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MASTER THESIS

3D Mixed Reality vs 2D Visualizations: Decision Support for Comparing Financial Data

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Abstract

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3D Mixed Reality vs 2D Visualizations: Decision Support for Comparing Financial Data

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In the financial world a lot of decision-making has to be made based on the different types of data. Although 2D visualization has proven to be useful for decision-making, it still have difficulty comparing multiple large data. Therefore we searched for new and innovative 3D technology and came upon 3D mixed reality.

This research explores the effectiveness of mixed reality visualization in comparison to traditional 2D visualization when selecting an optimal investment strategy. In order to select the optimal investment strategy, users need to compare different portfolios. However, before users can compare the portfolios, they have to find the relevant data and understand the data as well.

For this research we have designed a 3D version of an existing 2D financial decision support system OPAL. We also incorporated various mixed reality interaction into the 3D visualization to help users find relevant data faster. The virtual 3D space of mixed reality was used to give users a bigger viewing space for better comparison of data. To verify our work, we tested users' ability to perform the three tasks with both the 2D and the 3D visualization. The mixed reality HoloLens was used to view the 3D visualization. We measured the speed, accuracy and user confidence for each question they answered. Each question is related to one of the three tasks. We conclude that the overall difference in performance of the 2D and 3D visualization were minimal. The received feedback shows that participants prefer the 3D visualization over the 2D visualization OPAL. The 3D visualization is according to participants enjoyable and fun to use. Furthermore, the 3D visualization also have a higher accuracy in finding relevant data compared to 2D visualization. The mixed reality interaction was not as intuitive as we had initially thought, but participants believe that with better instructions and training that the 3D visualization could surpass the 2D visualization in helping users making better decisions.

Acknowledgements

This thesis would not be completed without the help and advice of many people throughout the process. I would like to take this opportunity to thank them for their assistance and support.

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I dedicate this to my mother and father.

Chapter 1

Introduction

This research project was designed around a case study provided by Ortec Finance. Ortec Finance is a company that provides various products which helps customers with their financial decision-making. Ortec Finance has noticed that customers experience difficulties with decision-making based on financial data. Therefore Ortec Finance has asked us to find a solution for this problem. The problem with financial decision-making is that it requires users to access different type of complex information. In order to make a good decision, users have to compare the pros and cons of the different portfolios. To be able to compare all the different portfolios, users have to know how to find the relevant data of each portfolio and they also have to understand the data as well.

The current 2D decision support system of Ortec Finance named OPAL, supports this decision-making to an extent, but is insufficient in comparing multiple portfolios. Therefore we looked in to 3D technology for solutions as there are growing evidences that 3D technology allows for more complex information to be comprehended (Robertson, Jock D Mackinlay, and Stuart K Card, 1991; Arthur, Booth, and Ware, 1993; Ware and Mitchell, 2008). The search led us to something new and innovative called 3D mixed reality. Mixed reality provides us with a virtual 3D space. Inside the virtual 3D space, more data can be shown without the need of scrolling or page swapping compared to the virtual 2D space. This is beneficial for the users as they can find data quicker due to less interactions are needed. Mixed reality also can blend virtual elements in to our real world, making the virtual element look as real objects. These augmented real objects created by mixed reality not only are engaging, but also has the potential to enhance the understanding of abstract and invisible concepts or phenomena (Mekni and Lemieux, 2014). Furthermore, mixed reality also provides users with intuitive interactions like hand gestures, voice commands and gaze. We believe that these intuitive interactions helps users with their understanding of data as less time has to be spent on figuring out the controls.

We build a 3D visualization based on an existing 2D visualization OPAL. We also conducted an interview and user observation to identify the problems with the 2D visualization. The identified problems were solved with 3D mixed reality technology. The data shown are financial data and users have to choose between certain portfolios.

1.1 Research Questions

The main research question is as follows:

How can 3D Mixed Reality be used to visualize financial data to improve financial decision-making?

For this research we focus on three tasks in order to improve the financial decision making.

Sub-questions:

1. What is the speed, accuracy and user confidence when trying to **find, understand and compare** relevant financial data with 3D Mixed Reality compared to with 2D visualization?

2. What are the differences in speed, accuracy and user confidence between financial experts and novices and the performed task?

The verification of our work involves a combination of qualitative and quantitative research. Quantitative data provides us with strong evidence regarding the effectiveness of visualization through the use of the HoloLens, while qualitative researches provides us valuable insights into the local perspectives of study populations (Mack et al., 2005).

1.2 Contributions

Scientific Contributions
This research demonstrated that even though participants were not familiar with the 3D mixed reality; the 3D mixed reality is still as suitable for comparing financial data as well as 2D visualization, based on speed, accuracy and user confidence.

Practical Contributions
This research contributes to the usefulness of 3D Mixed Reality for companies that use visualization to display financial data.

1.3 Outline

Chapter 2 provides an overview of the reason behind our research regarding 3D visualization. Chapter 3 introduces the user requirements and explains how we have gathered this information. Chapter 4 explains how we designed our 3D visualization based on the user requirements. Subsequently, the experiment with the 3D visualization compared to the 2D visualization regarding the three tasks is explained in Chapter 5. Chapter 6 shows and discusses the qualitative and quantitative results of the experiment. We draw our conclusions about the comparison of the 3D and 2D visualization based on speed, accuracy and user confidence in chapter 7, where we also discuss potential future work.

Chapter 2

Related Work

This chapter explains the relevance of Data Visualization for Decision Support System and gives you an insight on why we want to base our research on 3D Data Visualization.

2.1 Decision Support System & Data Visualization

Decision support system also known as DSS, combines human judgment and the power of computer technology in ways that can improve the effectiveness of decision makers, without intruding on their autonomy (Keen, 1987; Tsang, Yung, and J. Li, 2004). Since 1976 DSS had always been an useful tool for improving decision making of users, especially in the world of financial investment (W. Weber, 2008; Doroudyan et al., 2017). Users can only work effectively and efficiently with a DSS, if good usage of data visualization techniques is applied (T. Li, Feng, and L. X. Li, 2001; Lavrač et al., 2007; Bin et al., 2008). Therefore DSS and data visualization goes hand in hand.

Data visualization is defined by Stuart K. Card, Jock D. Mackinlay, and Shneiderman (1999) as “The use of computer-supported, interactive, visual representations of data to amplify cognition”, where amplify cognition means improvement of the use of knowledge (M. Khan and S. S. Khan, 2011). The power of data visualization lies in the ability to comprehend huge amounts of data into an easy understandable graphic. It provides short-term and long-term memory aid, so that the memory load can be reduced (Shneiderman, 1996). Good data visualization does more than just replacing the words or numbers; they reveal structure, patterns, trends, anomalies, and relationships in data (Tegarden, 1999; Rodriguez and Kaczmarek, 2016). This allows users to spend more time on analyzing the data instead of searching and discovering the data (Grinstein and Ward, 2002). Using data visualization, users can fully harness the knowledge of the data, because of the natural ability of humans to recognize and understand visual patterns (T. Li, Feng, and L. X. Li, 2001).

Wünsche (2004) explains that data visualization consists of encoding and decoding data. The encoding part is called visualization, and describes how data is packed into a clear and informative representation. The decoding part is called visual interpretation, and describes how the representation is unpacked to gain access to all the data within. The decoding part consist of two steps namely perception and cognition. The perception step is about how the visual information is perceived, while the cognition is about how users interpret and derive meaning from the perceived information.

2.1.1 Good Visualization

A fundamental question within the study of visualization is what makes visualization "good" and how can we measure good visualization. An empirically verified theory of good visualization still does not exist yet and a review of literature proved us that this is the case (J. Mackinlay, 1986; Dastani, 2002; Edward R. Tufte, 1986). For this thesis we consider "good" visualization when the decoding part can be performed efficiently and accurately. The two principles used to measure good visualization are therefore efficiency and accuracy (Wünsche, 2004; Zhu, 2007). The accuracy principle focuses on matching the structure of visualization with the structure of data. The efficiency principle tells us that visualization should be easy to understand for the user and improves task efficiency.

2.1.2 3D

Nowadays data visualization comes in two types; one is the standard 2D visualization that we are all familiar with and the second is the less used 3D visualization. Previous research about 2D vs. 3D visualization indicated that 2D visualization is superior to 3D visualization in accuracy of reading data for graphs (Russell and Bielewicz, 2005; Zacks et al., 1998). These studies mostly compare a 2D visualization with pseudo-3D visualization; a 2D visualization made to simulate the appearance of being 3D. We argue that the 3D visualization is heavily limited if it is displayed in 2D as we humans have built-in abilities that evolved from our normal dealings with the 3D world that surrounds us every day. By exploiting this built-in human ability for the 3D visualization, we can create more intuitive and engaging visualization (Arthur, Booth, and Ware, 1993; Ware, Hui, and Franck, 1993).

Furthermore the 2D space is limited if you compare it to the 3D world. The 2D space is mostly limited to the screen that displays it, while the 3D space can extend to beyond that screen. Having more space means we can spread out data in a more clear way instead of compressing it to show the same amount of data. Figure 2.1 shows how cluttered 2D visualization could be when three variables of data are displayed. One could say that by dividing the visualization into two parts the cluttering can be avoided, but there is still a limit in how much the visualization can be divided until the screen is full. In addition dividing data could force the user to scroll or even worse switch from screen. These extra interaction increases cognitive load of the user, which we want to avoid when creating visualizations (Fisher and Pylyshyn, 1994; Massaro, 1985). When it comes to large amounts of data, 3D visualization could give the user a better and clear overview of data compared to 2D visualization.

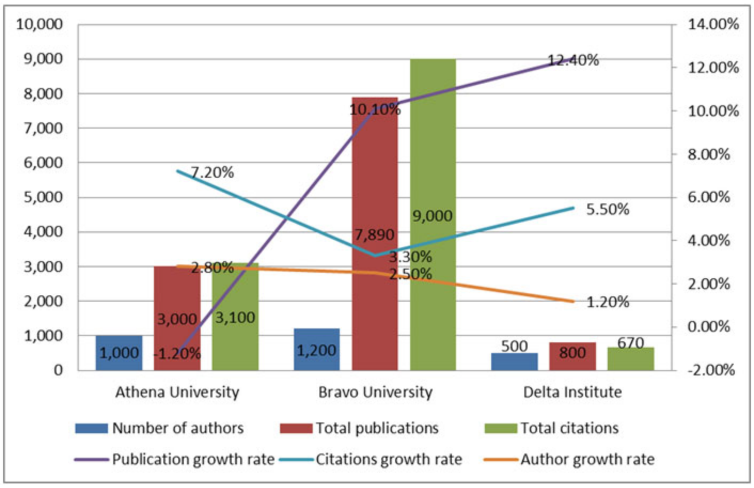

FIGURE 2.1: Bad 2D visualization

It is also proven that users can interpret and remember data better by interacting with data converted into physical object rather than on-screen object (Taher et al., 2015; Gwilt, Yoxall, and Sano, 2012). Although 3D visualization has not been that well developed yet to replicate the tangible feedback of a physical object, it can fully replicate the appearance of it. Our hypothesis is that 3D visualization (not the pseudo-3D) will improve the finding, understanding and comparing process through the use of engagement, intuitive and quantitative.

