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DATA VISUALIZATION OF VIRTUAL REALITY LIBRARY USER DATA

Bachelor's Thesis
Degree Programme in Computer Science and Engineering
June 2020

Jutila R., Kopsa M., Zhu S. (2020) Data Visualization of Virtual Reality Library User Data. University of Oulu, Degree Programme in Computer Science and Engineering, 44 p.

ABSTRACT

User research is an important part of developing software. In the gaming industry, different ways to analyse user behaviour is an increasingly important part of research. However, as game analytics are relatively new to the game industry, there is limited amount of research available. In this work, we discuss how to visualise collected data in virtual reality environments in a meaningful way to improve product quality and extract user behaviour patterns.

We use clustering algorithms and analytical functions to have a more comprehensive look on test participants' behaviour with our Data Visualization tool. This behaviour is then presented using different path maps, heat maps and data charts.

Originally our aim was to conclude research on user behaviour in the Oulu Virtual Library application, but due to the COVID-19 pandemic, we had to change our focus from user research to designing and implementing a tool for researchers to analyse similar data sets as our example data. Even though we had no concrete user data, researchers can use the tool we developed with relative small modifications, when dealing with similar data cases in the future. Usability improvements and real-word experiences are still needed to make the tool more robust.

Keywords: data analysis, data visualization, head-mounted display, heat map, path map, point-to-jump, virtual reality, visual analytics

Jutila R., Kopsa M., Zhu S. (2020) Virtuaalitodellisuuskirjaston Käyttäjädatan Visualisointi. Oulun yliopisto, Tietotekniikan tutkinto-ohjelma, 44 s.

TIIVISTELMÄ

Käyttäjätutkimus on tärkeä osa ohjelmistokehitystä. Koska pelianalytiikka on suhteellisen uutta peliteollisuudessa ja saatavilla oleva tutkimus vähäistä, loppukäyttäjien toiminnan analysointi on yhä tärkeämpi osa peliteollisuuden kehitystä. Tässä tutkielmassa pohditaan, kuinka virtuaaliympäristöistä kerättyä dataa voidaan esittää, merkityksellisellä tavalla, tuotteiden kehittämiseksi ja käyttäjien erilaisten käyttäytymismallien tunnistamiseksi.

Käytämme ryhmittelyalgoritmeja ja analyyttisia funktioita, jotta saamme esitettyä käyttäjien toimintaa datavisualisointityökaluamme hyödyntämällä. Käyttäjien toiminta esitetään erilaisten polku- ja lämpökarttojen sekä datakaavioiden avulla.

Alkuperäisenä tarkoituksenamme oli tutkia käyttäjien toimintaa Oulun Virtuaalikirjasto-sovelluksessa, mutta COVID-19-pandemian takia jouduimme siirtämään painopisteen käyttäjätutkimuksesta tutkijoille suunnatun datavisualisointityökalun suunnitteluun ja kehitykseen. Vaikka emme saaneet konkreettista aineistoa, tutkijat voivat käyttää työkalua, suhteellisen pienillä muunnoksilla, esimerkkiaineistoa vastaavan aineiston käsitelyyn ja analysointiin tulevaisuudessa. Työkalu tarvitsee yhä käytettävyysparannuksia ja todellisia käyttökokemuksia työkalun käyttövarmuuden parantamiseksi.

Avainsanat: lämpökartta, polkukartta, teleportaatio, tiedon analysointi, tiedon visualisointi, virtuaalitodellisuus, virtuaalitodellisuusnäyttö, visuaalinen analyysi

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LIST OF ABBREVIATIONS

PLATO	Play-graph Analysis tool
UI	user interface
VR	virtual reality

1. INTRODUCTION

In this work, we explore how to visualize user data collected in virtual reality (VR) environments and what behavioural patterns can be recognized based on the data. The main goal is to gain meaningful user research insights from raw data collected in the Virtual Library environment by taking advantage of visual analytics.

The Virtual Library is a VR application developed together by the Oulu City Library and the Center for Ubiquitous Computing at the University of Oulu [1]. In the application, powered by Unreal Engine developed by Epic Games, library visitors can explore a virtual version of the library and three fantasy worlds.

The Oulu City Main Library has a dedicated stand, which includes a VR headset, headphones and handheld controllers. In the virtual world, users can be guided how to find a specific shelf location or explore the first two floors of the Oulu City Main Library, a virtual art exhibition in the lobby and three fantasy worlds accessed by a lift. The three fantasy locations—Fantasy Village, Study with a fireplace and Future Alley—have hidden book recommendations that can be revealed by interacting with objects in the virtual environment.

For some users, the virtual library is an introduction to VR. That makes it important to measure the success of introducing a new environment with a new set of rules to a variety of people with different backgrounds. Game telemetry can be taken advantage of to remotely collect real-time measurements. Telemetry data helps developers to gain insight how the experience can be improved and what kind of affordances can be introduced to smoothen the learning curve. Affordance refers to the perceived possibility of actions that a person may take in an environment [2].

Data analysis methods can be divided into roughly two categories: supervised learning and unsupervised learning. Supervised learning methods include decision trees, support vector machines and neural networks. Clustering and correlation analysis are unsupervised learning methods. Various data mining algorithms can be utilized depending on the situation.

As for data visualization, there are many tools and algorithms available. Heat maps and path maps can be used to visualize user behaviour. Even though there are many problems and challenges with visual analytics, and data science, many problems can be solved using existing technology.

This work investigates how user behaviour in 3D virtual environments can be inspected using data visualization. First, we introduce prior research on visual analytics, data visualization, user telemetry and virtual environments. Then, we present our study design, test procedure and system design. Finally, we analyze our results and discuss how our system and study design could be improved.

1.1. Contributions

All authors have contributed to all sections of the work throughout the process. However, each person has had different responsibilities. Work with Unreal Engine has been done by Risto Jutila, while working with the map visualisations. User interface design and web implementation was managed by Mirko Kopsa. Data analysis and clustering was designed, implemented and evaluated by Sihan Zhu. Work hours are described in more detail in Table 7 (see Appendix D).

2. RELATED WORK

Data visualization is the art of placing data in a visual context. The goal of data visualization is to identify trends, patterns and contexts that are usually unrecognized in text-based data. Meanwhile, visual analytics also manages to represent data in an easily understandable format but combines automated analysis techniques with interactive visualizations [3].

Another important concept is information visualization. Information visualization uses visual contexts to represent patterns. All data visualization is information visualization but not all information visualizations are based on data, such as process visualization [3].

2.1. Visual Analytics

Visual analytics is an outgrowth of the fields of information visualization and scientific visualization that focuses on analytical reasoning facilitated by interactive visual interfaces [4]. More precisely, visual analytics is an iterative process that involves information gathering, data preprocessing, knowledge representation, interaction and decision-making [5].

Visual analytics combines automated analysis techniques with interactive visualizations for an effective understanding, reasoning and decision making on the basis of very large and complex data sets [6]. Instead of only visualization, it can rather be seen as an integral approach combining visualization, human factors and data analysis [5].

The ultimate goal of visual analytics is obtaining insight in problems described by a large number of scientific, business or forensic data from many sources. To achieve that, it combines the strengths of humans and machines [5].

2.2. Data Visualization

Data visualization is graphic representation of data. By using visualization, we can obtain a clear, descriptive view of the data. There is no doubt that data visualization plays an very important role in visual analytics.

2.2.1. Process

Kielman et al. [7] described the visual analytics process as repeating the activity of analyzing data and discovering important features until the target details are found. The process of any kind of Visual Analytics starts with analysis, using data analysis techniques such as cluster analysis or visualizing tools. Then, when important or interesting findings are made, they are analyzed further to get more details. [7]

Visual analytics suggests that in order to gain insight on the data and the visualization there is a loop where data can be interactively modified [8]. Jarke J. van Wijk proposed a framework of generalizing the process, which is evaluated and measured in terms efficiency and knowledge gained [9].

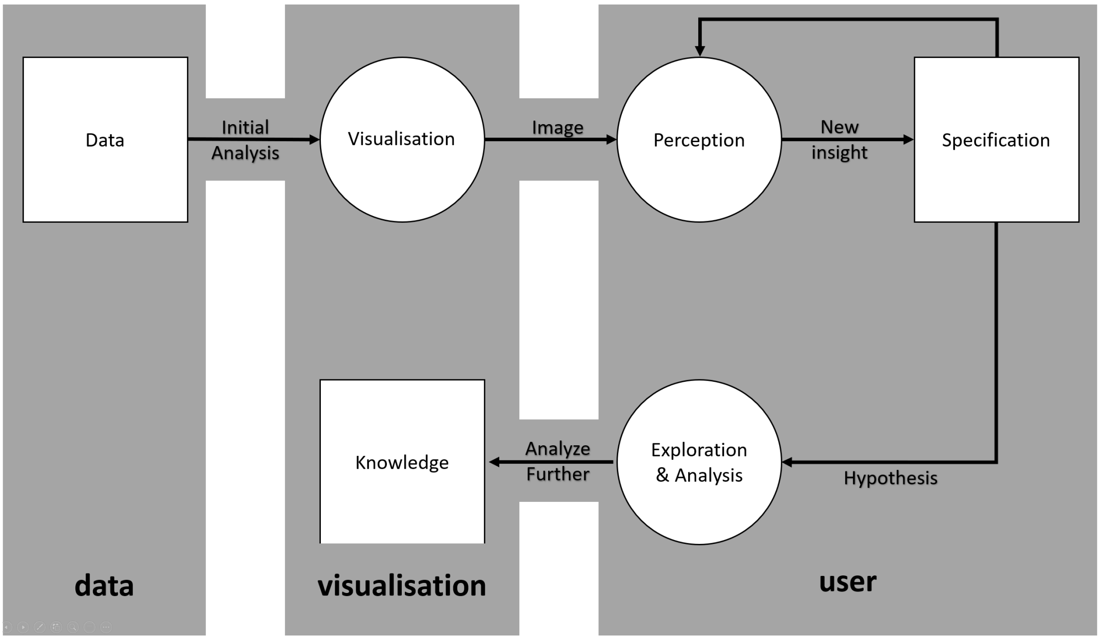

Figure 1. The sense-making loop for Visual Analytics based on the simple model of visualization by Wijk [6][8]. Image recreated from Wijk [6][8].

2.2.2. Game Engines

Game engines are known for providing user experiences that are similar to real-world situations. Despite the specificity of the name, game engines are often used for other kinds of interactive applications with real-time graphical requirements such as marketing demos, architectural visualizations, training simulations and modelling environments [10]. They can also be powerful tools to visualize data.

A well-known game engine in the industry, the Unreal Engine, features a high degree of portability and is used by many game developers today. With it, developers can provide virtual reality and augmented reality games on platforms using a single code base. There are already some studies about data visualization using the Unreal Engine. For example, by using the Unreal Development Kit, some researchers were able to create 3D terrain visualization of Geographic Information Systems data [11].

2.2.3. Heat Maps

Another way to visualize data is heat mapping. A heat map is a graphical representation of data where the individual values contained in a matrix are represented as colors [12]. For example, it can be used to display user interaction with website through a color-coding system, which highlights the areas of the page that receive most attention. There are different kinds of heat maps such as scroll maps and hover maps that are used for this purpose [13].

Usually heat maps are two-dimensional but they can be used in 3D models as well. For instance, a 3D heat map can be used to show where users are looking which is not possible in a traditional 2D heat map.

2.2.4. Play-Graph Analysis Tool

The Play-graph Analysis tool (PLATO) presented by Kriglstein et al. [14] converts raw data from log file input into two-dimensional play-graphs. The imported data can be analysed with an interface that provides high degree of interactivity. It supports multiple views to analyze data and offers several visualizations enabling the user to choose the appropriate representation based on their needs.

