GEO 511 - Master Thesis

Department of Geography - University of Zurich

Geographic Information Visualization and Analysis (GIVA)

30 September 2014

Designing and Evaluating a Mixed Methods Visualization Approach Combining Qualitative and Quantitative Data Through a Migration Case Study

Author:

Fabian Perler

06-910-210

Rainstrasse 8

8590 Romanshorn

fperler86@gmail.com

Advisor: Dr. Arzu Çöltekin

Co-Advisor: Dr. Susan Thieme

Faculty Member:

Prof. Dr. Sara Irina Fabrikant

Acknowledgements

I want to thank my advisors Dr. Arzu Çöltekin and Dr. Susan Thieme for their support, their patience, understanding and motivations they gave me during the last year. I also want to thank the participants of the experiment who shared their time.
Further I'd like to thank the staff from the Pädagogische Hochschule Thurgau in Kreuzlingen for letting me use their library and other infrastructure during the last year.
Finally, I would like to thank everyone who helped and supported me, especially my family and Michelle Moret for their support and invested time.

Abstract

The aim of the thesis was to contribute to the general research debate about qualitative and quantitative methods. Geographic information science is still dominated by quantitative methods and approaches. In order to gain new insights about the performance of using a combination of qualitative and quantitative methods in interactive data displays, the human geography topic of migration serves as the subject for this investigation. Existing migration visualization approaches have been explored and evaluated to provide guidance for the implementation and design of the displays. Three different visualization types have been constructed using qualitative, quantitative or mixed methods. In an evaluation, based on a task-related eye-tracking experiment with 15 participants, the visualizations were tested concerning usability and performance. By conducting this evaluation, we aimed to assess how well qualitative and quantitative methods can support each other in multimedia data visualizations.

The tested combined methods visualizations performed significantly better than the visualizations based on qualitative methods in terms of response time and usability. All participants preferred working with either quantitative or mixed methods displays, which indicates that combining qualitative and quantitative methods in interactive multimedia data visualizations can be reasonable.

Contents

Figures

Tables

1 Introduction

1.1 Synopsis

This project covers a variety of research fields, however, its primary contribution lies on the so-called “quantitative-qualitative debate” from a methodological perspective. More specifically, the performance of *mixed methods* (i.e., methods that combine the qualitative and quantitative approaches) is compared to the performance of qualitative as well as quantitative methods in the field of geographic data visualization through a case study implementation and a user study.

1.2 Motivation and Goals

> “Although most technical barriers to data integration have fallen, the analysis of mixed data types – quantitative and qualitative – in GIS remains a challenge. How can these diverse types of information be fused to generate new knowledge?” (McLafferty 2002, page 266)

McLafferty stated this in 2002, however, the analysis of mixed data types is still a challenge today. Especially in geography, where the quantitative-qualitative debate is a dominant issue, the evaluation of these different approaches could allow us to better understand their perspective benefits. Data visualization in the classical sense (whether it is geographic or not) focuses primarily on quantitative data often in form of numbers or diagrams. While numbers and diagrams are certainly useful and systematically reproducible, quantitative visualizations show only the extent or the amplitude of a phenomenon and do not typically show its reasons or explanations in an explicit manner. This is where the qualitative approaches excel – systematically utilizing and carefully reflecting on the logic of “real-world” events as experienced and reported by people in the field, it can provide insights and information about individual daily experiences. This type of knowledge and insights are considered complementary to quantitative attributes of an occurrence and vice versa. However, currently there are very few empirical studies focusing on understanding the benefits and shortcomings of each approach (qualitative, quantitative, mixed).

In order to observe, measure and demonstrate the differences and interactions between the complementary components of quantitative and qualitative approaches, an interactive visualization is implemented and user-tested in this project through two case studies. The interactive visualization consists of multiple linked views of multimedia data and the case studies deal with the topic of human migration flows. Migration phenomenon is widely studied in human geography in a qualitative manner, but also has attracted much attention from the GIScience as well as the newly emerging "computational social science" domain which dominantly uses quantitative methods. Migration, therefore, lends itself well also for mixed methods: It contains a statistical basis on the one hand, and is an inherently qualitative phenomenon with "explainable" functions of underlying processes on the other hand. In summary, this project aims at demonstrating possible exploration possibilities using mixed methods visualizations as well as to analyze pros and cons of each (qualitative, quantitative, mixed).

Three different visualizations have been implemented for a comparison of qualitative, quantitative and mixed data displays through measuring the user performances with each. Therefore, the goal of this thesis is to contribute further insights to the qualitative-quantitative debate by providing empirical results from a user experience study to scientists in human and analytical geography. Outcomes of the study should offer a framework for further analysis but also provide helpful information regarding future creations of interactive migration visualizations for the public or for educational purpose.

Extremely high amounts of qualitative data about migration flows have been gathered over the past decades, and the same is true for quantitative data (especially *open* data) in recent years. New ways of integrating them into each other are needed. Partially serving towards this goal, this thesis seeks to provide information about the integration and the usability of the two approaches.

1.3 State of the Art

Geographic Information Systems (GIS) are widely considered as exclusive tools for the analysis of *quantitative* data. However, the development of technology, the wide availability of qualitative geographic data as well as the critical discussion of such systems allow an integration of various data types into GIS (Kwan, 2002). Even though qualitative research and quantitative research are based on two different paradigms (Kuhn, 2012), today's approaches advocate the use of both paradigms in order to gain new insights and build new knowledge (Morgan, 2007). These combined methods might be incommensurable, but they can be (and are) used to study a phenomenon from different perspectives. The integration of qualitative data into visualizations can be especially helpful in human geography research since it allows supporting or contradicting quantitative findings with additional qualitative information. Hence, this integration can serve as a validation mechanism or a deeper understanding of the phenomenon. Such combinations allow displaying the spatial dimensions of a social process and its underlying dynamics and relations (Kwan & Knigge, 2006). For example, some researchers in *critical geography*[1] use combined approaches because of their ability to focus on subjectivity, differences and meanings, which results in a critical analysis of the processes (Knigge & Cope, 2006).

Studying the performance of multimedia displays requires an understanding of the way humans comprehend different types of information. The cognitive theory of multimedia learning (Mayer, 2005) is a useful theory in this domain. According to this theory, textual and pictorial information are processed differently and thus have different limitations and strengths. The performance of a visualization system in terms of generating new knowledge therefore depends a lot on the type of data displayed as well as on the individual perception and learning abilities (Mayer, 2005).

Colaso et al. (2002) compared the learning performance of participants between text, visualizations and text-visualization combinations. Participants were clearly dissatisfied with using text only. However, learning with the illustrated visualizations

[1] Critical geography combines the critical theory approach and the analysis and study of geographic phenomena. It focuses on the role of dominance and confrontation in the production of place and space (Blomley, 2006).

only resulted in gaps of knowledge. This means that participants were not able to understand all details of the presented process or phenomenon when using illustrations only. According to the authors, in the mixed version, the text ensures the coverage of the concepts illustrated by the visualization. Overall, they suggest to use a combination of text and illustration in order to increase the learning effect (Colaso et al., 2002). In 2008, Eilam and Poyas compared the performance of multiple representations (text and visuals) to single (text only) representations. Their findings indicate that multiple representations increase the visibility of information. Furthermore, the diversity of displays serves as an organization of information, which leads to an easier identification of information. Anyhow, they also stress out the most important problems of multiple representations. First, redundant information may lead to an unintended overload of the participants processing. Second, the high diversity of displays might lead to a higher motivation of participants and thus to a higher satisfaction using multiple representations (Eilam & Poyas, 2008). These two comparable studies show the effects of combining text and visuals as well as the use of multiple representations. Further existing theories regarding multimedia displays and the combination of qualitative and quantitative methods can be found in the next chapter.

1.4 Overview of Project Steps

Primarily, existing migration visualization solutions are surveyed. The knowledge derived from this survey helps determining the requirements of the visualization implementation for this project, especially for the representation choices of migration flows. The implementation of a multiple linked view visualization environment utilizing both quantitative and qualitative data about migration to Switzerland is an important portion of this project. Two specific case studies are gathered, processed and set up in an interactive form with multimedia data (i.e., text, photographs, videos, graphs) featuring two major migration-flows to Switzerland. The data set consists of *only* open data from various statistics organizations of the European Union and Switzerland (thus most likely it is limited in its representativeness, but will not hurt the objectives of this study).

1.5 Research Questions

As mentioned earlier, the findings of this thesis can contribute to the general qualitative-quantitative research debate. Especially in the field of information visualizations, this thesis may lead to new insights about the usability of different types of data. The resulting visualization system (the implementation part of the project) should be able to show two important human migration flows to Switzerland. Furthermore, users should be able to learn about possible triggers for these flows (i.e. what started the movement?) in an exploratory manner. A narrative visualization structure and a highly interactive design approach have been adopted as commonly suggested by the current visualization scholars for exploratory tasks (Keim et al., 2010) despite some evidence against interactive displays, especially for non-expert users (Hegarty et al., 2009). The evaluation of two case studies through a user study will deliver information regarding design decisions (i.e., validate or challenge them) and usability of the mixed method approach. Derived from the factors above, the following main research question emerged:

How well can qualitative and quantitative methods support each other in data visualizations?

To tackle this larger research question, following specific questions are necessary to answer:

1. How is migration displayed in existing geographic visualizations, and what are their limitations and strengths?

    Following a literature review additionally to a review of the implementations, the existing approaches will be analyzed through a qualitative (“top-down”) evaluation. While this survey documents the commonly practiced visualizations as a by-product; the main goal is to identify standards, strengths and weaknesses of the state-of-the-art methods to make informed choices for the implementation design of this project.

2. What kind of spatial, temporal and qualitative visualizations are necessary to include in a multiple-view visualization design?

   Decisions will be made based on the results of the previous step (review of existing solutions) and the multimedia learning theory to take the information about the human capabilities of processing different data types into account.

3. How do people use and how well do people perform with the different data type combinations of multiple-view visualizations of migration compared to each other?

   A user evaluation of the implementation (supported with eye-tracking) will show differences in the use and usability of qualitative, quantitative or mixed methods visualizations. The user preferences regarding visualized data types will also be analyzed and compared.

1.6 Target Audience

The resulting visualizations should be suitable to use for non-experts as well as experts. Different professional groups with varying interests, e.g. human geographers (who may *also* be interested in gaining insights from statistical information about the migration to Switzerland) as well as quantitative researchers (who may *also* be interested in knowing more about socio-economic triggers or build personal opinion about migration) are addressed. The target audience will be tested using eye-tracking combined with traditional usability methods.

1.7 Desired Contributions and Achievements

The results and interpretation of the user experiment will empirically contribute to the current understanding of the differences in usability and user preference between the tested visualization approaches. It may allow us to see if participants concentrate more on qualitative or quantitative data and how these decisions affect their performance. The outcome, both from the user study and from visualization survey leading to design decisions should contribute to the debate about qualitative and quantitative data visualization in information graphics and help researchers choose when to work with qualitative, quantitative or mixed methods, at least in studies similar to our case study.

1.8 Structure of the Thesis

Chapter 2 provides the necessary theoretical background for this thesis and reveals the range of the study within the research field. The third chapter of this thesis serves as an overview of existing approaches of migration visualization systems. Therefore, a selection of solutions is evaluated qualitatively and strengths and weaknesses are pointed out. The implementation process is described in chapter 4, followed by the evaluation part (Chapter 5), where the implementations are being tested. The last part of the thesis contains the discussion (Chapter 6) and the final conclusion (Chapter 7), which includes the answers of the research questions.

2 Theoretical Background

This sections covers the theoretical foundations of this thesis. A discussion of the qualitative-quantitative research debate ranging from the general controversy to the specific arguments in the discipline of geography and Geographic Information Science will be covered first. This will be followed by an explanation of the cognitive processes involved in multimedia learning in order to better relate these to the processing of different data types, therefore, to the design of multimedia visualizations created for this project. Generally, section 2 should allow putting the study into a broader research context, and motivate the implementation as well as user study design.

2.1 Qualitative-Quantitative Research Debate

This thesis is largely motivated by the general debate on qualitative versus quantitative research approaches. Understanding the development of this controversy is crucial for further discussion of the explicit implementation of qualitative and quantitative data in information visualizations.

Three different research approaches are widely used in geography as well as in other sciences: quantitative, qualitative and mixed methods. While quantitative approaches have been available to scientists for a long time, qualitative methods have become more popular during the last decades and the mixed methods are quite new and still developing. Today, the discourse seems to be less about *quantitative versus qualitative* and more about how research lies between the two of them (Creswell, 2013). This chapter covers the debate about qualitative versus quantitative research and the paradigm shift in the last decades as well as its impacts on the discipline of geography and the subfield of geographic information visualization.

Qualitative and quantitative research are based on two different paradigms. They originated in the positivism-idealism debate of the late 19th century (Sale et al., 2002). The quantitative paradigm is based on positivism. It says that science is characterized by empirical research and that all phenomena can be reduced to empirical indicators. In positivism, there is only one truth, an objective reality independent of human biases. Scientists can study a phenomenon without influencing it or being influenced by it. Quantitative methods are generally characterized by large sample sizes and predetermined responses, which does not allow too much room for subjective interpretation of the material. These factors have the goal to increase the representativeness. On the other hand, the qualitative paradigm is based on interpretivism and constructivism. There are multiple truths based on the individual construction of reality. Hence, this research paradigm emphasizes on processes and meanings. These truths can change over time and develop individually. In constructivism an access to reality independent from our minds is not possible. Techniques used in qualitative research are focus group interviews and observation of participants, which are characterized by small samples that provide important in-depth information (Sale et al., 2002).

Qualitative research appears to be at least as old as quantitative research and it has always been dominant in some research fields, for example in social anthropology. After the World War II, during the 1960s until the 1980s, there was a clear shift towards a dominance of quantitative methods. Then, qualitative research moved from its marginal position to equality with quantitative research (Morgan, 2007). As Morgan (2007) reports, this shift in historical pattern was due to a paradigm shift. He calls it “The Shift from the Positivist to the Metaphysical Paradigm” (Morgan 2007, page 55). It began in the late 1970s with a renewed attention to qualitative research. At that point, there was no agreed dominant paradigm in social science research. This was the opportunity for alternative approaches. Opponents to the positivism raised their voice against this “positivist paradigm” and thus challenged it. Basically, the advocates of qualitative research used the key elements for paradigm change as described by Kuhn (2012): 1) a clear characterization of the existing dominant paradigm, 2) an increasing sense of frustration caused by the problems of the existing paradigm, 3) a clear characterization of a new paradigm and 4) an agreement that the new paradigm resolves the problems with the existing paradigm. The advocates characterized the existing paradigm and revealed that it has only little to do with the formal movement in the philosophy of science that was known as “logical positivism”. Through these arguments, the positivist paradigm was made the center of the debate. Meanwhile, anomalies in existing practices were presented and therefore the existing paradigm was called into question. The next step was to create an alternative paradigm. Lincoln and Guba's (1985) ideas of a system for comparing different paradigms in social science research were the base of this alternative paradigm. The strength of the new system, called the metaphysical paradigm, was that it reduced positivism to just one among several competing paradigms. So the researchers did not shift from quantitative to qualitative research. Rather a legitimization of alternative paradigms such as constructivism or critical theory was achieved (Morgan, 2007). It can be said that the advocates of qualitative research actively used this tactic of paradigm shifts to seek changes at the heart of social science methodology.

Morgan (2007) argues that we are currently in the middle of a new paradigm shift that will replace the metaphysical paradigm as a dominant system. Again, the approach of Kuhn (2012) is used to challenge the existing paradigm. The main problem of the metaphysical paradigm is that the parallel existing paradigms are incommensurate. As an alternative, Morgan (2007) presents a new approach based on pragmatism. It relies on abductive reasoning that moves back and forth between induction and deduction. In practice, researchers first convert observations into theories and then assess the theories through action. In contrast to the qualitative approach, which is based on acknowledging the subjectivity of researchers as human beings and the quantitative approach, which relies on assumed objectivity, the new system uses *intersubjectivity*. There is no problem with having both – a single real world and that all individuals have their own individual interpretation of that world. The last point concerns the question whether knowledge is specific and context-dependent or universal and generalized. And again, the new approach involves a process of working back and forth between specific results and their general implications. It means that we always have to ask how much of our existing knowledge might be usable under other circumstances. In summary (see Table 1) the new pragmatic approach works between the two extremes of quantitative research, emphasizing deductive-objective-generalizing methods and qualitative research characterized by inductive-subjective-contextual approaches (Morgan, 2007).

	Qualitative Approach	Quantitative Approach	Pragmatic Approach
Connection of theory and data	Induction	Deduction	Abduction
Relationship to research process	Subjectivity	Objectivity	Intersubjectivity
Inference from data	Context	Generality	Transferability

Table 1: The pragmatic approach compared to the qualitative and the quantitative approaches. Source: Morgan (2007)

The pragmatic approach legitimates the renewal of qualitative research. It serves as a base for the combination of different approaches. Whereas the metaphysical paradigm treated the different approaches as opponents and incommensurate, the new system explicitly asks for working back and forth with both qualitative and quantitative research methods. Moreover, researchers are not trying to evolve new paradigms anymore, instead they focus on how existing worldviews can be combined.

There are several arguments for the combination of the two paradigms (qualitative and quantitative research) according to Sale et al. (2002):

1. Both paradigms share the goal of understanding the world
2. Both paradigms share the proposition of theory-ladenness of facts
3. The complexity of some phenomena requires data from different perspectives
4. Epistemological purity does not get research done.

Howe (1992) argues that both qualitative and quantitative paradigms are based on positivism covered by a certain amount of interpretivism. An argument supporting this theory would be that qualitative researchers operate within a positivist world (Sale et al., 2002). This would undermine the quantitative-qualitative debate in the first place. But it is hard to believe that one can be both a positivist and an interpretivist or constructivist. However, these ideas work in the same direction as the approach by Morgan (2007), as discussed above. The arguments of integrating the paradigms into each other legitimate also a combination of the qualitative and quantitative approaches. Two reasons for such combinations are dominant in the literature. The first is to achieve cross-validation. Combining several theories or sources of data may lead to a deeper understanding of the phenomenon. Secondly, using the strength of one theory to support the other may help to achieve more complete results. Sale et al. (2002) states that the quantitative and qualitative paradigms do not study the same phenomena and thus combining the two methods for cross-validation is not an option. But assuming that the different paradigms study different aspects of a phenomenon, it is also not advisable to use one theory for supporting the other. This finding is justified by the fact that there is always a risk when uniting results from two paradigms. United results often promote the selective search for similarities in data, even if the two approaches did not study the same phenomenon. The solution to these problems presented by Sale et al. (2002) who propose that each method should study different aspects of a phenomenon. To ensure the complete independency of each paradigm, the distinction of the phenomena is crucial and has to be clarified.

In summary, both authors (Morgan, 2007; Sale et al., 2002) accept the fact that there are two distinctly different paradigms, a qualitative one and a quantitative one. Neither of the two authors tries to develop a new paradigm nor do they question or disprove the existing approaches. In fact, both Sale (2002) and Morgan (2007) say that researchers should use both qualitative and quantitative methods in their studies even though they do not study the same aspect of a phenomenon. Morgan (2007) emphasizes the importance of working back and forth between quantitative and qualitative research while Sale et al. (2002) focus more on the distinction of the studied phenomenon and the independency of the two paradigms.

In recent years, the integration of qualitative and quantitative research into one and the same study has become increasingly common and some researchers even see it as a distinctive research approach (e.g. Bryman, 2006). Because of its popularity, the approach is variously called *multi-methods* (Brannen & Coram, 1992), *multi-strategy* (Bryman, 2012), *mixed methodology* (Tashakkori & Teddlie, 2010) and *mixed methods* (Creswell, 2013).

2.1.1 The Debate in Geography

The discipline of geography, because it has been designed to be a holistic study of the Earth, has always been a mixture of positive sciences, social sciences and humanities. Therefore, there is a notable diversity in geography and within each subfield. As Kwan (2004) reports, the field of geography has witnessed two major rifts during the 20th century with lasting effects on the discipline: First, the separation of physical geography from human geography, originated from the separation of nature and society in geography and secondly the separation of spatial-analytical geographies from social-cultural geographies due to the goal of separating spatial patterns and relations from social, cultural and political processes. These two rifts caused the view that social-cultural and spatial-analytical geographies are perceived as irreconcilable. Researchers have been divided into social theorists and spatial analysts. This rift has been magnified over time because of polarizing debates among the researchers. Disciplinary dynamics described above have started to raise serious concern among some of the researchers during the last decade. Kwan (2004) and others call for a unified geography as the new disciplinary identity and the use of *hybrid geographies*. Hybrid geographies are geographic practices that challenge the separation of social-cultural and spatial-analytical geographies. They attempt to connect the two sides. Many geographers have already used hybrid geographies. Most common are quantitative or GIS methods to address issues informed by critical geographies (e.g. Wyly, 1998). Another type to attempt crossing the boundary between GIS and the qualitative understanding of lived experiences of people in different cultural context has been studied by Bell and Reed (2004). Kwan and Lee (2004) investigated the relationships between critical social theory and GIS. They used GIS methods for understanding of lived experiences in daily human lives. These are all examples of hybrid geographies, which are basically boundary projects. Often, their goal is to challenge existing boundaries within the discipline of geography and forge connections between the separated fields (Sui & DeLyser, 2012).

Kwan (2004) calls for a future, in which social-cultural geographies and spatial-analytical geographies are no longer separated in form of conflicting poles. The major challenge to achieve this goal is the richness of perspectives in geography.

Researchers need to accept the incompatibility of some perspectives but also allow each other to enter constructive discussion. Instead of criticizing each other and point out advantages of their theories over others, scientists may consider spending more time exploring connections between different perspectives and how they may enrich each other. When attempting to overcome the rifts in geography, one also has to consider the evolutionary dynamics. As described earlier, the Kuhnian model (Kuhn, 2012) only accepts the dominance of one single version at once and describes the gaps between different perspectives as clean breaks. Kuhn (2012) does not believe in the existence of compatible viewpoints which could be combined or integrated. Thus, the Kuhnian model is not suitable for geography because of the variety of existing perspectives within the discipline. A better framework for combining methods may be evolution based on thematic networks as suggested by Kwan (2004). Networks cut across several perspectives and subfields based on a common theme. This way they encourage collaboration and bring together people with conflicting perspectives based on their common research theme (Kwan, 2004).

