective, its omission does not affect the primary findings, but it will be taken into account for future work.

5.1 User Study

This study seeks to answer the research questions introduced in Section 1: first, how much difference there is in task completion time and accuracy when participants perform use cases, and second, how user experience and data interpretation can be influenced by the visualizations. Both questions compare the use of the VR setting in 3D with the desktop 2D display environment. The final research question is how an interactive and distinctive filtering approach way of visually separating relationship types can improve user experience. The study employs a between-subjects design, dividing participants into two groups: one testing the 2D display setting (Desktop group) and the other in a 3D display (VR group). To effectively address the research questions, a sufficient amount of data and participant feedback is required. Therefore, we aimed to recruit between 20 and 30 participants, all of whom are at least 18 years old, regardless of their prior experience with data visualizations or familiarity with VR systems.

Participants in the desktop group have the option to test the framework remotely on their own setups, ensuring that their computers meet the appropriate requirements for the build version of our framework. The requirement for participants' laptops or computers was that they be capable of running Unity and include a GPU for improved performance. All participants who tested the framework remotely reported using either a gaming laptop or a desktop computer, while those who participated in person were provided with a laptop by the researcher. For the VR group, participants met on the company's premises to use the VR equipment with the experimenter, since the device was provided by the company and had to remain on-site. The specific VR device is the Meta (Oculus) Quest 3.

The user study is evaluated using a standardized user experience questionnaire, the System Usability Scale (SUS) [7], to assess the framework's usability and overall system based on 10 Likert scale statements [38] on a 5-point scale, measuring the system's usability based on user perception, which can be found in Appendix B. Additionally, a custom questionnaire featuring Likert scale questions was provided to the participants, focusing on user experience; specifically, engagement, immersion, and comprehension of the framework and its visualizations. The questions included in the questionnaire are presented in Appendix A.

5.1.1 Procedure

Participants assigned to the Desktop version group were given the option to complete the experiment either remotely or in person at a mutually agreed-upon location with the experimenter, ensuring that it takes place in a controlled environment (e.g. a room at the library). However, participants in the VR version group were required to complete the experiment on-site, as the VR equipment was provided exclusively on the company's premises. For remote participants, the experimenter first confirmed that their computer was capable of running the application smoothly before beginning the experiment. Since all remote participants met the requirements, the experiment was conducted over a Discord call, during which participants shared their screens, allowing the experimenter to observe, take notes, and provide assistance if necessary. An analytical flow for the conduct of the user study is demonstrated in Figure 5.1 for visual purposes.

The experiment begins with each participant provided an online consent form (part of the survey), informing them that they may withdraw from the experiment at any time, and that only non-personal data are collected, along with their rights throughout the experiment. Additionally, they are provided with an information page regarding all details of this master's thesis, including a short description and contact information.

To ensure a consistent level of familiarity with the system across all participants, and to minimize potential biases, the experiment begins with a training phase, after consenting to the aforementioned. During this phase, the experimenter explains some basic knowledge to the participant regarding the purpose of this master's thesis, additional information, such as how a social network graph works, that they need to know before starting and what they will be asked to do. Furthermore, the participants have the opportunity to explore the environment at their own pace, learn the controls, and the main functionalities. This preparatory step ensures that all individuals understand the social network graph structure, the tasks that are handed to them and are comfortable navigating the system before the actual study begins.

After they verbally confirm they feel comfortable enough to begin with the testing, the participants are handed three tasks in total. While no formal assessment was conducted to verify learning, they are informed that they are able to ask for help throughout the experiment. However, they are encouraged to try and find the solution by themselves first, to measure whether they would be able to operate the system if there wasn't someone available for assistance. The answer to each task corresponds to the name of a specific person in the generated dataset, therefore once the participants believe they have identified the correct person, they are asked to enter this name into a designated input field in the online survey.

Upon completion of all tasks, the participants are asked to fill out the SUS questionnaire which regards the system's usability for their user experience, and then a custom questionnaire that tackles aspects of the framework; intuitiveness and immersion, the incorporation of visually distinguishing the relationship types, and whether they would like to use it further either for their own studies or to explore new features.

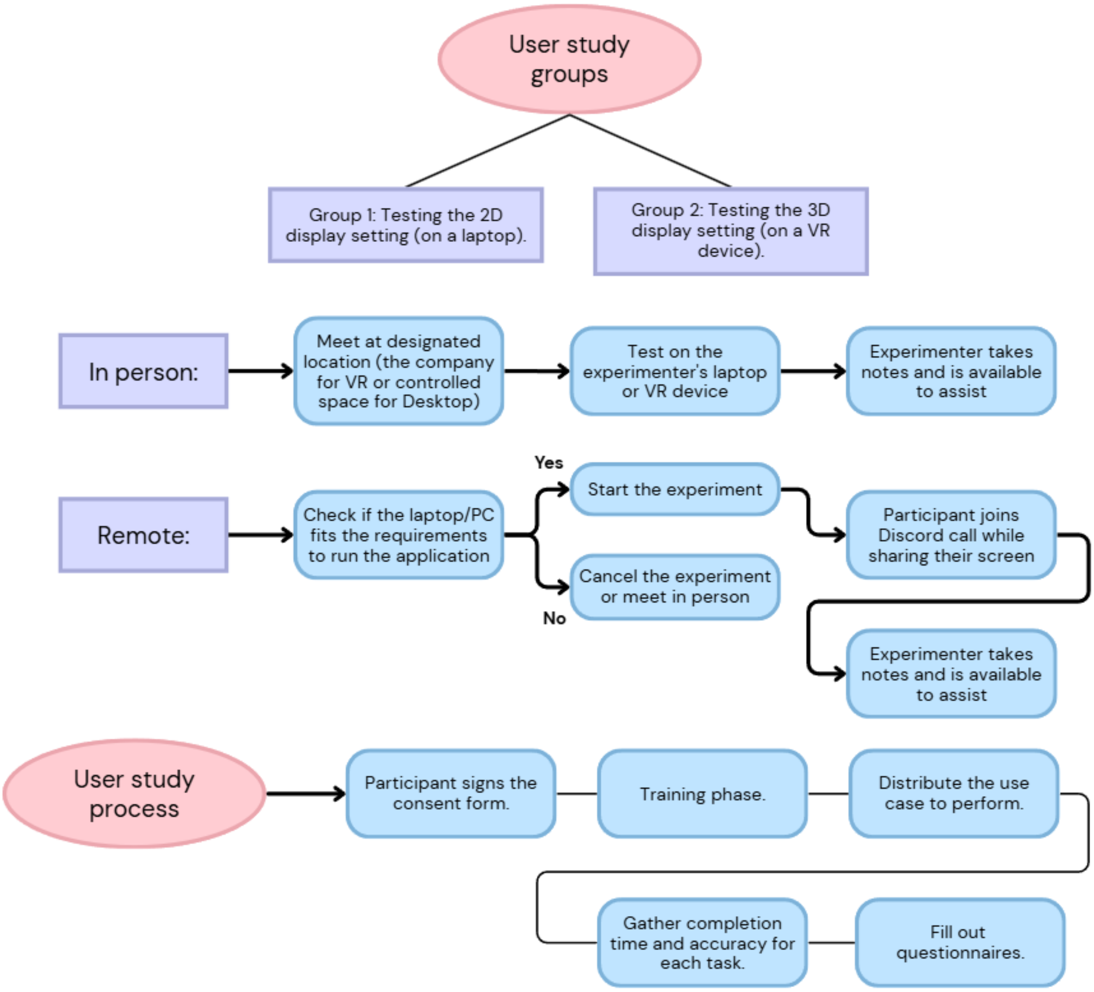


Figure 5.1: A visual representation of the user study group separation and the steps participants must complete.

5.1.2 Use Cases

The framework is evaluated based on the participants' performance and feedback. To facilitate this, we generate a dataset containing information about entities and nodes, with a particular focus on the relationships between them (the explanation of the dataset's creation can be found in Section 4.3.2). A set of use cases is designed, each consisting of multiple objectives that participants must complete. Each participant is assigned a set of three use cases, and all tasks are carefully balanced to ensure an increasing level of difficulty, starting with a simple task and progressing to more advanced ones. We aim to utilize the same three tasks across all participants and groups, thereby maintaining fairness and reliability in the evaluation process.

The use cases follow tasks that focus on relationships, navigation, and interpretation of the data, as well as on the available functionalities of the framework. We aim to test these factors to assess the understanding of the displayed data and whether our framework succeeds on making that effectively. The following tasks are:

1. Task 1 (level-easy): "Find the **Family** member of the **employee** named **Robert Urie**, who works at **Blockbuster**".

2. Task 2 (level-intermediate): "Find the name of the person who is the **Manager of Caroline Thomson**. Both individuals are **employees at Deutz AG**, and the manager must:
   - Speak Arabic.
   - Hold the role of a Public Relations Manager".

3. Task 3 (level-advanced): "There is a company that has connections to **only** the following companies:
   - Deloitte
   - Bloomberg L.P.
   - Deutz AG
   - Deutsche Oper Berlin

   After successfully identifying it, find the **Employee** who is connected to a **Legal Advisor** and an **HR specialist**".

Each task was carefully designed to evaluate a specific aspect of the framework, ensuring consistency in participants' responses to the questionnaires. Task 1 is the introductory easy task and focuses on basic navigation within the visualization, allowing participants to become familiar with the framework. Proceeding with Task 2, the intermediate task, which requires users to combine navigation with analysis of both the information panel and the displayed connections. Finally, Task 3 is represented as the advanced task, where participants were expected to spend more time to complete it, as it examined their ability to operate in an visually crowded environment with multiple overlapping connections and tested whether this complexity influenced their capacity to locate information.

The task design was structured to follow a specific sequence of steps. Tasks 1 and 2 consisted of predefined steps that participants were required to follow, a deliberate choice given that these tasks were relatively simple to intermediate in difficulty and well aligned with the available interactions provided by the framework. Task 3 on the other hand, was designed to offer more flexibility. After an initial set of predefined steps in which participants were asked to observe the visualization, they could choose between two different strategies to reach the correct answer: either exploring the network by hovering over connections or using filtering by relationship type to identify the correct answer. The complete step-by-step flow for each task is illustrated in Figure 5.2.