The approach proposed by Kriglstein et al. [14] considers the temporal dimension inherent to gameplay. The system also represents player attributes (e.g. age) and offers several techniques to explore and reduce the complexity of the data. The system is designed to be flexible and adaptable to a wide range of games.

PLATO is suitable for 3D games or virtual environments if the interaction with the system can be analyzed in two dimensions. The system provides node-link representation, matrix visualization, path visualization, heat map, animation and clustering. However, in some cases, the projection leads to losing critical information. [14]

2.2.5. Visualization in Virtual Environments

Moloney et al. [2] suggest that big data can be represented in information-dense virtual environments as opposed to a simplified visualization. Five principles have been identified to support developing immersive analytics applications. [2]

1. Abstractions of real-world environments, to which human perception is attuned, can be used.
2. Real-world metaphors can be integrated with interface affordances.
3. Cross-modal mapping can be used, e.g. by aligning sound with movement.
4. Rather than extreme contrasts, subtle differences in information in the intermediate zone where human perception is most discerning, should be preferred.
5. Granularity and distribution of data can be aligned with naturally occuring distribution patterns.

2.3. User Telemetry

In-game telemetry is used to collect data as people play games [15]. Virtual reality environments share many similarities with 3D games and the questions faced in game analytics are relevant also in VR development, which results in the two being comparable with each other in many cases.

Details of game telemetry data and analysis are often confidential information owned by game companies. This is one reason why case studies of academic-industry partnerships are rare [16]. As adopting analytics into game development is still fairly new, analysis of behavioural data in games is a topic that suffers from a shortage of knowledge [17].

Implementing in-game telemetry in the development process can be time-consuming and costly [16]. In addition to collecting the data, analyzing and presenting it in a way that provides value for developers, is another challenge.

A common problem with telemetry is that it shows what the player has done but not the reasoning behind actions [14]. Cluster analysis can be used to evaluate player behaviour but there are some challenges. They include validation, interpretation and visualization, time-dependency, progress dependency, high-dimensionality, and big data, data type mixing and feature selection [17].

2.4. Analyzing Data

Actionable insights should be derived from large amounts of high-dimensional and time-dependant data that people generate while playing games [17]. The demand for effectively analyzing this data increases as the data begins to accumulate over a period of time [15].

Bauckhage et. al [17] presented challenges in game development encountered when cluster analysis is used to evaluate player behaviour. Validating results requires expertise and validated results should provide insight while avoiding results of low practical value. In addition, results are time-dependant as player behaviour changes and the game evolves. Players can also be in different stages which makes some information without context redundant. [17]

2.4.1. Supervised Learning

Based on a set of training samples, deterministic or probabilistic algorithms are used to learn models for the classification (or prediction) of previously unseen data samples [18]. In supervised learning, some data is already labeled with a correct answer, while in unsupervised learning, no data is classified or labeled. A large number of algorithms, such as decision trees, support vector machines and neural networks, can be useful in this area.

In the most commonly used data science algorithms or techniques in 272 studies about game analytics data and/or learning analytics data from serious games, linear/logistic regression is used the most of supervised models [9]. All of them (see Table 1) can be very useful in virtual analytics as well.

Table 1. The most commonly used data science algorithms or techniques used in thestudies, and number of papers that use each technique (recreated from [9])

Data science technique	Number of papers using the technique
Supervised models	31
Linear/Logistic regression	18
Regression/decision trees	7
Bayesian networks	6
Neural networks	4
Naïve Bayes	3
Bayesian knowledge tracing	3
Support vector machines	2
Unsupervised models	35
Correlation	17
Clustering	16
Factor analysis	2
Visualization	36
Performance metrics	15
Gameplay pathways	7
Use in-game tools	5
Learning curves	4
Heat maps of interactions	2

2.4.2. Clustering

Clustering is an unsupervised learning method that groups data automatically into classes according to similarity and detects outliers in noisy data, which is widely used in game analytics. It can extract structure of data without knowing related information.

There are various clustering algorithms with different strengths and weaknesses, which are tailored based on the various problems in different fields [19]. Understanding of cluster models are vital for correct application. Clustering should be evaluated and validated before further used [20].

For example, k-mean and archetypal clustering was used to assess the performance of players in a massively multiplayer online role-playing game Tera. The author performed cluster analysis on 26000 players' data and many features regarding playing games. There are many distinctions between the two algorithms, and k-mean achieved a more broadly defined clusters than archetypal analysis [20]. [21]

2.5. Movement in Virtual Environment

The Virtual Library application [1] uses a head-mounted virtual display with point-to-move movement system to interact with the virtual environment with no external support or guides for the user. Point-to-move system means the user will use their controller to point at a target and move instantly there at a designated point when they decide to do so. The user is meant to do as little physical moves, e.g. steps, as possible due to the high amount of control they have with their existing controlling scheme.

This has been done to reduce the amount of safe-space the user needs to perform within the virtual environment.

"Do We Need to Walk for Effective Virtual Reality Navigation" by Bernhard E. Riecke [22] states that in most cases, by only rotating our bodies, we can achieve as effective navigation as walking when using head-mounted displays. In some cases this can also reduce the amount of actions needed to proceed in scenes or necessary tasks while moving.

Riecke presents a way for designers to proceed with their VR environments and systems: a VR environment is a human-generated world and thus does not need to follow the laws of the real physical world. Designers can bend the laws to generate different quality of life improvements for VR users e.g. by reducing the number of steps the user takes during their virtual experiences. [22]

2.6. Virtual Environment

Body movement and scene management play an important part in VR. Data can be retrieved from head-mounted displays and handheld controllers that are used to interact with the VR system. This data makes it possible to get an overview of the way the user tends to move in the environment.

Unfamiliar, large-scale virtual environments can be difficult to navigate, thus if we want to understand the data collected from the system, we also need to know how does the virtual environment itself look. We follow "Design guidelines for landmarks to support navigation in virtual environments" by Norman G. Vinson [23] and pick out the most notable landmarks that tend to affect the movement of the user in the virtual environment. A landmark must be easy to distinguish from nearby objects and other landmarks and always have distinctive features to make them easier to memorise. [23]

Table 2. Noticeable Structures [24]

Building Features Contributing to Memorability			
Significant height	Expensive building materials & good maintenance	Complex shape	Free standing (visible)
Bright exterior	Surrounded by landscaping	Large, visible signs	Unique exterior color, texture

On "The effect of landmarks in human path integration", Xiaoang Wang [24] agrees on this. Be it an unfamiliar or familiar environment, landmarks and other distinguishable objects play a large role on how the user behaves in VR environments and it should not be ignored.

However, all landmarks and unique objects are not easily distinguishable even though they would have been designed to be unique. "Saliency in VR: How Do People Explore Virtual Environments" by V. Sizman [25] goes trough how people actually see the environment.

Users are unpredictable and may not interact with the environment with the way we predicted or wanted them to. According to Sizman [25], predicting users time-dependant viewing behaviour is accurate only within the first few seconds after entering the scene due to the high inter-user variance [25].

In our case, a scene can be interpreted as a new point where the user moved using instantaneous movement with point-to-move sequencing. It is extremely important to get the users' attention to the specified objects within the few seconds we can predict, as it will be extremely frustrating for the user if they miss key components withing the designated areas due to the lack of highlighting elements in the point-of interest.

2.7. Motivation

The experiences offered by VR systems are inherently different from normal cinematic forms and the behaviour of users in VR environments is generally not well understood or predicted [26].

Compared to non-immersive computer displays, in VR, the user is immersed in an environment of data rather than observing graphic patterns on a visual display. Human perception within virtual reality compared to physical space is explored sparsely in research [2].

As users are familiar with interacting in a physical environment and non-immersive displays, but not with acting in virtual environments, they don't necessarily know how they are able to interact with the environment. What the users are interested in, how they behave and how immersed they are in the experience are aspects that can be studied in addition to usability issues. Interaction between the user and the VR environment should be enjoyable, engaging and appealing in addition to the system being usable, safe, effective and comfortable [26]. Research on virtual reality should therefore focus on improving the user experience and quality of life.

The small amount of research has left multitude of interesting questions open for answers, such as how do we design 3D scenes or place cuts in VR videos, how do we drive user attention in virtual environments and can we predict visual exploration patterns [25].

As there is little research that focuses on 3D environment and virtual reality analytics, and extracting information and visualizing it in a meaningful way is still fairly new, there is a need for research to study how user data collected from 3D environments can be visualized effectively to gain insight into user behaviour.

3. METHODS

3.1. System Design

We got a modified source code for the Virtual Library from the "Virtual Library: Blending Mirror and Fantasy Layers into a VR Interface for a Public Library" study [1], which can automatically gather data from its users.

The Virtual Library application allows us to get data from users' jumps and interactions when they are exploring the VR environment. Originally, we planned on adding more data collection features, but modifying the Virtual Library source code proved to be more challenging than we expected.

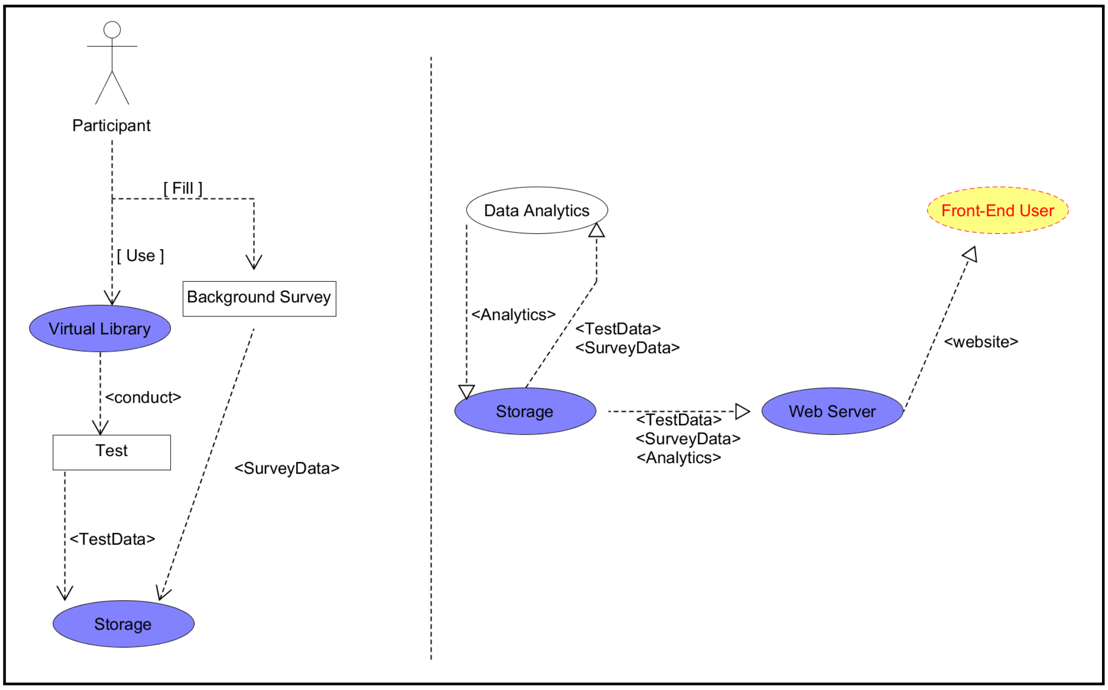

Figure 2. Study Flow Chart

The Data Visualization Tool is a web application developed with Python and Flask web application framework, while the front-end is written in HTML5, CSS and JavaScript.