When mixing qualitative and quantitative methods in geography, some aspects have to be considered. One of the most important factors is the diversity within geography in terms of paradigms as well as methodologies. As demonstrated earlier based on literature, the rift between the spatial-analytical and the social-cultural geographies is deep and has grown over time. Hybrid geographies seek to overcome this gap by using both, qualitative and quantitative methods to answer questions about a specific research theme. The Kuhnian model seems to fail in the discipline of geography because it asks for a single dominant viewpoint. But several successful examples exist - thus geographic research is able to access a phenomenon from multiple viewpoints, for example a trajectory (quantitative spatial analytics) of daily human movement experiences (qualitative social science).

2.1.2 The Impacts of the Debate on Visualizations

For a better understanding of the impact of qualitative-quantitative debate on graphical representations, a closer look on mixed methods for visualizations is useful.

In current years, the term visualization is most commonly used to describe any recently developed novel method for displaying data (Slocum, 1999). It ranges from the use of Geographic Information Science Systems (GIS-Systems) and other interactive tools for data exploration to the use of classical paper maps (Knigge & Cope, 2006). MacEachren and Taylor (1994) define geographic visualizations as activities that facilitate exploring unknowns in a highly interactive environment. These interactive computer tools expand the possibilities of interaction with maps, which itself facilitates visual thinking in qualitative and quantitative ways.

As we heard before, qualitative research has become recognized as an important element in human geography and other disciplines. It is especially helpful for linking individual experiences with the understanding of how social, economic and political processes are constructed. The subfield of Geographic Information Science (GIScience) uses mainly quantitative-analytical methods for data exploration and representation. Therefore, it has been criticized to be positivist and purely quantitative. Critical human geographers state that space is socially constructed and thus individual. Furthermore, critics emphasize that the technology based GIS might advance qualitative modes of analysis at the cost of other ways of thinking. The technology used in GIS is masking the possibility of multiple truths grounded in the strength of analytical-positivist science (Elwood, 2010). In the past 15 years many of these challenges have been addressed. The outcomes are, for example, public participation GIS, critical GIS, special journals, university courses and many more. Elwood (2010) emphasizes the importance of critical GIS which combines elements of critical geography with GIS. It consists of a set of responses to the general geography debate in the 1980s and 1990s about social, methodological and disciplinary impacts of GIScience (Schuurman, 2000). The main purpose of critical GIS is to study how and why GIS may be problematic and whether and how GIS might be restructured in response to the critique. The development of this critical view of GIS also inspired the development of GIS software. Kwan and Ding (2008) for example, adapted popular GIS software to enable linking of text and the qualitative narrative analysis of the text. In sum, critical GIS is brought and implemented into a wide array of new hybrid and alternative methods, modes of analysis and representations that break open the existing repertoire of GIS (Elwood, 2010).

More recent discourses in GIS are about subjectivity, positionality, reflexivity, context, everyday life, access and meaning of data (Kwan, 2002). These debates serve as a starting point for the development of *grounded visualization*. Grounded theory involves collection, coding and categorization of qualitative data. The goal is to build theories from data about people's everyday life experiences and actions. The methods work inductive and include multiple stages of collecting, coding and analyzing data. The reflections on emerging themes help for further data collection. Grounded theory is a useful tool for incorporating specific instances and broader trends. It is useful for critical geography because of its focus on subjectivity, differences, meanings, situated knowledge and similar (Knigge & Cope, 2006). It shows how GIS can be used for inductive exploratory visualizations of multiple form of evidence, for example spatial data, photographs, sketches and interviews. Grounded visualization offers integration at the analysis level and shows how visual representations may be analyzed to explore meanings and understand and explain processes of ethnographic data (Elwood, 2010). Even though grounded theory is mostly used in qualitative research, grounded theorists are more concerned about the reflexivity than with whether the data are qualitative or quantitative (Knigge & Cope, 2006). Therefore, grounded theory allows or even fosters the simultaneous use of qualitative and quantitative methods in order to achieve a bigger reflexivity and an integration of individual, subjective qualitative material for the understanding of processes.

Motivations to include non-geographic, non-quantitative knowledge into visualizations are diverse. Elwood (2010) states that including knowledge is an important step toward including people who may otherwise be excluded from the study. Another reason is the effort to accommodate new forms of knowledge and representation within GIS. These approaches range from multimedia GIS (Shiffer, 2002), over qualitative GIS to feminist GIS (Kwan & Lee, 2004). For example Al-Kodmany's (2000) and Kwan & Lee's (2004) works in research on community development, urban geographies and political ecologies of land reform included images, sketches, video animations and sound into GIS, linking these representations to particular geographic objects. Mixed methods can also be used for data collection, as Pavlovskaya's (2002) study shows. Interview data from people in Moscow were used to reconcile quantitative spatial data. Her strategy was reflexive, recursive and flexible and as a result she discovered patterns and explanations of the underlying process.

2.2 Multimedia Learning

In order to understand the comprehension of different information types, one has to take a closer look at the processes of learning from different sources. Mayer (2005) reports three assumptions underlying the *cognitive theory of multimedia learning* – dual channels, limited capacity, and active processing. Mayer's (2005) theory includes elements from classic information-processing models, such as two channels from Paivio's (1986) dual-coding theory, limited processing capacity from Baddeley's (1986) theory of working memory and the flowchart representation about cognitive processes from Atkinson and Shiffirin (1968).

The *dual-channel theory* assumes that the human information-processing system consists of an auditory/verbal channel and a visual/pictorial channel. Humans possess separate channels for processing visual and auditory information. One channel processes verbal material such as spoken or printed words while the other channel processes pictorial material and nonverbal sounds. A second assumption is that humans are limited in the amount of information that they can process in each channel at one time. Hence, the learner is able to hold a few images in working memory at one time when an illustration is presented. The memory stores only portions of the presented material rather than an exact copy. Text information is stored in the same way, thus the learner is only able to hold only a few words in working memory (Mayer, 2005). The third assumption is that humans are active processors who try to make sense of multimedia displays. Therefore, they use active cognitive processes such as paying attention, organizing incoming information and integrating information with other knowledge. This assumption suggests that the presented material should have a coherent structure and the message should provide guidance for the learner.

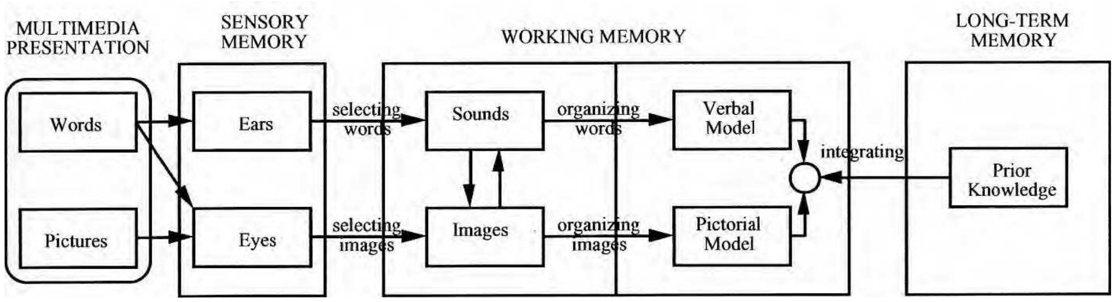


Figure 1: The cognitive theory of multimedia learning. Source: Mayer (2005)

Figure 1 represents a cognitive model of multimedia learning. It describes the human information-processing system and the way in which information is being stored in the memory. The illustrations and words from multimedia presentations enter sensory memory through the eyes and ears. Pictures and printed text can be held as exact visual copies for a short time period in the visual sensory memory. The same applies for spoken words and sounds in the auditory sensory memory (Mayer, 2005).

Working memory is mainly used for temporally storing and manipulating knowledge. The left side of the working memory box in Figure 1 represents the raw data that comes from the sensory memory, visual images and sound images. Selecting relevant words and images is the first cognitive process, which a learner has to engage. It is not possible to process all parts of a complex illustration or sound so learners must focus on only parts of the incoming data. This is mainly due to the limited processing capacity of the cognitive system. A mental representation of the selected words and images then is stored in the learner's working memory (Mayer, 2005).

The right side of the working memory in Figure 1 stands for the knowledge, which is constructed by organizing the raw material. Images and sounds can be converged into each other (for example the conversion from the spoken word "cat" into a visual image of a cat or vise versa). The organization of the selected words and images into a verbal and/or pictorial memorial model is the second cognitive process. As an output of this step, leaners possess a mental representation of selected images or sounds. In this process, learners build connections among pieces of knowledge. This process is not arbitrary; rather the rather tries to build a simple structure such as a cause-and-effect chain (Mayer, 2005).

The box on the right (see Figure 1) corresponds to the learner's long-term memory of knowledge. It can hold knowledge over long time periods and is able to link this information to the new data by integrating knowledge into the working memory. In the last cognitive process, learners integrate the verbal and pictorial representations with each other and the prior knowledge. It involves building connections between parts of the pictorial and verbal models and occurs in visual and verbal working memory. This process is highly demanding and needs a lot of cognitive capacity. Prior knowledge from the long-term memory helps learners to coordinate this integration (Mayer, 2005).

All the cognitive processes described above are applied segment by segment. It means that learners select for example relevant words and images from the first sentence and images from the first seconds of an animation and organize and integrate them. Then they proceed with the next segment and so on (Mayer, 2005).

For this project, two kinds of presented materials are important: illustrations and printed words. Let us take a closer look at how these two types are processed using the model of multimedia learning. The processing of pictures is shown in Figure 2 indicated by the darkened boxes. It starts with the presentation of the picture, for example a graph. The second box indicates the user seeing the graph, which results in a sensory image. For a short period of time, this image can be hold in sensory memory. After these two events the active cognitive processing begins. From this point on, the user has control over the processing, and only parts of the incoming images will be represented in working memory, which is displayed by the third darkened box. This process is called "selecting images" indicated by the thick arrow. At some point the working memory is full of illustration pieces and the second active cognitive process starts. Users organize the pieces and try to build some kind of coherent structure, a pictorial model. Therefore, the main parts of the graphic are stored as a visual representation. In a last step, this new knowledge is being connected with other knowledge from the long-term memory. This integrating process helps to construct the final mental representation of the graphic and explain details of the illustration analyzed. The result of this processing is an integrated learning outcome indicated by the circle in Figure 2 (Mayer, 2005).

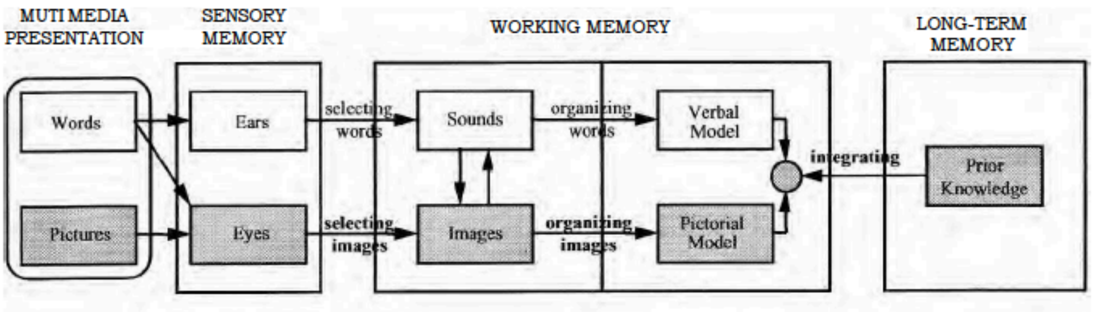


Figure 2: Processing chain of pictures. Source: Mayer (2005)

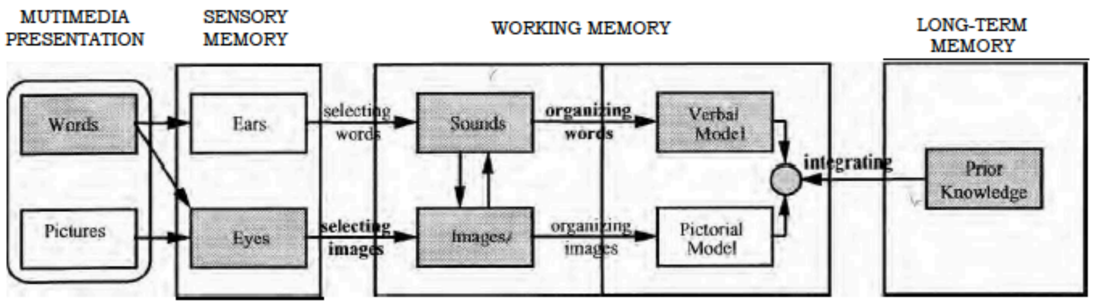


Figure 3: Processing chain of printed words. Source: Mayer (2005)

The cognitive processing of spoken words takes place mainly in the top channel of Figure 3, which could be called the auditory/verbal channel. Due to the fact that this project only covers the analysis of illustration and printed words, the detailed chain of processing spoken words is not further explained here. The presentation of printed text in multimedia displays is a special case in terms of cognitive processing. When a user reads a text, the words are presented visually so they have to be processed by the eyes (darkened boxes “Words” and “Eyes”). In the next step some of the words may be selected and brought into working memory as images. Now the images of the printed words may be pronounced mentally and change from the pictorial channel into the verbal channel, indicated by the box “Sounds”. Once the words are in the verbal channel they are processed like spoken words. This means that the pieces of words from the text are build into a coherent mental structure, the verbal model. In this organizing process, the representation of the words changes from being *based on sound* to being *based on word meaning*. Prior knowledge then helps again to explain the mental verbal model and may connect words with pictures. The verbal material entering through the visual channel – like printed words – must take a complex path through the cognitive system. Furthermore, when users see illustrations and text simultaneously the processing of printed words has to compete with the processing of illustrations because it also uses the visual channel (Mayer, 2005).

The main elements of the cognitive theory of multimedia learning are consistent with other theories. Sweller's (2003) *cognitive load theory* talks about separate channels for dealing with auditory and visual material and emphasizes the limited capacity of the working memory. Cook (2006) emphasizes the importance of the limited working memory interacting with an unlimited long-term memory. Incoming information is always processed in working memory, which is a burden. This problem may be solved by balancing the information load entering the visual and the verbal channels. Whenever new information is perceived through both of the channels simultaneously, the capacity of working memory can be increased. This is mainly due to the independent working memory spaces of the verbal and the pictorial channel. However, the cognitive load theory does not focus on the types of information processes in multimedia learning.

Schnotz and Bannert (2003) developed a similar model of text and picture comprehension. The model shown in Figure 4 basically consists of a descriptive side (left) and a depictive side (right). Text is processed on the descriptive side through symbol processing. This descriptive branch comprises the text itself, the mental representation of the text and the propositional representation of the semantic content. On the other side, pictures are processed using a visual mental image and a mental model of the depicted matter. Users read a text and construct a mental representation of the text surface. In a second step a representation of the semantic content (for example a text base) is built, which finally leads to a mental model of the subject described in the text. The same applies for picture comprehension where a visual mental representation is constructed and the result is again a propositional representation as well as a mental model. For both, picture and text comprehension, task-relevant information is selected through top-down activation and then organized through automated visual routines. Comprehension of text and picture are goal-oriented processes, in which the user actively selects and processes information. The goal of processing is the construction of mental representations through selection of verbal and pictorial information. It has to be mentioned, that this model does not emphasize limited capacity (Schnotz & Bannert, 2003).

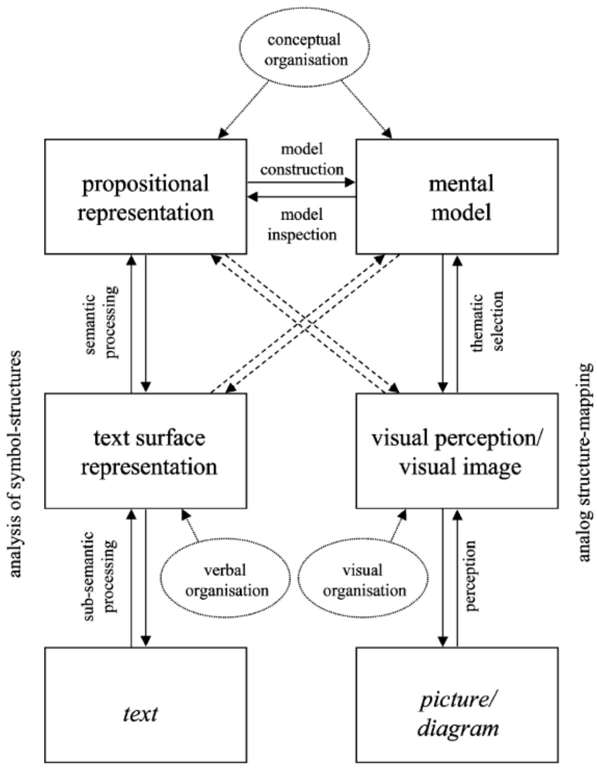


Figure 4: The integrated model of text and picture comprehension. Source: Schnotz and Bannert (2003)

The cognitive theory of multimedia learning (Mayer, 2005) combines the strengths of both, Schnotz and Bannert's (2003) and Sweller's (2003) theories. Multimedia learning is a demanding process including the selection of words and images, the organization of them into coherent mental representations as well as the integration of verbal and pictorial representations with each other and with prior knowledge. Visualizations containing multimedia messages should be designed to allow and boost multimedia learning processes. One has to consider how the human mind works when designing such visualizations for a better learning performance. Multimedia learning is a demanding process that requires selection of words and images and additionally organizing them into mental representations, which themselves can be integrated with each other and with prior knowledge. When designing multimedia displays, one should consider how the human mind works to ensure a meaningful learning (Mayer, 2005).

2.2.1 Individual Learning Differences

Prior knowledge is an important factor of learning. As described above, learners construct mental concepts and models from prior knowledge. Novices' knowledge is less coherent and integrated due to a fragmentation of their knowledge. In this case, the pieces of information are only held together through weak connections. Considering these reasons, novices tend to understand only surface features of visual representations (Cook, 2006). An empirical study about DNA representations supports these theoretical facts. Novices were able to distinguish the different DNA strands from each other by attending to the color difference. In behalf of their limited prior knowledge, they were unable to interpret meaning from it because of the missing cognitive resources for the exploration of the underlying themes of DNA replication (Patrick et al., 2005). On the other hand, experts can concentrate more on the information, which is relevant for the construction of a mental model on account of their bigger domain knowledge. Several studies (e.g., Schnotz et al., 1993; Larkin, 1981) show that experts are able to use prior knowledge for interpretation even when they are exposed to novel information because they possess a large number of existing schemas specific to the domain.

The different processing of visual representations by experts and novices is linked to cognitive architecture. Assuming that humans will not be able to process information when their limited working memory is overloaded, prior knowledge (stored in long-term memory) determines how much information can be held in working memory. This means that existing, stored prior knowledge keeps free the working memory space for novel information processing (Cook, 2006).

Schnotz (2002) talks about how different groups of readers differ in the processing of text and illustrations. Cognitive abilities, which are crucial for multimedia learning, are also age-dependent. Children in kindergarten tend to understand realistic pictures very well, whereas learning from reading is attained in primary school. The ability to understand graphs, called *visual literacy*, is acquired even later. Comprehension of abstract visual displays such as graphs require specific knowledge. A graph-schemata has to be acquired in order to understand these logical pictures. According to Bertin (1967), a graph reader must do three things: a) the reader has to identify the real-world referents that the graph is presenting information about. This connection between illustration and the real phenomenon is crucial, b) the dimensions of the graph have to be identified in order to understand the variables of the subject and c) the learner has to use the levels of each dimension to draw conclusions about the real-world phenomenon (Pinker, 1990).

2.2.2 Simultaneous Availability of Text and Illustrations

In general, scientists consistently report that information derived from text is remembered better when supporting illustrations are added to the verbal message. As Schnotz and Bannert's (2003) study shows, text information is remembered better when it is supported with illustrations. They justify this finding with the dual-channel theory but also emphasize that the results of such studies are always task-related. The human cognitive recognition processes work goal-oriented and thus, the results depend much on the given tasks. Other studies support these findings. Levie and Lentz (1982) for example also report that learners remembered text better when it was illustrated by pictures.

The supportive function of visual displays also depends on the learning content. Difficult material leads to a higher frequency of looking at adjunct visual displays as a support for the information in the text (Schnotz, 2002). Whenever text and pictures are presented simultaneously, illustrations like maps or graphs should be perceived first because they need less working memory capacity. After the illustrations have been processed, there is still enough memory space for text analysis. This advantage should be considered when designing a multimedia display (Schnotz, 2002).

Dual-mode presentations, where verbal and pictorial information is available next to each other, may exhibit redundant information. Presenting the same information in two different modes is discussed controversially in literature. Cook (2006) states that redundant information may decrease learning because students need to process the learning material twice and thus is using up cognitive resources. Rieber (1990) on the other hand suggests that learning material can be processed more effective when it is presented in graphic and text at the same time. Prior knowledge may again have an influence on the use of redundant information. Novice users benefit from the availability of different versions of the material because they might have problems understanding or interpreting one of the presentation types (Cook, 2006).

2.2.3 The Influence of Motivation and Attention

Text illustrations have several functions to enhance learning performance (see Table 2). One factor facilitating learning from illustrations may be motivation. Pictorial information attracts the attention of the user and in this way makes also the surrounding text more attractive. Furthermore, illustrations seem to direct learners' attention to the most important parts of the visualization. The colors of pictures seem to please people and arouse emotions. Additionally, illustrations facilitate comprehension of complex text information. They add appropriate imaginal memory store and hence facilitate retention of text information. Some information can be provided more effectively or efficiently with pictures than with words. And nevertheless, poor readers benefit from illustration when text segments are too complex to interpret (Levie & Lentz, 1982). Eilam and Poyas (2008) also mention the motivational effect of illustrations, which may be responsible for most of the results of multimedia learning studies. Users tend to be attracted by the images and thus rate information visualizations containing images higher than others.

	Functions
Attentional	1. Attracting attention to the material
	2. Directing attention within the material
Affective	3. Enhancing enjoyment
	4. Affecting emotions and attitudes
Cognitive	5. Facilitating learning text content via a. improving comprehension b. improving retention
	6. Providing additional information
Compensatory	7. Accommodating poor readers

Table 2: Possible functions of text illustrations. Source: Levie and Lentz (1982)

2.3 Design Principles

According to Shneiderman's (1996) overview first, allow zoom and filter, and display details only on demand principle, the design of advanced multimedia displays should have a hierarchical organization. Users should have the possibility to get an overview of the data at first glance. However, if they are interested in a particular part of the data collection a tool for zooming in should be available. A filter option can be useful to filter out uninteresting items. Details-on-demand allow selecting an item or group of data and thus extract detailed information when needed (Shneiderman, 1996). New technological developments allow interactive exploration and manipulation of data, multiple views of the same data and "the mixing of maps with other graphics, text, and sound" (MacEachren & Taylor, 1994, page 5). This is not only a difference in tools for representation but also a difference in the way of how users interact with the representations.