5.1.3 Evaluation of the Research Questions

In this master's thesis, three research questions were formulated to assess whether the framework can effectively offer a more immersive and interactive approach to visualizing social network graphs, as outlined in Section 1. The first question focuses on task completion time and accuracy,

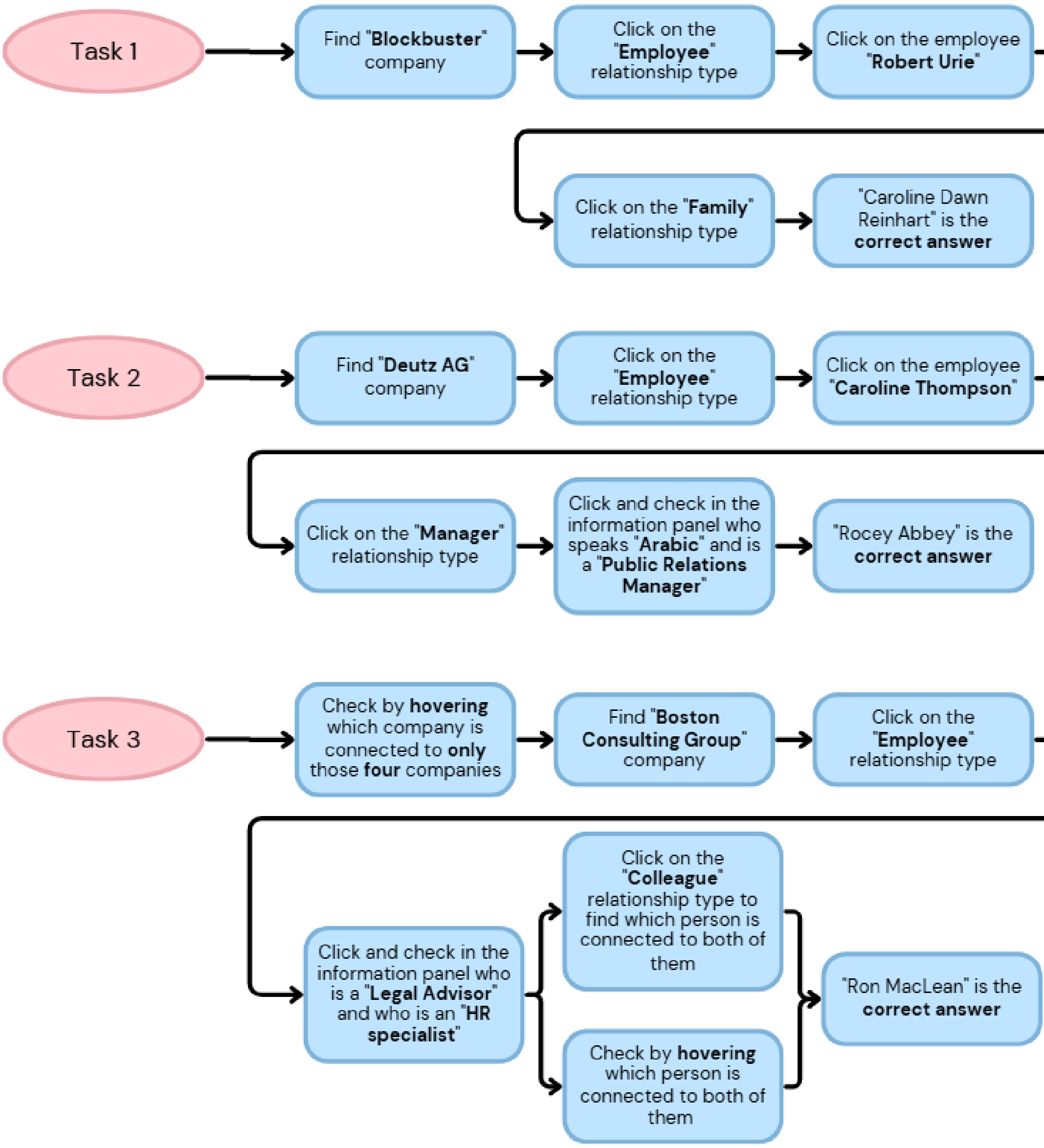


Figure 5.2: The three use cases for the user study. Task 1 and 2 consist of some specific steps, while Task 3 can have two different ways to find the correct answer.

the second on the overall user experience, and the third on the usefulness of the framework's distinctive filtering method for relationship types, specifically in reducing occlusion and enhancing interactivity. The first question involved quantitative analysis as the evaluation approach, while the latter two were addressed through qualitative methods.

Metrics

Aiming to answer the first research question, we gather metrics regarding the completion time for each given task. The time starts from the moment the participant receives the use case assigned to them. The time stops the moment they have a final answer.

Accuracy is measured as a percentage variable. For each objective, participants were allowed to take as much time as needed to complete each task, and they either provide the correct answer or indicate that they are unable to complete the task - thus find the correct answer - and wish to proceed to the next one. If a participant successfully identifies the correct answer, they receive a score of 100% accuracy for that objective. Otherwise, if they provide an incorrect answer or choose to skip the task, the accuracy for that objective is recorded as 0%.

Finally, we tracked the number of help requests made by participants throughout testing. While this was not a pre-specified measure in our research question, we included it as an exploratory indicator of which version required more external assistance, potentially reflecting differences in interface clarity or learnability.

Questionnaires

At the end of the experiment, each participant is handed a questionnaire filled with Likert scale questions, on a scale from 1 (Strongly Disagree) to 5 (Strongly Agree), regarding their user experience and satisfaction. The first part of the questionnaire is a System Usability Scale (SUS) questionnaire, which includes 10 Likert scale questions measuring the system's usability based on their perception throughout the experiment - an overview can be found in the Appendix Chapter 7.

Afterwards, in the second part, the participants are asked to answer a set of additional Likert scale questions (again from 1 to 5) regarding their overall user experience, to express their opinion on that experience, their feeling of engagement during the study, and the comprehension of how to interact with the system and its functionalities. Additionally, it includes some specific questions on how they perceived this approach of filtering data, and whether they would like to use the system again with more functionalities. All questions in this part aim to answer the second and third research questions and are in the form of Likert scales.

5.2 Participants

The user study was conducted with 22 participants in total, including 14 men and 7 women. The participants were equally separated into the two groups; 11 people tested the desktop version and the remaining 11 the VR version. The skill levels of participants across the two groups were not formally controlled, as group assignment was influenced by participant availability to visit the company premises for VR testing. As one of the requirements of the framework is the broad applicability to various fields and age groups, this study aimed to include as many diverse backgrounds as possible. Even though the majority of the participants were between the ages of 18 to 24 and in the field of Computer Science / Software Engineering, a wide variety was successfully gathered for both ages and fields of study or work. This generalization of gathering participants serves to accompany **R1** of the user requirements in Section 3.3.

The Figure 5.3 and Table 5.1 demonstrate the various ages and fields of background, respectively. For clarification, one participant explained that their field of study and work is not limited to a single option, therefore selecting "Other" and listing multiple fields. Based on the provided feedback, most of the participants believed that they could benefit from using this framework in

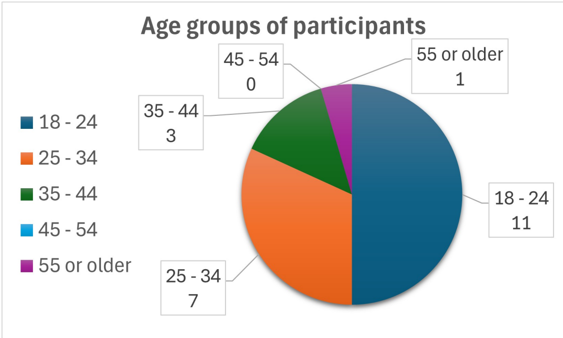


Figure 5.3: The age groups of the participants who took part in the user study.

their work or studies (Mean[1] = 4.27, SD[2] = 0.98), and that the framework effectively provides a more immersive experience -due to its navigation and incorporated techniques- than traditional 2D flat visualizations (Mean = 4.68, SD = 0.56). The low Standard Deviation scores indicate that the responses mostly aligned, as both questions had relatively low variability.

Out of the 22 participants in the user study, only 7 reported prior experience with data visualization frameworks. For the remaining 15 participants, this was their first encounter with such a framework. Despite the unfamiliarity, the results of the questionnaires indicate positive feedback, particularly regarding their willingness to use the framework in their own studies, suggesting that the majority had a favorable first experience.

Field of study or work	Number of participants
Computer Science / Software Engineering	11
Business and Management (e.g., marketing, finance, entrepreneurship)	3
Arts and Design (e.g., visual arts, graphic design, music, performing arts)	2
Social Sciences (e.g., psychology, sociology, political science, economics)	1
Law, Policy, and Government (e.g., legal studies, public administration, diplomacy)	1
Natural Sciences (e.g., Biology, Chemistry, Physics)	1
Other: Software engineering, Natural Sciences, Humanities, Art and Design	1
Other: Customer Support IT	1
Other: Purser and Safety Instructor	1

Table 5.1: The fields of study or professional backgrounds of the participants in the user study.

5.2.1 Desktop Testing Group

In total, 11 participants tested the desktop version of the visualization. All reported being familiar with using the keyboard and mouse to navigate applications (Mean = 4.55, SD = 0.82), and only two participants experienced some discomfort while using the application; one rated their discomfort as 1 out of 5, and the other as 2 out of 5.

[1] Mean Value
[2] Standard Deviation

5.2.2 VR Testing Group

Another 11 participants tested the VR version of the framework, representing a range of familiarity levels with VR devices. Only 3 participants reported being extremely familiar with VR, contributing to a more inclusive evaluation in terms of user experience and device expertise (Mean = 3.27, SD = 1.27). Notably, 3 participants had previously experienced discomfort in other VR applications but reported no such issues with this framework, proving that the design choices effectively minimized motion sickness. One participant did report slight discomfort (rated 1 out of 5), attributing it to brief initial disorientation, which was quickly resolved.