The tool generates heat maps, path maps and useful data and clustering charts from the data it reads from the file system. It also includes a command-line tool to update the data charts shown in the graphical user interface.

The code for generating path maps has been adapted from Python code provided by Toni Alatalo to JavaScript [27] while our heat maps are generated using the Heatmap.js library by Patrick Wied [28].

All data and analytical representations we gather will be stored in the computer's file system in JSON format. Data is read from the file system and converted to Python DataFrame for further parsing.

Correlations and similarities between user groups can be found by visualizing data with the tool. The tool's configuration is designed to be easily modified to accommodate different VR environments and settings.

The tool has three main views: Groups, Sessions and Histograms. The Groups view has a search form that can be used to specify search criteria for user data. The Sessions view lists all sessions which correspond to an analytics file in the uploads folder. When you select a session, the page shows the visualizations using the data from the selected session. The user can select a heat map or path map as the map type when they are viewing a visualization in the Groups or Sessions view. Histograms view shows the output from the command-line tool.

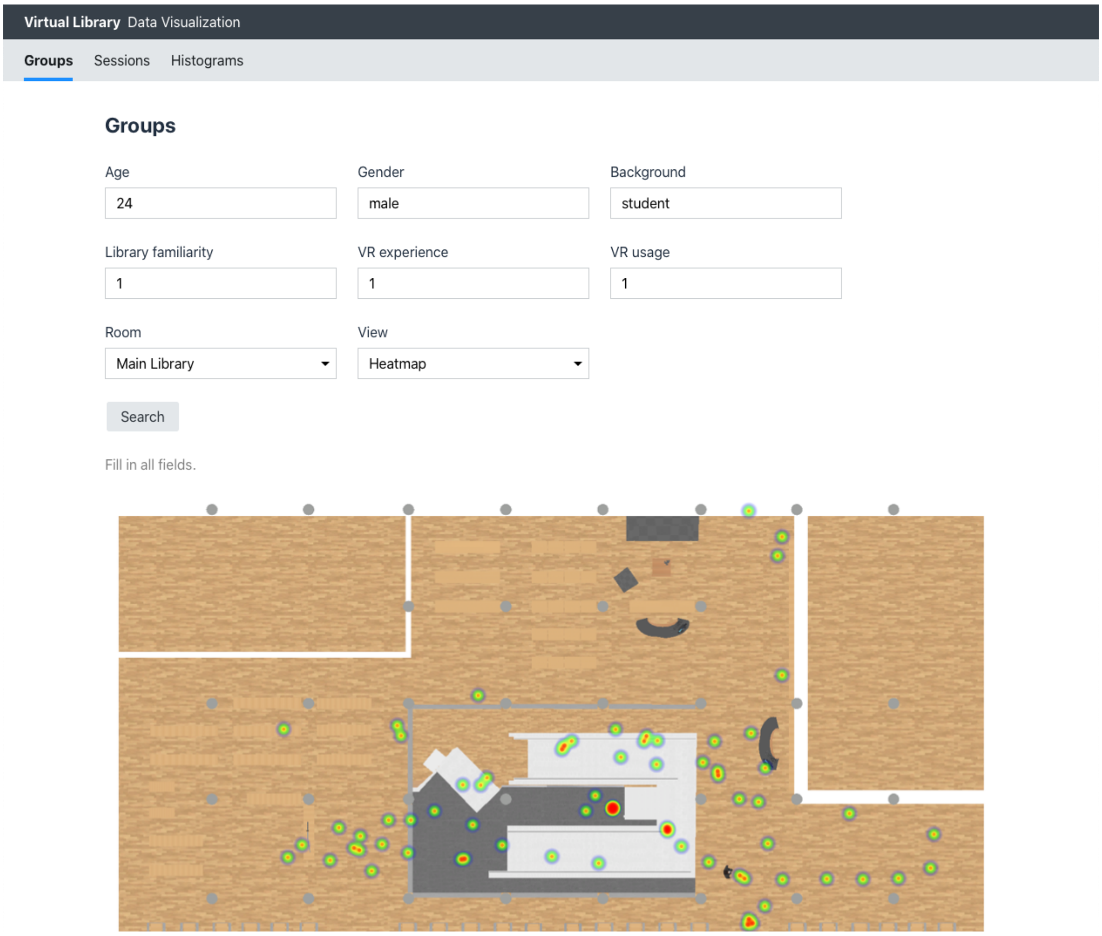

Figure 3. The final Groups view.

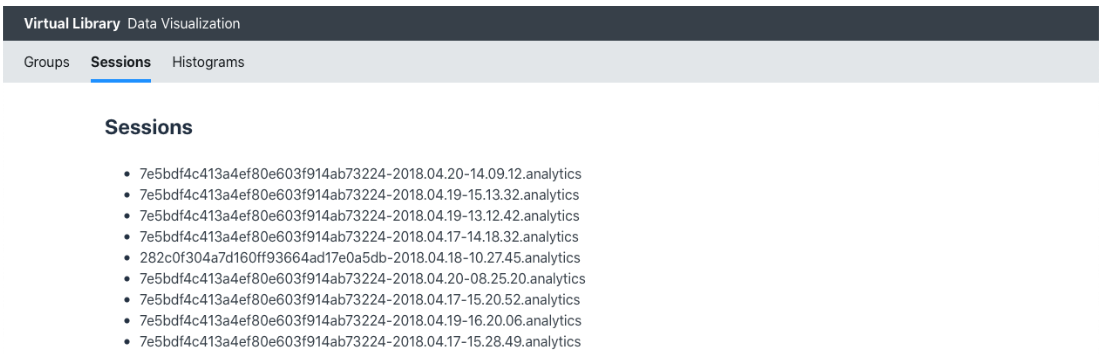

Figure 4. The final Sessions view.

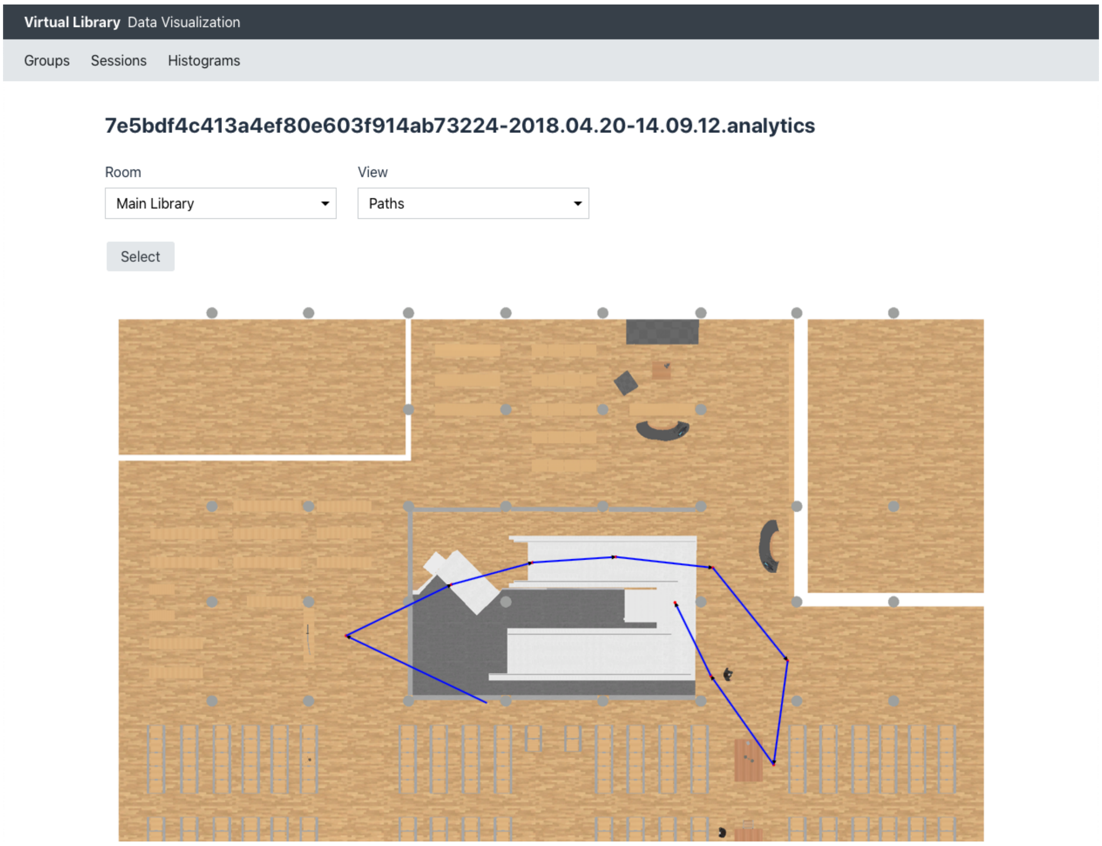

Figure 5. The final view for an individual session.

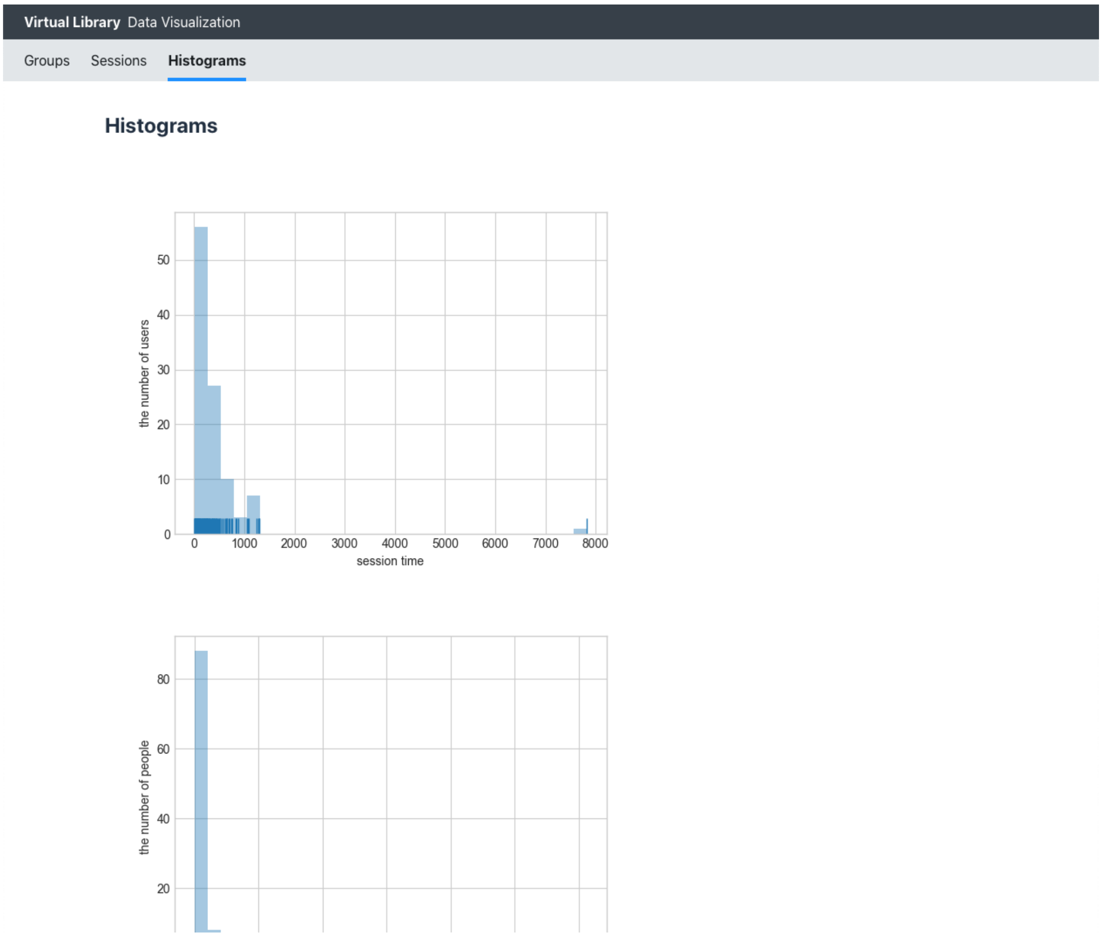

Figure 6. The final Histograms view.