Knigge and Cope's (2006) thoughts on the design of interactive multimedia visualizations aim at a better understanding of underlying processes of the studied phenomenon. According to them, *focusing and brushing* as an interactive highlighting tool allows to visually highlight a subset of the data and thus enhances the understanding as well as the data exploration possibilities. Multiple images representing data change over time in different ways facilitates the understanding of the temporal process and is especially helpful for the comparison of data changing over time. Furthermore, tools like interactive legends or data-exploration tools (for example filters) enhance visual, iterative exploration of the data. It allows paying attention to both, the particular and the general, and accommodates multiple interpretations of the relations of data. Linking maps and other forms or sources of data (charts, graphs, ethnographic data like text or photographs) provide rich contextual data for consideration in the analysis. This additional information of various types may be most helpful in order to explain underlying processes or build mental cause-and-effect chains (Knigge & Cope, 2006).

Visual multimedia displays can support communication, thinking and learning. But therefore the representations have to interact appropriately with the individual's cognitive system. The learning effect depends on prior knowledge and cognitive abilities of the user (Schnotz, 2002). Moreno & Mayer's (1999) cognitive theory of multimedia learning explains how learners perceive and process explanative graphics using different cognitive process chains. Again, prior knowledge is one of the strongest factors influencing the interpretation of representations.

When designing multimedia visualizations, one should consider the different interactive tools, which can enhance the understanding of the underlying process by directing the attention of the user and enhancing the data-exploring possibilities.

3 Existing Approaches of Migration Visualization

This chapter describes a selection of existing approaches to visualizing migration. Quantitative and qualitative solutions are presented, followed by a mixed method system. A construction of a custom checklist derived from existing guidelines allows the evaluation of the described approaches. The results then reveal strengths and weaknesses of the different types of visualizations included in this chapter.

The earliest visualization of social movement is probably Minard's information graphic about Napoleon's Russian campaign of 1812 (see Figure 5). This statistical graphic drawn in 1869 by Charles Minard, a French civil engineer, shows several attributes in a single two-dimensional image. The flow map shows the size of the army as well as its geographical location in terms of geographical coordinates and place names. Furthermore, the direction of the movement – advance and retreat – shows where units split up and retreaded. Another important feature is the visualization of the date and the weather temperature on the bottom of the graph. Only a few maps before or ever since have been able to show so many variables in a single static image. Charles Minard's work set the standard for excellence in graphical flows of people and goods in space (Tufte, 2001). Minard himself said, "The aim of my carte figurative is less to express statistical results, better done by numbers, than to convey promptly to the eye the relation not given quickly by numbers requiring mental calculation." (Corbett, N.N.). Already at this time, Minard tried to display the information in the most useful way, so that numbers and figures successfully support each other for a better understanding of the data.

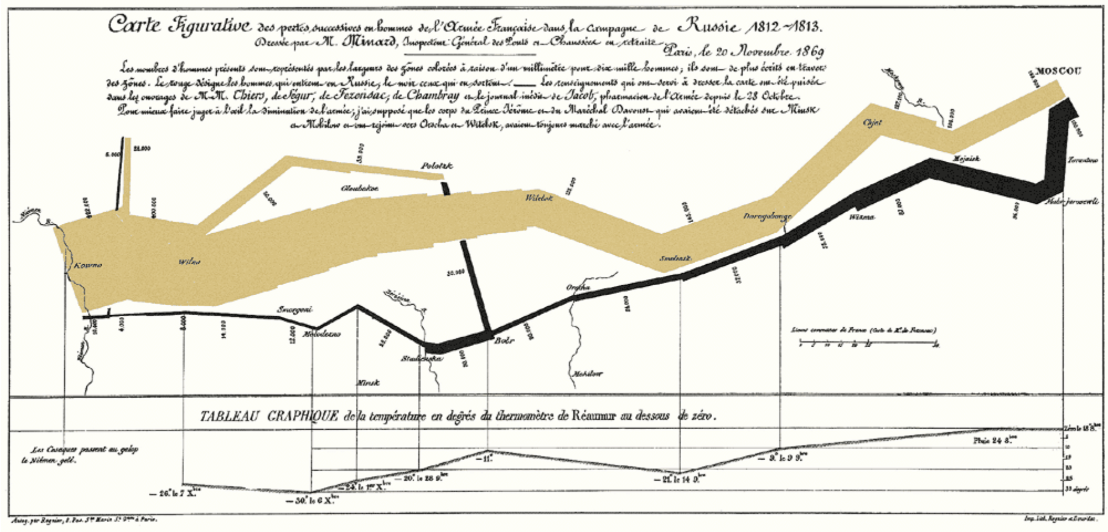


Figure 5: Minard's information graphic about Napoleon's Russian campaign. Source: http://www.edwardtufte.com/tufte/minard (Accessed: 08.09.2014)

Some of the first computerized flow maps were generated by Waldo Tobler in the 1980s (see Figure 6). These migration maps represent geographical movement by arrows between places. In his conclusion, Tobler talked about future developments of migration flow maps, which should be able to show the temporal change. He suggested representing migration over time in multiple static images connected through animation (Tobler, 2003).

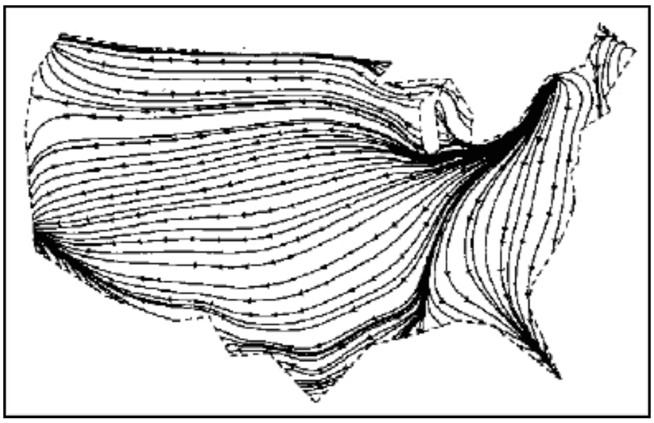


Figure 6: One of Tobler's first computerized flow maps. Source: Tobler (2003)

Nowadays, origin-destination maps (OD maps) are able to handle large data volumes. For example, Wood et al. (2002) presented new techniques for the visualization of large collections of geographic vectors. Their methods simplify and filter vector data, which authors suggest that it may increase the readability of the resulting OD maps (Wood et al., 2002).

A total of about 30 different interactive visualization systems about migration (national and international) have been found online in this research process. It appears that most visualizations are showing quantitative data only. A common feature is the representation as a flow map in order to show the migration origins and destinations. Alternative visualizations such as radial diagrams or choropleth maps are used less frequently.

3.1 Existing Quantitative Approaches of Migration Visualization

Interactivethings.com

Displaying migration flows as arrows between cantons in Switzerland in the most classical sense of a *flow map*. This approach is based on quantitative data only (see Figure 7). It uses one data frame (map) and a legend. These items are interactive and linked, which allows selecting flows or cantons and automatically highlighting them. Tooltips show the exact magnitude of flows when hovering. This visualization tool is able to show the dimensions of space as geographic locations as well as the magnitude of the migration flows in form of numbers of migrants. Simplicity and the clear design characterize this approach.

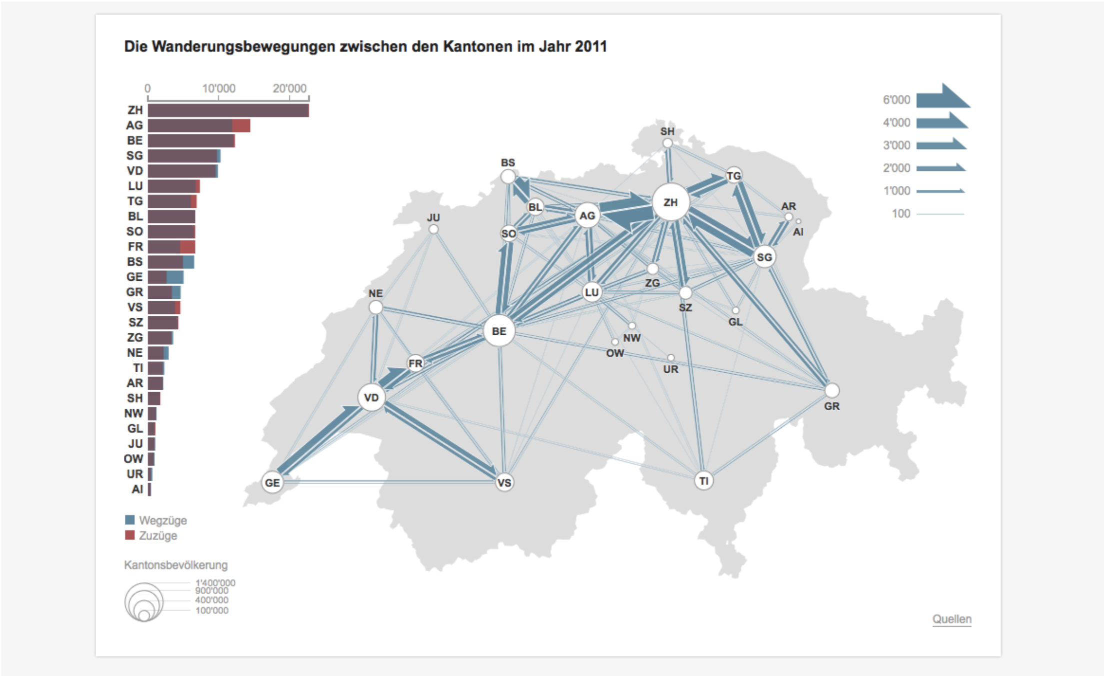


Figure 7: Screenshot of the internal Swiss migration visualization by Interactive Things. Source: http://work.interactivethings.com/nzz-swiss-maps/migrationsstroeme.html (Accessed: 08.09.2014)

Migrationsmap.net

Migrationsmap.net goes one step further, by providing (almost) an information system that covers migration globally (see Figure 8). It consists of one single data frame representing a world map with all countries. Migration flows are displayed by origin-destination connections for the selected country. Users can chose between arrivals and departures displayed. A legend on the left provides information about the size of the flows. A tooltip shows additional socio-economical information (e.g. population, GDP per capita or mortality under five) when hovering over a country. Even though the information comes in form of quantitative data, it could make users think about possible triggers for migration. Using quantitative data visualization only, this visualization tool brings in another dimension. The additional socio-economical information can generate knowledge, which could be used to explain reasons for migration flows or their magnitude.

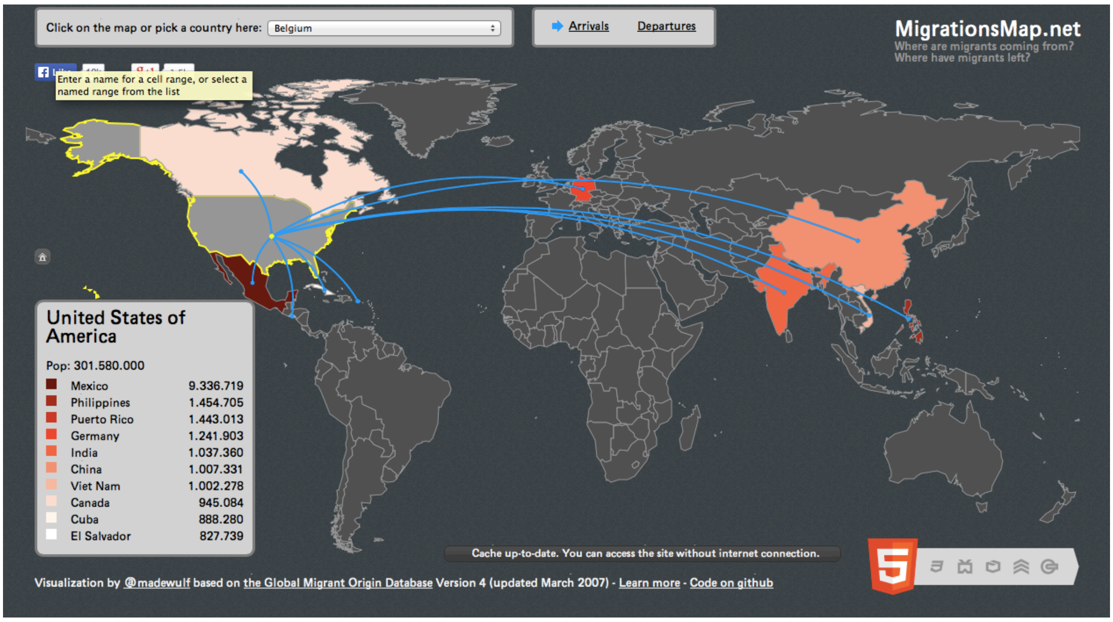


Figure 8: Global migration visualization realized by Martin De Wulf. Source: http://migrationsmap.net/#/USA/arrivals (Accessed: 08.09.2014)

Visualizing.org

This example is one of the most detailed visualizations of migration displays global migration flows over time (see Figure 9). Users have the possibility to select a year as well as the desired type of visualization, e.g. world map or connections. Thus, there is a lot of possible exploratory information in form of different visualizations for different years. It shows that the temporal dimension offers a lot of options for change detection or the development of phenomena over time.

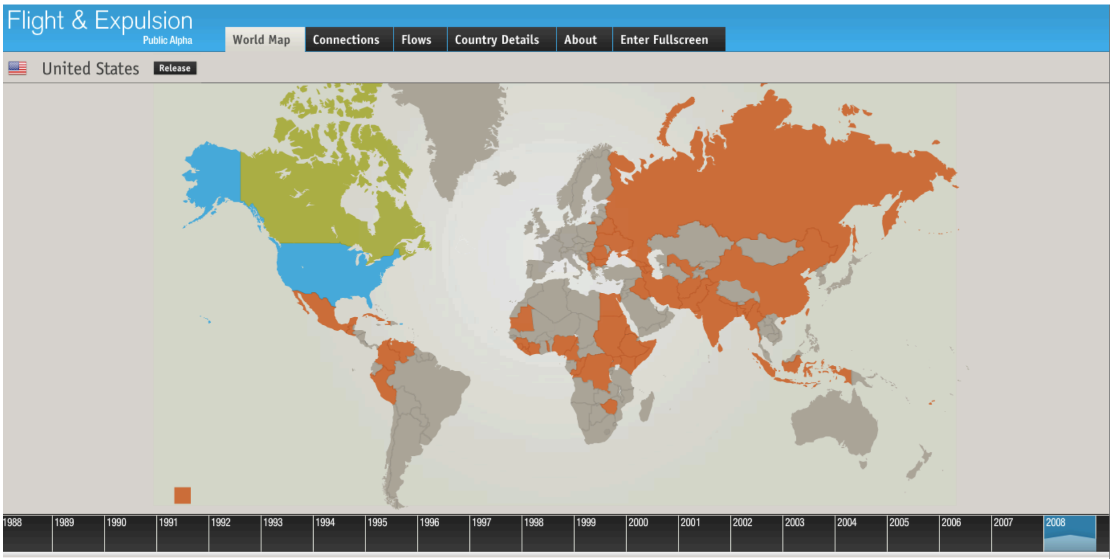


Figure 9: Global migration visualization created by Christian Behrens. Source: http://www.visualizing.org/full-screen/1767 (Accessed: 08.09.2014)

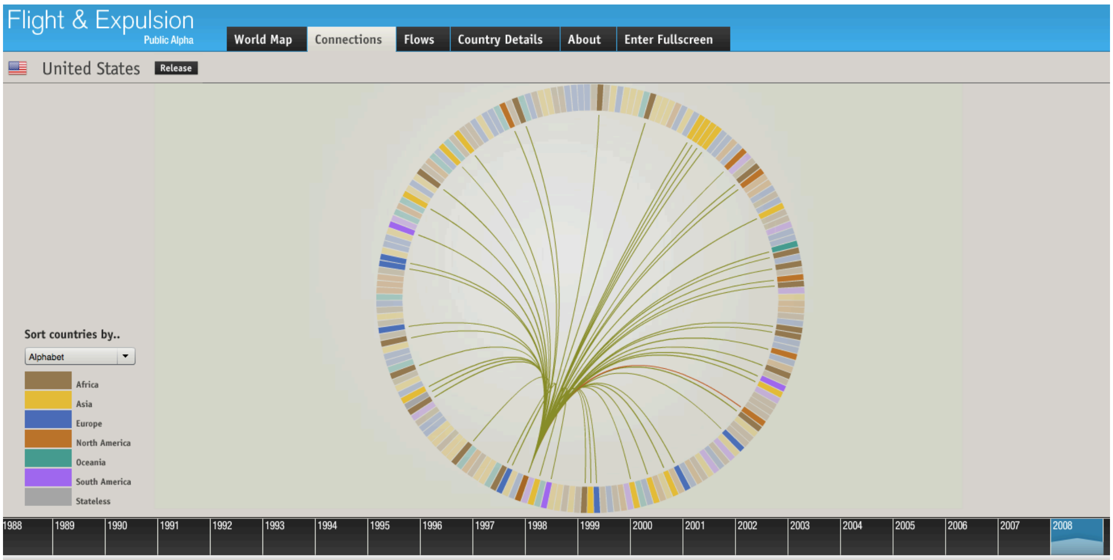


Figure 10: Radial connections of migration flows between countries. Source: http://www.visualizing.org/full-screen/1767 (Accessed: 08.09.2014)

Nytimes.com

This visualization created by the New York Times shows the settlement development of foreign-born people in the United States of America on the county level (see Figure 11). The user has the possibility to select the country of origin as well as the year, which results in one bubble per county representing the number of foreigners.

Additionally, the number of foreigners per county can be displayed absolutely or relative compared to the whole population. The tooltip shows exact numbers.

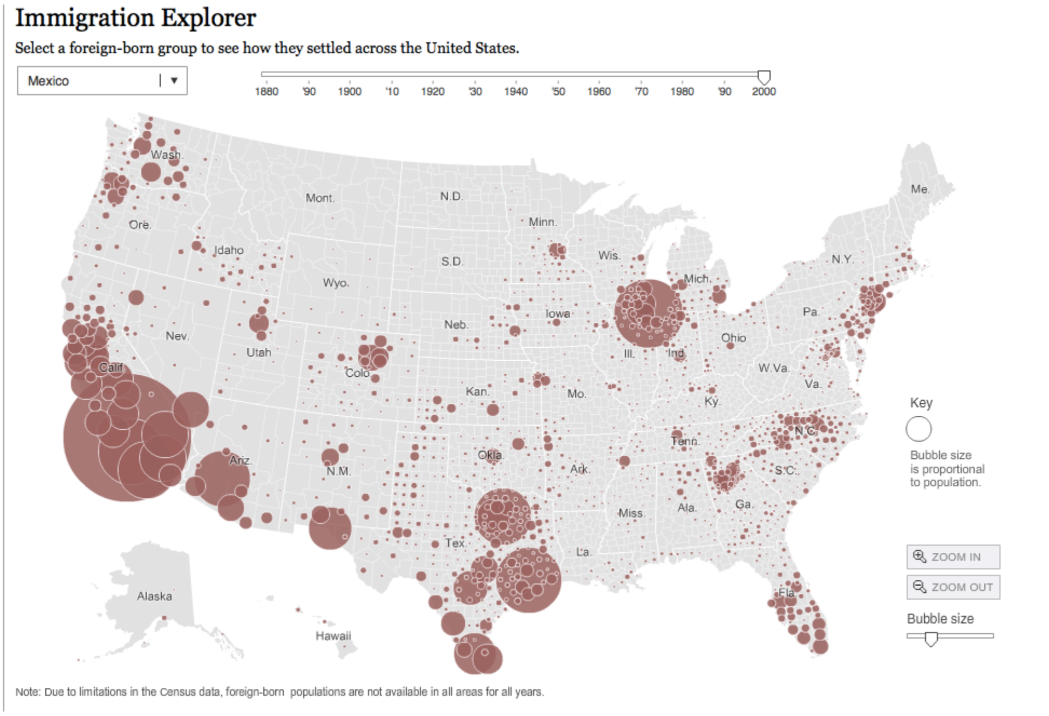


Figure 11: Bubble map showing settlement of foreign-born people in the USA, created by Matthew Bloch and Robert Gebeloff. Source: http://www.nytimes.com/interactive/2009/03/10/us/20090310-immigration-explorer.html (Accessed: 08.09.2014)

This is only a selection of existing approaches in quantitative migration visualization. There are undoubtedly many more information visualization systems representing different aspects of migration globally and locally. The examples described above were chosen due to their representativeness. Most of the other existing systems are based on the same principles or use the same kind of representation tools.

3.2 Existing Qualitative Approaches of Migration Visualization

Qualitative material is often not visualized but presented as collections of text, videos or photos, typically as independent repositories (e.g. International Migration "Photo

Stories”[2] or University of Washington “The Southern Diaspora”[3]). However, there are some examples where more than one qualitative form is contained in an interactive environment.

Contakt-spuren.ch

The visualization of the history of migration to Switzerland produced by Migros Schweiz is based on a central time bar (see Figure 12). This time slider is the main tool to control this visualization. Users can scroll through this virtual history book and stop wherever they want. Important events are marked on the time bar and linked to additional multimedia information like text, videos or photos. The time slider is the only quantitative part in this visualization because the rest of the data is provided in form of qualitative multimedia data. Despite the fact that this information system is aimed for educational use, it can still be seen as an information visualization based on qualitative data.

Figure 12: Screenshot of the interactive timeline showing the history of immigration to Switzerland. Source: http://www.contakt-spuren.ch/Wissen/Zeitstrahl (Accessed: 08.09.2014)

[2] http://www.iom.int/cms/en/sites/iom/home/news-and-views/photo-stories.html (Accessed: 08.09.2014)

[3] http://faculty.washington.edu/gregoryj/diaspora/photos.htm (Accessed: 08.09.2014)

Theage.com.au

This collection of migrant stories offers the exploration of different individual stories of people migrated to Australia. The start page (see Figure 13) lets the user chose a particular story by clicking on the link or on the photograph. Once selected a story, users can access further information about the migrant in form of videos, audio records, interview transcripts or pictures. All records have been collected by Age reporters and photographers in order to present the variety of problems which motivated people to migrate to Australia.

Figure 13: Screenshot of the interactive migrant stories created by Martin Daly. Source: http://www.theage.com.au/interactive/2008/national/migrants/ (Accessed: 08.09.2014)

More solutions based on qualitative data

Classical information visualizations about migration based on qualitative data are rare. But a lot of qualitative migration research has been done without creating explicit visualizations or information graphics (e.g. Thieme & Wyss, 2005). In the broadest sense, the results of these studies – interviews in form of text, videos or pictures – can be seen as visualized migration data as well. Furthermore, textbooks about migration and its triggers are visual solutions containing qualitative data as well.