5.3 Results

The framework was rated based on its effectiveness, efficiency, and user satisfaction using the SUS questionnaire [7], and the total SUS score, averaged across all 22 participants, was 86.37. When analyzed by group (11 participants each), the Desktop group achieved an average score of 86.18, while the VR group scored slightly lower at 85.91, indicating a slight preference for the Desktop setting. According to the scale, these scores place the framework in the "best imaginable" category[3], which corresponds to an A+ grade in terms of usability. Such a high score indicates that users found the framework highly intuitive, functional, and pleasant to use. To further evaluate the reliability of the questionnaire results, Cronbach's alpha was calculated for all three scenarios as shown in Appendix C., to showcase the potential consistency in the participants' answers [60]. While measuring for both groups, the questionnaire yielded a value of $\alpha = 0.758$, proving that the internal consistency was *acceptable* based on the corresponding value of Cronbach's alpha[4], suggesting that participants responded consistently across the various items of the SUS scale. Separately, the Desktop group resulted on $\alpha = 0.807$, which is indicated as *good*, however the VR group resulted on $\alpha = 0.635$ which is *questionable*. This indicates that the answers from the VR participants were not very consistent caused by variations in their answers, so the reliability of the results is uncertain.

In general, the combination of a high SUS score, acceptable reliability, along with feedback from participants, proves that the framework successfully delivered an immersive and interactive method of visualizing social network graphs. The incorporated design techniques and usability design choices efficiently contributed to the overall user experience and supported effective exploration and information retrieval. However, when examining the VR group separately, the results revealed that despite achieving a high SUS score, the group demonstrated questionable reliability. This outcome may be attributed to factors such as the flawed integration into the VR environment, the occurring of errors while testing, and the absence of the glowing visual effect, as discussed in Chapter 4.

5.3.1 Metrics

To answer the first research question (RQ1), we evaluated three main performance metrics across the Desktop and VR groups: task accuracy, help requests, and completion time. Help requests emerged as an additional metric during data collection since it was not originally planned, however they proved valuable for understanding differences in task difficulty and user confidence between conditions.

Accuracy

All participants in both the VR and Desktop groups successfully completed all three tasks with 100% accuracy. This indicates that the framework was successful in supporting participants to find the correct answer in the user tasks they had to complete, regardless of the device setting.

[3] https://blog.uxtweak.com/system-usability-scale/
[4] https://numiqo.com/tutorial/cronbachs-alpha

Help Requests

It is important to consider that several participants asked for clarifications during the user testing process. They were informed that they could request assistance if they required clarification on the task or framework, although help with the actual answer was discouraged. As shown in Figure 5.4, each time the participant requested help from the experimenter, it was noted along with the specific question asked for potential further analysis later on. The tasks mentioned in the next paragraphs are described in Section 5.1.2.

During Task 1, participants in the Desktop group asked one question about how relationship types worked (the answer was that it is the framework's filtering mechanism), while participants in the VR group asked none. For Task 2, neither group asked any questions. The higher number of questions emerged during Task 3, which indicates the increased difficulty to complete it. Participants in the Desktop group asked three questions, which focused on whether connections had to be specific to colleagues, or if the target person needed to hold specific roles (HR Specialist or Legal Advisor). All those questions were related to interpreting the task, not understanding the framework itself. In comparison, participants in the VR group asked a total of eight questions, where three of these sought clarification on whether the connections had to be restricted to colleagues. One participant misinterpreted the color of connections (white for the connections to the main entity and yellow for the immediate connections between nodes), which was quickly resolved. Another participant, aged 55 or older, required additional help to view the connections, which was reminded to her that it is the hovering action, or clicking on the person. This participant's limited prior experience with VR likely contributed to the need for more assistance to understand the workflow.

One VR participant, a 25-year-old from a computer science background, was a clear outlier. He took approximately 17 minutes (1045 seconds) to complete Task 3, largely because he was distracted during the initial explanation and later struggled with basic functionality. He asked three questions related to framework use, which were the basic functionalities that were initially explained to him, and due to high levels of frustration, it was decided to restart the third task after explaining some basic functionalities again. Despite being an outlier, there was conflict on whether to take into account his participation, since the reason was his distraction and not the framework itself. It was decided not to exclude him, because even though insights were unable to be derived or good measures from his participation, his data was kept to reflect real-world usability cases where users may not fully pay attention to the framework's tutorials.

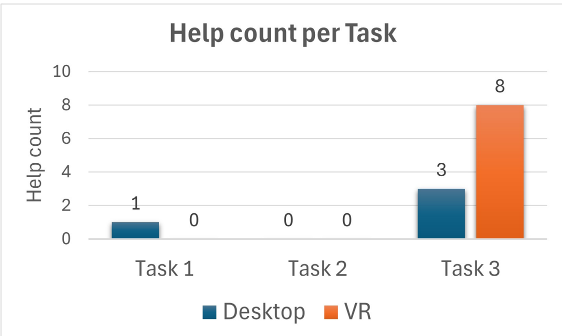


Figure 5.4: The number of times that participants asked for help during the experiment, for each group (desktop and VR).

Completion Time

The completion time was also a factor that we measured to answer the first research question, observing a significant difference between the two groups, specifically on the third task. To evaluate this metric, we utilized box plots as they provide multiple values that offer insights into the data distribution. Starting with the edges of the box, where the lower edge represents the lower quartile (LQ: the point below which 25% of the data falls) and the upper edge representing the upper quartile (UQ: below which 75% falls). Furthermore, the lower and upper lines outside of the box are called outliers, indicating potential extreme values (min outlier: MinO, max outlier: MaxO). The line inside the box marks the median, indicating the midpoint of the data, while the x showcases the mean value of all completion times. This visualization allows for a clear way to compare completion times for each task between groups. The time started automatically when the participants opened the task, and stopped when they had written their final answer into the online survey.

As demonstrated in Figure 5.5, Task 1 in both groups was completed relatively quickly, with low variability. It held the shortest average time in Desktop (Mean = 59.55s)[5] with no significant difference in the outliers (MinO = 35s, MaxO = 106s), as well as in the VR (Mean = 55.27s)[6], suggesting it was the most straightforward task to complete. It is observed that participants in the VR group showed slightly better results than in the Desktop group, by completing the task 1.08 times faster on average, but without indicating a significant difference ($p = 0.632 > 0.05$).

Similarly, Task 2 did not provide significant results between the two groups ($p = 0.540 > 0.05$), although since it took slightly longer to complete, it reflects a moderate increase in complexity. Specifically, participants in the Desktop group demonstrated slightly better results (Mean = 82s)[7] by completing the task 1.10 times faster on average than those of the VR group (Mean = 90.55s)[8], again without high variations.

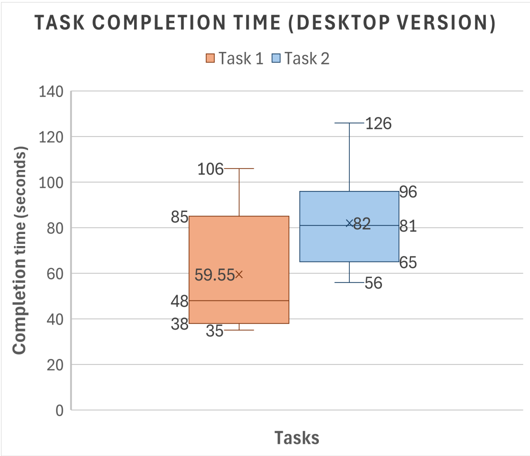
In contrast, as shown in Figure 5.6, Task 3 showcased a significant incline in completion time for both groups ($p = 0.042 < 0.05$). This increase is reasonable due to the design of the tasks, since the third task was the most complicated to complete. A considerable jump in completion time was observed in the VR group (Mean = 447s)[9], accompanied by a wider range of values, indicating that some participants needed significantly more time to complete it. This increase is considerably more than participants of the Desktop group (Mean = 232s)[10] therefore demonstrating **consistent performance** overall for this group, with some noticeable outliers that reflect individual differences in experience. The Desktop group was able to complete the third task 1.93 times faster on average than the VR group, which is a significant difference.

Summary

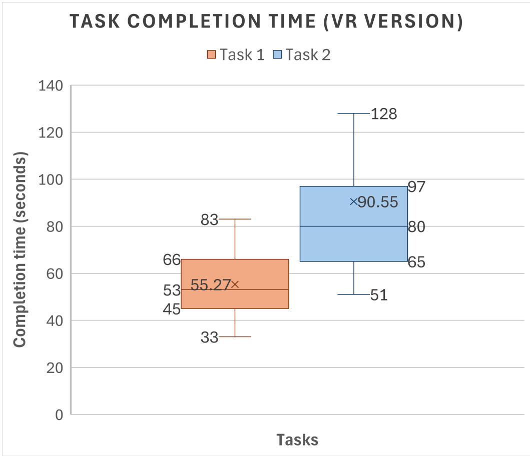
The accuracy for all participants across both groups was 100%, which indicates that on more difficult tasks, the framework can efficiently assist users to find the information they are looking for due to its mechanisms and techniques that are incorporated. From all three tasks, the third one was the most challenging, as most help requests occurred. Based on the description of Task 3, participants easily identified the company, but struggled with finding the right individual, especially when switching between views and interpreting roles. It was observed that the participants in the VR group requested more help from the experimenter, therefore indicating that people in the Desktop group could more easily identify the correct answer, for purposes such as familiarity with the mouse and keyboard (Mean = 4.55, SD = 0.82) than with the Virtual Reality devices (Mean = 3.27, SD = 1.27).