The JSON data is used in the data charts and clustering, which is done in Python using K-means clustering algorithms. The correlation is evaluated with Spearman's rank correlation coefficients, and we look into the correlations with relatively high correlation values.

K-means clustering is used, where people are allocated to groups by an algorithm according to their average jump length and total number of jumps [29]. As an unsupervised algorithm, K-means clustering can label data by attributes, effectively grouping them to K groups and centroids. Centroids are points which split the data into different groups and can be used to labeled new incoming data [30].

The K in our test is 5 (see Figure 7). We are not sure if it's still usable when there is more data. When we considered 20 users, the optimal K is 3, but when there are 100 users, K = 3 gives an inaccurate result and the optimal K is 5. We still need to further test the applicability of K-means clustering. At the moment we can find the best K for each scenario by calculating the cost function when K = 0, 1, 2, 3... until the cost is acceptable, or the K is greater than 10, in which case the K-means clustering is not feasible.

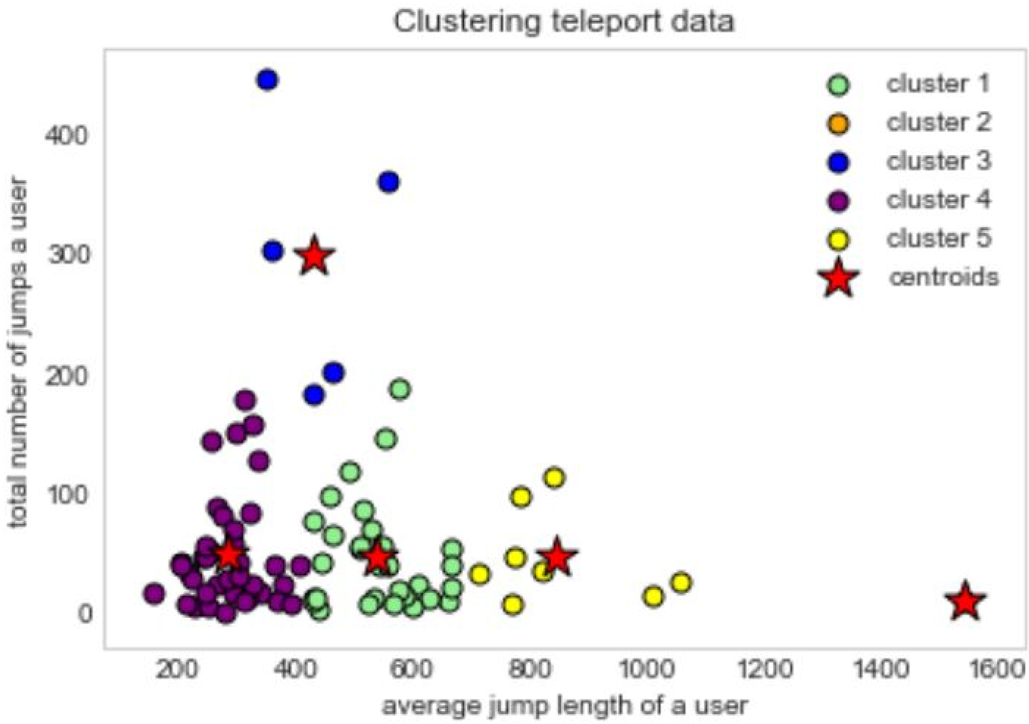

Figure 7. K-means clustering.

We learn more about the data by plotting the histogram of certain attributes since it is clear that many people tend to behave in similar ways. In the histograms, the distribution of the important attributes are displayed. There could be some correlations between different jump attributes, which can be discovered by calculating Spearman's Rank correlation coefficients and drawing two-dimensional plot [31].

3.2. Proposed Study Design

In our study, we want to find out what behavioural patterns, such as paths and interests, can be recognized from virtual reality environment user data when data visualization is taken advantage of to analyze it. Due to the COVID-19 pandemic, the presented study design is only a proposal as we were unable to carry out a live experiment.

To collect data for our study, we would have had random voluntary library visitors use the Virtual Library system at the Oulu City Main Library within library opening hours. First, the user fills in a background questionnaire. Before the user proceeds, they are briefed about the layout and levels of the Virtual Library and told about the existence of intractable objects. After briefing, they proceed to explore the Virtual Library freely without any given goals, in a non-controlled environment. There are no time limits, and the user can use the Virtual Library application for as long as they like. Session start and end times would be marked down by a researcher who would also help the user with the system if needed. The start and end dates currently function as identification between participant's questionnaire answers and the system data.

To get a more comprehensive image of our test users, data is gathered about their background with a questionnaire. This data is then linked with the analytics data, gathered from the Virtual Library. With this, we can now group users by their background data while searching for interesting findings in the test data itself. The data is then analyzed, focusing on grouping the users, by taking advantage of the Data Visualization tool we developed.

Our questionnaire data has been split into six different attributes with most of them having four different values, excluding gender (see Table 3). With this amount of background data, we get a comprehensive picture of users' relevant background information without infringing their privacy. As we do not try to verify participants' identity we have to trust their willingness to be truthful. We can encourage participation by offering a small reward for those who have taken part in our experiment.

Table 3. Questionnaire data format

Attribute	Values			
Age	Child (0–12)	Teen/Young adult (12–24)	Adult (24–50)	Elderly (50–)
Gender	Male	Female	Other/not specified	
Background	Working	Student	Unemployed	Retired
Familiarity with Oulu City Library	Not familiar (0)	Somewhat familiar (1-3)	Familiar (3-6)	Regular visitor (6 -)
VR experience	No knowledge	Some knowledge	Some experience	Experienced
VR usage	No usage	Weekly	Multiple times a week	Daily user

A computer to run the Virtual Library software, head-mounted display and handheld controllers are required hardware in the test. The questionnaires are either printed on paper or filled in with a tablet or smartphone. Chairs and water to drink should be available and at least one researcher should be present at all times.

For this study, the background information questionnaire includes user age, gender, professional background, familiarity with the library and previous VR experience (see Appendix B). This information is used for subject data clustering.

During the test, there is a researcher present who is ready answer any questions about the Virtual Library or otherwise help the users. The subjects' well-being should be monitored due to possible side effects of using head-mounted display. The researchers should look out for nausea, dizziness and general discomfort [32]. Older subjects and those who have not used Head Mounted Displays may feel worse than younger and more experienced users. Subjects can choose to explore the VR environment while standing up or being seated, whichever is more comfortable for them, and they are provided water if needed.

All library visitors are eligible to be test subjects as long as they can use the headset. Test subjects are random as voluntary users are selected. We are looking for approximately 10 test subjects who would preferably spend at least two minutes each in the VR environment. Test subjects get information of the research paper via email they provide in the questionnaire. The email address will not be used to identify the test users when test results are processed. Those who explore the VR environment for less than adequate time or spend longer time in the Virtual Library than expected, approximately over 15 minutes, would have their data subjected to revision in smaller chunks if needed.

We can use the Data Visualization Tool to get an overview of the participants' performance in the system (see Table 5). Data charts, that we decided to pay close attention to, are time between jumps, jump count, jump length and session time (see Appendix C).

3.3. Test Procedure

The following procedure can be utilized in the future when the restrictions imposed by the pandemic are over. The proposed live experiment is conducted as follows:

1. A library visitor arrives at the testing area and volunteers as a test subject.
2. The test subject fills in the background questionnaire (see Appendix B).
3. The test subject wears a head-mounted display, with the help of researchers, and takes handheld controllers.
4. The test subject is briefed of the controls, navigation, environments/levels and the possibility of interacting with objects.
5. The test subject explores the VR environment freely at their own pace for as long as they want.
6. The test ends, equipment is removed and the participant can leave unless they need water or other assistance.

From the tests, we gain quantitative and qualitative data, collected analytics and questionnaire information respectively. The analytics data includes where the user has moved (teleportation/jump information) with timestamps. User paths give information of how the participants navigate within the Virtual Environment and what may interest them.

Jump targets give us estimate of how the participants navigate within the Virtual Environment and what may interest them. Background data gives us means to inspect whether familiarity with VR systems or Oulu City Main Library or other attributes affect decision-making and navigation.

3.4. Actual Study without Users

As we didn't get any data from real users in our live experiment, we used the example data provided by Toni Alatalo that had been previously gathered using the Virtual Library prototype [1]. In addition to using the example data, we generated arbitrary questionnaire answers which we linked with the analytics data. This way, we could identify possible behavioural patterns in user groups.

The example data is in JSON format and consists of user jumps, interactions with the environment and the level the user is currently in (see Table 6). This data was then used to generate heatmaps, pathmaps and data charts that we found interesting.

We identified problems in the Data Visualization tool with expert evaluation. We didn't focus on usability evaluation but rather ensured the system is suited for its purpose by identifying potential drawbacks of the visualization tool.

We also performed statistical analysis on existing user data by inspecting plots and their deciding parameters. First, we plotted histograms for some interesting attributes that show the distribution of user behaviours, for example, how many jumps in total, and the average time between jumps. Then we calculated the Spearman's rank correlation coefficient to discover possible correlations between these attributes. We further analyzed the correlations by making scatter plots of the associated attributes. In addition, we used K-means clustering to group the users according to their average jump length and total number of jumps. The clustering is then evaluated with cost function.

4. EVALUATION

As we were told not to gather any actual data from participants, due Covid-19 pandemic, the evaluation and analytics will mostly be done with a hypothetical situation in mind.

We will go through decisions we made during the system's development and discuss what could be improved and what should be taken into account if the study is developed further and the live experiment is carried out.

4.1. Data Visualization Tool Design

Path maps were the only thing implemented at the point where mockups for the Data Visualization tool were designed. At that time it was still unclear what data could be collected from the Unreal Engine.

Gaze visualization and listing interactions with objects were planned but the user interface for presenting them was not designed. The Virtual Library version we worked on wasn't the latest stable version but we didn't know it at the time. This is why we struggled to develop additional data collection, so gaze and interaction sections were removed.

In the initial user interface design (see Appendix A), the user can search for sessions by date, session start time or user ID. Clicking a table row opens the corresponding session visualizations. If the user wants to open a specific analytics file, they can do so by entering the session ID, which is same as the file name, to the Session ID text field. In the final version, we only list the analytics files (i.e. sessions).

In addition to visualizations, a table containing session information was designed in the mockups. However, this was not implemented as the same information was visible in the file name.

The focus shifted from clustering to grouping users based on questionnaire answers. The Groups view was developed to search for multiple sessions by questionnaire answers. Clustering was later planned on for the Charts view which ended up becoming the Histograms view. We developed the clustering code for the graphs but chose not to use it, as development was fast-paced towards the end and quick decisions to cut features were needed.

In the design phase, we discussed dividing the heat map visualization to squares which would have numeric values, so the presentation wouldn't rely on ambiguous and accessibility-wise challenging colours. Traditional heat maps were chosen in the final implementation because this way, it was easier to perceive where the people had been on the map.

We planned on having similar grouping options with charts as we had in the heat map and path map visualizations (see Figure 15 in Appendix A). This feature was dropped due to time constrains along with analytics file management directly in the browser.