3.3 Existing Mixed Methods Approaches of Migration Visualization

The infographic shown in Figure 14 documents the history of migration in and out of the United Kingdom from 1964 to 2012. A line graph in the upper half of the visualization displays the number of migrants (in and out of the United Kingdom) as well as the net migration. A slider lets the user chose the desired year. Once the year is chosen, the bottom part of the system shows additional information in form of text and links about the corresponding year. The top three countries of last residence and next residence are shown on the right side. This visualization approach allows users to investigate the quantitative data while receiving additional qualitative information about a given time period.

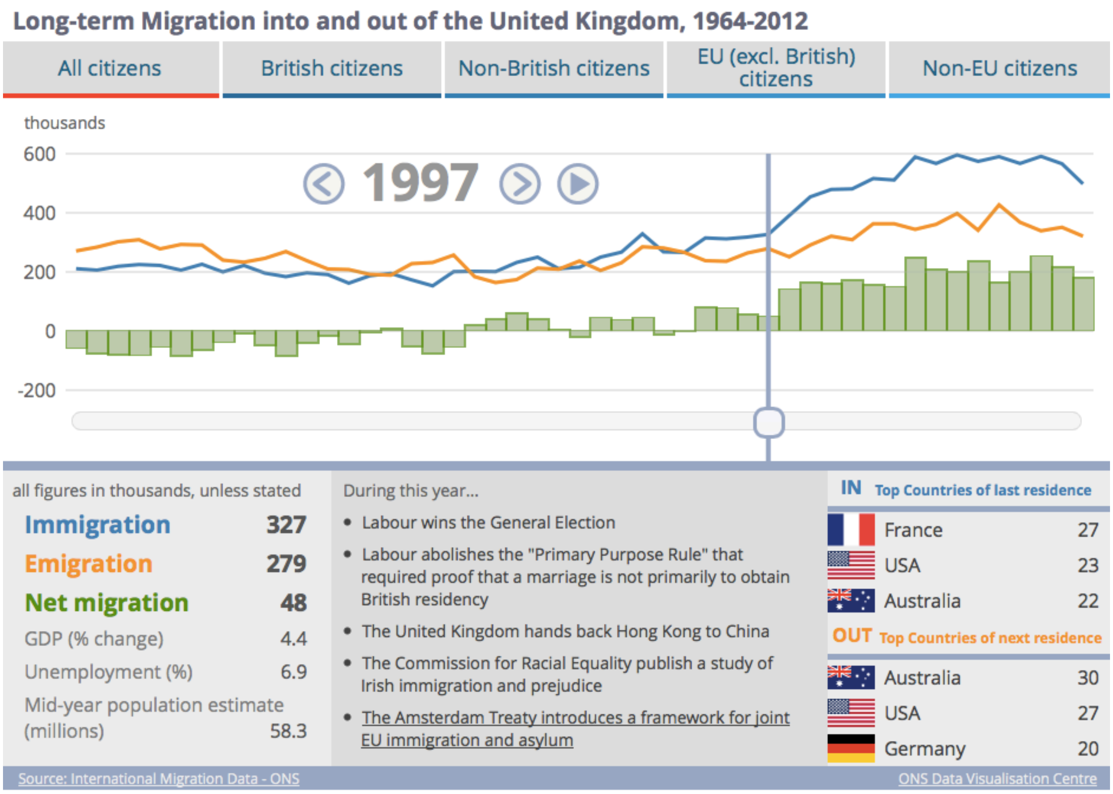


Figure 14: Screenshot of the infographic about migration into and out of the UK with quantitative data on top and qualitative data on the bottom, created by the Office of National Statistics. Source: http://www.neighbourhood.statistics.gov.uk/HTMLDocs/dvc123/migration.html (Accessed: 08.09.2014)

3.4 Comparison of Existing Approaches

As Andrews (2008) reported, evaluation methods of information visualization techniques can be classified into two types according to who performs the evaluation (Andrews, 2008):

- Inspection methods: Evaluators inspect the interface or the visualization and use their experience to assess it.
- Testing methods: Test users use interfaces or visualization systems and observations or measurements are made.

For reasons of extent, this case will use an inspection method and a qualitative evaluation of the existing approaches using guidelines and design principles from literature.

For a better comparison of the different visualization approaches, two guidelines will be used. Shneiderman's (2003) eight golden rules of interface design will serve as key principles for the evaluation of the interfaces. The rules are (Shneiderman, 2003):

1. Strive for consistency
   Consistent sequences of actions should be required in similar situations and identical terminology should be used in prompts and menus. If menus are consistent, the user can quickly figure out what is to be done in a next step.
2. Cater to universal usability
   Needs of diverse users have to be recognized.
3. Offer informative feedback
   For every user action, there should be system feedback.
4. Design dialog to yield closure
   Sequences of actions should be organized in groups with a beginning, middle, and an end. Feedback when completing a group of actions gives users the satisfaction of accomplishment.
5. Prevent errors
   The system design should not allow users to make serious errors. If an operator makes an error, the system should be able to detect the error and offer a simple instruction for recovery.

6. Permit easy reversal of actions
   As much as possible, actions should be reversible.
7. Support internal locus of control
   The system design should make users feel in charge of the system.
8. Reduce short-term memory load
   Interfaces in which users must remember information from one screen and then use that information on another screen should be avoided.

The evaluation of the visualizations requires a separate checklist of principles. A recently published data visualization checklist for the development of high impact data visualizations serves as a second guideline (Evergreen & Emery, 2014):

1. Graph
   The graph highlights significant finding or conclusion.
2. Type of graph
   The type of graph is appropriate for the data.
3. Level of precision
   The graph has an appropriate level of precision.
4. Comparisons
   Contextualized or comparison data are present to help the viewer understand the significance of the data.
5. Text
   The text size is hierarchical and readable. Data labels are used sparingly (avoid redundancy).

Furthermore, classical cartographic principles serve as guidelines for the design of the system (Buckley, 2012; Slocum et al., 2009):

1. Visual Contrast
   Visual contrast relates how map features and page elements contrast with each other and their background.
2. Legibility
   Legibility is the ability to be seen and understood.

3. Figure-Ground Organization

   Figure-ground organization is the spontaneous separation of the figure in the foreground from an amorphous background.
4. Hierarchical Organization

   The internal graphic structuring of the system is fundamental to helping people understand your visualization.
5. Balance

   Balance involves the organization of the map and other elements on the page.

With a combination of these three lists, all the visualization approaches described above will be evaluated. For the special case of migration visualizations, only the most relevant points of the guidelines above have been chosen to serve as evaluation criteria. The results of the evaluation will then help to provide information about pros and cons, strengths and weaknesses of different types of data visualizations.

The final checklist (derived from all the checklists above), used to evaluate existing approaches contains following points:

1. **Interactivity**
   a. Level of interactivity

      The degree of interactivity is being judged by simply evaluating the number of possible interactions between the user and the system.
   b. Linked-views

      As described by different authors (e.g. Knigge & Cope, 2006), linked-views help to compare and analyze data. The ability of the system to change the display of data in several frames.
   c. Tooltip

      A tooltip helps to extract exact information out of visualization system at any point.
2. **Layout**
   a. Text & Labels

      Evergreen & Emery (2014) advice to use text and labels sparingly and in a hierarchical order.

b. Colors

Derived from the cartographic principles (Buckley, 2012; Slocum et al., 2009), colors have to be chosen carefully to ensure the visual contrast and the figure-ground organization.

c. Design

The design points to the arrangement of all the objects of the systems. The ability to highlight the most important things and organize the system in a hierarchical way is crucial (Buckley, 2012; Slocum et al., 2009).

3. Content

a. Magnitude

In migration visualization systems, the magnitude of the migration flows should be visible to understand and compare them.

b. Triggers

Understanding migration includes knowledge about triggers or reasons for migration, which should be visualized as well.

c. Spatial Dimension

Since migration is a spatial phenomenon this geographic dimension has to be visible to the user.

d. Temporal Dimension

The analysis of the development of migration requires a temporal dimension displaying change over time.

The evaluation rooster described above has been used to rate the existing solutions. All of the 10 criteria are judged on a Likert-scale from 0 (low performance/not available) to 2 (high performance/very good solution). The central value of 1 (average performance) characterizes average solutions. To grant further reliability, the evaluation has been performed three times by different evaluators. All of them are Master of Science students in Geography at the University of Zurich.

3.4.1 Results

The results reveal that the performance of the mixed method solution is rated highest by all three evaluators with an average score of 14 points out of 20 possible points. Existing approaches with the focus on quantitative data reached an average score of 11.25 points while qualitative systems only scored 6.89 points on average (see Table 3). For detailed scoring results see Appendix A.1.

	Interactivity			**Layout**			**Content**				**Total**
	Level of Interactivity	Linked view	Tooltip	Text & Labels	Colors	Design	Magnitude	Triggers	Spatial	Temporal	
Interactivethings.com	1.3	0.3	0.7	1.7	1.7	2	2	0	1.7	0	**11.3**
Migrationsmap.net	1.7	1	1.7	1.3	0.7	0.7	0.7	0.7	2	0	**10.3**
Visualizing.org	2	1.7	1.7	1.3	1	1.3	0.7	0	1.3	1.3	**12.3**
Nytimes.com	1.7	0.7	1.3	1.3	0.7	1	2	0	1	1.3	**11**
Contakt-spuren.ch	0	0	0	1.3	0.7	1	0.3	2	0	1.7	**7**
Theoage.com.au	0.7	0.3	0	1.3	1	1	0	2	0.3	0.3	**7**
Books & Videos	0	0	0	1	1	1	1	2	0	0.7	**6.67**
Statistics.gov.uk	1.7	1.7	0	0.7	1.3	2	2	1.7	1	2	**14**

Table 3: Average results of the analyzed existing approaches.

These findings suggest that the mixed method outperforms the qualitative and quantitative approaches regarding the guidelines composed for this particular case. Additionally, a lower performance of the approaches working with qualitative data only is visible. This result can be explained by the low scores (0 points) for all the interactivity criteria.

3.4.2 Discussion

As seen in the previous section, the majority of existing visualization solutions works mainly with quantitative data. This brings several benefits, particularly for the comparison of data. Another advantage is the availability of exact measures for every object. The main strength of quantitative data visualizations remains the potential interactivity between the user and the information system. On the other hand, qualitative approaches outperform their quantitative counterparts in terms of information content for migration triggers and background information. The focus lies on the understanding and explanation of migration rather than on the comparison or analysis of the migration flows themselves.

Based on this initial “top-down” evaluation of existing approaches of migration visualization, we can hypothesize that it may make sense to integrate qualitative and quantitative data in order to reveal socio-economical processes as well as statistical-analytical patterns. Furthermore, the use of tools for interaction and highlighting might foster data-exploration.

4 Implementation

4.1 Case Study Migration to Switzerland

The case study is about the phenomenon of mass migration into Switzerland. Since the end of World War II, several waves of human migration into Switzerland could be observed. Due to its neutral politics and robust economic situation, Switzerland has always been a popular destination for migrants from all over the world (Wottreng, 2000).

Two migration flows have been chosen to serve as case studies. Migration from Kosovo to Switzerland was responsible for the massive increase of immigration in the late 1990s in Switzerland. Before 1960, Kosovars migrated to Switzerland mainly as seasonal work migrants. But due to the war between Serbians and Kosovars in 1998 and 1999, ten thousands of Kosovars fled to Switzerland. This case study serves as an example for a major migration flow with high numbers of migrants. The second case study describes the migration of Spanish people to Switzerland during and after the financial crisis in 2007/2008. Several southern European countries suffered from the economic crisis and as a direct consequence their grand domestic product (GDP) per capita dropped drastically. As a result of the crisis, the youth unemployment (under the age of 25) rate increased significantly and reached its highest level in 2013 with 55.7% (Burgen, 2013). Unemployment is one of the most important economic indicator affecting international migration (Mihi-Ramirez et al., 2013). This is why Spain turned from one of the top destinations for migration into one of the top origins of international migration. The mostly well-educated young workers hope to find jobs in countries with a lower unemployment rate and better prospect on the labor market (Bräuniger et al., 2011). The Spanish migration case study was chosen due to its timelessness and relevance in the last years.

4.2 Available Data

The raw dataset originates from EUROSTAT[4], the statistical department of the European Union as well as from the World Bank Database[5]. Some of the more detailed statistical data about Switzerland is derived from the Swiss Federal Statistical Office[6]. These datasets contain numbers only for selected countries and can be downloaded as Microsoft Excel tables. The Uppsala Conflict Data Program (UCDP) stores data about armed conflict around the world and conducts research in several major areas of peace and conflict studies. The UCDP/PRIO Armed Conflict Dataset is freely available on their website[7]. For the qualitative part of the data, various sources have been used. Text data for the case study of Kosovar migration has been extracted from a document published by the Swiss Federal Statistical Office (Sharani et al., 2010). Qualitative text data originates from several books (ILO, 2013), documents (Bräuniger et al., 2011; Dolado et al., 2013; Mihi-Ramirez et al., 2013) and newspaper articles (Burgen, 2013; Tagesschau, 2013). Photos and videos have been downloaded or linked from various portals (e.g. Youtube or Wikimedia). Since the evaluation of the implementation is only serving as a proof of concept, the variety and diversity of the data sources is not affecting the system in a negative way.

4.3 Available Software

Tableau 8.0, originally developed in order to increase people's ability to analyze information, is a program for exploring and analyzing relational databases. Its main target audiences are business analytics who want to make databases and spreadsheets understandable to ordinary people and other business partners. User can create interactive multimedia graphics containing plots, text, links, maps, pictures without almost any programming knowledge. The graphical user interface allows simple drag-

---

[4] http://epp.eurostat.ec.europa.eu/portal/page/portal/statistics/search_database (Accessed: 13.09.2014)

[5] http://data.worldbank.org (Accessed: 13.09.2014)

[6] http://www.bfs.admin.ch/bfs/portal/de/index.html (Accessed: 13.09.2014)

[7] http://www.ucdp.uu.se/gpdatabase/search.php (Accessed: 13.09.2014)

and-drop integration of data from Microsoft Excel spreadsheets. Various design options and interactivity possibilities are available in order to increase the readability of the data displays.

4.4 Preparing Data

The raw migration data tables have been downloaded from the statistical department of the European Union (EUROSTAT), from the World Bank Database and from the Swiss Federal Statistical Office. In a second step, the data has been filtered and cleaned up using Microsoft Excel. Furthermore, the UCDP/PRIO Armed Conflict Dataset v.4-2014 containing armed conflicts from 1946 to 2013 has been downloaded as a Microsoft Excel spreadsheet and has as well been cleaned up and filtered. The two resulting Microsoft Excel spreadsheets – one about armed conflicts and one about the migration data – then were connected to Tableau 8.0. This connection is live, which means live updates of changes in the spreadsheets are made automatically. The text data has been summarized from previously described sources and has been edited for a consistent appearance.

4.5 Design

Following the design principles described in chapter 2.3 of this thesis, three different visualizations have been constructed for each case study.

4.5.1 Case Study Spain

This visualization is based on text and pictorial data only. On the left side, text about the situation in Spain and about the migration to Switzerland is situated. The two subtitles divide the text into two paragraphs. Additionally, two photographs and two videos about the phenomenon have been placed on the right hand side of the visualization (see Figure 15). Although this visualization does not explicitly need to be realized with Tableau, the program has been used anyway to ensure equal conditions compared to the other visualizations.

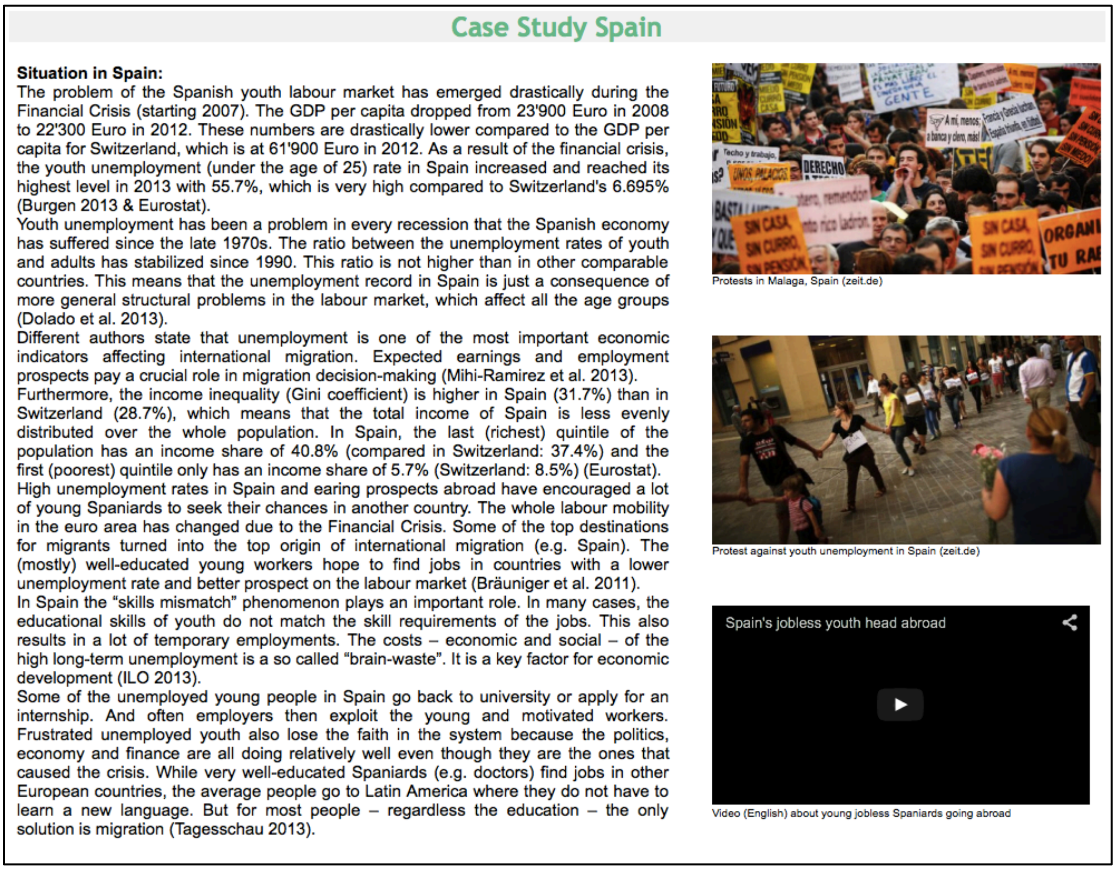


Figure 15: Screenshot of the qualitative visualization for the case study of Spain.

The second type of visualization is based on quantitative data only (see Figure 16). It displays migration of Spanish people to Switzerland (individuals per year) in the upper left corner as a line chart. In the upper middle, the top 10 destinations for Spanish migrants in the year 2011 are displayed as a pie chart. Some more basic statistical numbers about Spain and Switzerland (e.g. population) are placed in the upper right corner. The middle of the visualization shows the grand domestic product (GDP) per capita and the unemployment rate under the age of 25 for both Spain and Switzerland from 2002 until 2013. For both countries, the same axis scale has been used for a better comparison. The bottom part consists of two stacked bar charts representing the income distribution for both countries. All plots (except the basic statistical information) are interactive. Hovering over the data shows exact values (see

Figure 17) and selection of data highlights the it (see Figure 18). These tools allow a faster extraction of values as well as a better comparison of data.

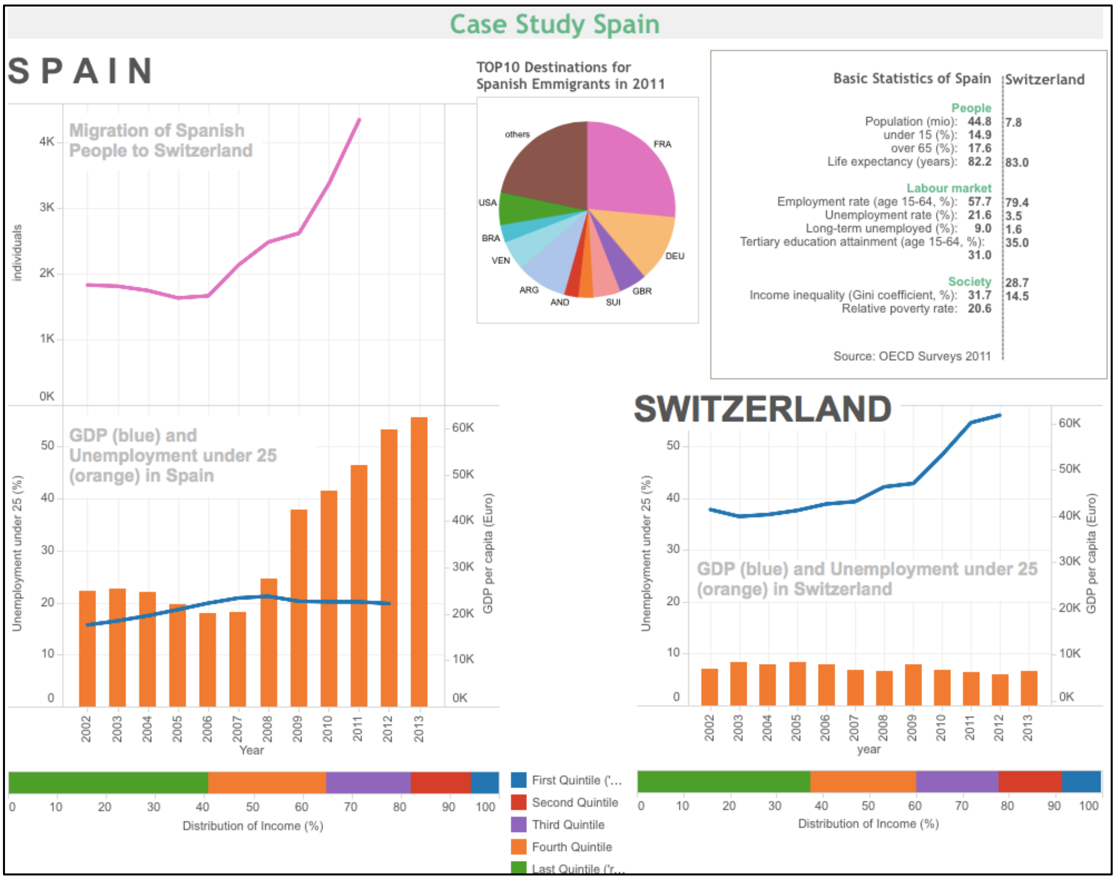


Figure 16: Screenshot of the quantitative visualization for the case study of Spain.