Between the two groups, according to the analysis as shown in Appendix D., Task 1 didn't show a significant difference in completion time ($t = 0.488$ *small difference*, $p = 0.632 > 0.05$, Cohen's $d = 0.208$ *small effect*), where Desktop users were on average 4.273 seconds (MD: Mean Difference) slower than the VR users. Similarly, no significant difference appeared in Task 2 ($t = 0.627$ *small difference*, $p = 0.540 > 0.05$, Cohen's $d = 0.267$ *small effect*), in which VR users were 8.545 seconds (MD) slower than Desktop users. Although the first two tasks didn't show important differences,

[5] Median = 48s, LQ = 38s, UQ = 85s
[6] Median = 53s, LQ = 45s, UQ = 66s, MinO = 33s, MaxO = 83s
[7] Median = 81s, LQ = 65s, UP = 96s, MinO = 56s, MaxO = 126s
[8] Median = 80s, LQ = 65s, UQ = 97s, MinO = 51s, MaxO = 128s
[9] Median = 360s, LQ = 213s, UQ = 568s, MinO = 213s, MaxO = 1045s
[10] Median = 200s, LQ = 135s, UQ = 306s, MinO = 81s, MaxO = 496s

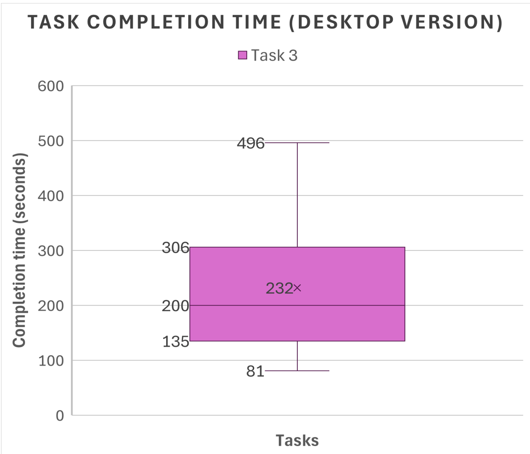


(a) The completion time (in seconds) for Task 1 and Task 2 of the Desktop Group.

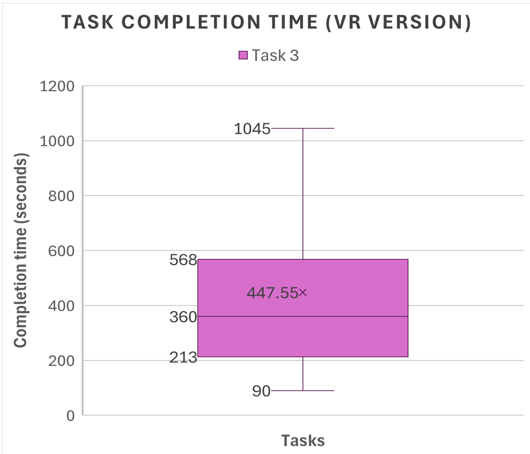


(b) The completion time (in seconds) for Task 1 and Task 2 of the VR Group.

Figure 5.5: Figure (a) demonstrates the mean, the median, the lower quartile, the upper quartile, and the min and max outliers for the task completion time of the Desktop group, and Figure (b) demonstrates those metrics for the VR group. All those metrics are measured in seconds for Task 1 and 2.



(a) The completion time (in seconds) for Task 3 of the Desktop Group.



(b) The completion time (in seconds) for Task 3 of the VR Group.

Figure 5.6: Figure (a) demonstrates the mean, the median, the lower quartile, the upper quartile, and the min and max outliers for the task completion time of the Desktop group, and Figure (b) demonstrates those metrics for the VR group. All those metrics are measured in seconds for Task 3.

the third Task showed a significant difference ($t = 2.249$), which is statistically significant ($p = 0.042 < 0.05$) in the completion times between the two groups, with the VR users taking almost twice as much to complete the task than the Desktop users. The effect size is large (Cohen's $d = 0.959$) and likely reflects the higher difficulty and complexity of navigation in VR for this task. Specifically, VR users were 215.55 seconds (MD) slower than Desktop users.

To answer the first research question (as found in Section 1.1), the **accuracy was consistent across both the VR and Desktop groups**, with all participants achieving 100%, indicating that our social network visualization framework effectively supports users in finding information. However, while Tasks 1 and 2 showed no significant differences in completion time between the two groups, Task 3 revealed that **VR users took significantly longer** to complete the task. This suggests that although immersive VR visualization maintains high accuracy, it can **increase completion time on more complex tasks**, likely due to **less familiarity** with VR navigation compared to standard desktop controls, or even the **lack of the glowing effect** in this version, as described in Section 4.2. Additional reasons for this increase include that some participants physically moved around within the 3D environment, which required **more time and energy**, or due to **high cognitive load** as participants had to get accustomed with the framework but also with using the VR devices, in case they lacked prior experience with them. Finally, as previously mentioned, the integration of the framework into the VR environment was flawed, leading to **errors** that may have contributed to increased task completion times.

5.3.2 User Experience

The participants were divided into two groups, with each group testing the framework in a different setting in order to analyze how it was perceived across conditions. Each group included 11 participants, and the purpose of this analysis was to address the second research question: how interactivity influences user experience and data interpretation in VR compared to desktop displays. Feedback and results were collected through three tasks of increasing difficulty, which allowed us to identify key differences between the two groups. All questions in this custom questionnaire were on a Likert scale, from 1 to 5. The corresponding correlation matrices for each group, the questions they answered from the questionnaire, along with descriptive measures such as mean values, standard deviations, and confidence intervals, are presented in Appendix F. (separate for Desktop and VR group). The results shown in this section are based on the user requirement **R2** and feature **F3** of the framework, as described in Chapter 3.

Framework Effectiveness

User feedback showcased that the framework successfully provided a clear visualization of social network graphs, with interactive actions that were understandable and provided easily distinguishable information. Participants in the Desktop group reported higher satisfaction overall, particularly with the framework's ability to visualize data and identify entities and relationships (Q1: Mean = 4.64, SD = 0.67), to clearly present the interactions to enable functionalities (Q2: Mean = 5.00), and to follow information even in cluttered parts of the framework (Q9: Mean = 4.64, SD = 0.50). The only lower rating in this group concerned the ability to observe the visualization from different viewpoints to understand better the data structure (Q5: Mean = 4.55, SD = 0.52), which was slightly higher in the VR group (Q5: Mean = 4.64, SD = 0.67).

Correlation analysis for the Desktop group showed that perceiving the framework as effective in visualizing entities and relationships was positively associated with engagement (Q1 with Q3: r = 0.47), intuitive navigation (Q1 with Q4: r = 0.52), and the ability to follow connections in cluttered areas (Q1 with Q9: r = 0.45). Furthermore, the ability to navigate cluttered areas was positively correlated with observing the network from multiple viewpoints (Q5 with Q9: r = 0.45). These patterns suggest that Desktop users generally experienced a coherent and positive use of the framework, where effectiveness, functionality, and navigation reinforced one another.

In the VR setting, participants reported noticeably lower ratings for the framework's ability to clearly indicate interactive functionalities (Q2: Mean = 4.27, SD = 0.65). This was likely influenced by the interaction techniques used to follow the overall style in the company's application, where design choices, such as requiring users to click on small buttons located on top of nodes to access the information panel, created frustration, particularly when distance made these interactions less convenient. Ratings for other measures of effectiveness were also slightly lower than in the Desktop condition, including the ability to identify entities and relationships (Q1: Mean = 4.45, SD = 0.52) and to follow edges in cluttered parts of the network (Q9: Mean = 4.36, SD = 0.67).

Despite these lower averages, correlation analysis in the VR group showed that effective depiction of entities and relationships was strongly linked with engagement and immersion (Q1 with Q3: r = 0.56), understanding the structure of the network (Q1 with Q6: r = 0.47), and following information in cluttered areas (Q1 with Q9: r = 0.44). However, unlike in the Desktop setting, some negative relationships were observed, such as the effective visualization of data that was negatively associated with viewpoint navigation (Q1 with Q5: r = –0.34) and with following information in cluttered areas (Q5 with Q9: r = –0.34). This suggests that the freedom to move through the visualization in VR did not always enhance clarity or effectiveness, and in some cases, frequent viewpoint changes may have made entities or relationships harder to follow; therefore, viewpoint navigation was also positively associated with reduced clarity in cluttered areas (Q5 with Q8: r = 0.43). In contrast, Desktop navigation was more constrained and predictable, which may have helped reinforce comprehension instead of working against it.

Engagement and Immersion

Although VR devices are often associated with delivering stronger immersion since users' entire visual field is occupied by the headset, it was initially expected that participants in the VR group would report higher engagement and presence in the framework. However, the results revealed that the Desktop group actually reported slightly greater immersion while performing the tasks (Q3: Mean = 4.82, SD = 0.40, Q4: Mean = 4.45, SD = 0.52) compared to the VR group (Q3: Mean = 4.73, SD = 0.47, Q4: Mean = 4.36, SD = 0.67). Both groups still showed consistently high engagement and found the navigation natural and intuitive, yet the Desktop group's advantage, although small, is worth noting. This difference may be attributed to technical limitations in the VR setting due to integration issues, where potential bugs disrupted the experience and influenced participants' perceptions during testing. Another possible explanation is the higher level of familiarity that most users have with desktop environments and navigation in them.

Correlation analysis in the VR setting showed that engagement was strongly positively related to participants' ability to follow relationships in cluttered areas of the network (Q3 with Q9: r = 0.66). In addition, engagement was strongly negatively correlated with feelings of overwhelm and reduced clarity (Q3 with Q7: r = -0.51, Q3 with Q8: r = -0.45, Q4 with Q8: r = -0.65). This suggests that participants who felt more immersed were also more capable of following connections in the graph without experiencing cognitive overload. However, while navigation was generally described as natural and intuitive, there was a moderate negative correlation between navigation and having a clearer understanding of the overall data structure from different perspectives (Q4 with Q5: r = -0.34). This indicates that although users could move through the network smoothly, this did not necessarily help them gain a better grasp of the data structure.

In the Desktop setting, immersion in the framework was negatively correlated with feelings of overwhelm, indicating that participants generally did not perceive the network's density as a negative influence (Q3 with Q7: r = -0.41). However, immersion showed a positive correlation with reduced clarity in cluttered areas (Q3 with Q8: r = 0.46), suggesting that participants who felt more immersed also experienced that high-density regions made it harder to maintain clarity. Overall, these findings suggest that VR interactivity enhances engagement and helps reduce cognitive overload during complex graph exploration, but Desktop displays currently provide a more familiar and slightly more effective environment for clarity and interpretation of data. Thus, VR shows promise for immersive engagement but may require further refinement to match or surpass the interpretability and satisfaction provided by standard 2D displays.