2.2 3D Data Visualization

The underlying motivation of 3D data visualization is to present data to a user so that he or she perceives and interacts with them naturally. We introduce two 3D visualization methods that allows the user to experience real 3D: 1) virtual reality and 2) mixed reality.

2.2.1 Virtual Reality

A first big step towards 3D visualization would be virtual reality (VR). Using VR glasses, one can enter the virtual world where imagination is the only limitation. Virtual reality gives a user the full 3D experience, unlike pseudo-3D. While using VR glasses one is shut off from the real world, thus the user can only see the virtual world. The reality lock down could be both good and bad at the same time. One could say that lock down of reality gives us full immersion for the virtual world, which increases the engagement of data (Van Dam, Laidlaw, and Simpson, 2002). The downside of reality lock down is of course not being able to see the reality anymore, which could make VR less intuitive. People for example will have to get used to a whole new interaction instead of our trustworthy keyboard and mouse (Sullivan, 2016). The VR glasses are always tethered to a strong computer so creating virtual world on the fly cost a lot of computing power. This forces the user to sit and use a joystick to travel in the virtual world. If the user does decide to walk around, he or she may to watch out for a wire in the real world which is not visible to him or her due to the reality lock down and the limited walking space. Both cases make virtual reality less intuitive.

2.2.2 Mixed Reality

Mixed reality (MR) also known as the enhanced version of augmented reality (AR), brings the virtual world to the real world. Through some sort of hardware, users can see virtual elements projected into the real world, creating a new level of virtual realism. AR involves interaction only between user and computer, whereas MR enhances the interaction of user and computer with environment interaction. Environment interaction gives us the possibility to create a map of the real world and extract data from it. These data can be used to let virtual elements behave according to the environment seen in figure 2.2. The environment data registers the flat surfaces making it possible to let the virtual elements stick to the surfaces seamlessly. Another usage of the environment data is anchoring. Anchoring a virtual element will map it to the global position in the real world, which helps blending the virtual element with the real world. As the user walks around, the virtual element will holds it position and will get closer like in the real world as if you walking closer to the virtual element. These augmented real objects created by MR has the potential to enhance the understanding of abstract and invisible concepts or phenomena (Mekni and Lemieux, 2014).

FIGURE 2.2: Mixed Reality Experience

	Virtual Reality	Mixed Reality
Realistic 3D	✓	✓
Full Immersion	✓	
Real World Interaction		✓
Gaze Interaction	✓	✓
Hand gesture		✓
Keyboard input	✓	✓
Untethered		✓

TABLE 2.1: Virtual Reality vs. Mixed Reality

While both VR and MR can show realistic 3D, MR lets you interact with the real and the virtual world, while VR is only limited to the virtual world. The extra real world interaction helps people understand and remember data better as stated before about converting data into physical object (Taher et al., 2015; Gwilt, Yoxall, and Sano, 2012). The controls used for MR is also more intuitive compared to VR. As you are locked out of reality, standard interaction like with a keyboard cannot be fully used, as it requires the sight of the user. For MR this is not a problem as the user is not looked out of reality. The usage of a keyboard is important, as it is still the most reliable way for text input. Furthermore the primary way of interaction with MR is by hand gesture, whereas VR uses their new designed controller. Our hypothesis is that hand gestures are more intuitive compared to learning how to interact with a new controller. Lesser time spent on figuring out the controls means more time spent on understanding the data. On top of this all, most MR hardware are all untethered, which gives MR more freedom to interact with your environment and room to walk around the virtual elements compared to AR. This prevents the users from falling or getting tangled in cables and as mention before less time fighting with the hardware means more time spend on interacting with the data. To test our hypothesis we will use the HoloLens as our 3D data visualizer, as it a mixed reality hardware, which uses hand gesture and is also untethered.

FIGURE 2.3: HoloLens

Chapter 3

User Requirements

Data visualization, by its very nature, should be user-centered, because by definition it is the process of designing information to match the processing characteristics of the human visual system (J. Zhang et al., 2002a). The way humans perceive and react to the visualization influences the understanding of the input data and its helpfulness. Thus, human factors can contribute significantly to the visualization process and they must have an important role in the design and development of computational tools suitable for data visualization and analysis (Alexandre and Tavares, 2010). In the end, human beings make the final decisions, not the computers (P. Zhang and Whinston, 1995).

3.1 OPAL

OPAL is the financial decision software we use for our case study as requested by Ortec Finance. A typical OPAL usage involves two people: 1) the adviser and 2) the customer. The adviser is the one who operates the OPAL software and the customer is the one who needs to understand the information. Customers who are planning to use OPAL usually have some sort of goal they want to reach within a certain period through the means of investment. Investment always involves some sort of risk and every customer has a different level of risk they are willing to take. OPAL helps the customer to determine the amount of risk they are willing to take in order to achieve their goals. According to the product owner of OPAL, helping customers determining the risks they are willing to take is a very difficult task. The risks in OPAL is determined by choosing between different portfolios. A portfolio contains a strategy for distribution of investments depending on the risk customers are willing to take. For example choosing a portfolio with high risk will increase the feasibility of reaching certain goals, while choosing a low risk portfolio will give the opposite effect. Figure 3.1 shows us the visualization of OPAL where customers have to make a choice between portfolios. The visualization consists of a table and a graph.

FIGURE 3.1: OPAL visualization

3.1.1 OPAL Graph

The graph is used to give an overview of the feasibility of certain goals depending on the portfolios. The x-axis shows the portfolios, the y-axis indicates probability of the goal's feasibility and the circles are the goals. Different colored circles indicate different goals. The graph should help customers understand the different feasibilities of the goals. It also should allow the customer to easily compare the different portfolios depending on the feasibilities.

3.1.2 OPAL Table

The table is used to give more in depth information about the different portfolio for an even better comparison. The table is divided into three parts.

- The first part indicates the feasibility of goals in colors. The colors goes from red being low feasibility to green being high feasibility. This part should let the customer understand the feasibility without focusing the numbers.
- The second part shows the risk in percentages. The annual loss is the money you could lose the first year and the expected return is de estimate gain.
- The last part shows the development of your financial situation at the end of the horizon, which is usually 45 years in the future. It indicates the good,

expected and poor market. The investment return is the expected market indicated in percentages.

3.2 Gather Requirements

To determine the user requirement we conducted interviews and observation. In this section we will explain how we conducted the interview and observation.

3.2.1 Interview

Interviews are among the collection techniques, the most familiar strategy for collecting qualitative data (DiCicco-Bloom and Crabtree, 2006). According to Harrell and Bradley (2009) interviews can be used as a primary data gathering method to collect information from individuals about their own practices, beliefs, or opinions. We have chosen a semi-structured interview rather than a structured interview, because a semi-structured interview gives the flexibility to approach different respondents. Moreover, it offers a chance to explore a particular issue by discussing other questions emerging in the interview (Noor, 2008).

Three semi-structured interviews were conducted about the visualization of OPAL. The people were all from Ortec Finance and have knowledge about OPAL. Every interview consists of a person who is or was an adviser before and one person without the adviser knowledge. This is to gain information about the perspective of both the adviser and non-adviser. The goal of this interview was to find problems with the visualization of OPAL and in which way it can be improved.

3.2.2 Observation

Observation is the process enabling researchers to learn about the activities of the people under study in the natural setting through observing (Kawulich, 2005). Mack et al. (2005) states that observation is a powerful check against what people report about themselves, because what people say they believe and say that they do are often contradicted by their behavior.

We observed three pairs of customers and advisers while they are using the OPAL software. During the observation we focus on the interaction of both adviser and customer with the OPAL visualization. We also take notes of the problems so that we can analyze it in more detail after the observation. The whole process will be recorded so that we can review it later as well.

Problem	**Explanation**
Information Clutter	The visualization contains too much information, which make it hard for the user to find relevant information and thus making it hard to understand the data. Instead of showing all the data in one go, it is better to show them in stages starting from easy to understand data to more complicated ones.
Scattered Information	As result of having too much data to show, users had to scroll and even switch between screens a lot. Scattering information may sever the connection of two data, making it hard for user to compare and understand data.

TABLE 3.1: User Requirement Summary

Chapter 4

Design Rationale

In this chapter we explain how we have designed the HoloLens application which is needed for the experiments. The visualization of OPAL in the HoloLens was created based based on the user requirements in chapter 3. The end product should be similar to the graph in OPAL, so that we can compare the influence of the HoloLens instead of the design influences. Our goal is to create an enhanced graph using elements that only the HoloLens can provide. Please note that the screenshots of our HoloLens application cannot fully convey the real 3D experience of the HoloLens and therefore may look like fake 3D.

4.1 Main Design

4.2 Graph

Graphs are one of the best visualization techniques when it comes to showing complex relationships among multivariate data (Kelly, Jasperse, and Westbrooke, 2005). Graphs are also more intuitive to understand compared to raw data (T. Li, Feng, and L. X. Li, 2001). M. Khan and S. S. Khan (2011) state that there are a lot of graph types that we can choose for data visualization. Each of these graph types has their own advantages and disadvantages. According to Abela (2006), for comparison of data, both table and bar chart are the most suited. Furthermore OPAL also makes use of both these visualizations so for consistency purposes we have chosen for table and bar chart.

Encoding three variables of data in a 2D graph could make the graph more cluttered then necessary, as it only has 2-axis to show the data. Forcing three variables into a graph that usually is made for two variables could confuse the user, as it is not common to see three variables in a 2-axis graph. It is more common to see three variables in a 3-axis graph, where each axis have there own variable. A 2-axis graph has to share an axis with two variables which will confuse the user. Therefore we want to make use of the 3D environment, turning the 2D graph into a 3D graph to decrease the clutter as shown in figure 4.1.