Figure 17: Screenshot of an example of the tooltip usage.

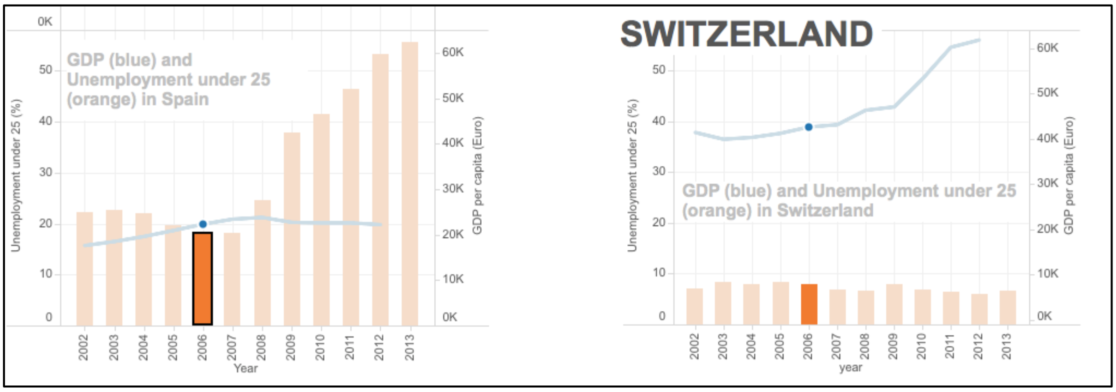


Figure 18: Screenshot of an example of the highlighting function.

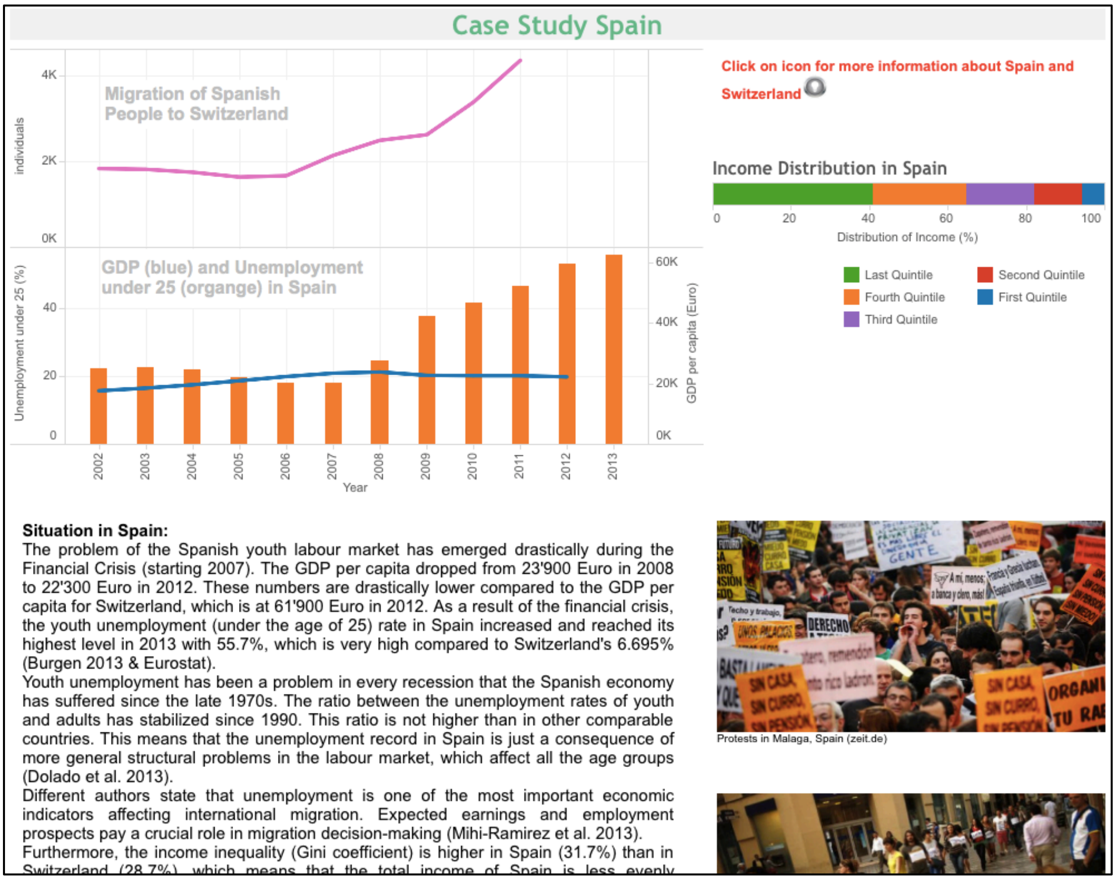


Figure 19: Screenshot of the mixed visualization for the case study of Spain.

The mixed version includes both data types – quantitative and qualitative, plots and text (see Figure 19). It basically combines all the information from both visualizations explained above. The top half of the visualization shows quantitative data in the same form as in the quantitative only visualization. Due to restricted space, some of the plots are accessible by activating a link. Highlighting and hovering tools have been integrated, too. The same text and pictures as in the qualitative only version can be found in the bottom half of the screen.

4.5.2 Case Study Kosovo

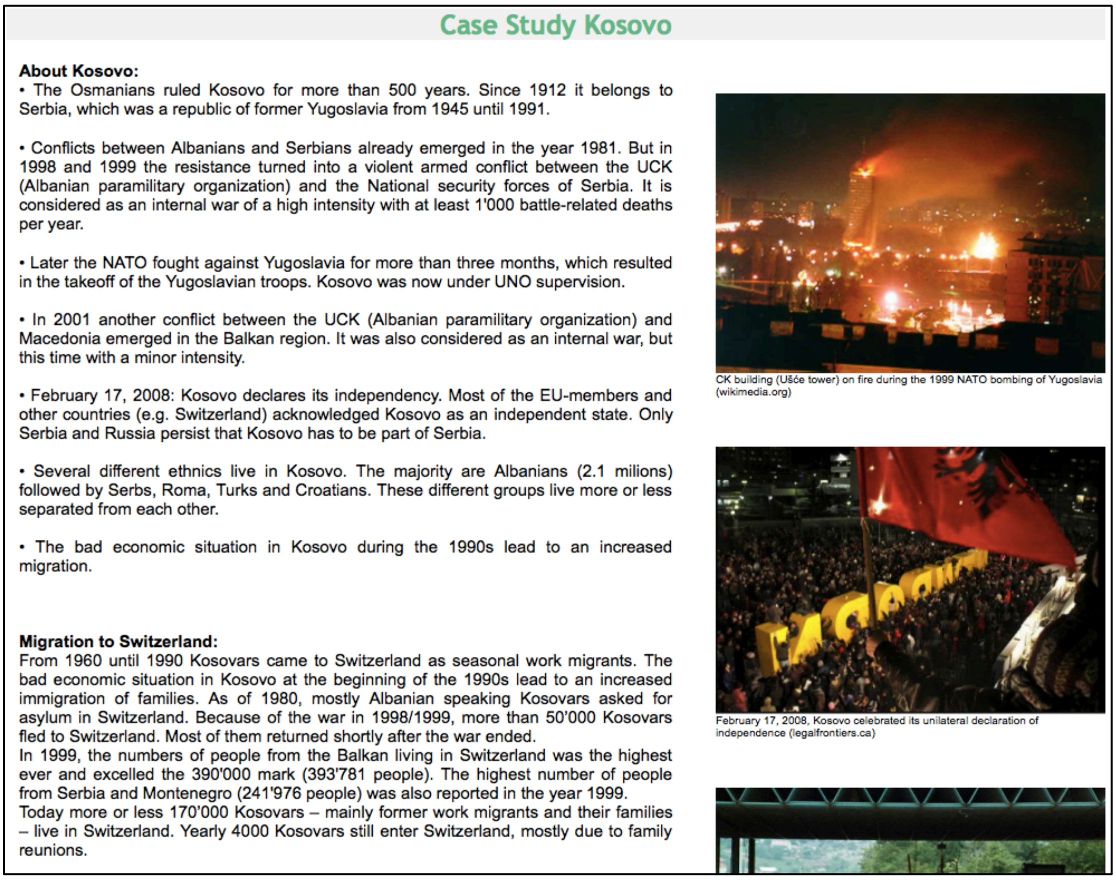


Figure 20: Screenshot of the qualitative visualization for the case study of Kosovo.

According to the Case Study Spain, the qualitative visualization is mainly based on text data (see Figure 20). It is divided by three subtitles for more structure. Additionally, three pictures and one video has been integrated on the right side of the screen.

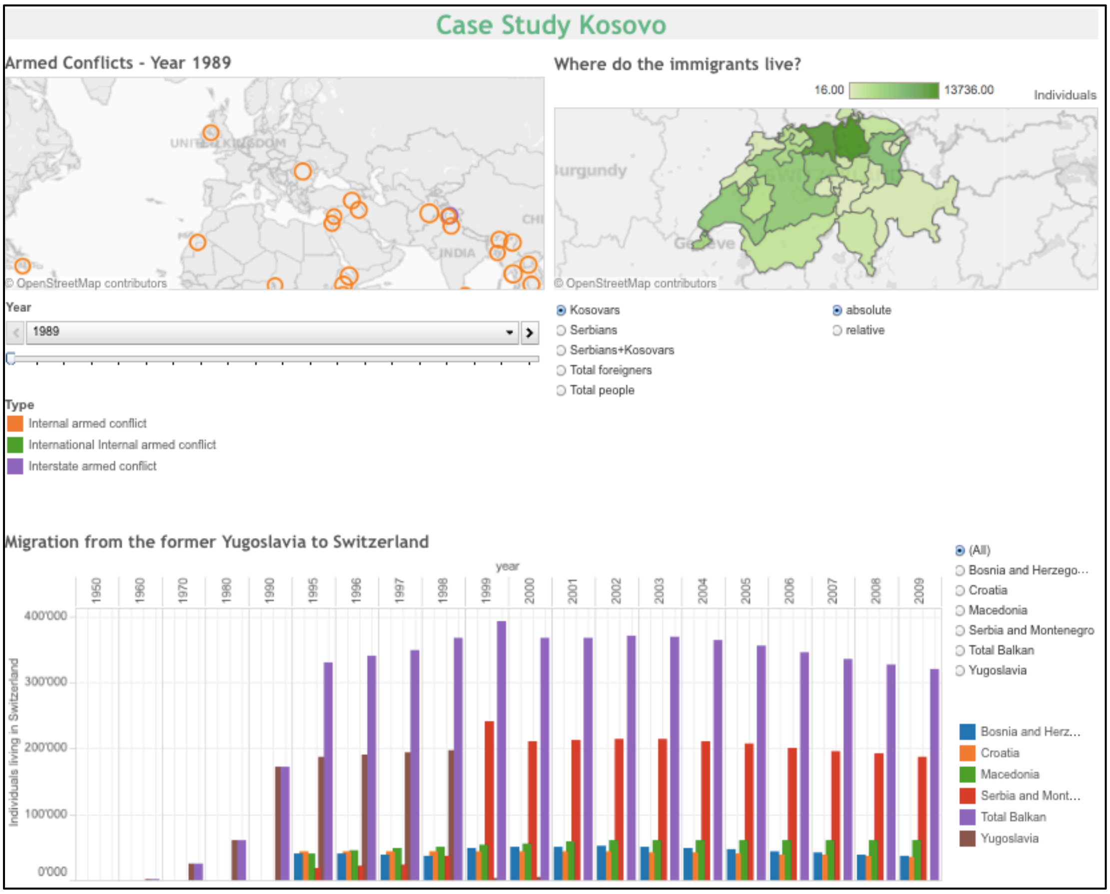


Figure 21: Screenshot of the quantitative visualization for the case study of Kosovo.

Similar to the previous case study, quantitative data about the migration from Kosovo to Switzerland has been displayed using different methods (see Figure 21). The map on the left side represents armed conflicts all around the world from 1989 to 2008. Users have the possibility to choose a year from the dropdown menu. According to the year chosen, all the conflict zones will be displayed as circles. Different conflict types (e.g. internal armed conflict, interstate armed conflict) are displayed in different colors and hovering over one of the regions allows access to further information about the conflict (e.g. number of battle-related deaths, parties involved, type of conflict). The second map on the right side shows the distribution of different ethic groups over Switzerland in 2011. Users can chose between different nationalities (e.g. Kosovars, Serbians) and two different visualization types (absolute numbers and relative numbers). According to the users' choice, the number (respectively percentage) of the chosen nationality is displayed per canton. Again, hovering shows exact values. The grouped bar chart on the bottom of the visualization shows the number of residents from different Balkan regions living in Switzerland from 1950 to 2009. Control buttons allow users to display only one ethnicity at the time or display all groups at the same time. The hovering and highlighting tool works according to all other plots.

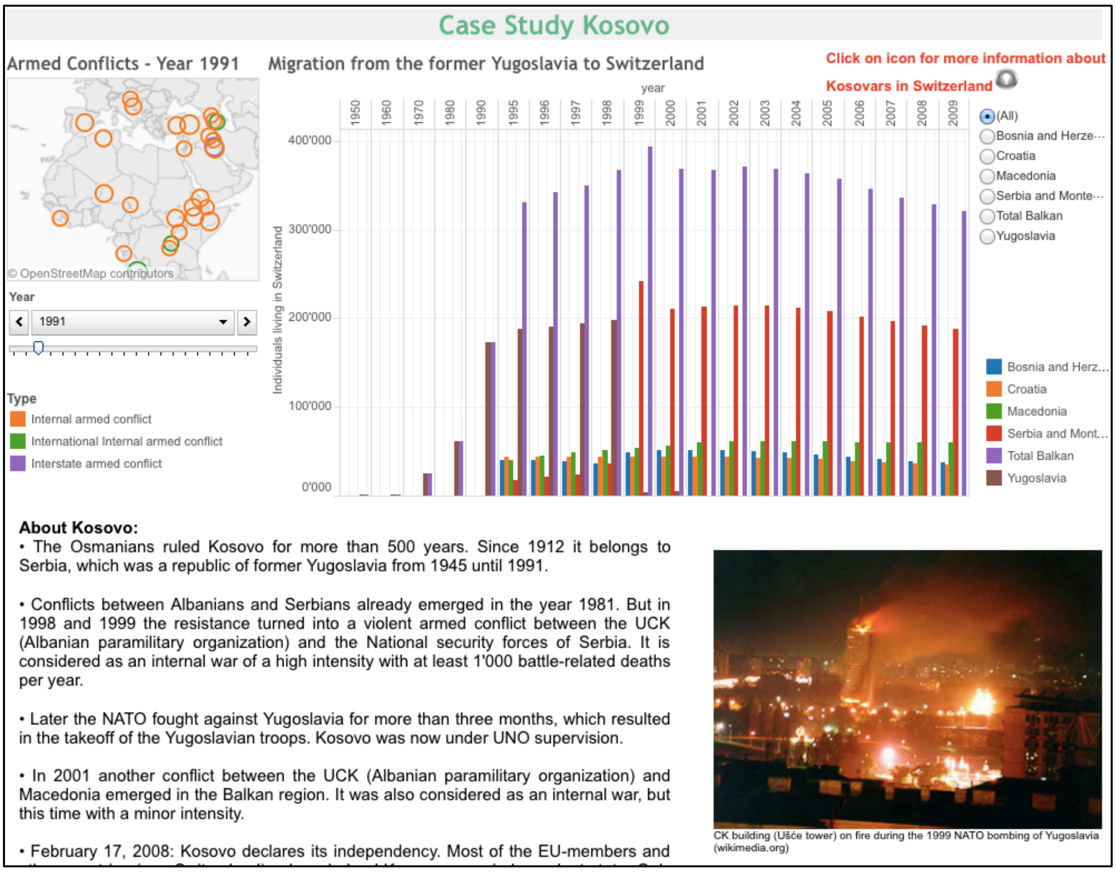


Figure 22: Screenshot of the mixed visualization for the case study of Kosovo.

Combining the qualitative and quantitative information results in this mixed version (see Figure 22). Again, some of the quantitative plots have to be accessed by activating a link.

5 Evaluation

This chapter deals with the evaluation of the implemented visualizations described in the previous chapter. First, an evaluation method has to be selected according to the goal of the experiment. The method will be described in detail before the characterization of the participants. Details of the experiment design as well as the stimuli are explained and a step-by-step proceeding of the experiment covers the last part of this chapter. Basically, all the visualizations may be tested in terms of performance (accuracy, satisfaction, usability and speed).

According to the findings of the literature research, following hypotheses emerged:

> *H1: There are differences in the performance of the three visualization types regarding the variable "SUS"-scores.*

Literature suggests an increased satisfaction and usability using mixed methods displays (e.g. Colaso et al., 2002). The possibility to derive information from both text and illustrations allows participants to take advantage of their individual processing strengths.

> *H2: There are differences in the performance of the three visualization types regarding the variable "Average Response Time".*

Quantitative data displays are showing a higher level of structure and thus, information can be extracted faster (e.g. Eilam & Poyas, 2008).

> *H3: Participants' different educational backgrounds have an influence on their performance using the three visualization types.*

Daily work and experience with different data types might differ between participants with natural science and social science backgrounds. Qualitative methods have a long historical tradition in social sciences (Morgan, 2007), hence social scientists might be more familiar with qualitative data representations. On the other hand, participants with a natural science background may be more used to the quantitative type of data due to their professional experiences.

H4: Participants' different levels of experience have an influence on their performance using the three visualization types.

Prior knowledge is a key factor for processing new information (e.g. Cook, 2006; Patrick et al., 2005). Thus, participants' different levels of experience are crucial for their performance using the three visualization types. According to literature, illustrations are processed more efficient by users with more experience, whereas novice users tend to come back to textual information in case they do not understand a quantitative graphic (e.g. Mayer, 2005; Larkin, 1981).

In respect to equality of information, only comparisons between qualitative and mixed version or quantitative and mixed version are possible. A comparison between qualitative and quantitative visualizations is not acceptable since it can not be assured that the amount of information in the text is consistent with the information delivered in the plots. Considering this restriction the test environment (see Figure 23) consists of two case studies (Spain, Kosovo) with three visualizations each (qualitative, quantitative, mixed). The performance of the mixed type visualizations will be analyzed in detail and compared to the corresponding qualitative and quantitative control visualizations.

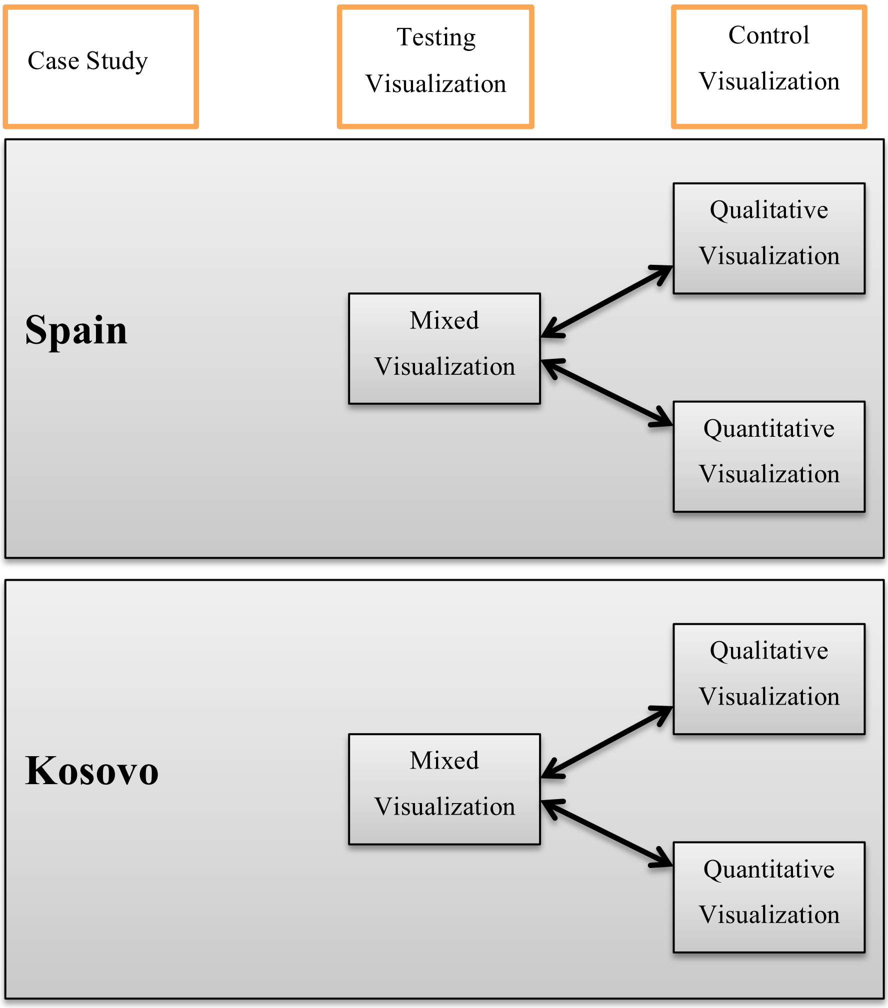


Figure 23: Test environment consisting of 2 case studies with 1 tested visualization and 2 control visualizations each.

5.1 Evaluation Methods

At this point an evaluation method had to be selected. Since the goal of this thesis is the evaluation and comparison of different visualization settings, a method for the analysis of the user's attentional patterns over a given stimulus is required. As the setting – in our case the information type – of the visualization changes, the eye-tracking method is ideal to record and later analyze the participants' eye movements and their changing locus of attention (Duchowski, 2007). The eye-tracking method can help to understand visual information processing and the factors impacting the usability of the system (Poole & Ball, 2005).

In order to evaluate the performance of the designed visualizations, users will be asked to perform different tasks using all the systems implemented in this thesis.

5.1.1 Eye-Tracking

The *eye-tracker* used in this study consists of a standard desktop computer with an infrared camera integrated at the bottom of the display monitor and equipped with the image processing software Tobii Studio 3.2. During recording, infrared light from a LED is directed into the eye of the participant. After the light entered the retina, a large proportion of it is reflected back. The pupil appears as a bright disc (known as "bright pupil" effect) and can be tracked by the infrared camera. Additionally, the LED creates a strong reflection in the cornea, which appears as a small glint (Poole & Ball, 2005).