4.2. Data Analysis and Evaluation

In this section, we will go through the problems that our data, data presentation and its handling may introduce for us. We will also check if our study design questionnaire is reliable.

The main concern for us is whether or not our data representation and the data itself can give us answers which are clear and can help us with different research problems.

4.2.1. Interpreting User Behaviour from Path Data

The first thing that we have to take note of is the path map format, which is used to follow the user's pathing within the Virtual Library (see Figure 8). It is true, that we can now gain information on the paths that most of the participants have taken in our example data, but information about more congested areas is mostly inaccessible due to "noise" provided by blue path lines. This makes fine-tuned information of micro movements of the participants completely unavailable. To get around this problem, we can group users by certain categories or inspect interesting individuals alone when wanting more information on what paths the user takes towards their goal (see Figure 9).

In order to gain information on more congested areas, or attractiveness of certain areas, we are using heat maps instead of path maps (see Figure 10).

First problem with our heat map is its readability, as its color scheme is one of the worst for any kind of color blindness. Moreover, it does not have information about its color scale. This problem is extremely noticeable when we try to compare two different heat maps to each other. As we have generally no ground zero in our analytic base with heat maps, the comparison becomes ambiguous. This could be fixed by taking the most active coordinates within our heat map and making that to be 100% and telling the analysers the points when the color changes from one another.

4.2.2. Scaling and Unit-Related Issues

Flawed scale is present in both heat maps and path maps, as map scaling is done after it has been drawn, this makes it so that the area of individual coordinates is relatively different when comparing to other level formats. For example, levels *Study* and *Main Library* both have the same coordinate lengths, but as the Main Library is bigger than *Study*, the area each jump-coordinate marks is smaller than in the *Study*. This can be avoided by standardizing the coordinate lengths before placing any jump points into the system.

Scale is not the only unit-based flaw here. Neither heat map nor path map have any indication of scale of the units needs to travel to go from A to B. This may give us flawed perception of the length of the path the participant decided to take. This flaw is also reflected in any data charts dealing with unit jumps, making labeling ubiquitous.

4.2.3. Possible Pitfalls

After going trough flaws that definitely do exist in the system, we can now go through possible flaws that may reside within the system, but which may not affect the functionality of it in the long run. First, there exists a small possibility of a rounding error which may affect the placing of the coordinates within the system, but even if it existed, it should not affect the end-results for visualisation. It is also possible that, in the future, when reading the data in JSON format, the JSON reader we have used may function differently, creating complications that need to be fixed, before the Data Visualization tool is usable.

Now that we know that we cannot compare different levels with each other, we should still note that comparing one level with itself with different groups will give us information that we can use to scientifically prove hypotheses. For example, we could compare "Female" group to "Male" group to see if they have different movement patterns or active time in the system. The reason, such a comparison is not done here is plainly due the fact that our example data had no external information, which we would use, making it so that anything we would be able to show would be completely artificially made.

4.2.4. Evaluation of Potential Findings

We can also use the system's heat maps to identify what objects or landmarks, interest different groups. For example the elevator in the Virtual Library should be one of the highly sought places as it functions as an intersection between levels. Mainly we want to get to know if different interactables within the system get the attention they are meant to get.

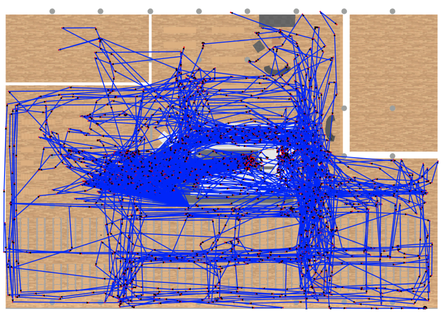

Figure 8. The *Main Library* path map with all users.

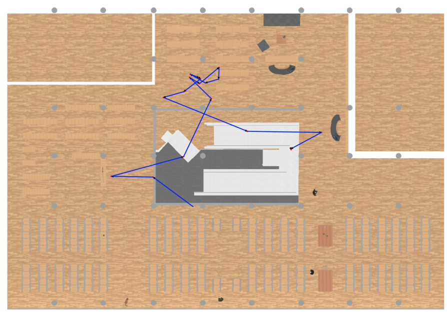

Figure 9. The *Main Library* path map with one user.

Our correlation data charts tracking the user's time within the system, and various aspects about participants' jumps should be effective tools when comparing different user groups and their behaviour within the system. Even if we don't get any correlation or fail to split users to relevant clusters, the discovery of "nothing" is also a discovery in itself.

The findings we have are visualized with scatter plots, which can be shown on the web tool (see Figure 3). In addition, we take histograms to display the distribution of our jump attributes (see Figure 6). These findings are then plotted and are useful for laying out the distribution of some important factors such as how jump count of a participant or group looks like.

When the time between jumps is high, the user may be immersed into the virtual reality or amazed about their environment. It may also tell us that the participant is lost and needs to think their next move, which is not a good sign. It can also tell us that the participant is currently interacting with their environment leisurely. When the time between jumps comes down, it may tell us that the user is able to navigate around and knows what they want and where to get it, which is generally a good sign.

For example, if we found out that when the session length got stretched and jump length started to get longer too, we could find out if it is only in a particular user group in which this kind of phenomena manifests.

4.2.5. Results

Based on the example data, we could conclude that most people do not pay much attention to the environment, which could mean that they are not very interested in the Virtual Library. However, jump count and jump length being high or low alone, cannot give us any comprehensive insight into the participant's experience. An efficient explorer gets to the places where they want with few long jumps whereas an exited explorer stops in between to explore the area. The values thus need to be paired with something else, like session length or time between jumps to gain more insight on how the participant feels about their VR experience.

We plotted histograms, including the total number of jumps, to gain insights on user behaviour (see Appendix C). Most people have the average time between jumps of less than five seconds, total number of jumps of less than 100cm, average jump length of less than 700cm, and session time of less than 1000 seconds. In addition, we calculate the Spearman's correlation coefficients of the attributes mentioned above (see Figure 4).

Table 4. Correlation Coefficients

Attributes	Correlation value
Average jump length and total number of jumps	-0.030
Average time between jumps and total number of jumps	-0.175
Average jump length and session time	0.047
Average jump length and average time between jumps	0.298
The number of jumps and session time	0.374
Average time between jumps and session time	0.377

There are clearly some moderate correlations between the jump attributes. We plotted the two pairs with the highest correlation value. It's often that people with lower number of jumps had shorter session length, and people who took longer time between jumps actually spent longer time on the system. If we first remove all the outliers from the data set, we could have a better result with higher correlation values.

Generally a long session is a good sign in a study where no definite goal is given. However we have to take a note on the fact that different participants take different time to get fed up on bad environment, control schemes or overall feelings. This is usually the reason why session time is paired with some other values to gain a more comprehensive look on the participant's experience.

With how our system is coded, it is currently impossible to precisely note the time, when user decides to stop their participation. thus possibly making the time user spent in the system seem less that it could actually be. This is only a minor inconvenience though, as the researcher can note the end timing to be added for the participants. As for the timed jump data itself, it should be enough to analyse participants interests and behaviour to a certain degree.

The values on Table 5 are all needed for deep analysis of the user's behaviour in any VR environment which uses point-to-jump control schematics. All of the values in the table can be paired with any other value to gain more insight into the participant's experience in virtual reality. These values become even more interesting when paired with a constraint from Questionnaire Data Format to create multitude of groups which may have different behavioural patterns (see Table 3).

Table 5. Data Analytics

A	Total # of users	ppl.
B	Average Jump Length	cm
C	Average # of Jumps	num.
D	Average Time Between Jumps	mm, ss
E	Average Time Spent in System	mm, ss

Table 6. Data Format

Name	Value	
Teleport	Location	DateTime
BeginLevel	LevelName	DateTime
Interact	Target	DateTime

5. DISCUSSION

This section discusses the findings presented in the previous section and introduces suggestions for future work.

5.1. Experiment and Questionnaire

When data is digitized, human errors in data transfer can affect the validity of data. Filling in questionnaires digitally can prevent this kind of mistakes so what the participant has answered can be directly archived and processed (e.g. exported and merged).

The questionnaire options are not always suitable for all users. Adding an "Other" option the user can specify would be helpful in some cases.

The possibility that experience with Virtual Reality and familiarity with cutting-edge technology may affect the results should be taken into account by asking questions about knowledge of current and future technology. Otherwise it may lead us to incorrect correlations or no correlations at all. There also exists a chance that our layout of answer options affects the answers when we ask about events in not-so-recent past.

In the study session, there may be a situation of too few participants or too great of a diversity between participants which may result in no correlations or coherent findings. This can be avoided by making multitude of data-gathering attempts and maybe even focusing on certain groups of people in the session itself.

In future cases, it may also be important to entice the users to move around the Virtual Environment, for example, by hiding interactables around. This way we may get a clearer idea of how the user interacts with an environment that they pay close attention to. It also would eliminate many "idle" cases from the study, idle meaning participants who decide not to execute any jumps and will not provide much data for the study.

Overall, the study session should give us enough information to further analyze it with our system. If the questionnaire is found faulty at some point, the changes to it should be simple enough that the study can be done without complex changes to the system itself. Also, even if our participants act unexpectedly, we should note the behaviour down for the individuals and analyze them as is.

5.2. Data Visualization Tool

One big shortage the system has, is that we have to fill in all search criteria in order to search for analytics in the Groups view. This can be a little too specific, for example, you can't search for age groups without filling in other details.

In the search form, the Room (environment/level) and View (map type) inputs aren't actually related to the search query itself so they could be moved below the Search form. The View input could be replaced with a segmented control as there are only two options. Also, the visualization could update every time the user changes a value without having to press any button to submit changes.

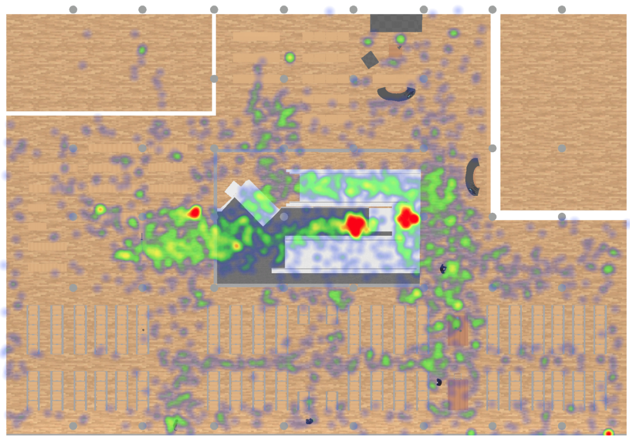

Figure 10. The heat map of the *“Main Library”* level.

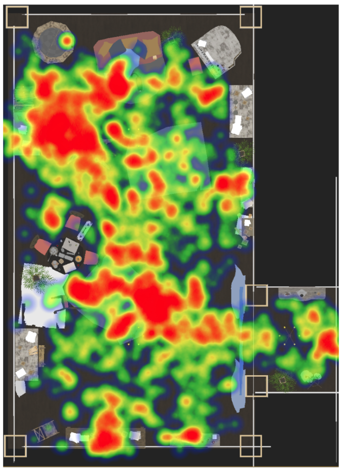

Figure 11. The heat map of the *"Study"* level.

The user can’t select analytics or update histograms in the UI. Instead the user has to use the operating system’s file manager and run the Python file for updating histograms in a command-line interface. The command-line code could be integrated to the web system.

If there is a lot of data, path maps look messy. In addition to accessibility improvements to heat maps (what colours mean and taking colour blindness into account), data presentation could be improved. For example, adding an option for zoom path maps would help to examine micro movements.