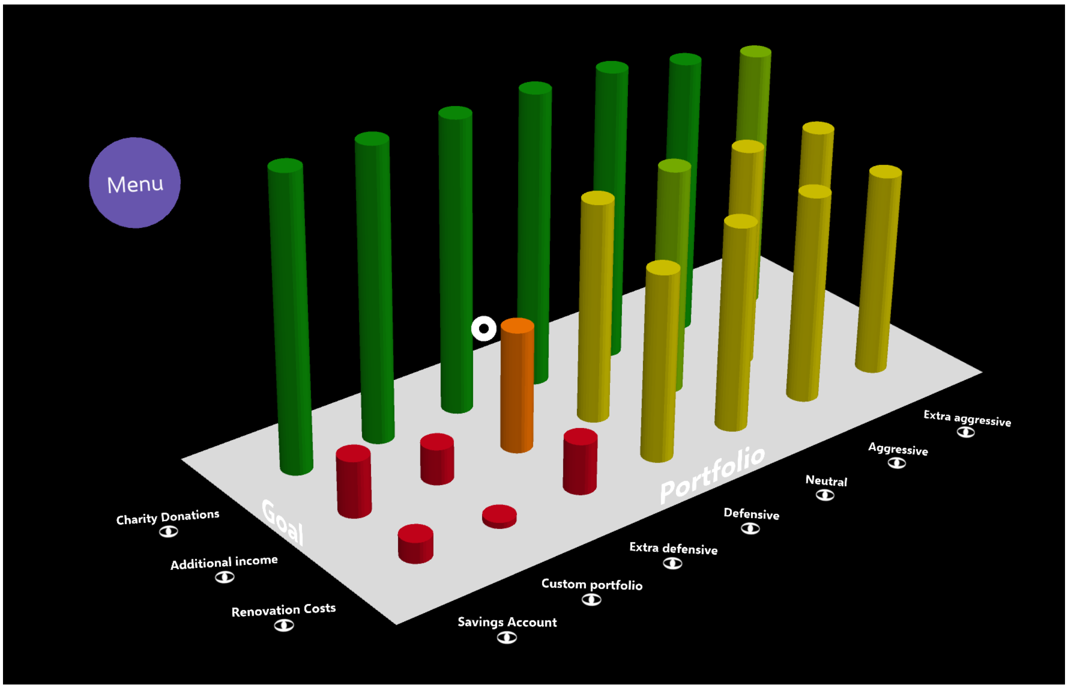

FIGURE 4.1: HoloLens Graph

4.3 Bar

The empty space between the bars of the bar chart should be $\frac{1}{2}$ bar width (Visage, 2014), but putting the bar to close to each other could block the view of other bar. Therefore we changed it to $1\frac{1}{2}$ bar width instead to also avoid the clutter, but not too far so that comparison of data will not be influenced.

All the bars are colored according to the feasibility they are showing. This is so that the user can see which goal has the highest feasibility depending on the different portfolio in one go even without knowing the exact percentages. The exact percentage of the feasibility is shown above the bar. We choose to set the percentage on top of the bar, because that is the only location where the user can see it from every angle except from below. Combined with the fact that the percentage is also set to follow the gaze of the user, putting the percentages on top will give the user a comfortable way to read the percentages.

The bars can also be interacted to show a pop-up with extra information. The best way to associate the bars with the pop-up is using highlights (Yi, Kang, and Stasko, 2007). We also made the cursor change from a dot to a ring shape when it is hovering over the bar. When the bar is pressed ir will further light up and a sound will be played as well to indicate the pressing action.

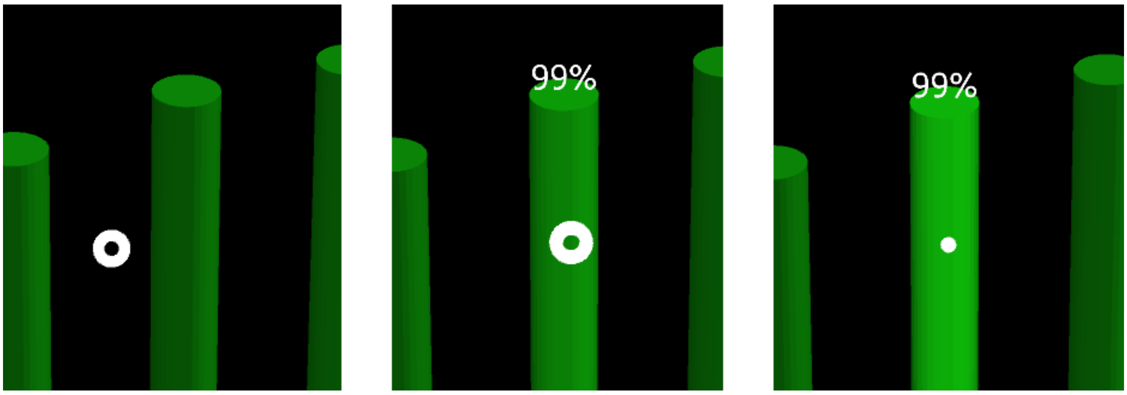

FIGURE 4.2: Left: Not selected or highlighted bar, Middle: A highlighted bar, Right: A selected bar

4.4 Pop-up

As explained in chapter 3, OPAL consists of a graph and a table and both can be seen on one page (depending on the screen size). Having both graph and table on one page will clutter the screen with complex data, making it harder to find useful information (Edward R Tufte, 1990). We removed the table information from sight and only show it when the user asks for it. The user will therefore not be overloaded by information, which allows for better focus on the data (Shneiderman, 1996). During portfolio comparison with the table information it is possible that multiple pop-ups has to be opened. To associate the pop-up with the right bar we connect them with a line. By doing this we also give the user the feeling that the visualization is one whole instead of multiple scattered pieces. We also gave some parts of the pop-up the same color as the bar, to let the user know about the feasibility when choosing for this portfolio. The pop-ups can also be moved in all direction. This could be used to move the pop-up closer for more comfort reading it or putting two pop-ups together for better comparison. The pop-up also automatically rotates towards the user, making it readable from any direction.

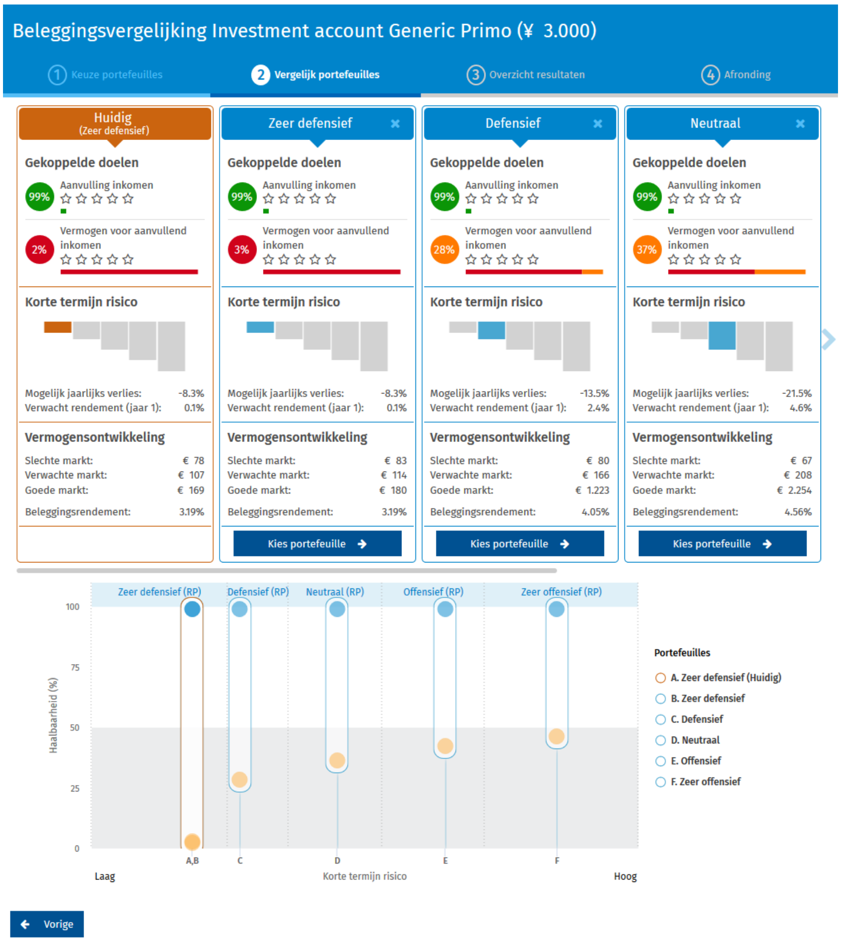

FIGURE 4.3: Complete OPAL visualization for decision making

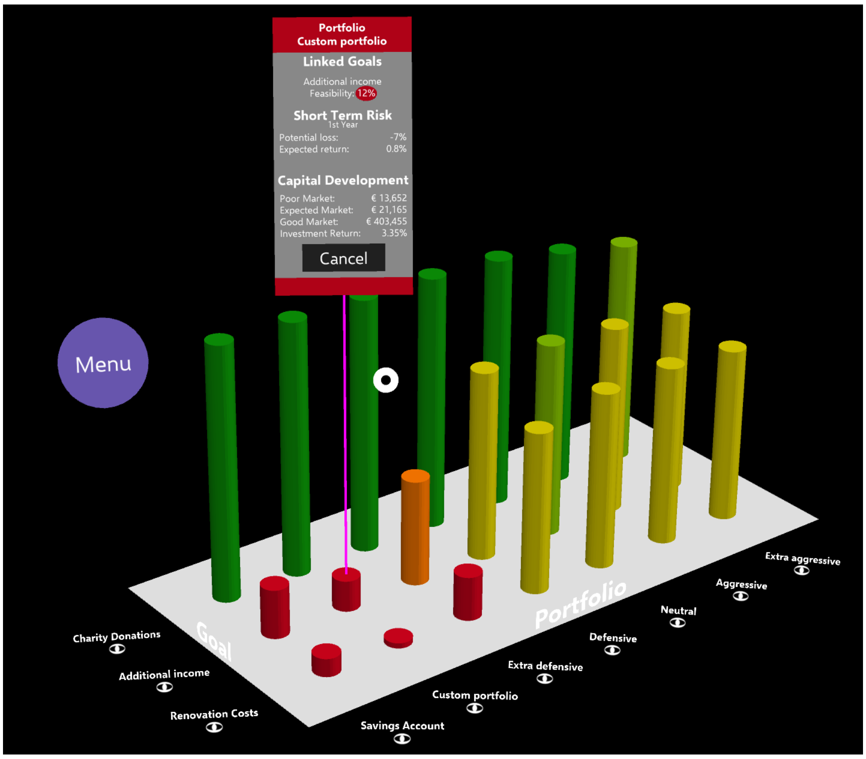

FIGURE 4.4: Pop-up with extra information

4.5 Label

Labels were added to give clarity about the information that is displayed. All labels are displayed horizontally to improve readability. The danger in using labels in a 3D environment is that a label can be seen from a lot of angles, while in 2D environment you are forced to look in a certain angle. This freedom of view angles could prevent the user to see certain labels like in figure 4.5. To solve this, the labels have been made to always rotate towards the user's direction. Now the user can see the label from every angle. Although the labels could be seen from every angle, the view of the labels can be blocked by the bars. To solve this problem we duplicated the labels so that the labels can be seen from both side like in figure 4.6. Unfortunately this was not the best solution as empty spaces were filled with duplicate information, which leads to clutter. Our new solution was that we removed the duplicates and let the labels jump to the right side according to the gaze like in the figure below. To further reduce the clutter, users can hide certain bars if they think it is unnecessary. The "hide" function is indicated with the eye icon below each label. This means that each row can be hidden for a clearer overview.