User Satisfaction and Data Interpretation

The framework proved effective in helping participants from both groups understand the structure of the social network, as indicated by the results, with the users in the Desktop setting demonstrating a slightly higher level of understanding (Q6: Mean = 4.82, SD = 0.40) than the users of the VR setting (Q6: Mean = 4.55, SD = 0.52). Feedback also revealed that participants generally did not feel overwhelmed by cluttered areas of information within the visualization, with users in the Desktop group reporting higher levels of overwhelm (Q7: Mean = 2.18, SD = 0.98) compared to the VR group (Q7: Mean = 1.45, SD = 0.69). In addition, reports indicate that users did not feel that cluttered areas reduced their clarity and ability to follow the visualization. This effect was less pronounced in the Desktop setting (Q8: Mean = 1.82, SD = 0.87) than in VR (Q8: Mean = 2.73, SD = 1.35). Notably, the higher variance in the VR group suggests that while some participants experienced minimal impact on clarity, others found it considerably more challenging.

In the desktop setting, understanding the network structure was positively associated with feelings of being overwhelmed by the density of information (Q6 with Q7: r = 0.60), suggesting that even when participants found the framework helpful, they still experienced cognitive load due to visual complexity. In contrast, participants in the VR group showed the opposite pattern, with understanding the structure linked to feeling less overwhelmed (Q6 with Q7: r = –0.48). Furthermore, in VR, participants who reported that the framework helped them understand the structure were also more likely to follow edges even in cluttered areas (Q6 with Q9: r = 0.52), while feelings of overwhelm were negatively associated with this ability (Q7 with Q9: r = –0.21). These results indicate that in VR, comprehension and clarity tended to reinforce each other, whereas in the desktop environment, understanding could coexist with, but not reduce, feelings of overload.

Overall, the findings suggest that while both desktop and VR settings effectively supported participants' understanding of social network structures, they differed in how this understanding related to user experience under visual complexity and cluttered environments, within the limits of a small dataset. Desktop users demonstrated slightly higher comprehension but also reported greater feelings of overwhelm and less clarity in cluttered areas. In contrast, VR users, despite slightly lower average ratings of understanding, showed a pattern where comprehension and clarity reinforced each other; those who felt they understood the structure also reported less overwhelm and better ability to follow nodes or relationships in the visualization. This means that VR interactivity might ease the effects of clutter for certain users, whereas in the desktop setting, understanding does not necessarily reduce cognitive load.

Summary

The results show that both Desktop and VR settings provided effective means for exploring and interpreting social network graphs, but interactivity shaped user experience differently across the two environments. Participants in the Desktop group reported slightly **higher satisfaction with the framework** overall, especially in terms of **clarity, presentation of interaction elements, and effectiveness in identifying entities and relationships in cluttered areas**. Their experience was generally consistent, with engagement, navigation, and interpretability reinforcing one another, though **cluttered areas** often led to increased feelings of **overwhelm and high cognitive load**.

In contrast, VR participants rated effectiveness and clarity slightly lower overall, particularly due to interaction design choices that occasionally caused frustration. However, the correlations revealed that interactivity in VR created **stronger links between engagement, comprehension, and clarity**. Those who felt immersed also tended to report less overwhelm and a greater ability to follow connections in cluttered areas, suggesting that VR interactivity helped **reduce cognitive load** for some users. At the same time, the freedom of viewpoint navigation in VR did **not always improve interpretability**, and in some cases, it **undermined clarity in complex regions of the graph**.

To conclude and answer the second research question (see Section 1.1), the results indicate that VR interactivity can **boost engagement and link users' sense of immersion with their ability to understand and interpret the data**. However, these benefits were not experienced equally by all participants, as **clutter and navigation freedom sometimes reduced clarity**. By contrast, the Desktop environment provided a more **stable and consistent experience, offering slightly higher satisfaction with accuracy and ease of use**. This highlights that the Desktop setting ensures reliability, while **VR proposes improvement** for deeper engagement and potentially stronger comprehension if interaction design is refined.

5.3.3 Visual Separation of Relationship Types

A crucial part of this framework was the distinctive way of filtering different relationship types in social network graph visualizations. The users had the opportunity to test an distinctive way of separating information, aiming to avoid occlusion and prevent users from being overwhelmed by the clutter of nodes or displayed data. To evaluate how they experienced this feature, a custom questionnaire was created including question in Likert scale (from 1 to 5) regarding how they perceived it. An overview of the mean/standard deviation values, the correlation matrix, the confidence intervals, and the questions themselves is included in Appendix H.

The findings from this questionnaire provided valuable insights into participants' perceptions of the technique and helped address the third research question. Since the technique was used by all participants across both groups, the analysis was conducted collectively rather than comparing responses between groups. The feedback enabled the creation of a correlation matrix, illustrating the strength of relationships between questions, with values of the correlation coefficient ranging from -1 (indicating a very strong negative correlation) to 1 (indicating a very strong positive correlation). In addition, measures such as the mean, standard deviation, and confidence intervals were calculated to capture the overall level of agreement among participants for each question.

Correlation Matrix

Q1 and Q4 show a strong positive correlation (r = 0.69), indicating that participants who found the visual separation of relationship types helpful for completing tasks also felt it helped them focus on specific relationships without distraction. In addition, Q4 shows a strong positive correlation with (r = 0.57) and Q2 (r = 0.52), suggesting that the focus on specific relationships has made users confident in navigating the graph without confusion due to this technique and the incorporated visual cues. Those questions are moderately correlated to each other, as is Q1 with Q2 (r = 0.41), Q1 with Q6 (r = 0.46), and Q2 with Q6 (r = 0.33).

Some questions are negatively correlated, indicating a negative relationship between them. Most of these are exhibited in Q5, which is the only negative statement of this custom questionnaire. The most notable observation is with Q2 (r = -0.44), Q4 (r = -0.50) and Q6 (r = -0.52), suggesting that participants who agreed that it helped them focus, navigate clearly, or distinguish relationship types based on visual cues, were less likely to feel that the visual distinction was frustrating.

The rest of the correlations are weakly connected questions, which means that there is minimal relationship between these perception measures. Overall, positive relationships among Q1, Q2, Q4, and Q6 suggest a consistent theme: visual distinctions in the graph improved task clarity, focus, and navigation for most users. In contrast, Q5 acts as a counterpoint, capturing users who perceived these distinctions negatively.

Confidence Intervals

To test whether this custom questionnaire could provide insights into the consistency and reliability of user responses, we calculated the confidence intervals for each question. Q6 has the highest mean (4.82) with a tight confidence interval (CI) (4.64 to 4.99), suggesting strong and consistent agreement that visual separation helped users navigate without confusion. Similarly, Q1 has the second-highest mean (4.68), however even though there is a bigger variation of the CI (4.36 - 5.00), which indicates that it enhanced their ability to complete the tasks accurately. As Q5 is the negatively phrased question with a low mean of 1.45 and a narrow CI (1.13 to 1.78), it shows a strong consensus that the visual distinction was not frustrating but, on the contrary, supports the positive feedback in other responses.

For Questions 3 and 7, the confidence intervals were noticeably wider compared to the other items (Q3: 3.93 - 4.68, Q7: 3.36 - 4.43). This wider range suggests a higher degree of variability in participants' responses, indicating less agreement. While the mean values still fall within the positive side of the scale, the spread implies that there was a contradiction between participants' responses, leading to greater uncertainty about the true average perception. Based on the correlation matrix, this can be caused due to Q3 and Q7 showing weak or near-zero correlations with several other questions (e.g., r = -0.03 between Q4 and Q7, r = 0.17 between Q3 and Q5), suggesting that the factors measured by those questions were not strongly aligned with the perceptions captured in the other items. This reinforces the idea that these questions might fall into more individual or context-specific experiences, which could explain the greater spread in responses.

The remaining questions have means between 4.18 and 4.68, with reasonably tight intervals, reflecting generally positive and moderately consistent user experiences. These confidence intervals help confirm that the central tendencies seen in the means are statistically reliable and not due to random variation. It is important to note that Q3 and Q7 are questions subject to more attention in further research, since there may not have been a sufficient number of participants to explore further those findings.

Summary

Based on the feedback, most participants believed that incorporating this filtering technique enhanced their ability to complete tasks (Q1: Mean = 4.68, SD = 0.72), it effectively limited their focus not to be distracted by unrelated information (Q4: Mean = 4.36, SD = 0.73) and helped them to navigate the graph (Q6: Mean = 4.82, SD = 0.39). Additionally, users found that this distinction was not unnecessary and frustrating, with an acceptable deviation in their answers, with most participants stating that either they found it slightly or not at all frustrating (Q5: Mean = 1.45, SD = 0.74). In general, there is a pattern of **high agreement across all questions** regarding this distinctive technique, suggesting that all participants found it to be **helpful as a filtering mechanism**. This is observed through the mean values of all responses that are positive towards this approach, all being higher than 4 in agreement (out of 5); somewhat to strongly agree.

These results provide clear evidence that the visual separation of relationship types **positively impacts user experience by improving information clarity and managing occlusion**. The consistently high agreement scores, combined with the strong correlations between questions related to task completion, focus, and navigation, indicate that the technique successfully **reduced visual clutter and allowed users to concentrate on relevant connections**. The **low level of reported frustration** further supports its effectiveness. Taken together, these findings confirm that the third research question (described in Section 1.1) is answered positively; **it enhances clarity and usability** in social network graph visualizations for the majority of participants, providing a **more immersive method** of filtering relationship types. However, this result is based on a small dataset, and further evaluation would be required to confirm its scalability to larger networks.

Chapter 6

Discussion

In this chapter, we derive key findings by contrasting the results from Chapter 5 with insights from existing studies discussed in Chapter 2. The aim is to analyze the collected evidence to address the research questions (Section 1.1) and situate our conclusions within the broader context of existing work on data visualization systems.