5.3. Online System

To gain more enhanced analysis of the environment, we could add certain "beacons" to which we could compare the user’s current positioning. These beacons could be items or memorable landmarks within the Virtual Library. This would allow us to more precisely track users’ decision-making when it comes to navigation in complex or cluttered virtual environments.

Even though our system was running completely on one computer offline, meaning the system itself has all the data and code files it would need, the whole process can be divided to independent applications to be made accessible from anywhere in internet. The Virtual Library would be one part. This part could be made to be downloadable by the end user. The Virtual Library would then be responsible for gathering data of multiple users who have the system.

The storage and server would be another entity. This part would be responsible for receiving data and displaying it for others to see. The visualisation would be done with a website responsible for it. The website would include methods to see all data as one analyzed chunk, get data from a certain user group or focus on one individual. This all would be working online in a cloud-based system. This way, sharing the visualization along with other possible information, such as statistics, would be possible.

After analyzing and collecting the analysis results, they could be integrated to the server itself or used in a front-end web page as an independent entity. If we do this, the whole project could easily be accessible from anywhere and used in conjunction with other projects or systems. This would, however, need some polishing in our server-interface and communication documentation.

6. CONCLUSIONS

Originally our aim was to conclude research on user behaviour in the Oulu Virtual Library application, but due to the COVID-19 pandemic, we had to change our focus from user research to designing and implementing a tool for researchers to analyse similar data sets as our example data.

Even though we could not draw any conclusions from collected data due to the COVID-19 pandemic, as our Data Visualisation tool has been assembled, we can use it with relative ease when dealing with similar data cases in the future. Our tool still needs usability improvements and real-world user feedback to make it a robust data analytics and visualisation tool for future research. However, the existing features, such as heat maps and path maps, are working, despite their shortcomings and can be adapted to different needs with only minor tweaks.

Our example study case can be done as is, or with more concrete constraints in the future, and our Data Visualisation tool is ready to be used and adapted for new data. We use clustering algorithms and analytical functions to take a more comprehensive look on test participants' behaviour with our Data Visualization tool. This behaviour is then presented for researchers to draw their conclusions and decide their hypothesises using different path maps, heat maps and data charts.

7. REFERENCES

[1] Pouke M., Ylipulli J., Minyaev I., Pakanen M., Alavesa P., Alatalo T. & Ojala T. (2018) Virtual library: Blending mirror and fantasy layers into a vr interface for a public library. In: Proceedings of the 17th International Conference on Mobile and Ubiquitous Multimedia, MUM 2018, Association for Computing Machinery, New York, NY, USA, p. 227–231. URL: https://doi.org/10.1145/3282894.3282927.

[2] Moloney J., Spehar B., Globa A. & Wang R. (2018) The affordance of virtual reality to enable the sensory representation of multi-dimensional data for immersive analytics: from experience to insight. Journal of Big Data 5.

[3] Data Visualization and Visual Analytics Are Not the Same – Know the Difference. URL: http://www.ascentt.com/data-visualization-and-visual-analytics-are-not-the-same-know-the-difference/. Accessed 25.1.2020.

[4] Kovalerchuk B., Kovalerchuk B. & Schwing J. (2004) Visual and Spatial Analysis. Springer.

[5] Keim D.A., Mansmann F., Schneidewind J., Thomas J. & Ziegler H. (2008) Visual analytics: Scope and challenges. In: Visual data mining, Springer, pp. 76–90.

[6] Van Wijk J.J. (2005) The value of visualization. In: VIS 05. IEEE Visualization, 2005., IEEE, pp. 79–86.

[7] Kielman J., Thomas J. & May R. (2009) Foundations and frontiers in visual analytics. Information Visualization 8, pp. 239–246.

[8] Keim D., Andrienko G., Fekete J.D., Görg C., Kohlhammer J. & Melançon G. (2008) Visual analytics: Definition, process, and challenges. In: Information visualization, Springer, pp. 154–175.

[9] Alonso-Fernández C., Calvo-Morata A., Freire M., Martínez-Ortiz I. & Fernández-Manjón B. (2019) Applications of data science to game learning analytics data: A systematic literature review. Computers & Education , p. 103612.

[10] Al-Najdawi N. (2007) Introduction to visualization using game engines. In: AHRC Methods Network Workshop.

[11] Mat R.C., Shariff A.R.M., Zulkifli A.N., Rahim M.S.M. & Mahayudin M.H. (2014) Using game engine for 3d terrain visualisation of gis data: A review. In: IOP Conference Series: Earth and Environmental Science, vol. 20, IOP Publishing, vol. 20, p. 012037.

[12] Heat map- Wikipedia. URL: https://en.wikipedia.org/wiki/Heat_map. Accessed 9.11.2019.

[13] What Is Heat Map Analysis? What Heat Mapping Is and How to Use It. URL: https://www.impactbnd.com/blog/what-to-know-about-heat-mapping-and-how-to-use-it. Accessed 9.11.2019.

[14] Kriglstein S. & Wallner G. (2014) Plato: A visual analytics system for gameplay data. Computers & Graphics 2014, pp. 341–356.

[15] Bowman B., Elmqvist N. & Jankun-Kelly T.J. (2012) Toward visualization for games: Theory, design space, and patterns. IEEE Transactions on Visualization and Computer Graphics 18.

[16] Gnadlinger F., Heiml M., Kranzer J., Kriglstein S. & Wallner G. (2014) Game user telemetry in practice: A case study. ACM International Conference Proceeding Series 2014.

[17] Bauckhage C., Drachen A. & Sifa R. (2015) Clustering game behavior data. IEEE Transactions on Computational Intelligence and AI in Games 7, pp. 266–278.

[18] Unsupervised VS Supervised Learning. URL: https://towardsdatascience.com/supervised-vs-unsupervised-learning-14f68e32ea8d. Accessed 18.5.2020.

[19] Estivill-Castro V. (2002) Why so many clustering algorithms: a position paper. SIGKDD explorations 4, pp. 65–75.

[20] Bauckhage C., Drachen A. & Sifa R. (2014) Clustering game behavior data. IEEE Transactions on Computational Intelligence and AI in Games 7, pp. 266–278.

[21] Drachen A., Sifa R., Bauckhage C. & Thurau C. (2012) Guns, swords and data: Clustering of player behavior in computer games in the wild. In: 2012 IEEE conference on Computational Intelligence and Games (CIG), IEEE, pp. 163–170.

[22] Riecke B.E., Bodenheimer B., McNamara T.P., Williams B., Peng P. & Feuereissen D. (2010) Do we need to walk for effective virtual reality navigation? physical rotations alone may suffice. In: C. Hölscher, T.F. Shipley, M. Olivetti Belardinelli, J.A. Bateman & N.S. Newcombe (eds.) Spatial Cognition VII, Springer Berlin Heidelberg, Berlin, Heidelberg, pp. 234–247.

[23] Vinson N.G. (1999) Design guidelines for landmarks to support navigation in virtual environments. Institute for Information Technology, National Research Council, Canada, Ottawa, 278–285 p.

[24] Wan X., Wang R.F. & Crowell J.A. (2012) The effect of landmarks in human path integration, vol. 140. ScienceDirect, 7 - 12 p. URL: http://www.sciencedirect.com/science/article/pii/S0001691811002435.

[25] Sitzmann V., Serrano A., Pavel A., Agrawala M., Gutierrez D., Masia B. & Wetzstein G. (2018) Saliency in VR: How Do People Explore Virtual Environments?, vol. 24. IEEE Transactions on Visualization and Computer Graphics, 1633-1642 p.

[26] Rebelo F., Noriega P., Duarte E. & Soares M. (2012) Using virtual reality to assess user experience. Human factors 54, pp. 964–82.

[27] PathMap - GitHub. URL: https://github.com/antont/parse-unreal-analytics. Accessed 18.5.2020.

[28] Wied P., heatmap - source. URL: https://www.patrick-wied.at/static/heatmapjs/. Accessed 18.5.2020.

[29] sklearn - source. URL: https://scikit-learn.org/stable/modules/generated/sklearn.cluster.KMeans.html. Accessed 18.5.2020.

[30] k-means clustering. URL: https://blogs.oracle.com/datascience/introduction-to-k-means-clustering. Accessed 19.5.2020.

[31] Wikipedia contributors (2020), Spearman's rank correlation coefficient — Wikipedia, the free encyclopedia. URL: https://en.wikipedia.org/w/index.php?title=Spearman%27s_rank_correlation_coefficient&oldid=953109044, [Online; accessed 18-May-2020].

[32] Davis S., Nesbitt K. & Nalivaiko E. (2014) A systematic review of cybersickness. In: Proceedings of the 2014 Conference on Interactive Entertainment, IE2014, Association for Computing Machinery, New York, NY, USA, p. 1–9. URL: https://doi.org/10.1145/2677758.2677780.

8. APPENDICES

Appendix A Data Visualisation Mockups:

Appendix B: Virtual Reality Background Survey

Appendix C: Data Charts

Appendix D: Work Allocation

Data Visualization Tool Mockups

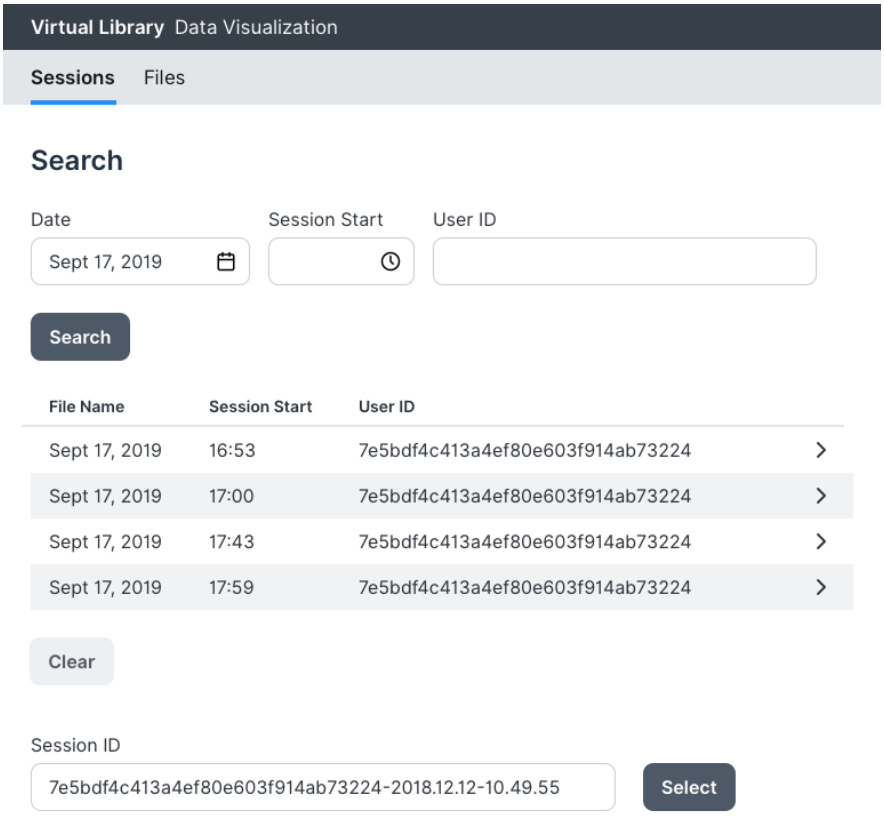

Figure 12. Session search.