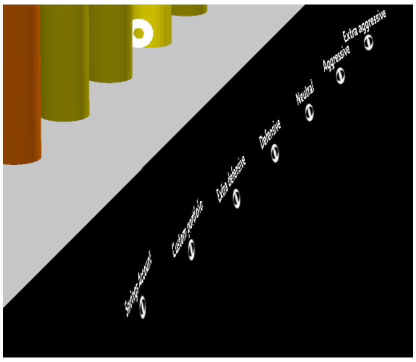

FIGURE 4.5: Unreadable Label

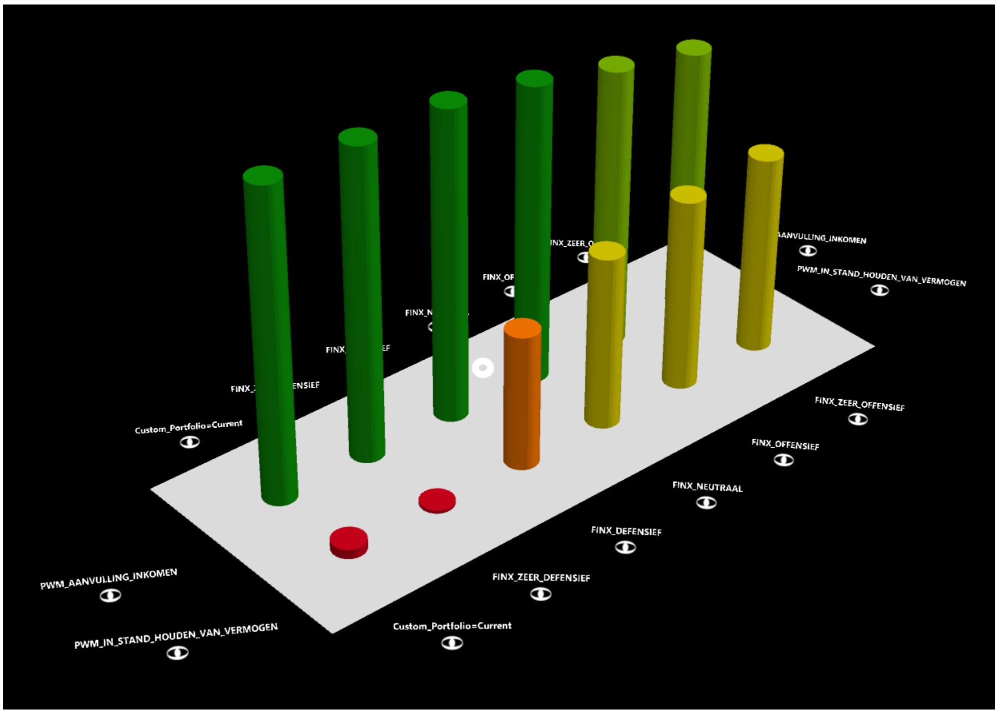

FIGURE 4.6: Duplicate Labels

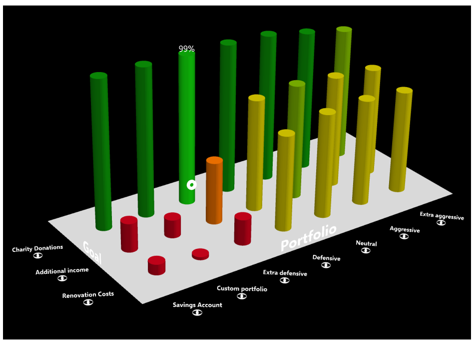

FIGURE 4.7: Front

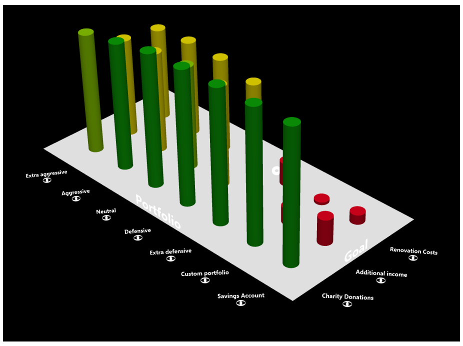

FIGURE 4.8: Back

In principle, these improvements can also be implemented in a 2D graph, but only the HoloLens is able to provide the 3D space and 3D interaction. The 3D space gives the user more room to place information and using the 3D interaction they are able to place the virtual object at their own desired location in the 3D space. Both interactions are more intuitive for a human being compared to a limited 2D screen. Breaking the visualization from the 2D chains could lead to better finding, understanding and comparison of data.

Chapter 5

Implementation

The 3D visualization we created based on the design of chapter 4 can be used to display other data aside from financial data. The application is written in C# code in the Unity environment. For this experiment we connected the HoloLens with OPAL to extract data from it. This is done with OPAL REST calls.

We used the HoloLens "Development Edition" (release year 2016) provided to us by Ortec Finance.

- The following setup was used for the development of the HoloLens application:
  - 64-bit Windows 10 Enterprise
  - 64-bit Intel i7 CPU @ 2.70 GHz
  - CPU with 8 cores
  - 16 GB of RAM
  - Intel HD graphics 530 GPU
- The software we used:
  - The windows 10 SDK
  - Unity 5.6
  - Visual Studio 2015 update 3
  - HoloLens Emulator (build 10.0.14393.1358)
  - Unity Holographic Remoting (HoloLens application)

Chapter 6

Experimental Design

To evaluate if graph-based visualization of the HoloLens can improve the financial decision-making, we conducted an experiment with the two visualizations:

- **HoloLens** visualization
- **OPAL** visualization

The HoloLens visualization is the 3D visualization we designed as explained in Chapter 4. The OPAL visualization is the 2D visualization that Ortec Finance is using for their decision software OPAL. Both visualizations displays data from the OPAL database.

The experiment is conducted based on three tasks related to the first sub-question:

- **Find** relevant data
- **Understand** the found data
- **Compare** two data

The first task solely focuses on looking for the data you are interested in. This also means that you will not have any further interpretation or correlation of that data, as that belongs to the second task. The last task is to integrate multiple data.

We assess the visualizations based on three aspects:

- **Accuracy**: whether a participant's answer was correct.
- **Speed**: time spent on answering the question.
- **User confidence**: the confidence level of the user in their data interpretation 4-likert scale: Absolutely certain — Fairly certain — rather uncertain — Absolutely uncertain

6.1 Questions

For our experiment we used questions to evaluate the visualizations and to gain useful feedback from the participant. This section provides insights about the reasons we have chosen a particular question. The overview of all the questions can be found in Appendix B.

6.1.1 Background Information

Gathering background information of participants provides us with an overview of all the participants we are working with, which depending on the background can influence the data of the experiment. Questions 1 to 5 are standard demographic questions, which are useful to determine the profile of a participant. The last four questions are specific used for our experiment to determine the prior experience in 2D and 3D visualization. Question seven in particular is used to separate the experts from the novices. The 4-likert scale is used instead of the 5-likert scale, to prevent the participant of being neutral all the time.

6.1.2 Experiment

As mentioned at the beginning of this chapter every experiment question requires you to do one of the three tasks: 1) find, 2) understand or 3) compare. The table below explains the basic structure of each question and how the tasks are distinguished.

Task	**Related Question**	**Explanation**	**Example Question**
Find	Q1, Q2, Q3, Q4	This task requires participant to find a certain portfolio, goal or even both by looking at the feasibility. The questions are designed to be simple and solvable without any prior knowledge of OPAL. Participants can just find and match the term from the question with the one in the visualization to get the answer.	What is the probability of a portfolio given a goal?
Understand	Q5, Q6, Q7	This task introduces a use case where a single portfolio is given. The participant needs to find the answer by understanding the data displayed by the visualization. The use case consists of questions about Capital development and Short-term risk. Instead of using the term that is displayed in the visualization we give an explanation of it. By doing this we force participant to understand the task in contrast to the find task. Prior knowledge of OPAL is helpful when answering the questions, but not essential.	Given a portfolio, how much money will you end up with at the end of the horizon?
Compare	Q8, Q9, Q10, Q11	The task introduces a use case where multiple goals or portfolios are given. This task forces the participant to look at the multiple goals or portfolios by comparing the given criteria in the use case. The criteria are based on Capital development, Short-term risk and feasibility. Prior knowledge of OPAL is helpful when answering the questions, but not essential.	Given multiple portfolio, which one suit you the best if you want to satisfy your list of criteria?

To avoid anchor bias of the experiment questions we created two sets of questions. Both sets can be used for either visualization as the questions are quite similar to each other.

6.1.3 Feedback

After each usage of the visualization, we let the participant fill in feedback questions about the visualization they just worked with. The questions are based on the System Usability Scale method from Brooke (1996). The participant can choose from the 5-likert scale answers: I strongly disagree — I disagree — I neither agree nor disagree — I agree — I strongly agree. We also added an extra question about the fun factor of visualization. According to Patterson (2016) having fun with the visualization will improve the data engagement.

6.1.4 Comment

These questions are used to give the participant some idea's to fill in the comment section. Beside these questions we also created some questions on the fly based on the participant observation. This way we gain extra data, which we did not specifically asked for during the experiment, but may still be useful for our experiment.

1. Were the questions clear?
2. Were the terminologies clear?
3. Do you have any suggestions for improvement?
4. What did not go well?

6.2 Experimental Setup

The experiment was conducted in a room where the lighting depends on the light in the room and not the sun. Using the sun as lighting may influence the data gained from both the graphs. The room had also enough space to move around in. Aside from the HoloLens, two laptops were used; one to display the OPAL graph and one is used for answering the questions. All the questions used for this experiment can be found in the next section.

Most of the time participants will have to fill in the answer themselves. Only during the interaction with the two visualizations, will the experimenter fill in the answers as instructed by the participants. This helps them focus better on the visualization and also speed up the experiment.

We divided the participants into two groups:

- **Experts**
- **Novices**

We assume that experts have an advantage with using the OPAL software and therefore could influence the data. For this reason we separated the experts from the novices. Expert participants are mostly people working at Ortec Finance. We let every participant interact with both visualizations during one session. We think that a participant can compare the two different visualizations better if they have interacted with both of them. To prevent an anchor bias, half of each group saw HoloLens visualization first, resulting in four groups:

- **Experts** with both visualizations, **HoloLens** visualization first
- **Experts** with both visualizations, **OPAL** visualization first

- **Novices** with both visualizations, **HoloLens** visualization first
- **Novices** with both visualizations, **OPAL** visualization first

6.3 Experimental Layout

The experiment was carried out as follows:

1. Experiment Introduction
2. Background information questions
3. One of the two visualization
   (a) Show the visualization and let them answer questions based on the visualization
   (b) Feedback
4. The other visualization
   (a) Show the visualization and let them answer questions based on the visualization
   (b) Feedback
5. Comment

(1) Before the experiment starts, an introduction is given followed by a background information question list. The introduction explains the research goal and the reason for this experiment. The introduction also indicates the number of questions and time the experiment will take.