Section 6.1 presents an analysis of the framework's functionalities, discussing their relevance to prior studies and summarizing the findings from Chapter 5 in relation to the three research questions addressed in this thesis. Following that, Section 6.2 then outlines in detail how this work contributes to filling the research gaps identified in previous studies. Moreover, Section 6.3 highlights the limitations of the study and suggests possible solutions to address them. Finally, Section 6.4 concludes with directions for future work, including proposed features and adjustments to the user study aimed at further enhancing and improving the framework.

6.1 Summary of Findings

In this master's thesis, we propose an immersive and interactive data visualization framework that incorporates techniques to enhance user experience and immersion, focusing on social network graphs. The functionalities and features that are integrated into this framework are inspired by related studies and enhancements or gaps that were detected in them. The features and the user requirements that shape this framework can be found in Section 3.3 and 3.4 accordingly.

A key study that influenced the development of this framework focused on guiding principles for creating systems that foster **immersion** and user engagement (see Section 2.4). Building on these principles and supported by user feedback from the conducted user study, the proposed framework was shown to effectively provide an immersive experience and the sense of **presence** within the virtual environment, on both conditions; Desktop and VR. Beyond providing basic functionalities, it emphasizes the overall user experience, achieved through its techniques and the proposed methodology for visually filtering relationship types. In addition, particular attention was given to the **emotion and affect** of the participants during interaction with the framework. Results indicated that participants generally enjoyed the experience, expressed curiosity to further explore the framework, and reported little to no frustration apart from minor technical issues occasionally occurring in the VR setting. The framework also incorporates several **interface tasks** designed to support a clearer understanding of the dataset, and an enhanced and user-friendly experience.

This study focuses on answering three research questions, as outlined in Section 1.1, each one tackling a different aspect of the user study. The first two questions focus on the difference between Desktop (2.5D visualization) and VR (3D visualization) users, and the third one focuses on introducing a distinctive filtering mechanism and how users perceive it. Starting with the first one, we focus on the differences between Desktop and VR users when using the framework, specifically how the environment can influence task completion time and accuracy on some given tasks. The results showed that all participants across both groups were able to find the correct answer to all tasks accurately, and the only noticeable difference in the completion time was on the third task; the most complex one. Participants of the VR group took significantly longer to find the answer, which indicates that the Desktop environment can benefit users due to familiarity and limited movement to find the answer, as it causes less cognitive load. Various factors may have affected the completion time on VR, as users moved physically around which takes more time and energy, thus causing cognitive load, in addition to the technical errors that were caused due to integration. Therefore, the results suggest that, for small social network visualizations, desktop interaction provides greater efficiency in task completion compared to the VR environment, particularly for more complex tasks.

In response to the second research question, the results show that interactivity in 3D visualization through VR and desktop displays impacts user experience and data interpretation in distinct ways. While both environments achieved high satisfaction and engagement, the Desktop setting provided a more stable and consistent experience, with clearer comprehension of the overall data structure and stronger alignment between navigation, functionality, and effectiveness, however with potential increased feelings of overwhelm in areas with more occlusion. In contrast, the VR setting offered reduced overwhelm and lower cognitive load, enabling participants to more easily follow connections and edges within cluttered areas, though frequent viewpoint changes did not necessarily enhance clarity or understanding of the network data structure. Together, these findings validate the expected comparison between Desktop and VR, where Desktop displays support higher clarity and structural understanding with a more stable experience, whereas VR facilitates smoother exploration and reduced cognitive strain when navigating more complex parts of the visualization (i.e. occlusion). Further evidence of usability and user satisfaction was provided by the SUS score of 86.37 (overall both groups), which corresponds to the "best imaginable" usability range, suggesting that the framework was perceived as intuitive, immersive, and easy to use. However, our evaluation focused on a small network dataset aiming to assess usability and interaction effectiveness, and future work should examine the user experience on large-scale networks.

To conclude with the third question, we focus on how this distinctive approach of filtering relationship types can influence user experience, on aspects of information clarity and occlusion management. The findings indicate that the visual separation of relationship types had a positive impact on user experience, particularly in terms of improving information clarity and managing occlusion. Participant feedback highlighted that this method provided a more visual and interactive way of filtering nodes, effectively reducing clutter and minimizing the display of irrelevant information. Users reported that by focusing only on the according relationship types, the visualization became clearer and easier to interpret, with occlusion being significantly reduced, and moreover, frustration levels were reported as very low, further demonstrating the effectiveness of this approach. Therefore, the results suggest that the proposed filtering method enhances usability and clarity, while offering an immersive and intuitive way of filtering information within the visualization.

6.2 Filling the Research Gap

Even though this framework does not introduce a novel node layout algorithm, it applies the Fibonacci lattice algorithm to evenly distribute nodes in the visualization [28]. By employing this approach, it positions nodes on an imaginary sphere, maintaining consistent spacing and effectively minimizing visual clutter and node occlusion. While other frameworks have relied on algorithms such as Force Atlas [4] or Spring Embedder [31] to ensure reduction of clutter, the use of the Fibonacci lattice for social network graph visualizations is a distinctive choice that has not been implemented by other frameworks.

A review of related work revealed that most existing approaches relied on conventional filtering panels to manage displayed information, instead of immersive techniques that align with the visualization environment, which is a limitation that this master's study addresses. VRige [23] incorporated a filtering cube, which while is functional and playful, essentially replicated a standard filtering approach with added gamification. Similarly, IATK [16], provided a GUI-based filtering panel with sliders within Unity's interface, which represents another instance of a traditional panel. These approaches may reduce immersion, as they require users to interact with elements that feel external to the visualized environment. To address this challenge, the proposed framework introduces an interactive method of visually separating relationship types (as shown in Chapter 4), especially as network graphs are structured around them. Evaluation results demonstrated that this technique was effective in helping users distinguish relevant from irrelevant information without frustration, while maintaining immersion inside the virtual environment, and significantly improved the overall visualization experience with cognitive clarity, proving its valuable addition to the framework.

While other frameworks offer a wide range of functionalities, the proposed framework integrates multiple techniques, insights and features inspired from these frameworks, aiming to deliver an enhanced user experience into a single solution. Specifically, a key advantage of this framework is its accessibility from different devices, allowing users of varying levels of experience to use it with ease. Unlike most prior studies, which typically support either 2D displays (desktop) or 3D displays (VR), our approach accommodates both. For instance, Flow[1], Noda[2], and ImAxes [17] focus on supporting explicitly 3D (the VR version), and further details on the supported setup of these and other frameworks are provided in Table 2.1. Although these frameworks demonstrate innovative user experiences, their limitation to specific display modes reduces their broader applicability.

6.3 Limitations

This framework is designed to provide an immersive and user-friendly experience for social network graph visualizations by addressing the User Requirements and Features outlined in Sections 3.3 and 3.4 accordingly. However, it was not possible to evaluate **R3** and **F4**; the collaborative exploration and co-existence of multiple users in the same virtual space. The generated dataset used in this user study did not include scenarios where collaboration would be more beneficial than individual exploration and provide clear advantages, meaning that testing these features with multiple participants would likely not provide significantly different results. Since the proposed research questions focus exclusively on the individual experience of each participant with the framework and its functionalities, the absence of testing for this particular setting does not affect the validity of the present study.

The original aim was to recruit between 20 and 30 participants to evaluate the framework, divided evenly between the Desktop and VR groups in line with the between-subjects design of the study. Ultimately, 22 participants were recruited (11 in each group), which falls within the intended range and was sufficient to conduct the present study. However, a larger sample size would have provided more robust data for analysis, reducing the influence of individual differences and outliers on the results. With only 11 participants per group, there are limitations to the participants' experience of the framework, meaning that subtle effects of interactivity on user satisfaction, engagement, or data interpretation may not have been fully captured. Moreover, a larger and more diverse participant pool would have captured a wider range of experiences, backgrounds, and ages. Since one of the framework's goals is to be easily accessible to different types of users, such diversity would have strengthened external validity and allowed the findings to be generalized with greater confidence.

A crucial limitation of this study was the technical issues that arose during the integration of the framework into the VR environment. The framework had originally been developed and thoroughly tested as a desktop application in Unity. However, since the VR functionalities were part of the company's application and access to the full implementation was not granted, integration into VR was only finalized a few days before participant testing began on the VR group. As a result, the glowing effect was not incorporated in the VR setting, and some bugs appeared during the user testing sessions, which may have affected task completion time and perceived usability, though not

[1] https://flowimmersive.com/
[2] https://store.steampowered.com/app/578060/Noda/

accuracy. Despite these issues, all participants were still able to successfully complete the three tasks and find the correct solutions.

Furthermore, as observed in Chapter 5, all participants across both groups successfully completed all three tasks with 100% accuracy. While this outcome confirms that the tasks were clear to the participants and the framework was usable, it limits our ability to compare performance differences between the Desktop and VR groups. This suggests that the tasks, despite being designed with increasing difficulty, may have been too simple to reveal potential differences in performance or error rates between conditions. Consequently, task difficulty itself represents a limitation of this user study, however, given the scope and constraints of the current study, designing such tasks was not feasible.

Additionally, the scope of this thesis limited the framework's ability to visualize a dataset to 50 nodes. While this user study successfully assessed user interactions, usability, and core functionalities within the framework, these findings are constrained to small-scale networks and cannot be generalized to large-scale visualizations. In existing frameworks (as described in Chapter 2), dense network visualizations typically involve thousands of nodes, where challenges such as severe density, rendering performance issues, and increased cognitive load become critical factors. Since these density-related issues do not manifest at the scale examined in this study, the validity of the user study results is limited to small-sized networks, and the framework's effectiveness under conditions of visual density remains empirically unvalidated.

Finally, the last-minute change that was originally set for the company to supply the dataset, introduced several placeholder nodes within the visualization that lacked associated information and therefore appeared empty. As the primary objective of the study was to assess the overall usability of the framework under conditions of high node clutter and potential occlusion, the presence of these placeholders may have influenced participants' perceived immersion and engagement during the training phase. Additional clarification was required to explain that the absence of information was due to external factors unrelated to the framework itself, and participants occasionally had to navigate back and forth as a result. Although this constitutes a minor limitation, it remains important to acknowledge its potential impact on the user experience.