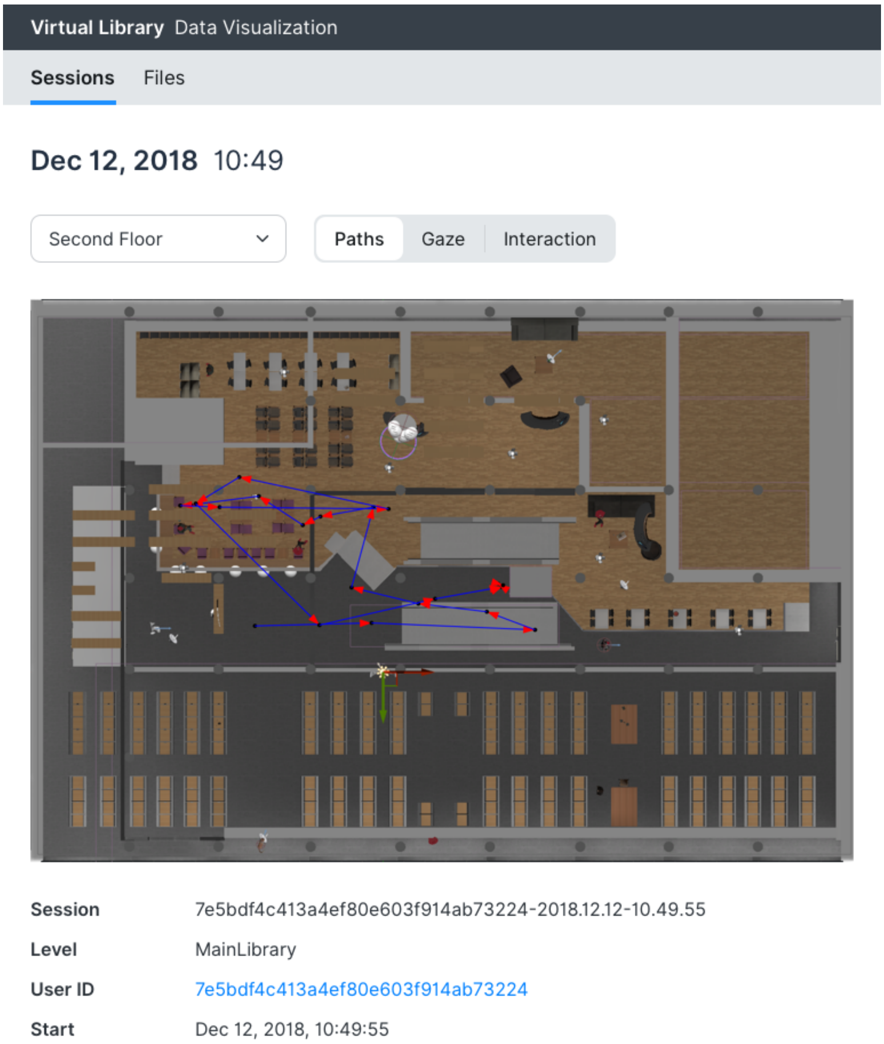

Figure 13. Session view with the Path map option selected.

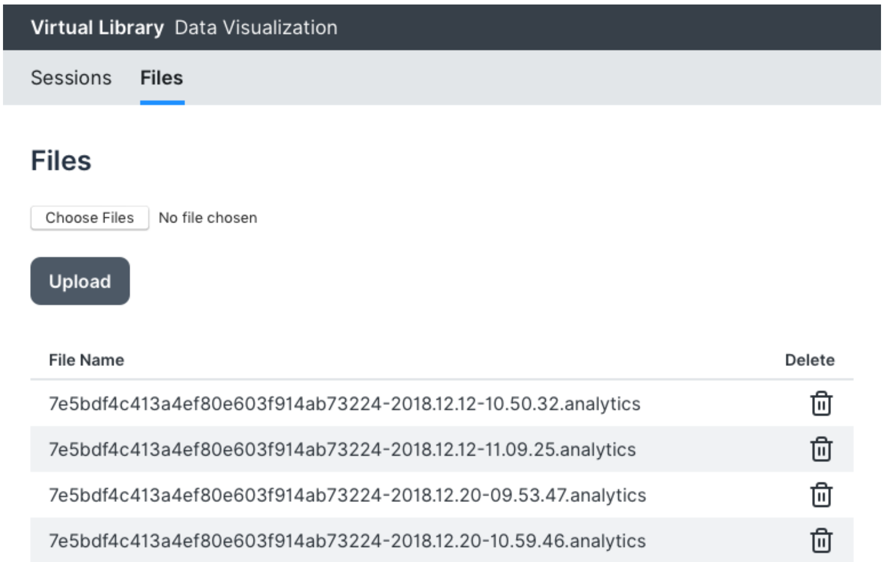

Figure 14. Analytic files can be managed in the UI.

Figure 15. View for charts. The original idea was to have chart groups and individual charts could be filtered based on groups.

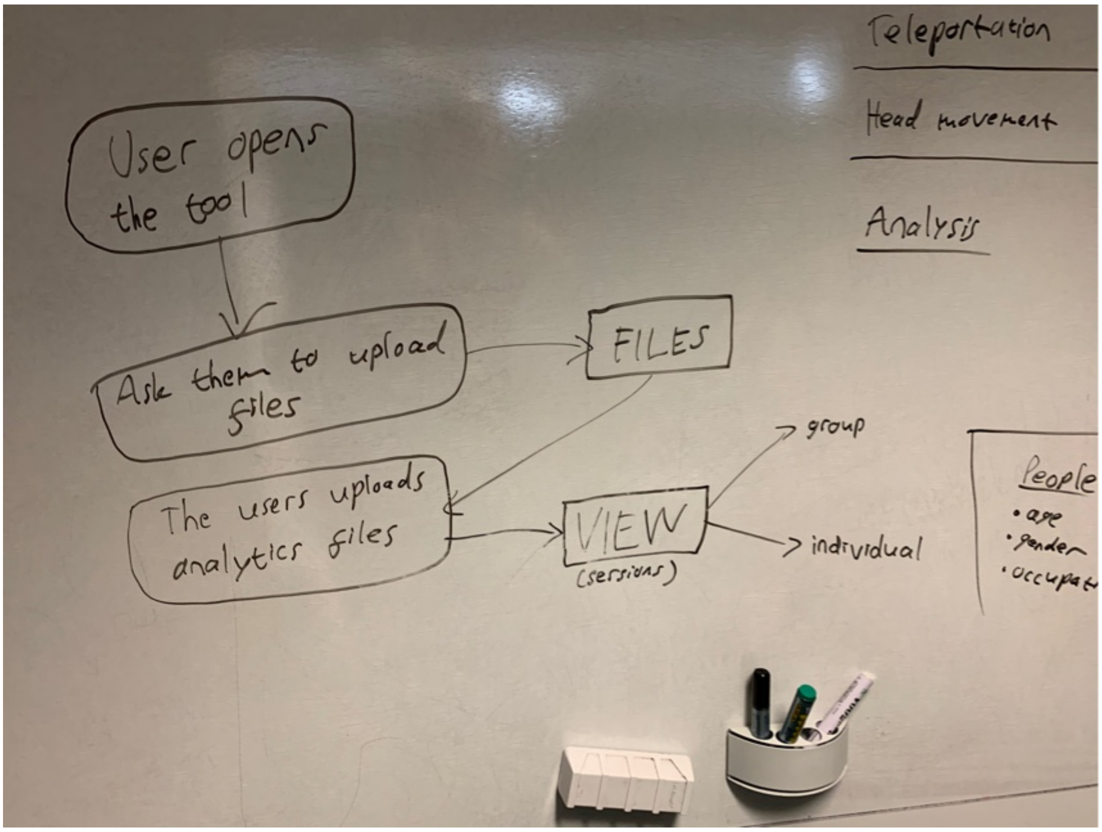

Figure 16. Data Visualization tool flow chart made in the design phase.

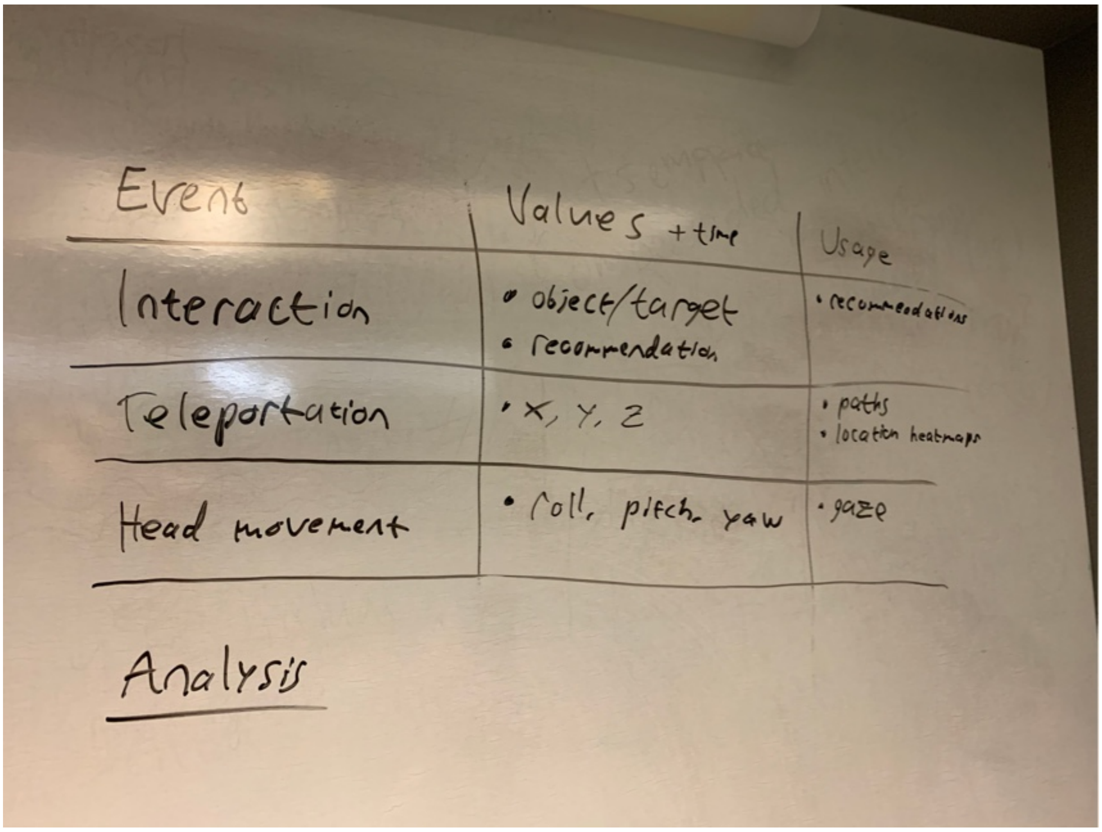

Figure 17. Data types, values and usage for collected data in the design phase.