(2) The background information gave us more insight about the background of the participant we are working with.

(3,4) During the experiment each participant is asked to perform the three tasks with both the visualizations. The experiment starts with scenario explanation, which allows the participants to familiarize themselves with a given situation. After that the visualization was shown to the participant with a paper questionnaire. If the participant is a novice OPAL user, a terminology list was given along with a short explanation about OPAL. All the materials that the participant received can be found in Appendix A. For each question the participant is asked to read the question, look at the visualization for the answer, give the answer and the confidence of their data interpretation. After answering all the questions the participant is asked for feedback about the visualization they just used. A similar set of questions for the second visualization is then presented. At the end of the experiment there is room for comments. If participants are not sure what to write the experimenter will ask some questions to help them. Before starting with the HoloLens experiment, we allowed participants to familiarize themselves with the interaction of the HoloLens. Users who are unfamiliar with the HoloLens may experience difficulties in using the HoloLens and therefore a short introduction session of 5 to 10 minutes is used to train them.

(5) A semi-structured interview was conducted to help the participant with the comment section.

Chapter 7

Results & Discussion

We have gathered 30 participants in total to experiment with the HoloLens visualization as well as with the OPAL visualization. From the 30 participants 17 were experts and 13 were novices. The gathered background information from the participants can be found in appendix C. On average the HoloLens has an accuracy of 94% and OPAL has 91%. The HoloLens visualization has a slightly higher accuracy, but the difference was not significant (p=0.4292). The same goes for speed as the HoloLens had an average speed of 47 seconds for each question and OPAL has 38 seconds. OPAL is slightly faster however the difference was still not significant (p=0.4177). As for the user confidence there is no significant difference (p=0.7618). Of all the correct answers, 78% of the HoloLens participants were absolutely certain of their answer and for OPAL it was 77%. We used one-way ANOVA for the statistical analysis with $p<0.05$. Our data are normal distributed and one-way ANOVA is a good test for finding differences between two or more groups.

7.1 Quantitative Result

While there was no significant difference in general, it is still beneficial to look into the data per question. This section shows the results of the HoloLens visualization compared to the OPAL visualization and also shows the comparison of experts and novices. For each of these comparison we will discuss the result at the end. The result of each comparison is discussed at the end of the section.

7.1.1 HoloLens vs OPAL

Accuracy

Figure 7.1 shows the average percentage of participants that gave the correct answer. This percentage is shown per question for both HoloLens and OPAL. We see that the HoloLens has a slightly higher accuracy when it comes to the **find** questions. Especially for question 2 the HoloLens is significant more accurate than OPAL (p=0.0022). The accuracy of both visualization were quite similar for the **understand** questions, except for question 5. For question 5, OPAL was significant more accurate than the HoloLens (p=0.0225). For the **compare** questions, the accuracy of both visualization was quite similar and there was no significant difference among the visualizations.

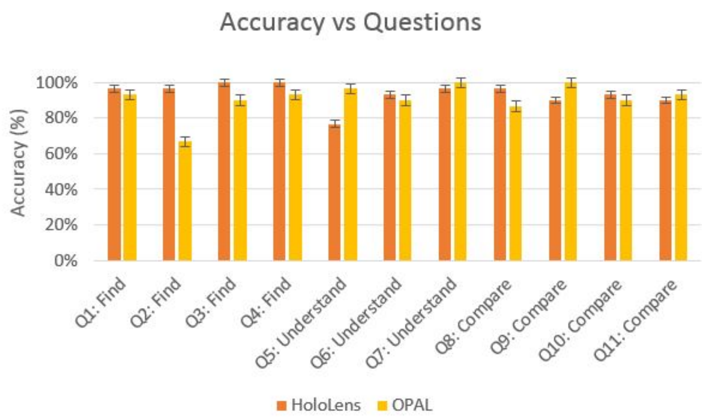

FIGURE 7.1: The percentage of correct answered question among all participants

Speed

Figure 7.2 shows the average time that is needed for answering a question using either the HoloLens or OPAL. We can see for the **find** questions that the speed of HoloLens was slightly faster than the OPAL. There was no significant difference in speed between the two visualizations with regard to the **find** questions. The **understand** questions were in favor of OPAL, especially for questions 5 and 6. OPAL was significantly faster compared to the HoloLens for questions 5 and 6 (p=0.00003 and p=0.0003 respectively). For the **compare** questions OPAL was again faster than the HoloLens. Question 10 and 11 shows that OPAL was significantly faster than the HoloLens (p=0.0021 and p=0.0043 respectively).

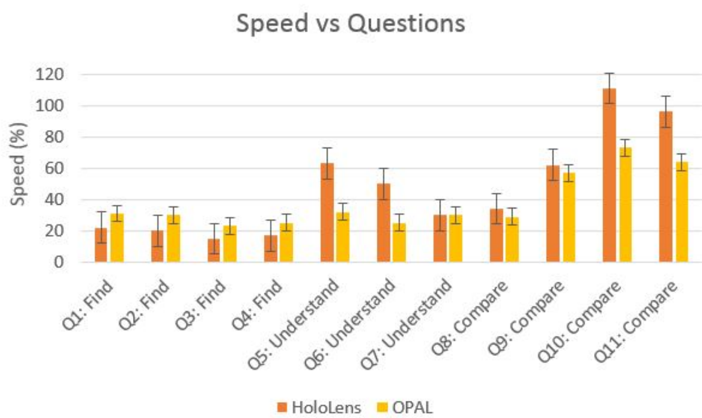

FIGURE 7.2: The average time needed to answer questions

User Confidence

Figure 7.3 shows for each question which percentage of the participants that had given the correct answer were absolutely certain of the given answer. Among the **find** questions, participants with the HoloLens were slightly more confident in their answer compared to the OPAL participants. Questions 1 and 2 shows a bigger difference among the two visualizations, but none of the differences were significant (p=0.079 and p=0.084 respectively). For the **understand** questions, the two visualizations were quite similar to questions 5 and 6 which cancels each other out. OPAL had an overall higher user confidence compared to the HoloLens for the **compare** questions. The biggest difference was found in question 10 and 11, but the differences were not significant (p=0.061 and p=0.2097 respectively).

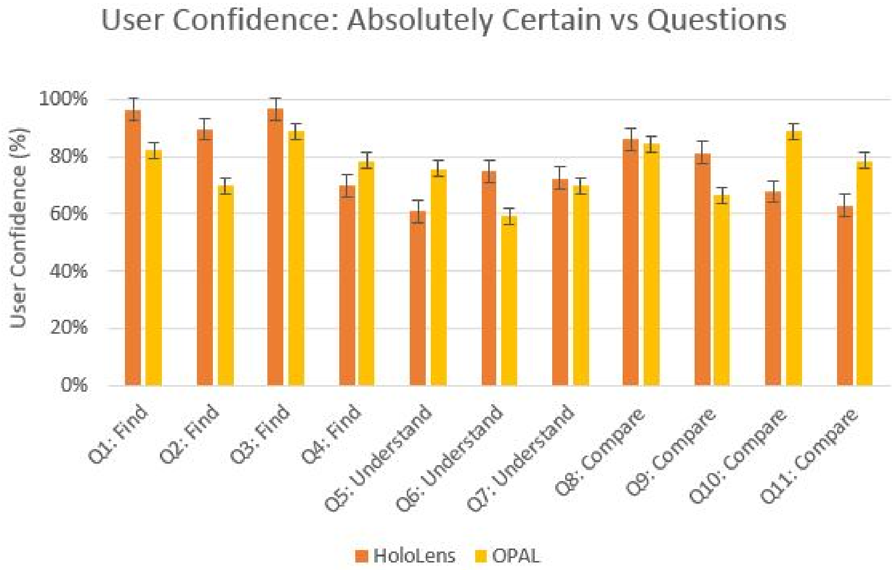

FIGURE 7.3: User Confidence with HoloLens and OPAL

Discussion

The **find** questions were more in favor of the HoloLens. We think that the reason for this is that the HoloLens visualization had a clearer overview compared to the visualization of OPAL. This problem is mostly caused by the way it is designed, but there are some cases where we think design was not the problem. One of the **find** question requires participant to click on the arrow button for more information. Some of the participants did not noticed the arrow and with the lack of information participants could not answer the question correctly. This was the reason for the significant lower accuracy of OPAL for question 2. The HoloLens did not have the accuracy drop and therefore we could conclude that extra viewing space helped participant providing a better and clearer overview of data. We also think that the slightly faster speed and higher user confidence is due to the improved overview, where participant could see all the data in one go without clicking for more.

The **understand** questions were more in favor of OPAL. We think this is because of the unfamiliar interaction of the HoloLens. Every **understand** question required the user to click on the bar for more information. Apparently the interaction of HoloLens is not intuitive enough as some participant did not know that clicking the bar provides extra information. This could be the reason why the accuracy of the HoloLens was significantly lower for question 5. The speed of HoloLens was significantly lower for questions 5 and 6, also indicating that the interaction of HoloLens was indeed not intuitive and therefore participant needed more time to answer the **understand** questions. Although the interaction of HoloLens was not intuitive, we could see that people get used to the HoloLens quite fast at the last **understand** questions, where there was no significant different between the visualization. From this we can conclude that the HoloLens interaction is not as intuitive as initially thought, but participant could get the hang of it quite fast.

The **compare** questions were also more in favor of OPAL. We believe that it lies in the design of the HoloLens visualization. The **compare** questions require participants to compare multiple portfolios. For participants with the HoloLens to answer **compare** questions, they have to click on multiple bars for more information. Clicking multiple bars requires a lot of time and that is why the HoloLens was significant slower for questions 10 and 11. Furthermore users may have been confused by the multiple bars and pop-ups, which could have decreased their confidences in the given answers.