6.4 Future Work

6.4.1 Study

Participants in the VR group differed in their prior experience with the technology, with several having little familiarity with VR applications. This may have contributed to some of the lower user experience ratings compared to the Desktop group, where most participants were already highly comfortable with desktop environments, and as a result, the disparity in prior familiarity could have influenced the outcomes. In future work, VR participants could be given more time to familiarize themselves with the devices before beginning the study tasks. This would help ensure that both groups have a comparable level of experience with their respective platforms, reducing bias and allowing for a more balanced evaluation of user experience.

The design of this user study focuses on participants' first interaction with the framework and evaluating three timed tasks, and this relatively short exposure time may also have influenced the study's results. Although participants received a training session before starting, for as long as they liked to feel familiar with the system, the entire process lasted only about 30 minutes, which may not have been sufficient for some to fully adapt to the framework. Moreover, participants only completed three tasks of increasing difficulty, which limits insights into long-term use or how performance might improve with extended practice. Future iterations of the study will incorporate additional tasks that address diverse and combined aspects of the framework to provide a more comprehensive evaluation.

Moreover, the task design could be refined to better differentiate participant performance across conditions. Although the current tasks were designed with increasing difficulty and allowed participants to explore different aspects of the framework, the consistently high accuracy rates (100% accuracy) observed across both groups (Desktop and VR) limited meaningful comparisons. In future work, a beneficial improvement would be to introduce more challenging and complex tasks that encourage participants to engage in deeper problem-solving, such as working with denser graphs, performing multi-step filtering operations, or completing time-constrained objectives. These adjustments would likely produce a broader range of accuracy and completion time results, providing meaningful insights into performance differences between the two groups and potentially revealing additional usability considerations that in this state were not observed.

6.4.2 Framework

The node distribution algorithm (i.e. Fibonacci Sphere) was implemented with a predefined radius centered on the currently visible main entity. For the scale of the generated dataset used in this study, the algorithm performed effectively, preventing both excessive spacing between nodes and overly cluttered regions. However, this outcome does not guarantee consistent performance with larger datasets containing a greater number of nodes, where increased occlusion may occur. As part of future work, the algorithm will be refined to dynamically adapt to the number of nodes being displayed, ensuring a smoother and more evenly distributed layout around the main entity. Additionally, the framework currently supports up to 50 nodes, a limitation set by the scope of this master's thesis, and future research will focus on extending its capabilities to handle larger datasets.

At the end of the questionnaire, participants were asked to share their opinions and suggest features to improve the framework. Many suggestions focused on navigation improvements. For example, participants recommended using the mouse wheel to zoom instead of the W and S keys, drag-based navigation similar to smartphones for desktop use, and faster movement via the "Shift" key (a common gaming technique). An approach that was incorporated into various frameworks, such as Graph2VR [39] and NodeTrix [32], was the ability to manipulate the graph itself rather than the camera. This is a functionality that could benefit users that may feel dizziness or fatigue while moving around in the visualization and would prefer to manipulate the data graph instead of their position in the virtual environment. These features could be incorporated into a customizable menu at the startup of the framework or in the pause menu, allowing users to choose their preferred controls.

Other suggestions aimed to enhance user experience and information tracking by incorporating additional features. One participant proposed adding transparency to unfocused nodes when hovering, making connections easier to follow without excessive navigation to view the visualization from different viewpoints. Some suggested applying filtering on nodes by traits of the initial visualization nodes, such as the company type (gaming, software, consulting, etc.), in addition to the visual separation of relationship types. Additionally, there were recommendations for the glowing effect or the elements themselves to remain active, like connecting lines or nodes, even when not hovered, to make it easier to follow the connectivity. Furthermore, since the framework relies on color distinctions, a future improvement would be to use color-blind–friendly palettes or distinct shapes.

A particularly useful suggestion was to add a hierarchy tree–style history, which would show the previous visualization steps the user had encountered. In the Desktop setting, this would appear on the side of the screen, while in the VR this feature could be enabled with a designated controller button. This would allow users to see the steps they have taken without repeatedly using the back button, and this would provide the ability to jump directly to any previous stage by clicking on it. Such a feature would improve usability by providing clear context of their progress and reducing frustration when navigating back through earlier visualizations. Finally, future work will focus on improving the VR setup, as some participants reported encountering bugs during testing, intending to make it more stable.

Finally, as outlined in Section 2.4, one of the key interface requirements is to provide functionalities that enhance the user experience and support a deeper understanding of the dataset's visual representations. Among these tasks, the only feature not yet implemented is the **extract** function, which would allow users to export or save the currently visualized data. This functionality is planned for future development and will be integrated into a pause or customizable menu, enabling users to adjust visualization settings, modify controls, or download a screenshot of the visualization's current state.

Chapter 7

Conclusions

This master's thesis demonstrates how different displays, Desktop or VR displays, of experiencing a data visualization framework of social network graphs can impact various aspects, from metrics to user experience. In this proposed framework, numerous techniques and mechanisms were incorporated based on previous studies, research gaps, and insights from other literature studies to provide an immersive and interactive experience. In addition, a distinctive approach of filtering was developed and tested in this framework, which separated different relationship types in a more visual and interactive way.

In the user study, participants were required to complete three tasks of increasing complexity in order to assess the extent to which the integrated techniques facilitated an effective and coherent experience of navigating within a social network visualization environment. The evaluation criteria focused on task completion time and accuracy, user experience and data interpretation, as well as participants' perceptions of the introduced filtering technique with respect to information clarity and the management of visual occlusion. A total of twenty-two participants were recruited, distributed evenly across two experimental conditions, Desktop and VR, resulting in eleven individuals per group. The sample included participants of varied professional and educational backgrounds, in addition to a range of age groups, thereby ensuring a broad perspective on the framework's usability, independent of prior familiarity with VR technologies or data visualization frameworks. The findings further indicate that participants not only engaged effectively with the system but also expressed considerable interest in the incorporation of additional functionalities, highlighting the potential applicability and value of the framework within their own academic or professional fields.

The results demonstrated that participants in both groups were able to accurately identify the correct answers for all three tasks; however, those in the VR group required significantly more time to complete the third and most complex task. To evaluate user experience, three key dimensions were examined: framework effectiveness, engagement and immersion, and user satisfaction and data interpretation. Feedback from the study indicated that while participants in both groups considered the framework effective in visualizing information and representing the underlying data structure in an accessible manner, distinct differences emerged between conditions. Users in the Desktop group reported a more stable, immersive, and consistent experience overall, albeit accompanied by higher levels of overwhelm when interacting with cluttered areas of the network. Conversely, participants in the VR group described lower cognitive load, improved comprehension, and greater clarity in navigating the visualization, though their experience was hindered by technical challenges such as frequent viewpoint changes, which made it more difficult to consistently follow connections. Finally, the technique of visually separating relationship types was found to be effective, as participants perceived it to reduce visual clutter by allowing them to focus on the most relevant information rather than the entire network. Moreover, reports of low frustration levels suggested that this approach offered an efficient and immersive filtering mechanism.

In conclusion, the findings of this thesis are encouraging, demonstrating that the proposed framework provides a solid foundation for immersive and interactive exploration of social network graphs. While the current implementation proved effective in enabling participants from diverse age groups and professional backgrounds to comprehend the data structure and accurately follow information, there remains significant potential for further enhancement. Future work could focus on incorporating additional techniques and functionalities aimed at improving user experience and increasing immersion, and improvements in the VR setting integration. Nonetheless, the framework has shown considerable promise in delivering an engaging and comprehensive visualization experience, effectively supporting users in navigating and interpreting complex relational data.

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Appendix

A. Custom Questionnaire

A..1 Introductory questions

1. Which display version did you test; the desktop version with a 2.5D visualization (a 3D navigation framework shown on a flat 2D screen) or the Virtual Reality (VR) version of the framework? (assigned by the experimenter)
2. Have you had previous experience with Data Visualization frameworks?
3. How familiar are you with Virtual Reality (VR) devices? *(if chosen VR version)*
4. In previous applications using VR, have you felt any discomfort (e.g. motion sickness, neck/head pain, etc.)? *(if chosen VR version)*
5. On a scale from 1 - 5, how much discomfort did you experience? *if 'yes'*
6. While testing this specific framework, did you feel any discomfort (e.g. motion sickness, neck/head pain, etc.)? *(if chosen VR version)*
7. On a scale from 1 - 5, how much discomfort did you experience? *if 'yes'*
8. How familiar are you with using the mouse and keyboard to navigate applications (including gaming, websites, etc.)? *if chosen Desktop version*
9. While testing this framework, did you feel any discomfort (e.g. visual fatigue, interaction frustration, etc.)?
10. On a scale from 1 - 5, how much discomfort did you experience? *if 'yes'*

A..2 User experience questions (satisfaction and engagement)

1. The framework was effective in visualizing the depicted data, easily identifying entities and relationships.
2. The framework clearly indicated the interactions I needed to do to enable its functionalities (i.e. view information, going to the previous visualization).
3. The interface kept me engaged and immersed throughout the tasks.
4. Navigating through the 3D environment felt natural and intuitive.
5. Being able to navigate inside the visualization and observe it from different viewpoints contributed to a clearer understanding of the data structure.
6. The framework helped me understand the structure of the social network.
7. I felt overwhelmed by the density of information shown in the visualization.

8. Dense or cluttered areas of nodes reduced clarity and made it hard to follow the visualization.
9. I was able to follow individual edges or relationships even in dense parts of the network.

A..3 Relationship types separation questions

1. The visual separation of different relationship types enhanced my ability to complete the task accurately.
2. The different relationship types were clearly distinguishable through visual cues (e.g., colors, glowing effect, spacing).
3. The visualization avoided occlusion despite having multiple relationship types.
4. I felt that by utilizing the visual distinction of relationship types, I could focus on specific relationships without being distracted by unrelated ones.
5. I felt that the visual distinction of relationship types was unnecessary and frustrating.
6. Visual separation helped me navigate the graph without confusion.
7. The separation of relationship types reduced my cognitive load during exploration.

A..4 Collaboration questions (if tested with someone else)

1. The framework's interface made collaboration confusing or unintuitive.
2. The framework's visualization successfully supported collaborative exploration.
3. Collaborating in the visualization made it easier to find the solution to the tasks.