Virtual Reality Background Survey

Email: ________________________
Date: ________________________
Age: ________________________

Gender:
☐ Male
☐ Female
☐ Prefer not to say

What is your working background?
☐ Working
☐ Student
☐ Unemployed
☐ Retired

How often have you visited Oulu City Library in the past month?
☐ Once (this is my first time in the past month)
☐ Twice
☐ 3–5 times
☐ 6 times or more

What is your experience with Virtual Reality?
☐ I had not heard of Virtual Reality before
☐ I know about it, but have not used VR headsets before
☐ I have once used Virtual Reality Headsets
☐ I own Virtual Reality Headsets

How often do you use Virtual Reality systems?
☐ I don't use VR systems
☐ Once a week
☐ 2–4 times a week
☐ Daily

Virtual Reality Data Charts

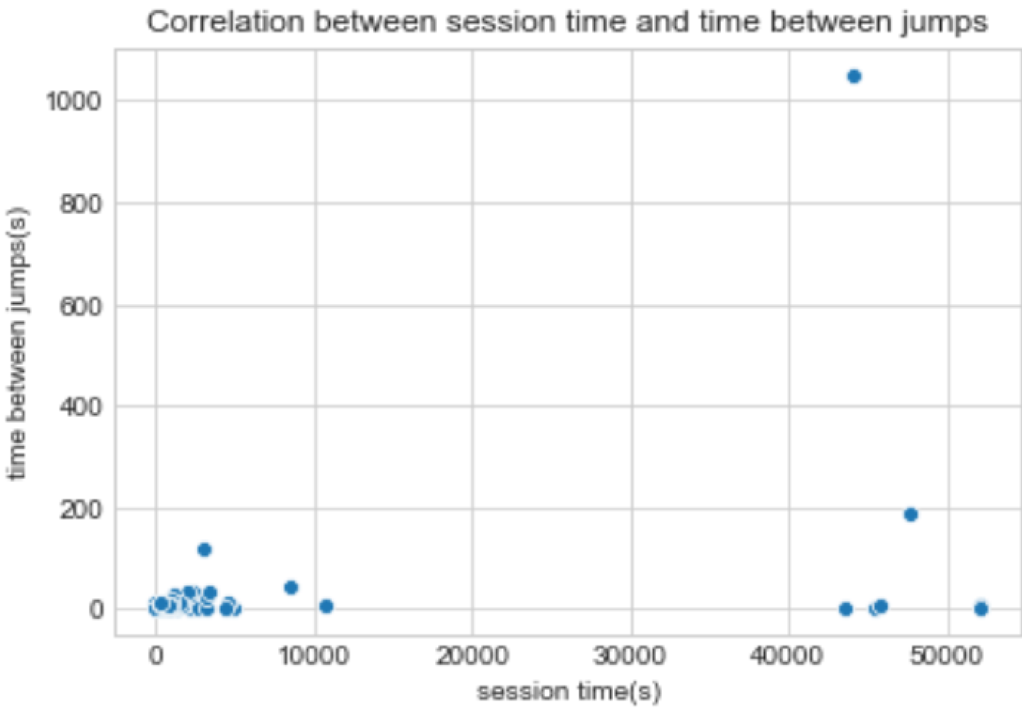

Figure 18. Correlation: Session time and average time between jumps.

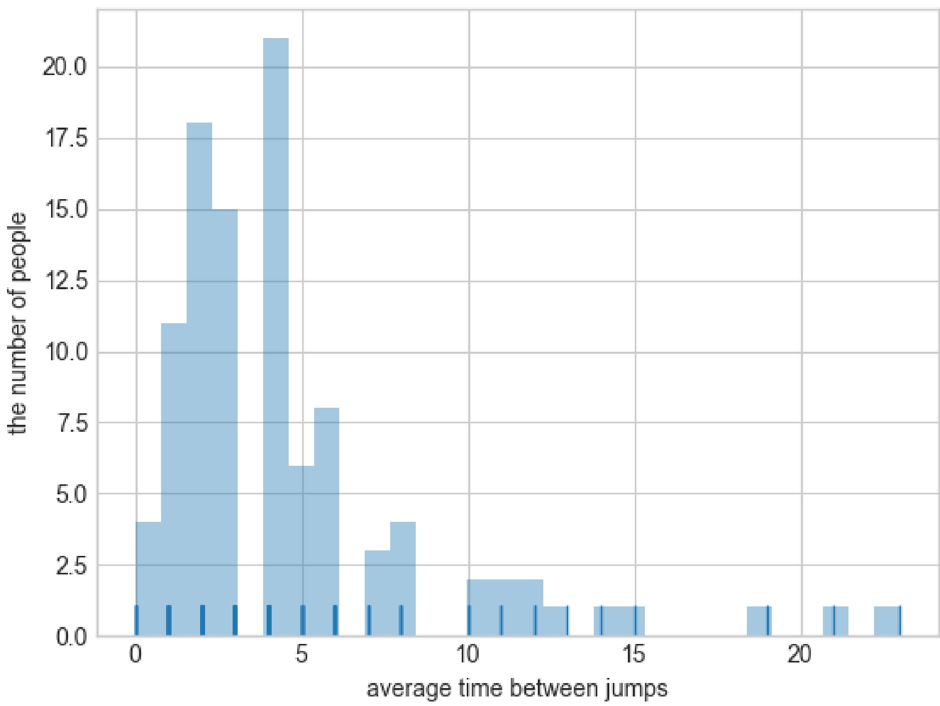

Figure 19. Jump time.

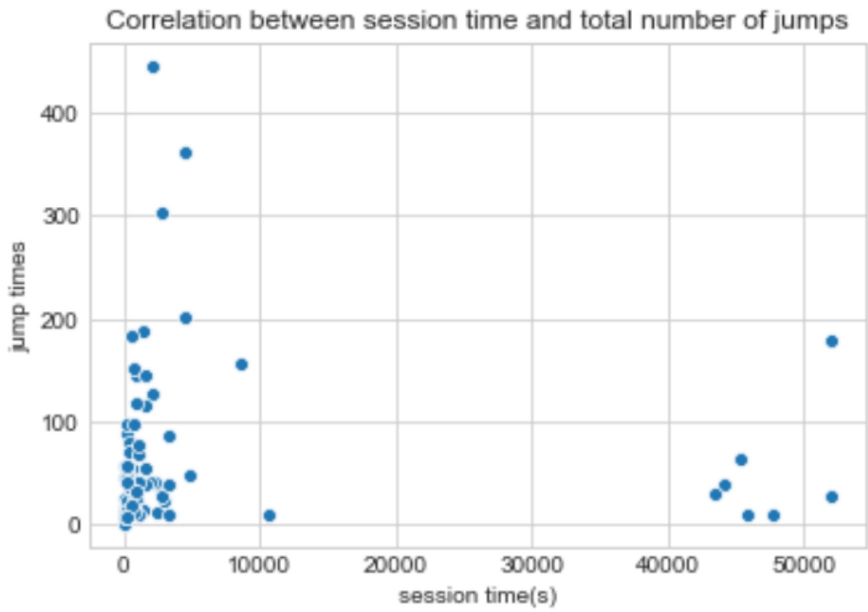

Figure 20. Correlation: Session time and the number of jumps.

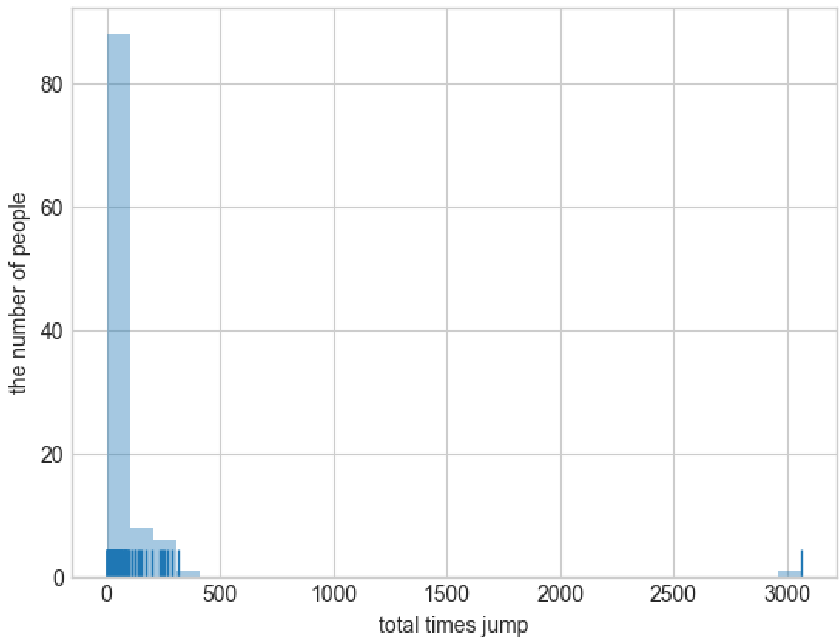

Figure 21. Histogram: the number of jumps.

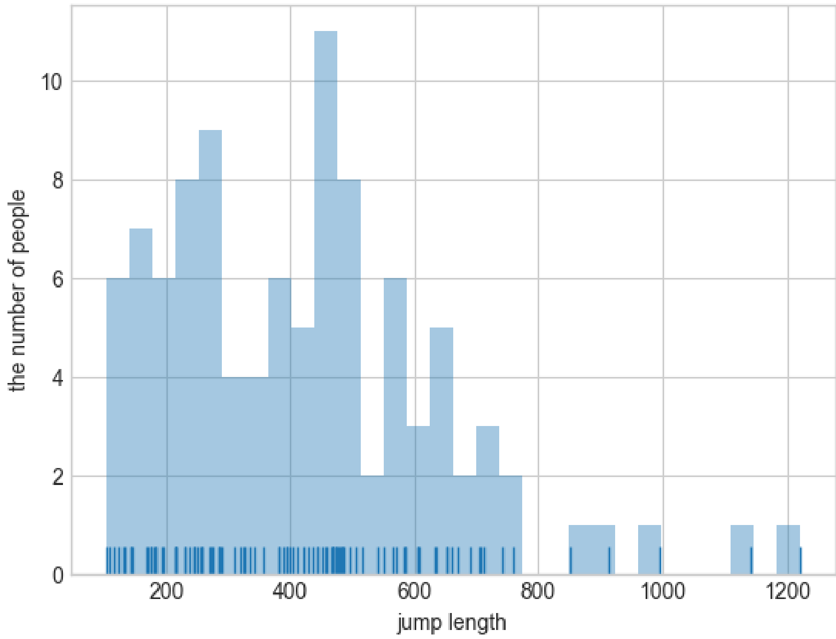

Figure 22. Histogram: average jump length.

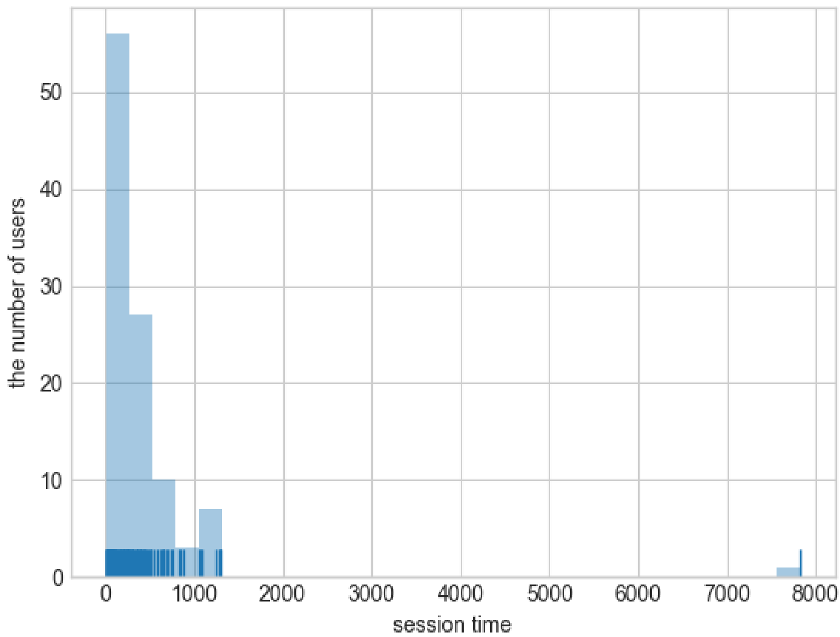

Figure 23. Histogram: session time.

Work Allocation

Table 7. Work Allocation

Researcher	Literature review [h]	Failed-Unreal-Engine [h]	Design and Implementation [h]	Final Deliverable [h]
Sihan	45	0	45	18
Mirko	34	0	56	31
Risto	7	100	175	40