7.1.2 Expert vs Novice

Accuracy

Figure 7.4 shows the average percentage of expert and novice participants who gave the correct answer. This percentage is shown per questions for both HoloLens and OPAL. For the **find** questions the novice OPAL participant were slightly more accuracy than their expert counterparts, especially for question 2 there is a big difference. Although the difference is not significant (p=0.3139). For the HoloLens participant the accuracy of both experts and novices were quite similar. There were no big difference in accuracy for the **understand** questions aside from question 5. In questions 5 the novices has a higher accuracy than the experts for both visualizations. The differences between experts and novices were the biggest for the HoloLens participants, although not significant (p=0.0813). For the **compare** questions, question 10 has some note worthy differences. In both visualization the experts had a lower accuracy compared to the novices, but both cases were not significant (HoloLens p=0.2139) and (OPAL p=0.1181)

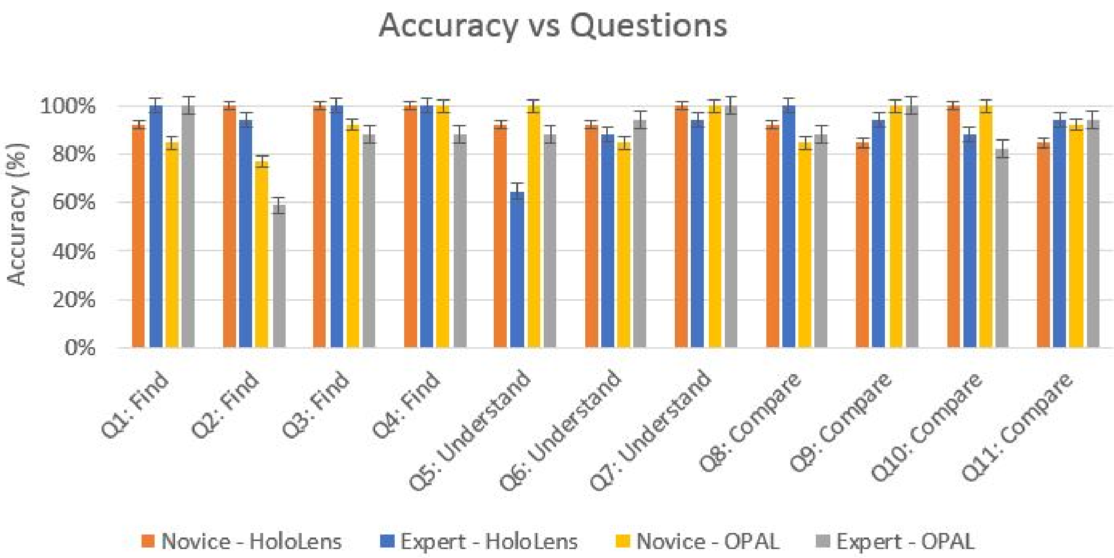

FIGURE 7.4: The percentage of correct answered question among novices and experts

Speed

Figure 7.5 shows the average time that is needed for answering each question by expert and novice participants for both HoloLens and OPAL. Question 1 of the **find** question is note worthy. We can see that novice OPAL participants spend a long time answering the question, compared to expert OPAL participants. The difference was significant (p=0.0059). For the **understand** questions, the biggest difference can be found at question 5 and 7 for the OPAL group. Question 5 shows that experts was significantly faster in answering the question compared to novices with the OPAL visualization (p=0.0418). Question 7 also shows that experts were faster than novices but the difference was not significant (p=0.1670). The speed of **compare** questions were overall the same between experts and novices beside question 8 and 10. Question 8 shows that the novices were significantly slower than the experts for the HoloLens group (p=0.0053). Question 10 also shows that the novices were slower than the experts but this time for the OPAL group and it is not significant (p=0.0559).

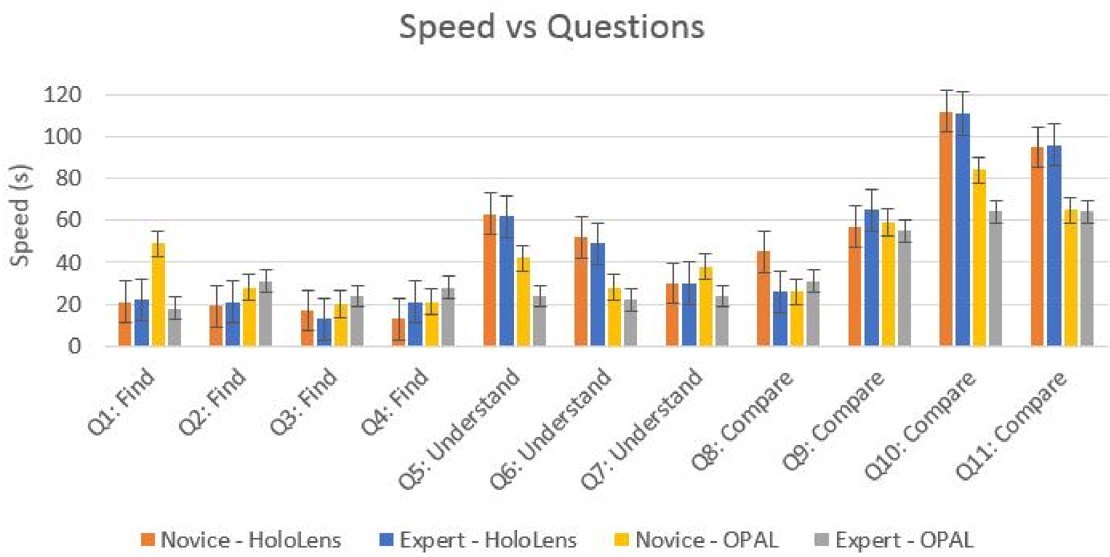

FIGURE 7.5: The average time needed to answer questions among novices and experts

User Confidence

Figure 7.6 shows per question which percentage of the participants that had given the correct answer were being absolutely certain of the given answer comparing experts and novices. For the **find** questions we can see that in general experts have more confidence in their answers in comparison to novices no matter the visualization. Only at question 4 do we see the opposite where novices have more confidence in their answer compared to the experts (p=0.1355). Again the case that experts were more confidence than novices is also the same for the **understand** questions. Only at question 6 does the novices have more confident, but it is only slightly. The **compare** questions were all in the favor of the experts.

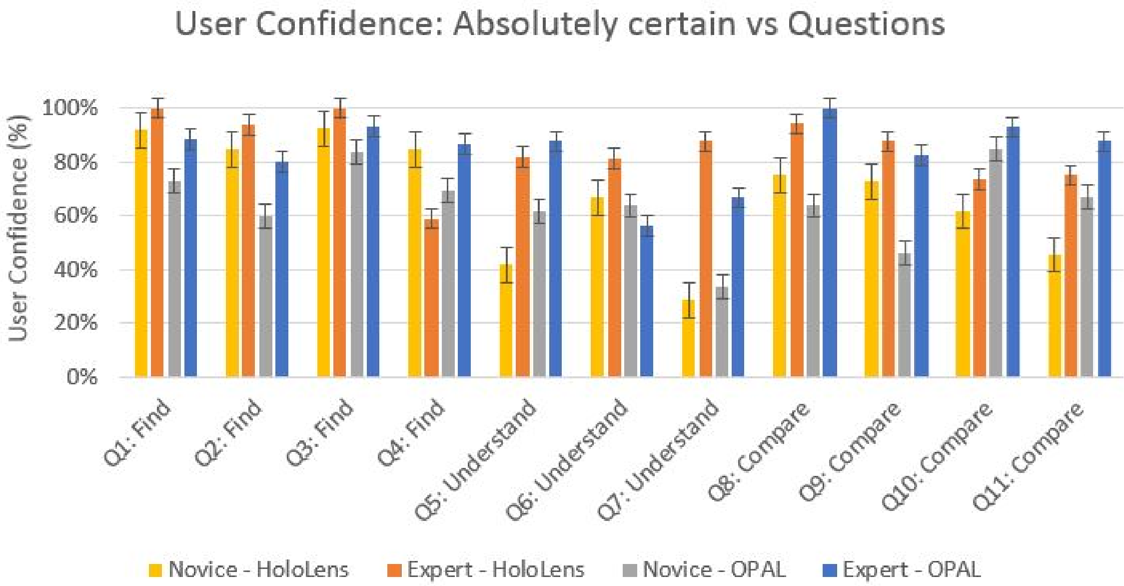

FIGURE 7.6: User Confidence among novices and experts

Discussion

Overall experts had better results compared to the novices, but this was as expected. Experts have prior knowledge of OPAL and therefore are more familiar with the financial term that were used in the experiments. Although overall experts were better, there are several cases where novices did better than experts. When we look back at the results we see that at question 2, 5 and 10 novices were more accurate than the experts for both visualization. When we look at question 2 we see that the difference between the accuracy of experts and novices from the OPAL group were bigger than the HoloLens group. We think that this is because the experts could be over thinking some question with their prior knowledge and therefore gave a wrong answer. Question 5 is the opposite of question 2 where the differences are bigger within the HoloLens group. We think that this is because the experts were used to the 2D visualization and that the change to 3D visualization has surprised them. While the novices did not have the prior experience and therefore did not get influenced. We believe that this was also the case for question 10.

When we look at the speed and accuracy in general the difference between experts and novices were minimal. From this we can conclude that novices can almost work as good as expert with both visualizations. This means that both the HoloLens and OPAL are beginners friendly.

From the user confidence we can see that the differences between experts and novices are bigger regarding speed and accuracy. The result of experts being more confident in their answers lies in their prior knowledge, which gave them greater certainty in their answers.

7.2 Qualitative Result

This section provides a summary of the participants' comments and behaviors during the experiments.

7.2.1 HoloLens Experience

At the beginning of the experiment, all participants were excited for the HoloLens. They were all eager to know how the mixed reality experience looks like. During the experiment, participants were really surprise about how nice and realistic the virtual elements are. They did not expect the mixed reality experience to be this good, which explains why majority of the participants have chosen the HoloLens as the most fun visualization as state in feedback questions 11 Figure 7.7. From this we could conclude that the HoloLens is a good way to improve engagement of visualization, which increases the likelihood of using the visualization (feedback question 1 in 7.7).