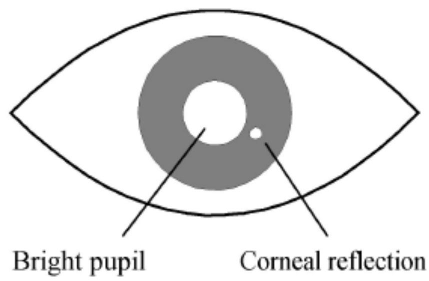


Figure 24: Corneal reflection and bright pupil as seen in the infrared camera image. Source: (Poole & Ball, 2005)

The Tobii Studio software then identifies the center of the pupil and the location of the corneal reflection and measures the vector between them. Further trigonometric calculations help to calculate the point-of-regard (Poole & Ball, 2005). Tracking both pupil center and corneal reflection allows the software to disassociate eye movements from head movements. This is because the positional difference between pupil center and corneal reflection changes with pure eye rotation. The difference remains relatively constant with minor head movements (Duchowski, 2007). At the beginning of a recording session, video-based eye trackers need to be calibrated to match the particularities of each participant's eye movements. Therefore, participants have to pursuit a dot on the screen and if the eye fixes for a certain time within a certain area, the system identifies that pupil/corneal-reflection pair as corresponding to specific coordinates on the screen. This steps are repeated over the whole screen (Poole & Ball, 2005).

5.2 Participants

A total of 15 people took part voluntarily and without any compensation in the experiment. The group of participants of the evaluation is composed of 8 females and 7 males with different age and different educational background as well as different experience levels. A total of 80% of all participants have obtained or are obtaining a higher education degree. 13 out of the 15 participants were aged between 20 and 30 years, whereas 2 participants were over 40 years old. The educational background of 8 participants can be described as “Natural Science Background” (BSc, MSc diploma or equivalent). On the other hand, 6 participants stated to have a “Social Science Background / Humanities” (BA, MA diploma or equivalent).

All participants agreed to evaluate and test the implemented visualization systems prior to the actual testing sessions.

It is known that the results from an evaluation of 15 participants may not be very representative and do not allow a transfer of the results to the whole target audience. Nevertheless, we are confident that the results of this evaluation may contribute to current research debates in the fields of Human-Computer-Interactions (HCI), multimedia learning and the general debate about qualitative and quantitative research. Additionally, all participants’ eye-movements will be recorded several times, thus the gathered amount of evaluation information should permit a reasonable analysis.

5.3 Experiment Design

This experiment analyzes the influence of the type of information displayed in a visualization system on the performance of the system. Thus, the independent variable of the experiment is:

- The visualization type
    - Visualization system based on qualitative information (text, pictures and videos)
    - Visualization system based on quantitative information (charts, plots, maps and tables)
    - Visualization system based on a combination of qualitative and quantitative information

The dependent variables describing the performance of the visualizations are:

- The System Usability Scale (SUS) provides a reliable tool for measuring the usability (Brooke, 1996).
- The accuracy of the answers in the questionnaires
- The response time
- The preferred visualization type
- The total fixation time for the two different Areas of Interest (AOI) “Qualitative” and “Quantitative”

Some dependent variables can be derived directly from the questionnaires (SUS, accuracy, preferred type) whereas others can be analyzed using the eye-tracking records (response time, total fixation time for AOIs).

This is a within-subject design experiment in which the same group of participants serves in more than one treatment. Every participant sees all the stimuli, which has some statistical advantages. Less participants are required (Field, 2009) and individual differences between participants are minimized (Martin, 2007). However, all participants seeing all stimuli is also the major disadvantage of the within-subject design. Participants accumulate experience and knowledge throughout the experiment proceeding, which leads to a learning effect. This effect can have impacts on the participant’s performance in a later test of the experiment. In order to minimize this phenomenon, all questions as well as the order of the visualization types for the experiment have been randomized.

5.4 Stimuli

Participants have to answer four questions by using the provided visualization described in Chapter 4.5. The questions are embedded in an HTML file, which is partitioned into a left and a right half. Questions can be found on the right hand side in form of an online survey provided by SurveyMonkey.net. The left half of the screen is used to display the visualization system itself. Hence, users read a question on the right hand side and answer it by tracking information on the left side (see Figure 25).

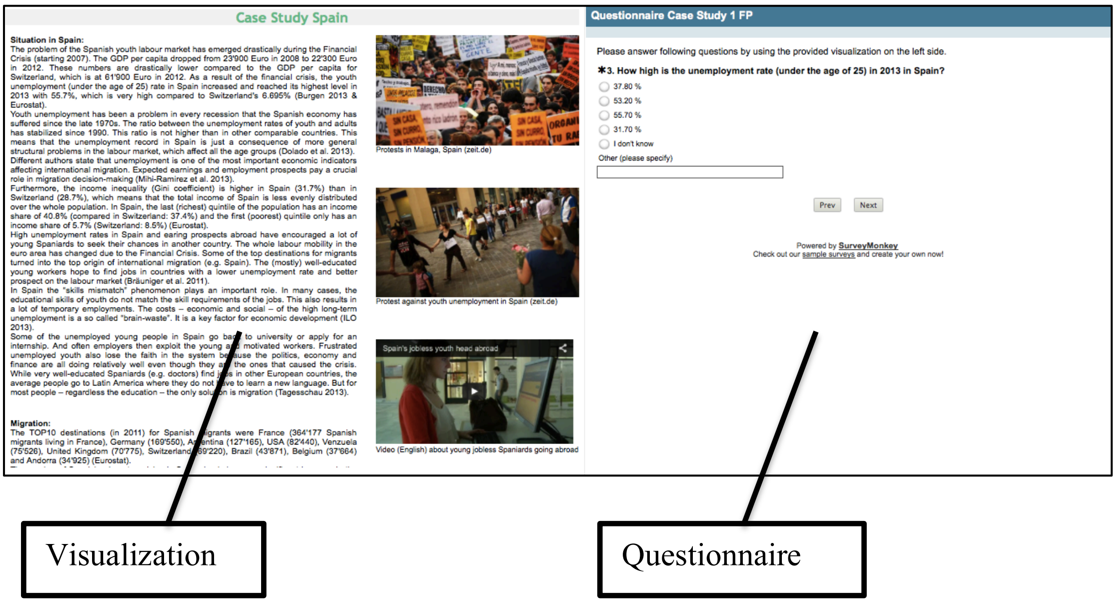


Figure 25: Screenshot of the split-screen test environment with the visualization on the left and the questionnaire on the right side.

Each participant is asked to answer four questions about each of the three different visualization types (qualitative, quantitative, mixed). For a total of two case studies this implements a total of 24 questions per participant. Participants can see only one question at a time and are free to control the mouse themselves. The time limit for each question is set to two minutes in order to apply some pressure on the participant's performance as well as to avoid an undesired long recording time. The time left is announced verbally 15 seconds before the time limit by the experimenter.

Three out of the four questions provide multiple-choice answers. Two questions ask for explicit numbers, for example "How high is the unemployment rate (under the age of 25) in 2013 in Spain?" or "What is the highest number of Spanish migrants entering Switzerland in one year?". A third question represents a more complex question, for example the comparison of two values "Comparing the GDP per capita of Spain and Switzerland, the GDP of Spain is…" with the possible answers 1) significantly lower, 2) significantly higher, 3) more or less equal to the GDP of Switzerland. However, every multiple-choice question also provides an "I don't know" answer possibility. The last question of every questionnaire is an open question asking for the most important trigger for migration showed in the corresponding visualization: "What is the most important factor for migration of young Spanish people to Switzerland?". (For detailed questionnaires, see Appendix A.2).

Areas of Interest (AOI) have been defined for all stimuli. The first AOI-Group covers all the areas of the visualizations displaying qualitative information (text, pictures, videos), whereas the second AOI-Group stands for all areas containing quantitative information (plots, maps, tables). These AOIs will later help to analyze the fixation time of the different information types in the mixed visualizations.

5.5 Installation and Circumstances

The evaluation took place in a lab room of the Geographic Institute of the University of Zurich. We used a common desktop computer (Dell, Intel Core i5-760 Processor, 8MB Cache, 2.80 GHz, Microsoft Windows 7) combined with the Tobii TX300 Eye Tracker, which is an integrated eye tracker with a removable 23" TFT monitor. For the presentation of the stimuli as well as for the analysis and storage of the data Tobii

Studio (Version 3.2.2) analysis software was used. To ensure the validity of the experiment, conditions were kept equal for all participants.

5.6 Experiment Proceeding

After a participant's arrival at the research lab, a consent form has to be read and signed. It assures the anonymity of the experiment, explains the coarse process of the experiment and offers an option for withdrawal at any time of the experiment (see Appendix A.3). In a first step, the participant is asked to fill out the Pre-Questionnaire in order to gain information about his/her socio-economic status as well as about the level of experience in various fields (see Appendix A.2.1). Afterwards, a short introduction and demo of all three types of visualization is given to ensure that the participant is familiar with the functions of the visualization systems. After the eye-tracking device is fully calibrated, a total of six recording sessions (green boxes Figure 26) are held. During the recordings, participants are free to verbally ask questions about the translation of words and the functions of the system at any time. If they wish to leave a comment on a question or on a questionnaire, they can state the comment verbally. Furthermore, they have the control over the mouse and can proceed individually through the questionnaire.

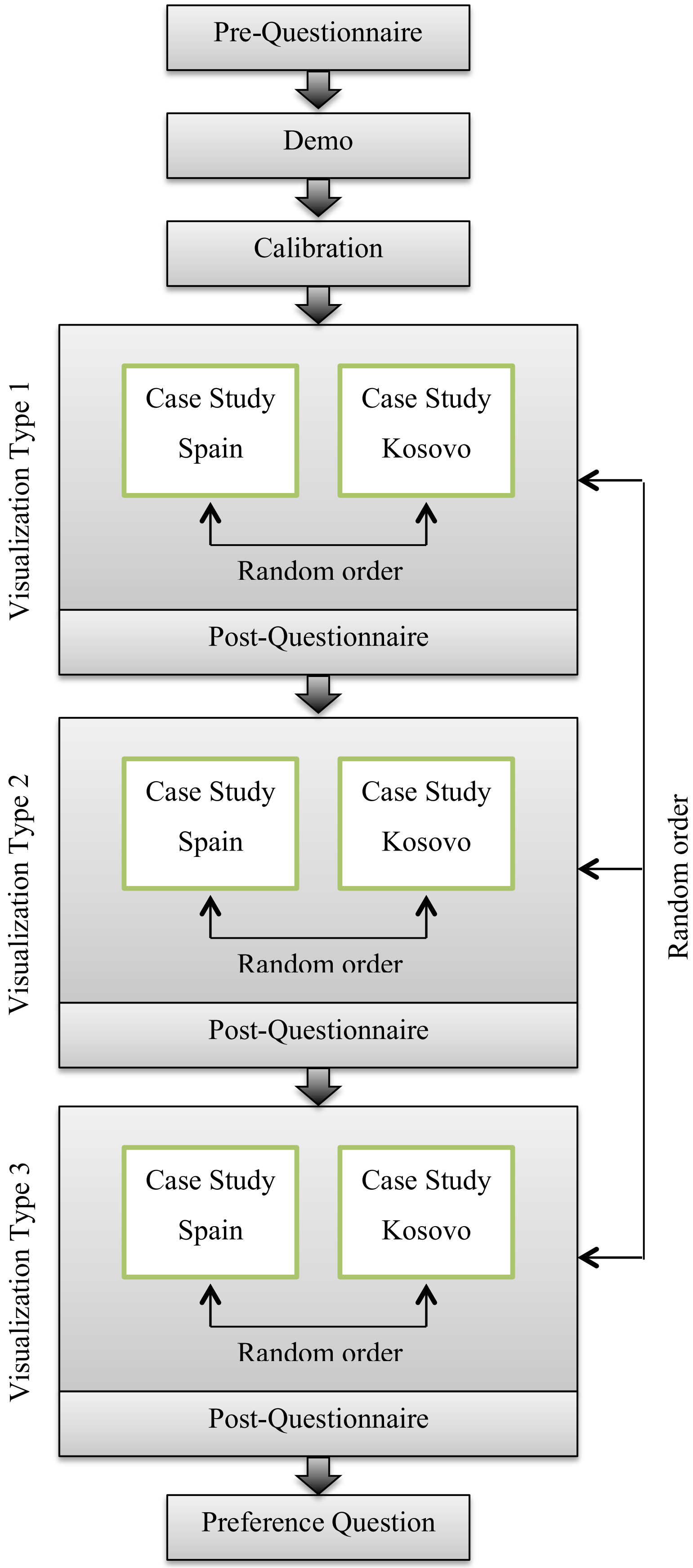


Figure 26: Experiment flow

The order of the visualization types as well as the order of the case studies within the visualization types is randomized to minimize the learning effect. After two recordings of the same type of visualization, the participant has to fill out a Post-Questionnaire (see Appendix A.2.2). This questionnaire consists of 10 questions regarding the usability of the system and the satisfaction of the user. All questions have to be answered on a Likert-Scale with 5 levels ranging from “strongly agree” to “strongly disagree” (Brooke, 1996). It serves as an indicator for the performance of the three different visualization types (qualitative, quantitative, mixed). Finally, the participant is asked to choose his/her preferred type of visualization (see Appendix A.2.3).

5.7 General Results

This chapter describes the results of the experiment. The experiment flow is presented in Figure 26. The results are divided into four sections, which correspond to the four dependent variables “System Usability Scale (SUS)”, “Preferred Visualization Type”, “Accuracy”, “Response Time”, and “Total Fixation Time” and participant analysis. The first two variables are independent from the two case studies and serve as overall indicators for the performance of the three visualization types. “Response Time”, “Accuracy” and “Total Fixation Time” are analyzed for both case studies individually for comparison.

In this thesis only statistically significant results are presented. Non-significant findings are only commented briefly. The results will be presented as followed: First, descriptive statistics give an overview of the data. Therefore, median and mean as well as the standard deviation are shown. Additionally, the results will be presented graphically (box plot or bar chart) in order to show the trend of the data. Finally, results of the statistical tests are presented. The detailed test results can be found in Appendix A.5. Statistical tests used in this thesis are:

- Kolmogorov-Smirnov test: The data is tested for normality.
- Variance Analysis (ANOVA): The differences between means are tested.

- Post Hoc Test: The differences between means are tested in detail to see which variables show significant differences.

Generally, a level of significance (α) of 0.05 was used. Box plots are 5-numbers summaries: The top line indicates the maximum value, the top line of the gray box represents the upper (third) quartile, the thick black line shows the median, the bottom line of the box indicates the lower (first) quartile and the last line indicates the minimum value.

Density maps have been created with Tobii Studio using default settings (Type: count, radius: 50px).

The statistical tests have been conducted using the software SPSS Statistics (Version 22.0.0) by IBM.

5.7.1 Participants

The answers from the Pre-Questionnaire regarding the level of the participants' experience have been analyzed. Spider diagrams created with Microsoft Excel (Version 14.3.8) show the characterization of each participant's experience in a meaningful way (see Appendix A.4.1).

Applying a k-means clustering algorithm using SPSS allowed to classify the 15 participants according to their cumulative level of experience (see Appendix A.4.2). The result is three clusters of participants:

- Cluster 1: Low level of experience (8 participants)
- Cluster 2: Medium level of experience (2 participants)
- Cluster 3: High level of experience (5 participants)

Clustering of participants offers a clearer analysis of data regarding the previous level of experience.

5.7.2 System Usability Scale (SUS)

This part measures the performance variable "System Usability Scale (SUS)". The score of the SUS-Questionnaire represents the satisfaction of the user regarding the tested system and the usability of the system itself. After testing a type of visualization (e.g. qualitative visualization) for both case studies, the participant was asked to rate the system with this specific Post-Questionnaire. This procedure has been done for all three types of visualizations (qualitative, quantitative, mixed). The descriptive statistics of the SUS scores for the three visualization types looks following:

Visualization Type	Qualitative	Quantitative	Mixed
Mean	56.33	84.83	81.50
Median	57.50	90.00	82.50
Standard Deviation	17.44	11.15	13.92

Table 4: Descriptive statistics of SUS-scores for the three visualization types.

Table 4 shows that the quantitative visualization system has the highest mean of SUS-scores compared to the qualitative and the mixed visualizations, even though the mixed visualization scores are relatively high as well. The median shows that the qualitative visualization holds the lowest SUS-values. On the other hand, the median also indicates that the quantitative visualization type holds the highest SUS values. Relatively low standard deviation values stands for a low number of outliers.

Figure 27 shows the box plots of the SUS values for both comparisons (qualitative-mixed, quantitative-mixed).

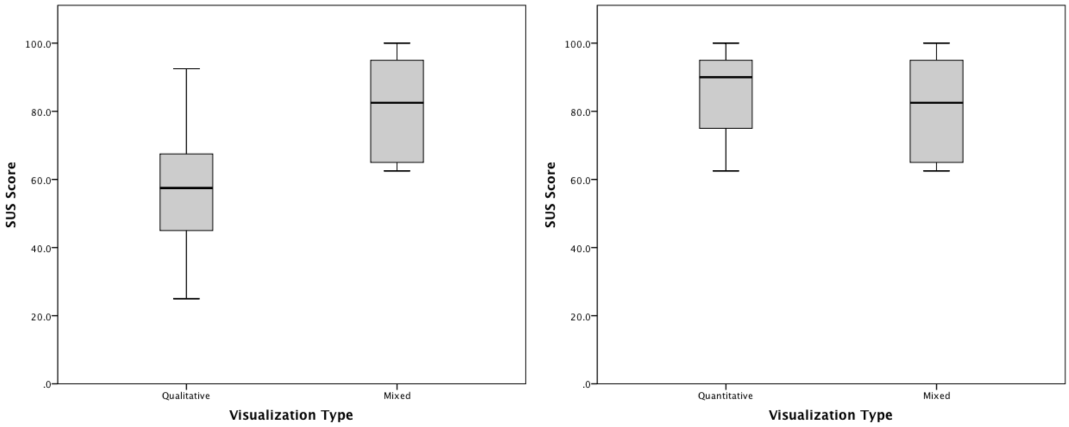


Figure 27: Box plots of the SUS-scores for the two comparisons qualitative-mixed and quantitative-mixed.

The qualitative visualization type shows the lowest SUS values of about 25 while the highest values of 100 can be found for the quantitative and the mixed versions. Again, the difference between the medians (indicated by the thick line) is clearly visible. The qualitative visualization shows the lowest median value.

The test for normality shows that the data of all three visualization types – qualitative ($D(15) = 0.09$, $p > 0.05$), quantitative ($D(15) = 0.21$, $p > 0.05$) and mixed ($D(15) = 0.18$, $p > 0.05$) – are normally distributed.

The ANOVA results show significant differences in SUS scores between the three visualization types ($F(2) = 16.95$, $p < 0.05$). However, the Post Hoc test reveals that there is a significant difference between the qualitative and the mixed visualization only ($T = 25.17$, $p < 0.05$). The SUS-score of the qualitative version is significantly lower than the score of the mixed visualization system. The quantitative and the mixed visualization do not show a significant difference.

5.7.3 The Influence of Educational Background

As stated in the hypotheses previously, education might have an influence on the behavior of participants due to everyday use of certain kinds of information types.

Considering this assumption, the differences of SUS-scores are analyzed again under the consideration of the different educational backgrounds of the participants.

Visualization Type	Qualitative	Quantitative	Mixed
Mean	49.06	88.44	84.38
Median	50.00	91.25	90.00
Standard Deviation	13.36	9.35	14.87

Table 5: Descriptive statistics of SUS-scores for the three visualization types of participants with natural science background.

The descriptive statistics show a similar trend as in the general analysis of the SUS. Quantitative and mixed versions show obviously higher mean values and median values than the qualitative visualization type (see Table 5).

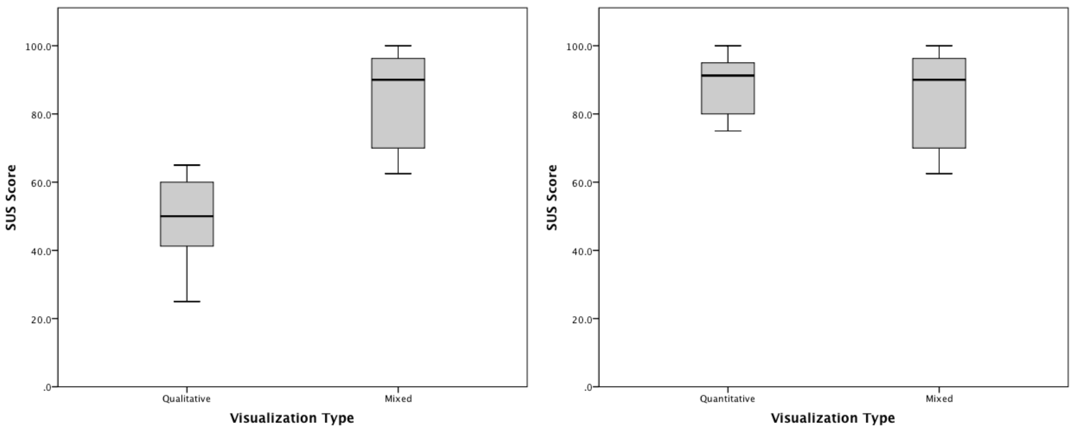


Figure 28: Box plots of the "SUS"-scores for the two comparisons qualitative-mixed and quantitative-mixed of participants with natural science background.

Also the box plots show the same data trends as in the previous analysis of the SUS scores (see Figure 28).

Tests of normality show that the data for all three visualization types are normally distributed (Qualitative: $D(8) = 0.13$, $p > 0.05$, Quantitative: $D(8) = 0.19$, $p > 0.05$, Mixed: $D(8) = 0.21$, $p > 0.05$).

After running the ANOVA, results indicate a significant difference between the SUS values of the three visualization types ($F(2) = 23.12$, $p < 0.05$). Detailed results are delivered by the Post Hoc test, which shows a significant difference of SUS scores between the qualitative and the mixed type visualizations ($T = 35.31$, $p < 0.05$), but no significant difference between the quantitative and the qualitative versions. These results suggest that participants with natural science educational background rate the usability of the qualitative visualization system significantly lower than the system, which combines qualitative and quantitative information.

The comparison of SUS-values for all participants with social science background revealed no significant differences between the three visualization types. This means that these participants did not rate one of the visualization types significantly better than the other in terms of satisfaction or usability.

5.7.4 The Influence of Level of Experience

According to Cook (2006) and Schnotz (2002), the level of expertise or experience can have an influence on the behavior of participants and their performance using multimedia displays. In order to analyze this impact, SUS values are tested for each level of experience separately. Participants have been assigned to experience clusters explained previously in this thesis (see Section 5.7.1).

Visualization Type	**Qualitative**	**Quantitative**	**Mixed**
Mean	51.80	89.69	82.81
Median	50.00	93.75	90.00
Standard Deviation	17.20	9.49	16.55

Table 6: Descriptive statistics of SUS-scores for the three visualization types of participants with a low level of experience.