A..5 Future use questions

1. I believe that I could benefit from using this framework in my own work or studies.
2. This framework provides a more immersive experience due to its navigation and incorporated techniques compared to traditional visualizations (i.e. 2D/flat visualizations, like in the following picture).
3. I would be interested in exploring more features of the framework.

B. System Usability Scale (SUS) Questionnaire

System Usability Scale

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

C. SUS Cronbach's Alpha Analysis

Results

Unidimensional Reliability

1) Both groups (Desktop and VR)

Frequentist Scale Reliability Statistics

			95% CI	
Coefficient	Estimate	Std. Error	Lower	Upper
Coefficient ω	0.742	0.081	0.583	0.901
Coefficient α	0.758	0.059	0.642	0.874

2) Desktop group

Frequentist Scale Reliability Statistics

			95% CI	
Coefficient	Estimate	Std. Error	Lower	Upper
Coefficient ω	0.810	0.059	0.693	0.880
Coefficient α	0.807	0.105	0.511	0.919

3) VR group

Frequentist Scale Reliability Statistics

			95% CI	
Coefficient	Estimate	Std. Error	Lower	Upper
Coefficient ω	0.706	0.090	0.499	0.796
Coefficient α	0.635	1.099	−2.668	0.862

D. Task Completion Time t-test Results

Results

Independent Samples T-Test

Independent Samples T-Test

	t	df	p	Mean Difference	SE Difference	Cohen's d	SE Cohen's d
Task 1	0.488	16.142	0.632	4.273	8.762	0.208	0.429
Task 2	−0.627	14.553	0.540	−8.545	13.629	−0.267	0.430
Task 3	−2.249	13.158	0.042	−215.545	95.823	−0.959	0.473

Note. Welch's t-test.

Descriptives

Group Descriptives

	Group	N	Mean	SD	SE	Coefficient of variation
Task 1	Desktop Group	11	59.545	25.073	7.560	0.421
	VR Group	11	55.273	14.691	4.429	0.266
Task 2	Desktop Group	11	82.000	19.915	6.005	0.243
	VR Group	11	90.545	40.579	12.235	0.448
Task 3	Desktop Group	11	232.000	118.685	35.785	0.512
	VR Group	11	447.545	294.817	88.891	0.659

E. Correlation Matrix and Confidence Intervals for User Experience of Framework (Both Groups)

Questions	Q1	Q2	Q3	Q4	Q5	Q6	Q7	Q8	Q9
Question 1	1.00								
Question 2	0.19	1.00							
Question 3	0.51	0.42	1.00						
Question 4	0.42	0.32	0.38	1.00					
Question 5	-0.01	-0.04	-0.01	-0.18	1.00				
Question 6	0.14	0.25	0.10	-0.02	-0.15	1.00			
Question 7	-0.07	0.23	-0.36	-0.12	0.03	0.19	1.00		
Question 8	-0.15	-0.46	-0.15	-0.43	0.23	-0.01	-0.30	1.00	
Question 9	0.53	0.41	0.46	0.07	-0.07	0.42	0.00	-0.27	1.00
Mean	4.50	4.33	4.75	4.42	4.58	4.58	1.58	2.58	4.42
Standard Deviation	0.60	0.59	0.44	0.60	0.59	0.46	0.91	1.23	0.60

Red = -1	White = 0	Blue = 1

Confidence Intervals	Q1	Q2	Q3	Q4	Q5	Q6	Q7	Q8	Q9
Lower CI	4.23	4.07	4.56	4.15	4.32	4.38	1.18	2.04	4.15
Higher CI	4.77	4.59	4.94	4.68	4.84	4.79	1.99	3.13	4.68

Question 1: The framework was effective in visualizing the depicted data, easily identifying entities and relationships.

Question 2: The framework clearly indicated the interactions I needed to do to enable its functionalities (i.e. view information, going to the previous visualization).

Question 3: The interface kept me engaged and immersed throughout the tasks.

Question 4: Navigating through the 3D environment felt natural and intuitive.

Question 5: Being able to navigate inside the visualization and observe it from different viewpoints contributed to a clearer understanding of the data structure.

Question 6: The framework helped me understand the structure of the social network.

Question 7: I felt overwhelmed by the density of information shown in the visualization.

Question 8: Dense or cluttered areas of nodes reduced clarity and made it hard to follow the visualization.

Question 9: I was able to follow individual edges or relationships even in dense parts of the network.

F. Correlation Matrix and Confidence Intervals for User Experience of Framework (Desktop Group)

Questions	Q1	Q2	Q3	Q4	Q5	Q6	Q7	Q8	Q9
Question 1	1								
Question 2	X	1							
Question 3	0.47	X	1						
Question 4	0.52	X	0.43	1					
Question 5	0.34	X	0.04	0.10	1				
Question 6	-0.27	X	-0.22	-0.04	0.04	1			
Question 7	-0.04	X	-0.41	-0.18	0.18	0.60	1		
Question 8	0.22	X	0.46	-0.02	-0.20	0.18	-0.31	1	
Question 9	0.45	X	0.13	-0.07	0.45	0.13	0.35	-0.16	1
Mean	4.64	5.00	4.82	4.45	4.55	4.82	2.18	1.82	4.64
Standard Deviation	0.67	0.00	0.40	0.52	0.52	0.40	0.98	0.87	0.50

Red = -1	White = 0	Blue = 1

Confidence Intervals	Q1	Q2	Q3	Q4	Q5	Q6	Q7	Q8	Q9
Lower CI	4.18	X	4.55	4.10	4.19	4.55	1.52	1.23	4.30
Higher CI	5.09	X	5.09	4.81	4.90	5.09	2.84	2.41	4.98

Question 1: The framework was effective in visualizing the depicted data, easily identifying entities and relationships.

Question 2: The framework clearly indicated the interactions I needed to do to enable its functionalities (i.e. view information, going to the previous visualization).

Question 3: The interface kept me engaged and immersed throughout the tasks.

Question 4: Navigating through the 3D environment felt natural and intuitive.

Question 5: Being able to navigate inside the visualization and observe it from different viewpoints contributed to a clearer understanding of the data structure.

Question 6: The framework helped me understand the structure of the social network.

Question 7: I felt overwhelmed by the density of information shown in the visualization.

Question 8: Dense or cluttered areas of nodes reduced clarity and made it hard to follow the visualization.

Question 9: I was able to follow individual edges or relationships even in dense parts of the network.

G. Correlation Matrix and Confidence Intervals for User Experience of Framework (VR Group)

Questions	Q1	Q2	Q3	Q4	Q5	Q6	Q7	Q8	Q9
Question 1	1								
Question 2	0.19	1							
Question 3	0.56	0.60	1						
Question 4	0.34	0.44	0.35	1					
Question 5	-0.34	0.02	-0.03	-0.34	1				
Question 6	0.47	0.11	0.26	-0.05	-0.23	1			
Question 7	-0.35	-0.08	-0.51	-0.18	-0.04	-0.48	1		
Question 8	-0.37	-0.36	-0.45	-0.65	0.43	0.09	-0.07	1	
Question 9	0.62	0.44	0.66	0.12	-0.34	0.52	-0.61	-0.21	1
Mean	4.45	4.27	4.73	4.36	4.64	4.55	1.45	2.73	4.36
Standard Deviation	0.52	0.65	0.47	0.67	0.67	0.52	0.69	1.35	0.67

Red = -1	White = 0	Blue = 1

Confidence Intervals	Q1	Q2	Q3	Q4	Q5	Q6	Q7	Q8	Q9
Lower CI	4.10	3.84	4.41	3.91	4.18	4.19	0.99	1.82	3.91
Higher CI	4.81	4.71	5.04	4.82	5.09	4.90	1.92	3.63	4.82

Question 1: The framework was effective in visualizing the depicted data, easily identifying entities and relationships.

Question 2: The framework clearly indicated the interactions I needed to do to enable its functionalities (i.e. view information, going to the previous visualization).

Question 3: The interface kept me engaged and immersed throughout the tasks.

Question 4: Navigating through the 3D environment felt natural and intuitive.

Question 5: Being able to navigate inside the visualization and observe it from different viewpoints contributed to a clearer understanding of the data structure.

Question 6: The framework helped me understand the structure of the social network.

Question 7: I felt overwhelmed by the density of information shown in the visualization.

Question 8: Dense or cluttered areas of nodes reduced clarity and made it hard to follow the visualization.

Question 9: I was able to follow individual edges or relationships even in dense parts of the network.

H. Correlation Matrix and Confidence Intervals for Visual Distinction of Relationship Types

Questions	Q1	Q2	Q3	Q4	Q5	Q6	Q7
Question 1	1						
Question 2	0.41	1					
Question 3	-0.23	0.18	1				
Question 4	0.69	0.52	0.06	1			
Question 5	-0.34	-0.44	0.17	-0.50	1		
Question 6	0.46	0.33	0.15	0.57	-0.52	1	
Question 7	0.24	0.09	0.17	-0.03	0.08	0.23	1

Mean	4.68	4.45	4.27	4.36	1.45	4.82	4.18
Standard Deviation	0.72	0.67	0.88	0.73	0.74	0.39	0.91

Red = -1	White = 0	Blue = 1

Confidence Intervals	Q1	Q2	Q3	Q4	Q5	Q6	Q7
Lower CI	4.36	4.16	3.88	4.04	1.13	4.64	3.78
Higher CI	5.00	4.75	4.66	4.69	1.78	4.99	4.58

Question 1: The visual separation of different relationship types enhanced my ability to complete the task accurately.

Question 2: The different relationship types were clearly distinguishable through visual cues (e.g., colors, glowing effect, spacing).

Question 3: The visualization avoided occlusion despite having multiple relationship types.

Question 4: I felt that by utilizing the visual distinction of relationship types, I could focus on specific relationships without being distracted by unrelated ones.

Question 5: I felt that the visual distinction of relationship types was unnecessary and frustrating.

Question 6: Visual separation helped me navigate the graph without confusion.

Question 7: The separation of relationship types reduced my cognitive load during exploration.