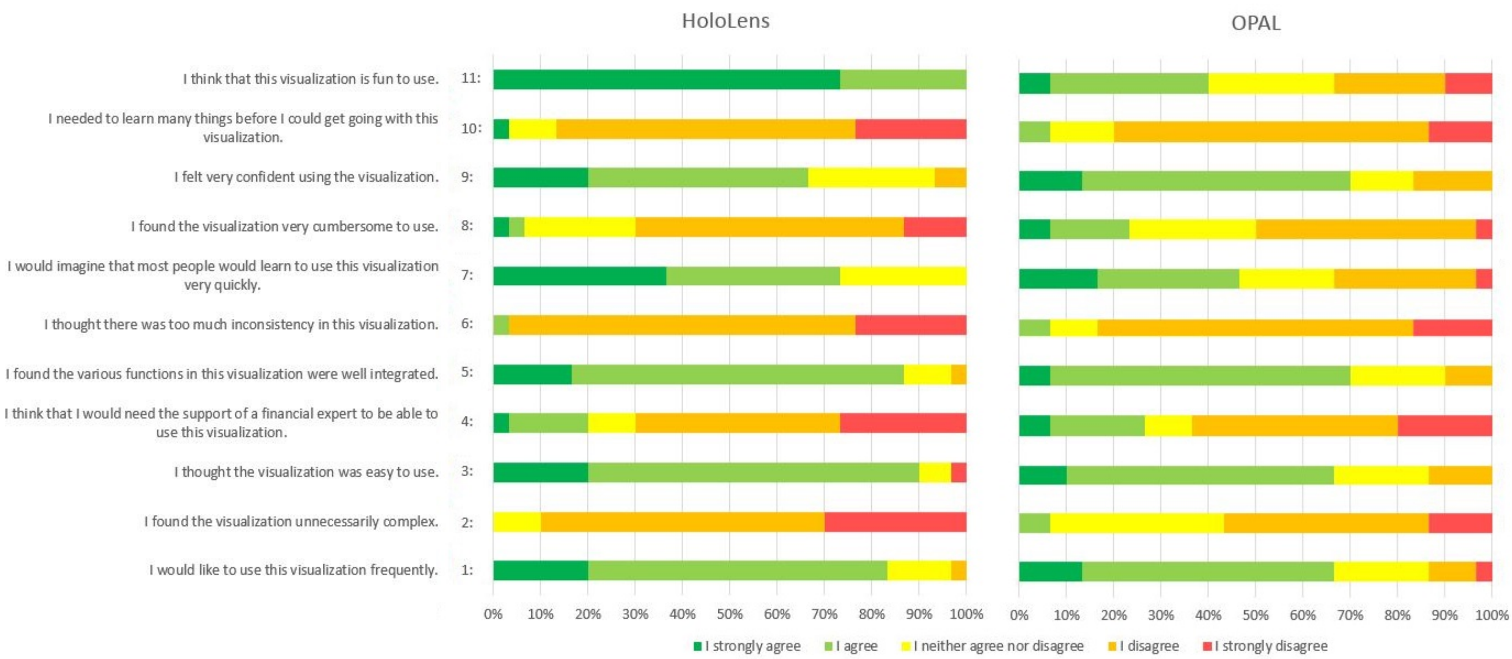

FIGURE 7.7: Feedback about HoloLens vs OPAL

7.2.2 HoloLens Interaction

The interaction of HoloLens was not as intuitive as we initially thought, because a lot of the user had difficulties using the interaction even after the tutorial. Although the interaction was not intuitive enough, participants believe that learning this new interaction would not take long as shown in the feedback question 7 in figure 7.7. Just as we got used to the keyboard and mouse, we also have to get used to the HoloLens interaction. Participants also believe that when they have gotten used to the HoloLens interaction that they would be able to answer the questions better.

7.2.3 Walking in 3D space

When using the HoloLens, most participants were sitting and only moved their heads or upper body to see the pop-ups better as sometimes pop-ups could block each other. As for the remaining participants who were standing, they never walked around the graph. These participants only moved a little to the left or to the right to see the blocked pop-up. Therefore we can conclude that all participants did not have the need to walk around in order to see the graph from different angles. Participants also claimed that they could answer the questions by sitting in a certain angle. Especially with the given interaction walking was redundant. And for the participant that did stood up, they never walked around the but only moved a little to the left or right. We can conclude that the participant did not had the need to walk around the graph to see it from a different angle. Participants also claimed that they could answer the questions by sitting in a certain angle. Especially with the given interaction walking was redundant.

7.2.4 Unused graph

We noticed that participants did not use the graph part of the OPAL visualization and only used the table part for answering the questions. The reason for this is because the OPAL visualization was displayed on a 15.7-inch laptop screen. The screen was not big enough to show the whole visualization, as only a small part of the graph was visible. When we informed the participants that there was a graph part, all participants were surprised, because they were not aware of the part and never bothered to scroll down. Participants also claimed that the table provided enough information and therefore they did not have a reason to look for the graph. From this we can conclude that if another visualization option is not shown or linked with the other visualization, participants will not look for it. Additionally, we can conclude that the HoloLens is proven more useful with larger data compared to OPAL.

As participants did not use the OPAL graph at all, we have gained a different kind of result than initially expected. This could also be the reason why feedback question 2, 3 and 8 were in favor of HoloLens. The following claims from the participants are about the HoloLens visualization vs OPAL table:

- Participants claimed that the HoloLens visualization provides a better overview compared to the OPAL table.
- The OPAL table contains too much clutter, as it was mostly numeric non-visual data.
- With the colored bars of the HoloLens visualization, comparison of feasibility was easier than using the OPAL table.

Chapter 8

Conclusion & Future Work

This chapter summarizes the conclusions from our experiments for our research questions:

1. What is the speed, accuracy and user confidence when trying to **find, understand and compare** relevant financial data with 3D Mixed Reality compared to with 2D visualization?
2. What are the differences in speed, accuracy and user confidence between financial experts and novices and the performed task?

8.1 Conclusion

We described how we have designed and created a 3D visualization in mixed reality in order to compare 2D visualization with 3D visualization. The 3D visualization was based on an existing 2D visualization of a financial decision software. We also added mixed reality related interaction to make 3D visualization intuitive and engaging. We demonstrated that a 3D visualization for financial decision-making is possible in mixed reality.

From our experiment we conclude that overall the 2D visualization is slightly faster in answering the questions. We believe that it is because the 3D visualization was not inherently intuitive as we thought it would be. All participants were new to mixed reality and needed to get accustomed to the interaction. On the other hand the 3D visualization was slightly more accurate than the 2D counterpart. This is due to the amount of data that the 2D visualization was able to show. The 2D screen has limited viewing space if participants do not scroll or change to a different screen. The participants were sometimes not aware of the scrolling function, which resulted in missing essential data and causing a slight decrease in accuracy. The overall user confidence was for both visualizations nearly the same, which means that 3D visualization is as good as 2D visualization when it comes to confidence of data understanding. Overall, expert users had better results compared to novice users in both visualizations as we expected. There are some cases where expert users did worse compared to novice users. Again we suspect that the new 3D interaction is the cause of these cases, as among participant some may get used to the interaction faster than others. Furthermore, expert users have prior knowledge which can sometimes causes them to over-think the questions and resulting in some negative cases.

From the user feedback, we can conclude that mixed reality is a fun and engaging way to interact with data. Although mixed reality was not significantly better it is also not significantly worse, we think that 3D visualization could obtain better result once the user become more comfortable with the interaction. Therefore, future research about mixed reality is needed as other approaches could lead to significant differences. This mixed reality technology is promising for future data visualization and is certainly worth pursuing additional research.

8.2 Future Work

Our experiment was focused on comparing 2D tables with a 3D graph and table. A research about the comparison of 2D graph with a 3D mixed reality graph would be interesting, because this would give us more insight about the impact of the 3rd dimension on graphs. The goal of that study would be to see if 3D graphs displayed through mixed reality would make any difference in terms of speed, accuracy and user confidence.

From our research we concluded that the 2D working space is limited due to the display screen size and therefore limited data could be shown. Our research used a 15.7-inch screen to display 2D visualization and never had the chance to test the same experiment with different screen sizes. The aim of that research is to compare mixed reality with different 2D screen sizes to see if there are any differences in terms of speed, accuracy and user confidence.

Interaction is an important element of visualization. During our experiment, the mixed reality interaction was not intuitive enough resulting in a slightly worse result in the speed section. A lot of participants claimed that if they got used to the mixed reality interaction that they could get much better results. Hearing participants saying this made us wonder if the results would be different if they had proper training. This research is also fair towards mixed reality, because the 2D visualization used existing familiar interaction, which gave 2D visualization an edge in interaction. The goal of this research is to compare experts with novices in mixed reality interaction.

In the finance world there are times where multiple user will be using a visualization to convey their ideas. Most of the time only one person is in control of manipulating the visualization or the control has to be passed on. Mixed reality offers multiple user interaction of the virtual elements displayed. The multiple user interaction can help user convey their ideas better because of ease of use and engagement.

Appendix A

Materials for Participant

A.1 Scenario

You have €2,500,000 and you want to realize 3 of your **goals** which are:

- Additional Income
- Charity Donations
- Renovation Costs

You have heard that investing money is a better way to gain money than putting it in a savings account. You select the decision software OPAL to help you decide how much of your money you should be investing and estimate the expected risk. OPAL can estimate 45 years into the future, called the "**horizon**" of your financial plan. With this estimate you can see the changes in your money and the feasibility of your goals, depending on the chosen portfolios. You can choose from 7 **portfolios** starting from low risk going to high risk:

- Savings Account
- Current/Custom Portfolio
- Extra Defensive
- Defensive
- Neutral
- Offensive
- Extra Offensive

Each portfolio contains a different strategy for distributing your investments.

A.2 Terminology

- **Feasibility**: the probability of achieving a particular goal with the chosen portfolio.
- **Short term risk**: the risk of choosing a particular portfolio for the first year.
  - **Potential loss**: percentage of money lost.
  - **Expected return**: percentage of money gain if the future is like OPAL estimated.

- **Capital development**: the estimate of the changes of your money at the end of the horizon.
  - **Bad market**: the worst case estimation of the future by OPAL.
  - **Expected market**: the future that OPAL estimated.
  - **Good market**: the best case estimation of the future by OPAL.
  - **Investment return**: the percentage of money gained from investment.

A.3 Question set 1

- **Q1**: You are looking at the "Aggressive" portfolio and wonder which goal has the highest feasibility (probability)?
- **Q2**: Given the "Additional Income" goal, which of the portfolios has the lowest feasibility (probability)?
- **Q3**: Which goal and portfolio combination has a feasibility (probability) of 70%?
- **Q4**: Which goal has neither the highest nor the lowest overall feasibility (probability)?
- **Q5**: You have chosen the "Extra aggressive" portfolio, but investing money does not come free of charge. What percentage of your money could you lose in the first year?
- **Q6**: The future of your investment went according to OPAL's estimation. How much money will you have with the "Extra defensive" portfolio at the end of the horizon?
- **Q7**: What is the value of an "Aggressive" portfolio in the case that the economy is developing very well at the end of the horizon?
- **Q8**: You are focusing on the "Additional income" goal. What is the difference in feasibility (probability) between the "Savings Account" and "Extra aggressive" portfolio?
- **Q9**: You are comparing the "Savings Account", "Defensive" and "Extra aggressive" portfolios. You want to have a minimum of €12,500 in your portfolio at the end of the horizon and also do not want to lose more than 20% of your money in the first year. Which portfolio would you choose?
- **Q10**: You focus on the "Additional income" and "Renovation Costs" goals and try to find the right portfolio that matches your preference. You want at least 50% feasibility (probability) for both of your goals, a minimum money of higher than €13,100 at the end of the horizon and also if everything goes according to OPAL's estimation a gain of at least 4% for the first year.
- **Q11**: You are interested in the "Savings Account" portfolio. Although you are happy about the not losing money at all the first year, you were not satisfied with the feasibility of the goals. Therefore you decided to choose a portfolio where you could only lose 10% to 30% of your money the first year, so that your "Renovation Costs" goal has a feasibility (probability) of higher than 65% and also you want to have as small risk as possible. Which portfolio would you choose?