Descriptive statistics (see Table 6) show a similar result as in the general analysis of the SUS-values. The quantitative and the mixed type visualizations show higher mean as well as median values than the qualitative version.

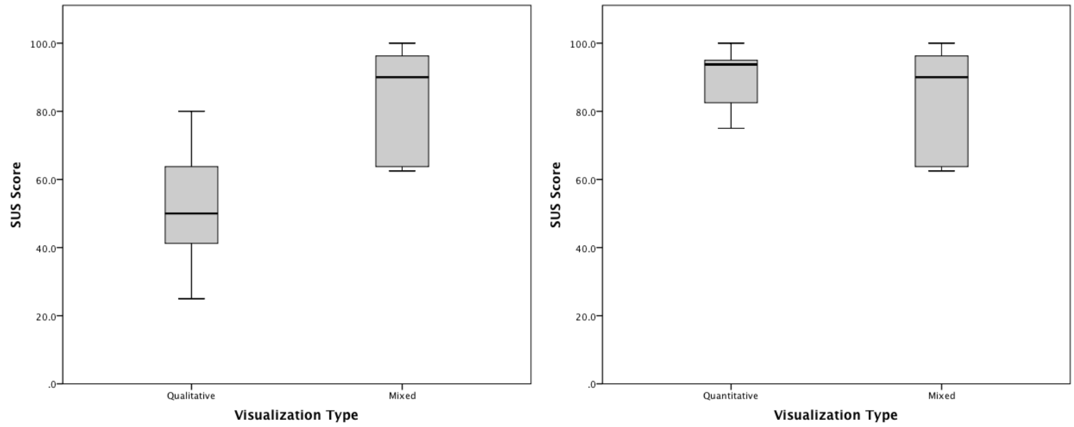


Figure 29: Box plots of the SUS-scores for the two comparisons qualitative-mixed and quantitative-mixed of participants with a low level of experience.

The box plots (see Figure 29) support the results of the descriptive statistics. The general trend of lower SUS-values for the qualitative system and relatively high values for both, the quantitative and the mixed versions, are clearly visible.

Due to the test of normality, the data for all three visualization types can be considered as normally distributed (Qualitative: $D(8) = 0.11$, $p > 0.05$, Quantitative: $D(8) = 0.26$, $p > 0.05$, Mixed: $D(8) = 0.24$, $p > 0.05$).

For the low level of experience, the ANOVA indicates significant differences of SUS values between the three visualization types ($F(2) = 14.75$, $p < 0.05$). The post hoc test reveals that there is again a significant difference of SUS values between the qualitative and the mixed visualization type ($T = 30.94$, $p < 0.05$) but no significant difference between the quantitative and the mixed type. Thus, participants with a rather low level of experience are significantly less satisfied with the usability of the qualitative visualization type.

No significant differences of SUS values could be found for participants with medium level of experience. This result may be explained by the small cluster containing only 2 participants.

No significant differences of SUS values could be found for participants with high level of experience, although the trend of lower SUS values for the qualitative visualization system can be supported.

5.7.5 Preferred Type of Visualization

A comparison of the preferred visualization type (derived from the Preference-Questionnaire) of a participant and the usability rating (SUS) for the three different visualization types of the particular participant may give some insights about how well the satisfaction/usability and the preference match.

First, it has to be mentioned that all participants have chosen either the quantitative or the mixed type of visualizations to be their preferred visualization to work with.

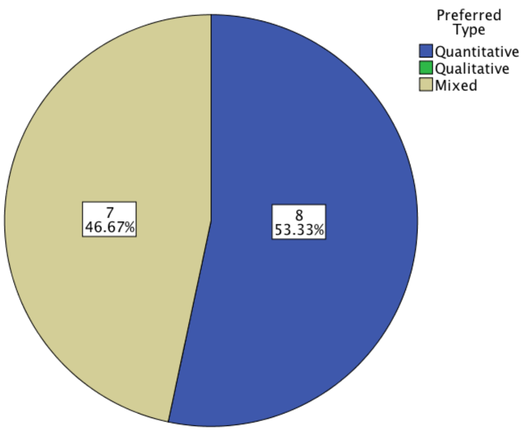


Figure 30: Pie chart representing the preferred visualization types.

The pie chart shows that 7 participants prefer the mixed type and 8 participants prefer the type based on quantitative data only (see Figure 30).

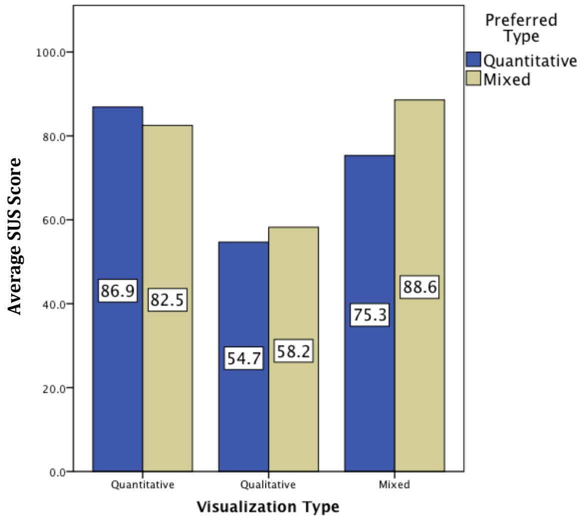


Figure 31: Bar chart comparing the preferred type of visualization (color) with the average SUS-scores (magnitude of bar).

Additionally, it seems that participants that preferred the mixed type also rated the usability of the mixed type higher than the usability of the quantitative type and vise versa (see Figure 31).

In a next step, the SUS-values of the two participant-groups "Quantitative Preferred" and "Mixed Preferred" are analyzed in order to test the significance of the differences.

Visualization Type	Qualitative	Quantitative	Mixed
Mean	54.69	86.88	75.31
Median	50.00	88.75	70.00
Standard Deviation	22.06	8.74	13.98

Table 7: Descriptive statistics of SUS-scores for the three visualization types of participants preferring the quantitative visualization type.

The descriptive statistics shows that the quantitative type has the highest mean value as well as the highest median. This time, the differences between the quantitative type and the mixed type seem to be slightly bigger than in the tests before. In this case, the visualization based on quantitative data seems to outperform the mixed type.

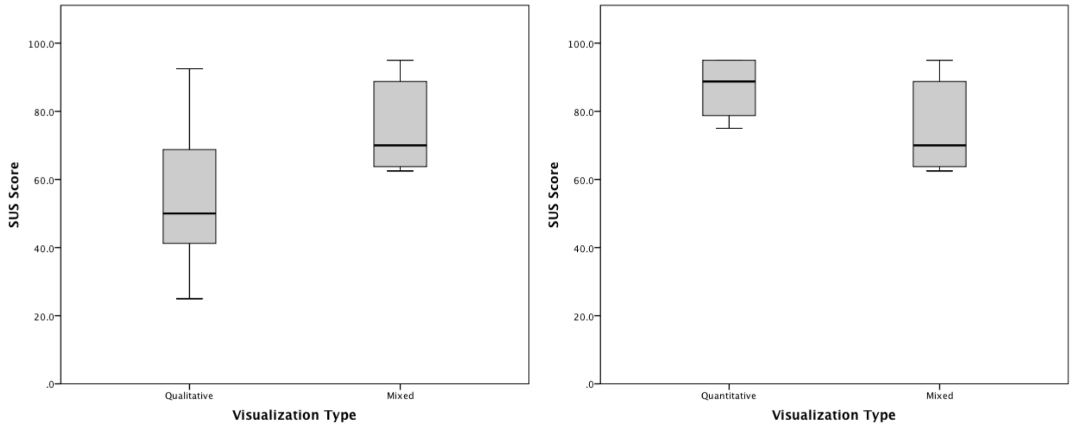


Figure 32: Box plots of the SUS-scores for the two comparisons qualitative-mixed and quantitative-mixed of participants preferring the quantitative visualization type.

The box plots show a visible difference between the SUS-values of the qualitative and the mixed visualization type again. But as mentioned above, the difference of SUS-values between the quantitative and the mixed version seems to be bigger than in previous tests. This might have to do with the fact that only participants preferring the quantitative visualization type are analyzed.

All data is normally distributed (Qualitative: $D(8) = 0.20$, $p > 0.05$, Quantitative: $D(8) = 0.24$, $p > 0.05$, Mixed: $D(8) = 0.27$, $p > 0.05$).

The results of the ANOVA indicate significant differences between the three visualization types ($F(2) = 8.42$, $p < 0.05$). While the difference between the qualitative and the mixed type can be considered significant again ($T = 20.63$, $p < 0.05$), the difference of SUS scores between the quantitative and the mixed visualization system is not significant. Summarized, the participants preferring quantitative visualizations rate quantitative visualizations highest in terms of satisfaction and usability, but the difference of the rating between the quantitative and the mixed types is not statistically significant.

Visualization Type	Qualitative	Quantitative	Mixed
Mean	58.12	82.50	88.57
Median	62.50	90.00	92.50
Standard Deviation	12.64	14.14	11.44

Table 8: Descriptive statistics of SUS-scores for the three visualization types of participants preferring the mixed visualization type.

The descriptive statistics support the suggestions from the previous section that participants preferring a visualization type also perform best with this type. Obviously, the mixed type visualization has the highest mean and median values.

The box plots support this theory. However, the differences between the SUS-scores of the quantitative and the mixed visualization types seem to be minimal.

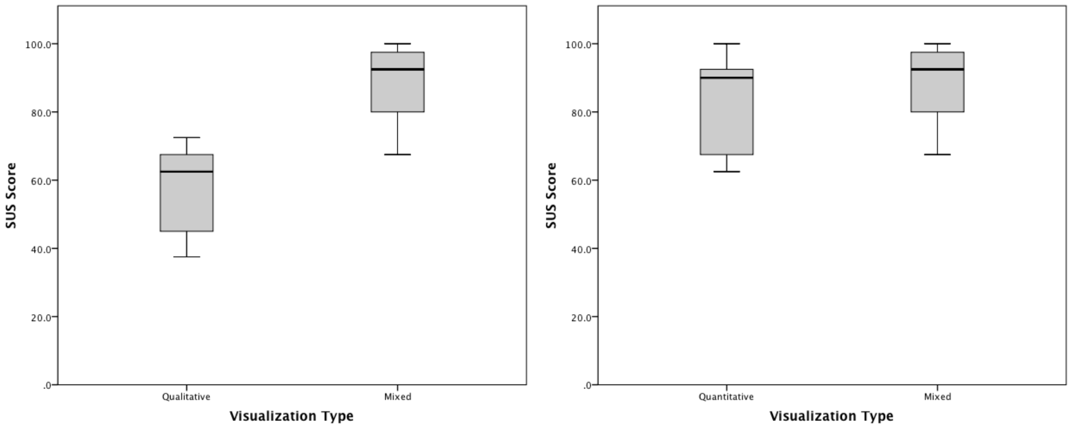


Figure 33: Box plots of the SUS-scores for the two comparisons qualitative-mixed and quantitative-mixed of participants preferring the mixed visualization type.

All data of the three visualization types are normally distributed (Qualitative: $D(7) = 0.20$, $p > 0.05$, Quantitative: $D(7) = 0.27$, $p > 0.05$, Mixed: $D(7) = 0.21$, $p > 0.05$).

As in the previous test, the ANOVA indicates that differences between the SUS-scores of the three visualization types are statistically significant ($F(2) = 11.04$, $p < 0.05$).

The differences between the SUS-scores of the qualitative type and SUS-scores of the mixed type are statistically significant ($T = 30.36$, $p < 0.05$) but no statistical significant difference was found between the quantitative and the mixed visualization type. Participants preferring the mixed visualization type rate the usability of this type higher than for the others but the difference is not statistically significant.

The analysis of the preferred visualization type regarding the different educational background of the participants may implement a diverse choice of the preferred visualization type.

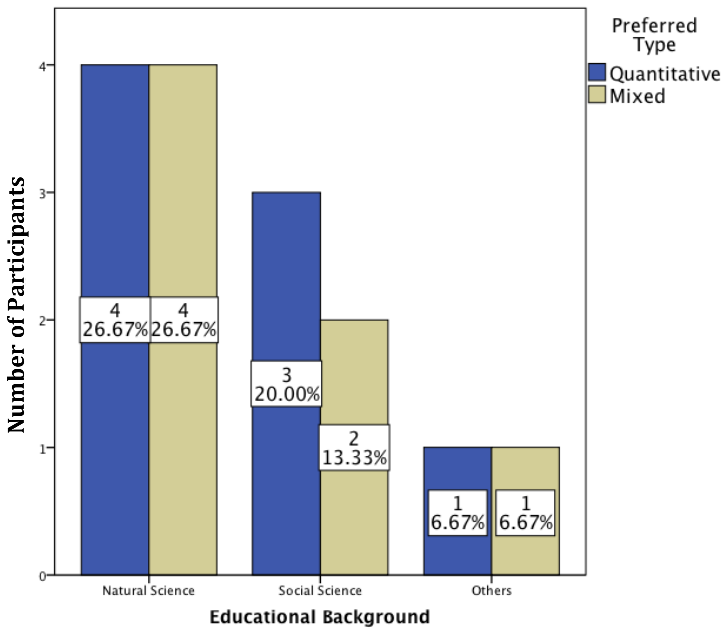


Figure 34: Bar chart comparing the preferred type of visualization (color) of participants with different education background.

As seen in bar chart (see Figure 34), participants with natural science background chose equally between the quantitative and the mixed visualization to be their preferred type. On the other hand, participants having a social science background chose the quantitative visualization type more frequently to be their preferred type. This result may be explained with the novelty effect. Participants with social science background were attracted by the interactive quantitative visualizations and thus were curious.

5.7.6 Summary

The two performance variables “SUS” and “Preferred Visualization Type” were analyzed. Results showed that SUS-values for the qualitative visualization type are significantly lower than the values for the mixed type. However, the comparison of SUS-scores between the quantitative and the mixed version showed no significant differences. Generally, descriptive SUS-values were more or less on the same level for those two visualization types.

A detailed analysis of SUS-values showed the same significant differences between SUS-values of the qualitative and the mixed visualization types for participants with low or high level of experience. Again, SUS-scores showed no differences when comparing qualitative and mixed type displays.

The SUS differences of qualitative and mixed visualizations could also be shown for participants with natural science background only. But for participants with social science background these differences could not be considered to be significant.

Nobody, not even one participant prefers the qualitative visualization type. About half of all participants favor the mixed display and the other half prefers the system with quantitative information.

The preferences of the participants match their SUS scoring pattern. This means that participant preferring mixed displays also ranked (SUS) mixed displays better than the other two types of visualization. Vise versa, participants favoring the quantitative visualizations were most satisfied (SUS) with the quantitative type.

Participants with social science background seem to like quantitative visualizations even better than mixed visualizations.

5.8 Results of the Case Study Spain

The variables “Response Time”, “Accuracy”, “Total Fixation Time” and density maps derived from the eye-tracking data are analyzed for both case studies separately. The “Response Time” values (seconds) were extracted manually from the eye-tracking records and then averaged over the four questions per visualization.

“Accuracy” stands for the percentage of wrong answers for each stimulus. The “Total Fixation Time” is calculated by Tobii Studio automatically for each of the two AOI-groups. According to Tobii Technology (2012), a window length of 20ms and a velocity threshold of 30°/s were used.

5.8.1 Response Time

In order to gather more information about the performance of the different display types, the average response time is analyzed and compared.

Visualization Type	Qualitative	Quantitative	Mixed
Mean	42.57	32.23	25.14
Median	41.75	30.50	22.25
Standard Deviation	9.68	7.22	7.08

Table 9: Descriptive statistics of “Average Response Time” (s) for the three visualization types.

The descriptive statistics show that the mean and median values are lowest for the mixed visualization type, indicating a relatively short response time. The values for the quantitative type are slightly higher and the ones from the qualitative display are highest (see Table 9).

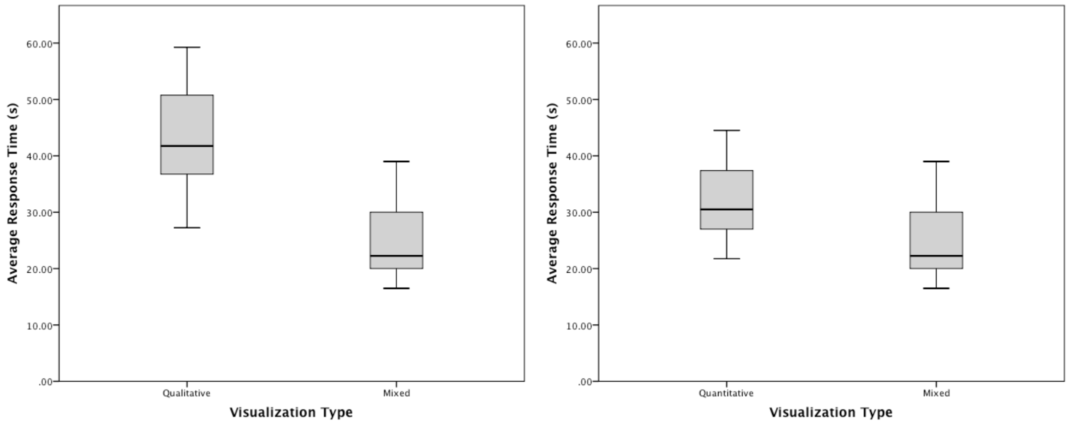


Figure 35: Box plots of the "Average Response Time" for the two comparisons qualitative-mixed and quantitative-mixed.

The box plots show that the differences between the qualitative and the mixed visualization types are higher than the differences between the quantitative and the mixed type (see Table 35).

The Kolmogorov-Smirnov test shows that all the data is normally distributed (Qualitative: $D(15) = 0.11$, $p > 0.05$, Quantitative: $D(15) = 0.13$, $p > 0.05$, Mixed: $D(15) = 0.20$, $p > 0.05$).

The ANOVA results show that there are statistically significant differences in response time between the three visualization types ($F(2) = 17.01$, $p < 0.05$). More detailed results about the differences are derived from the Post Hoc test results. The difference of average response time between the qualitative and the mixed type is significant ($T = 17.42$, $p < 0.05$), whereas the difference between the quantitative and the mixed display is not significant. This result indicates that questions were answered significantly faster with mixed version compared to the qualitative visualization system.

5.8.2 The Influence of Education Background

Analog to the procedure in the section of the general results, the influence of the education background of the participants is analyzed in order to detect differences in performance.

Visualization Type	Qualitative	Quantitative	Mixed
Mean	42.66	34.19	22.68
Median	41.50	32.50	20.50
Standard Deviation	9.86	6.51	4.52

Table 10: Descriptive statistics of "Average Response Time" (s) for the three visualization types of participants with natural science background.

As shown in the results of the descriptive statistics (see Table 10), the same trend as in the previous test occurs for participants with natural science education background. The mixed type seems to allow faster answers than quantitative and an even bigger difference occurs between the mixed and the qualitative visualization type.

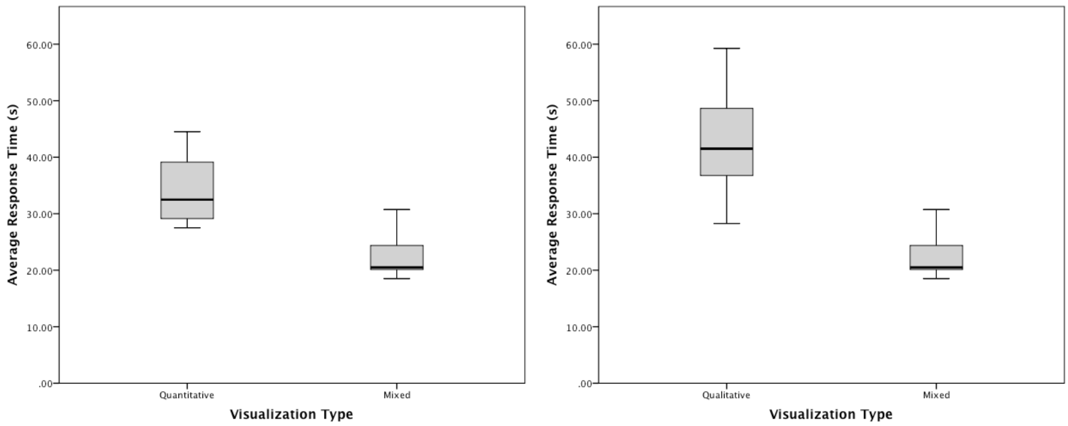


Figure 36: Box plots of the "Average Response Time" for the two comparisons qualitative-mixed and quantitative-mixed of participants with natural science background.

The box plots support the findings of the descriptive statistics and differences between the mixed and qualitative type as well as between the mixed and quantitative type can be identified (see Figure 36).

The data of the qualitative and the quantitative visualization type is normally distributed (Qualitative: $D(8) = 0.21$, $p > 0.05$, Quantitative: $D(8) = 0.22$, $p > 0.05$). But the data of the mixed version is not normally distributed ($D(7) = 0.32$, $p < 0.05$). Thus, the analysis of variances has to be tested with a non-parametric Kruskal-Wallis Test.

The results of the Kruskal-Wallis test indicate significant differences between the response time values of the three visualization types ($X^2(2) = 13.19$, $p < 0.05$). The Post Hoc test reveals a statistically significant difference between the mixed and the qualitative type of visualization ($T = 12.60$, $p < 0.05$). The difference of response time between quantitative and mixed versions is again not significant.

Visualization Type	Qualitative	Quantitative	Mixed
Mean	44.85	29.70	30.25
Median	49.00	26.50	30.00
Standard Deviation	9.51	7.30	8.85

Table 11: Descriptive statistics of "Average Response Time" (s) for the three visualization types of participants with social science background.

As the descriptive statistic shows (see Table 11), participants with social science education background seem to answer questions fastest with the quantitative visualization system. Even though the mean and median values of the mixed version are only slightly higher. The qualitative type shows the highest values of response time.