A.4 Question set 2

- **Q1**: You are looking at the "Neutral" portfolio and wonder which goal has the lowest feasibility (probability)?
- **Q2**: Given the "Charity Donations" goal, which of the portfolios has the highest feasibility (probability)?
- **Q3**: Which goal and portfolio combination has a feasibility (probability) of exactly 41%?
- **Q4**: Which goal has the lowest overall feasibility (probability)?
- **Q5**: You have chosen the "Aggressive" portfolio, but investing money does not come free of charge. What percentage of your money could you lose in the first year?
- **Q6**: The future of your investment went according to OPAL's estimation. How much money will you have with the "Extra aggressive" portfolio at the end of the horizon?
- **Q7**: What is the value of an "Current/Custom Portfolio" portfolio in the case that the economy is developing very well at the end of the horizon?
- **Q8**: You are focusing on the "Renovation Costs" goal. What is the difference in feasibility (probability) between the "Savings Account" and "Extra aggressive" portfolio?
- **Q9**: You are comparing the "Savings Account", "Defensive" and "Extra aggressive" portfolios. You want to have a minimum of €11,500 in your portfolio at the end of the horizon and also do not want to lose more than 25% of your money the first year. Which portfolio would you choose?
- **Q10**: You focus on the "Additional income" and "Renovation Costs" goals and try to find the right portfolio that matches your preference. You want at least 60% feasibility (probability) for both of your goals, a minimum money of higher than €13,000 at the end of the horizon and also if everything goes according to OPAL's estimation a gain of at least 6% for the first year.
- **Q11**: You are interested in the "Extra aggressive" portfolio. Although you are happy about the high feasibility (probability) of your goals, you were not satisfied with amount of money you could lose in the first year. Therefore you decided to choose a portfolio were your "Renovation Costs" goal has a feasibility (probability) of higher than 65% and your "Additional income" goal a feasibility (probability) of higher than 40%, so that you only lose 5% to 20% of your money the first year. Which portfolio would you choose?

Appendix B

Questions

B.1 Background Information

- **Question 1**: What is your age?
  <20 — 21-30 — 31-40 — 41-50 — 51-60 — >60
- **Question 2**: What is the highest degree or level of school you have completed?
  No Degree — High-school Degree — Bachelor Degree — Master Degree — PhD Degree
- **Question 3**: What is your current occupation?
  A student — An employee — Self-employed — Currently not employed or studying
- **Question 4**: In case of student what is your field of education?
  Own answer
- **Question 5**: In case of employee / self-employed, what is your work role?
  Own answer
- **Question 6**: How often do you see data visualization? (e.g. graphs, data tables)
  Few times per day — Few times per week — Few times per month — Few times per year — Never
- **Question 7**: How experienced are you with the OPAL decision software?
  4-likert scale: Very experienced — Experienced — Unexperienced — Very unexperienced
- **Question 8**: How experienced are you with using 2D graphs? (e.g. reading, understanding)
  4-likert scale: Very experienced — Experienced — Unexperienced — Very unexperienced
- **Question 9**: How experienced are you with using head mounted displays? (e.g. HoloLens, Vive, Oculus Rift?
  4-likert scale: Very experienced — Experienced — Unexperienced — Very unexperienced

B.2 Experiment

TABLE B.1: Question set 1

Question	Task	Right answer
Q1: You are looking at the "Aggressive" portfolio and wonder which goal has the highest feasibility (probability)?	Find	Charity Donations
Q2: Given the "Additional Income" goal, which of the portfolios has the lowest feasibility (probability)?	Find	Custom portfolio
Q3: Which goal and portfolio combination has a feasibility (probability) of exactly 70%?	Find	Renovation Costs and Aggressive
Q4: Which goal has neither the highest nor the lowest overall feasibility (probability)?	Find	Additional income
Q5: You have chosen the "Extra aggressive" portfolio, but investing money does not come free of charge. What percentage of your money could you lose in the first year?	Understand	31.6%
Q6: The future of your investment went according to OPAL's estimation. How much money will you have with the "Extra defensive" portfolio at the end of the horizon?	Understand	€31,341
Q7: What is the value of an "Aggressive" portfolio in the case that the economy is developing very well at the end of the horizon?	Understand	€72,488,340
Q8: You are focusing on the "Additional income" goal. What is the difference in feasibility (probability) between the "Savings Account" and "Extra aggressive" portfolio?	Compare	53%
Q9: You are comparing the "Savings Account", "Defensive" and "Extra aggressive" portfolios. You want to have a minimum of €12,500 in your portfolio at the end of the horizon and also do not want to lose more than 20% of your money in the first year. Which portfolio would you choose?	Compare	Defensive
Q10: You focus on the "Additional income" and "Renovation Costs" goals and try to find the right portfolio that matches your preference. You want at least 50% feasibility (probability) for both of your goals, a minimum money of higher than €13,100 at the end of the horizon and also if everything goes according to OPAL's estimation a gain of at least 4% for the first year.	Compare	Neutral
Q11: You are interested in the "Savings Account" portfolio. Although you are happy about the not losing money at all the first year, you were not satisfied with the feasibility of the goals. Therefore you decided to choose a portfolio where you could only lose 10% to 30% of your money the first year, so that your "Renovation Costs" goal has a feasibility (probability) of higher than 65% and also you want to have as small risk as possible. Which portfolio would you choose?	Compare	Neutral

TABLE B.2: Question set 2

Question	Task	Right answer
Q1: You are looking at the “Neutral” portfolio and wonder which goal has the lowest feasibility (probability)?	Find	Renovation Costs
Q2: Given the “Charity Donations” goal, which of the portfolios has the highest feasibility (probability)?	Find	Savings Account, Custom portfolio, Extra defensive, Defensive
Q3: Which goal and portfolio combination has a feasibility (probability) of exactly 41%?	Find	Additional income and Extra Defensive
Q4: Which goal has the lowest overall feasibility (probability)?	Find	Renovation Costs
Q5: You have chosen the “Aggressive” portfolio, but investing money does not come free of charge. What percentage of your money could you lose in the first year?	Understand	25.5%
Q6: The future of your investment went according to OPAL’s estimation. How much money will you have with the “Extra aggressive” portfolio at the end of the horizon?	Understand	€4,856,501
Q7: What is the value of an “Current/Custom Portfolio” portfolio in the case that the economy is developing very well at the end of the horizon?	Understand	€403,455
Q8: You are focusing on the “Renovation Costs” goal. What is the difference in feasibility (probability) between the “Savings Account” and “Extra aggressive” portfolio?	Compare	61%
Q9: You are comparing the ”Savings Account”, “Defensive” and “Extra aggressive” portfolios. You want to have a minimum of €11,500 in your portfolio at the end of the horizon and also do not want to lose more than 25% of your money the first year. Which portfolio would you choose?	Compare	Defensive
Q10: You focus on the “Additional income” and “Renovation Costs” goals and try to find the right portfolio that matches your preference. You want at least 60% feasibility (probability) for both of your goals, a minimum money of higher than €13,000 at the end of the horizon and also if everything goes according to OPAL’s estimation a gain of at least 6% for the first year.	Compare	Aggressive
Q11: You are interested in the “Extra aggressive” portfolio. Although you are happy about the high feasibility (probability) of your goals, you were not satisfied with amount of money you could lose in the first year. Therefore you decided to choose a portfolio were your “Renovation Costs” goal has a feasibility (probability) of higher than 65% and your “Additional income” goal a feasibility (probability) of higher than 40%, so that you only lose 5% to 20% of your money the first year. Which portfolio would you choose?	Compare	Neutral

B.3 Feedback

- I would like to use this visualization frequently.
- I found the visualization unnecessarily complex.
- I thought the visualization was easy to use.
- I think that I would need the support of a financial expert to be able to use this visualization.
- I found the various functions in this visualization were well integrated.
- I thought there was too much inconsistency in this visualization.
- I would imagine that most people would learn to use this visualization very quickly.
- I found the visualization very cumbersome to use.
- I felt very confident using the visualization.
- I needed to learn many things before I could get going with this visualization.
- I think that this visualization is fun to use.

Appendix C

Results

C.1 Background Information

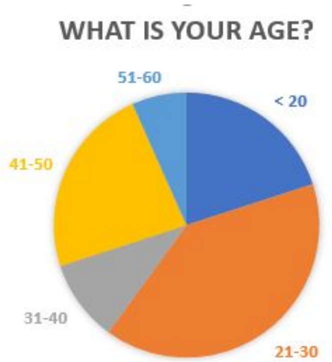

FIGURE C.1: Age of participants

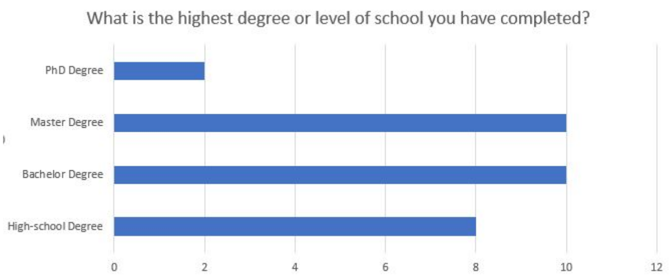

FIGURE C.2: Highest Degree or level of school of participants

FIGURE C.3: Occupation of participants

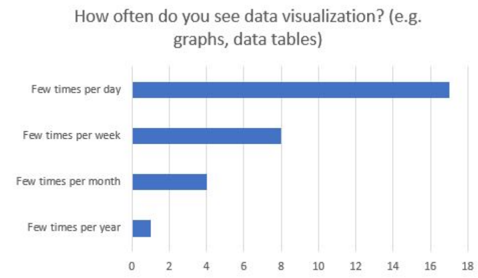

FIGURE C.4: Overview of how often participants see visualization

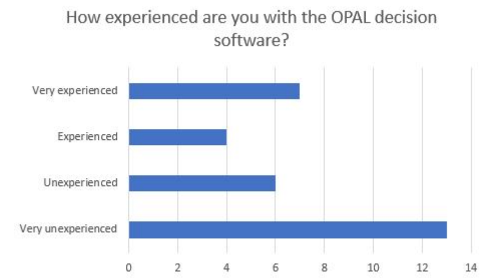

FIGURE C.5: The experiences of participants with OPAL

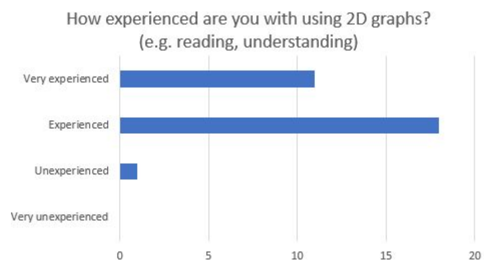

FIGURE C.6: The experiences of participants with 2D graphs

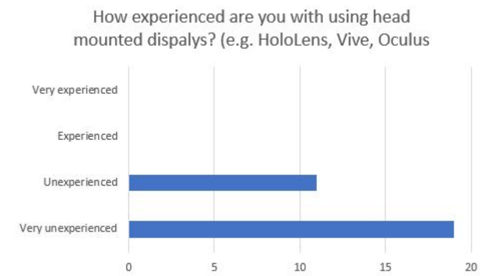

FIGURE C.7: The experiences of participants with Head Mounted Display

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