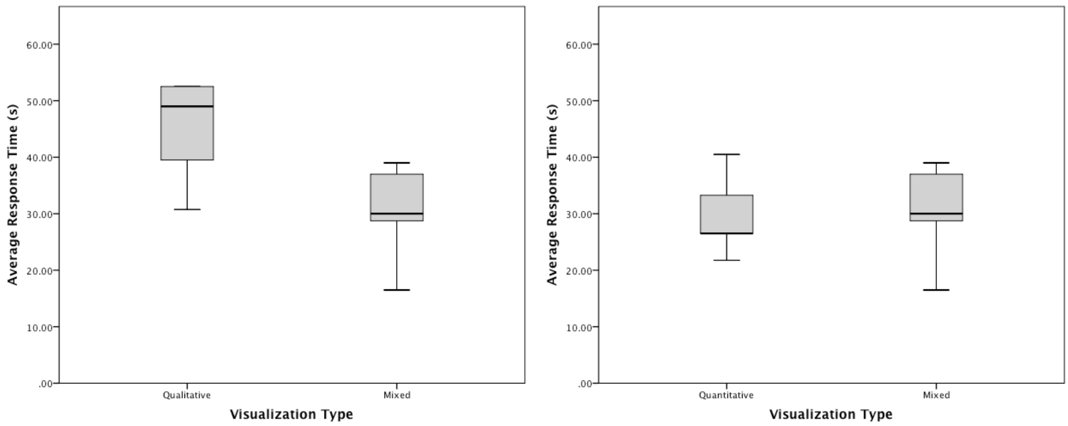


Figure 37: Box plots of the "Average Response Time" for the two comparisons qualitative-mixed and quantitative-mixed of participants with social science background.

The box plot shows (see Figure 37) that the difference between the response time of the quantitative type and the mixed type is rather small, whereas the values of the qualitative version are again higher.

All data is normally distributed (Qualitative: $D(5) = 0.27$, $p > 0.05$, Quantitative: $D(5) = 0.27$, $p > 0.05$, Mixed: $D(5) = 0.23$, $p > 0.05$).

As the ANOVA test shows, there are significant differences between the three visualization types ($F(2) = 4.99$, $p < 0.05$). The Post Hoc test indicates, similar to the test before, a statistically significant difference between the response time of the visualization system based on qualitative information and the one combining qualitative and quantitative data ($T = 14.60$, $p < 0.05$). Participants with social science background seem to perform the same way (with minor differences) as participants with natural science background.

5.8.3 The Influence of Level of Experience

The same trend as in previous tests regarding response time is visible. It seems that participants perform faster with mixed than with quantitative displays and need longest with the qualitative type to answer the questions (see Table 12 and Figure 38).

Visualization Type	Qualitative	Quantitative	Mixed
Mean	41.34	34.06	25.32
Median	40.13	32.50	21.50
Standard Deviation	10.73	6.66	6.60

Table 12: Descriptive statistics of "Average Response Time" (s) for the three visualization types of participants with a low level of experience.

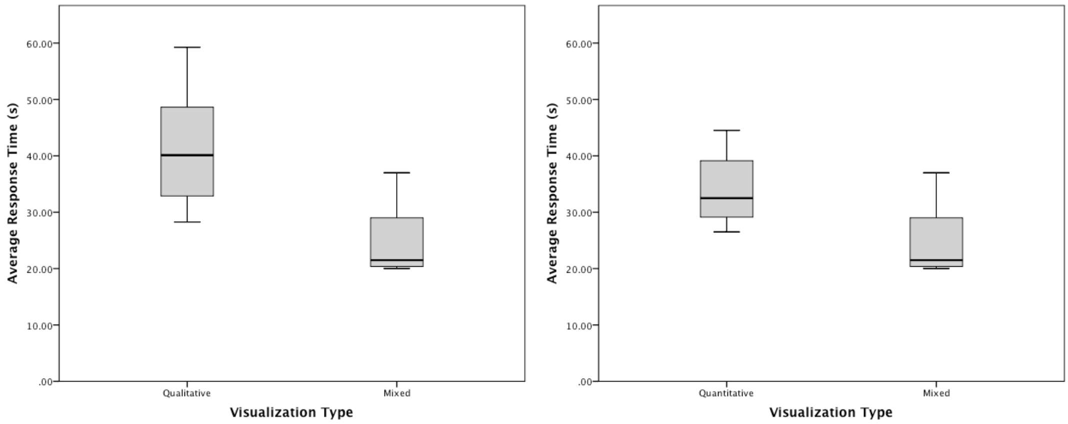


Figure 38: Box plots of the "Average Response Time" for the two comparisons qualitative-mixed and quantitative-mixed of participants with a low level of experience.

The Kolmogorov-Smirnov test of normality shows that all data is normally distributed (Qualitative: $D(8) = 0.16$, $p > 0.05$, Quantitative: $D(8) = 0.20$, $p > 0.05$, Mixed: $D(7) = 0.29$, $p > 0.05$).

The ANOVA results show that there are significant differences between the three visualization types ($F(2) = 6.95$, $p < 0.05$) and the Post Hoc test reveals that the significant differences are again between the qualitative and the mixed versions ($T = 16.02$, $p < 0.05$).

Regarding the response time, no significant differences could be found for participants with medium level of experience. This result may be explained by the small cluster containing only 2 participants.

Visualization Type	Qualitative	Quantitative	Mixed
Mean	45.40	31.40	27.95
Median	49.00	33.25	28.75
Standard Deviation	10.53	9.13	7.61

Table 13: Descriptive statistics of "Average Response Time" (s) for the three visualization types of participants with a high level of experience

The descriptive statistic shows (see Table 13) the same pattern of mean and median values for participants with a high level of experience as for the low level of experience.

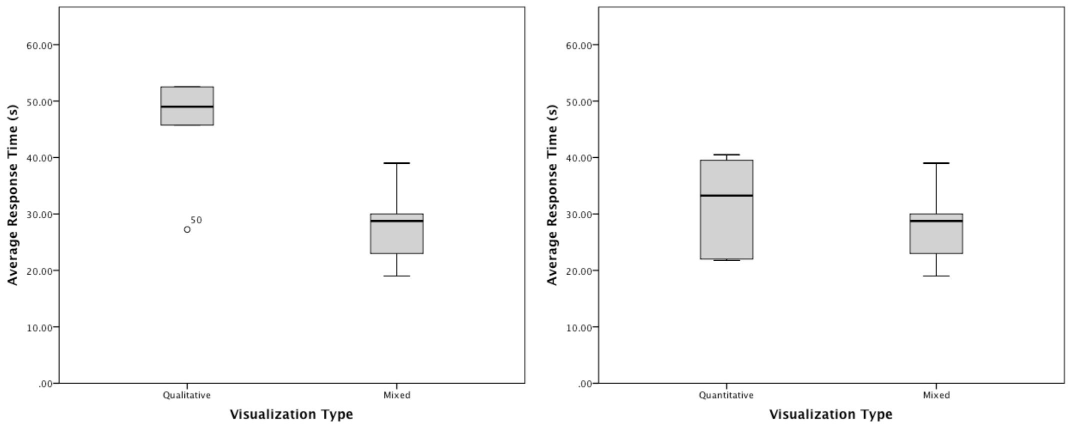


Figure 39: Box plots of the "Average Response Time" for the two comparisons qualitative-mixed and quantitative-mixed of participants with a high level of experience.

The box plots (see Figure 39) show a higher response time of the qualitative visualization type. Furthermore, outliers occur in the data of the qualitative version.

However, all data is normally distributed (Qualitative: $D(5) = 0.31$, $p > 0.05$, Quantitative: $D(5) = 0.25$, $p > 0.05$, Mixed: $D(5) = 0.19$, $p > 0.05$).

Due to the ANOVA test results we can assume that there are significant differences between the three visualization types ($F(2) = 5.08$, $p < 0.05$). The significant differences can again be found between the qualitative and the mixed visualization type ($T = 17.45$, $p < 0.05$).

5.8.4 Accuracy

The accuracy is indicated by the number of wrong answers given, working with each of the three visualization types. For the case study of Spain a total of 180 questions were asked.

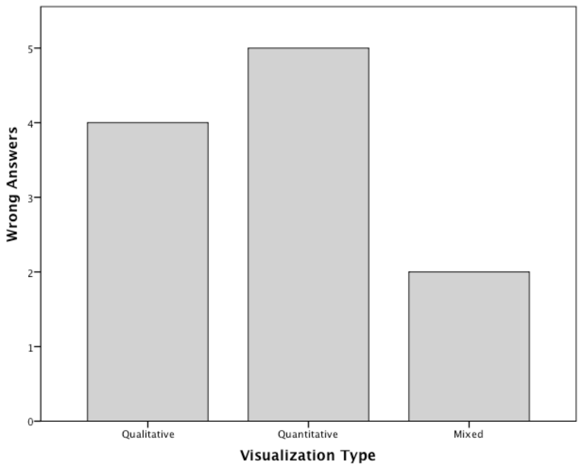


Figure 40: Bar chart comparing the sum of wrong answers between the three visualization types.

As the bar chart shows (see Figure 40), between 2 and 5 answers were wrong per visualization type. This number is very low compared to the total questions asked. Therefore, no significant differences between the visualization types were found.

5.8.5 Total Fixation Time

The total fixation time can be extracted from Tobii Studio automatically for each of the defined areas of interest (AOI). In this case only two different AOIs were defined, namely a qualitative AOI covering all areas of the visualization containing qualitative information (text, photographs, videos) and a quantitative AOI with all areas used for displaying quantitative data (plots, diagrams, tables, maps). Since we are interested in whether participants use the quantitative or the qualitative part of a visualization display in order to answer questions, only the mixed visualization type has been analyzed.

	Qualitative AOI	Quantitative AOI
Scientific Education	33.93%	66.07%
Social Education	34.38%	65.62%
Low Experience	37.01%	62.99%
Medium Experience	4.67%	95.33%
High Experience	33.57%	66.43%
All Recordings	33.86%	66.14%

Table 14: Relative total fixation time per AOI for different user groups.

Table 14 shows the relative fixation time of all 15 participants using the mixed visualization. There is no relevant difference between participants with different educational background. For both education directions the time fixating objects in the quantitative AOI is times two longer than the time spend in the qualitative AOI. The only abnormal relation can be found for participants with medium experience. Again, this finding can most certainly be explained by the small sample size (2 participants) for the medium level of experience. Generally, about 30-35% of the fixation time is spent in the qualitative AOI and 65-70% of the time is used to look at information in the quantitative AOI (see Figure 41).

5.8.6 Density Maps

A density map of the mixed visualization type shows the density of fixation counts over the whole website used as stimulus. Clearly, most counts are situated in the area where the questions are stated (red area in Figure 41). This phenomenon was predictable but does not contribute to the understanding of the participants' behavior. The left half of the screen represents the actual visualization. The pattern shows, which elements of the visualization have been used most (green areas in Figure 41). Most of the fixations are situated in the top half of the visualization display, namely in the quantitative AOI.

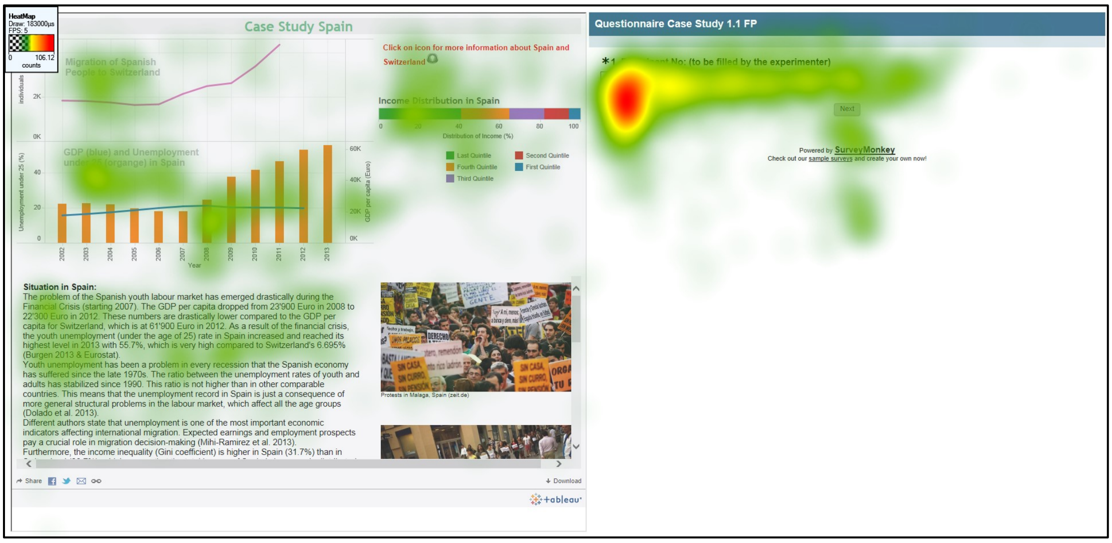


Figure 41: Density map of the mixed visualization type of all participants.

Further analysis revealed only minor differences between the patterns of participants with natural science background and participants with social science background.

Participants coming from a natural science background seem to concentrate less on the qualitative part of the visualization (see Figure 42), whereas social science participants seem to use the text more frequently (see Figure 43).

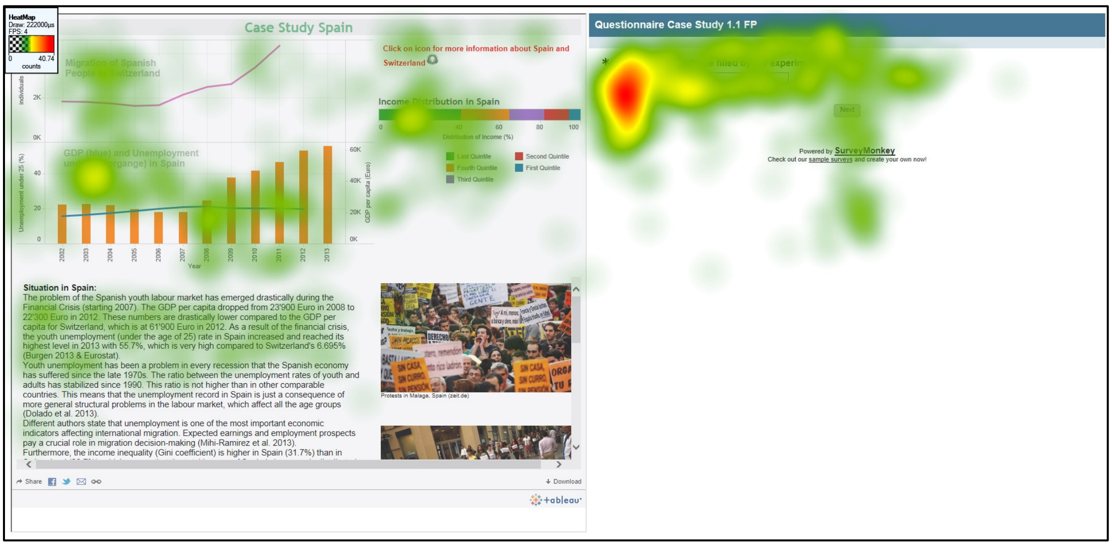


Figure 42: Density map of the mixed visualization type of participants with natural science background.

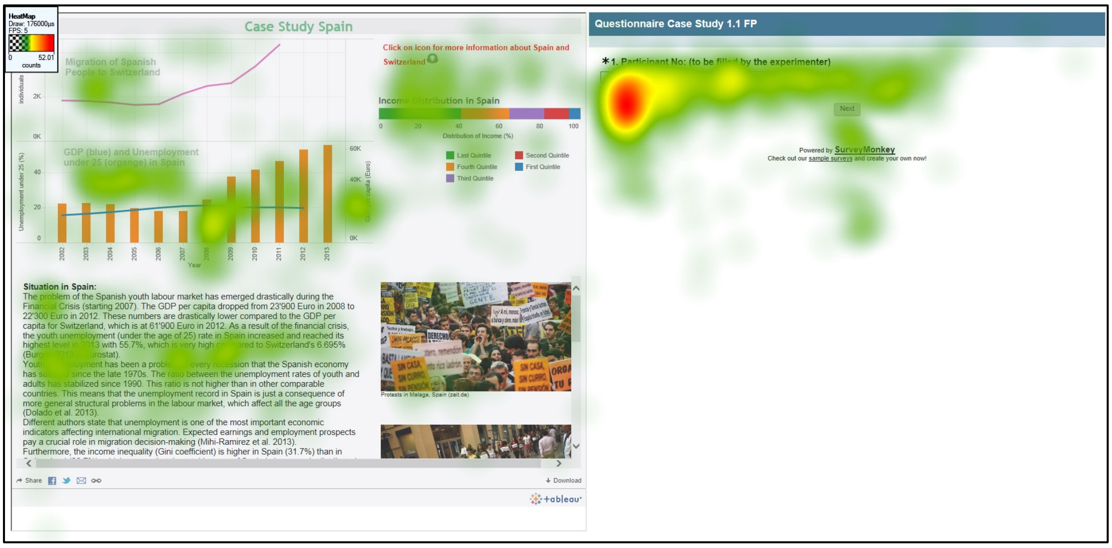


Figure 43: Density map of the mixed visualization type of participants with social science background.

5.8.7 Summary

The two performance variables "Average Response Time" and "Accuracy" have been analyzed. The results match the results of the SUS-analysis prior to this case study. Participants needed significantly more time to answer the questions when working with the qualitative visualization type. Thus, the performance of the mixed version was better than the qualitative display type. Between the quantitative and the mixed type no significant differences in the response time could be found. These two visualization types seem to perform equally well regarding the average response time.

The educational background influences the response time only marginal. For both education backgrounds (natural science and social science) significant differences were found between qualitative and mixed display types. Participants with social science background seemed to perform a little better with the quantitative visualizations than participants with a natural science background.

The response time differences of qualitative and mixed visualizations could also be shown for participants with low and high level of experience.

Due to the small number of wrong answers, no statement about the accuracy of the three visualization types can be made.

The analysis of the relative fixation time of each AOI revealed that more or less two third of the recording time was spent looking at objects in the quantitative AOI. This finding is valid for both education backgrounds as well as for all levels of experience.

5.9 Results of the Case Study Kosovo

5.9.1 Response Time

Visualization Type	Qualitative	Quantitative	Mixed
Mean	38.27	38.83	28.69
Median	35.50	38.25	26.75
Standard Deviation	12.51	12.71	9.82

Table 15: Descriptive statistics of "Average Response Time" (s) for the three visualization types.

The descriptive statistic (see Table 15) show that in this case the qualitative type compares better than in the previous case study. Participants seem to need less time to answer the questions using the qualitative visualization.

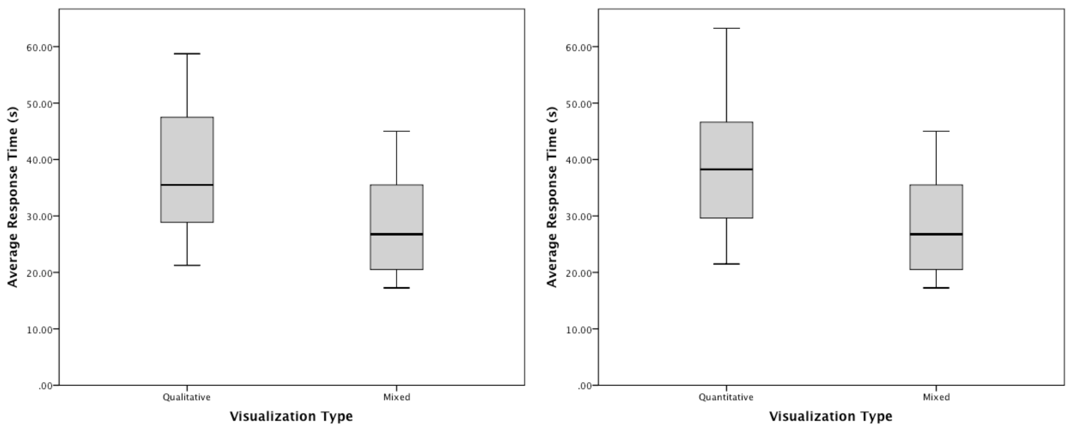


Figure 44: Box plots of the "Average Response Time" for the two comparisons qualitative-mixed and quantitative-mixed.

The box plots (see Figure 44) support the findings of the descriptive statistics. Now, the qualitative visualization seems to increase its performance regarding the response time. The qualitative and quantitative visualization types are now almost on the same level of performance.

Accordingly, the ANOVA showed no significant differences between the three types of visualization. It took participants the same amount of time answering questions uninfluenced by the type of visualization they used.

5.9.2 The Influence of Education Background

No significant differences between the response time values of the three visualization types could be found, regardless of the educational background.

5.9.3 The Influence of Level of Experience

No significant differences between the response time values of the three visualization types could be found, regardless of the level of experience.

5.9.4 Accuracy

Also in this case study a total of 180 questions were asked.

As the box plot (see Figure 45) shows, between 4 and 10 answers were wrong per visualization type. These numbers are higher than in the previous case study. Additionally, it seems that the quantitative visualization type causes more wrong answers in this case study. But still the numbers are low compared to the total questions asked. Therefore, no significant differences between the visualization types were found.

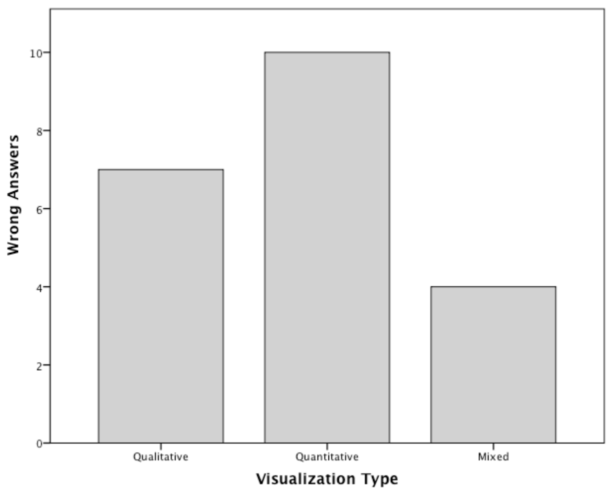


Figure 45: Bar chart comparing the sum of wrong answers between the three visualization types.

5.9.5 Total Fixation Time

Analog to the first case study, only two AOIs were defined (qualitative and quantitative) and only the mixed visualization type has been analyzed.

	Qualitative AOI	Quantitative AOI
Scientific Education	36.26%	63.74%
Social Education	52.98%	47.02%
Low Experience	43.33%	56.67%
Medium Experience	36.93%	63.07%
High Experience	45.89%	54.11%
All Recordings	44.22%	55.78%

Table 16: Relative total fixation time per AOI for different user groups.

Table 16 shows the relative fixation time of all 15 participants using the mixed visualization. This time the relative fixation durations show a difference between participants with natural science and participants with social science background. Social scientists spend more of their time looking at contents of the qualitative AOI (text, photos, videos) compared to natural scientists. Explicitly they spend about half of the time looking at qualitative information whereas participants with natural science background only spend about 35% of their time on this type of data. The only abnormal relation can be found for participants with medium experience. Again, this finding can most certainly be explained by the small sample size (2 participants) for the medium level of experience. Generally, about 35-45% of the fixation time is spent in the qualitative AOI and 55-65% of the time is used to look at information in the quantitative AOI.

5.9.6 Density Maps

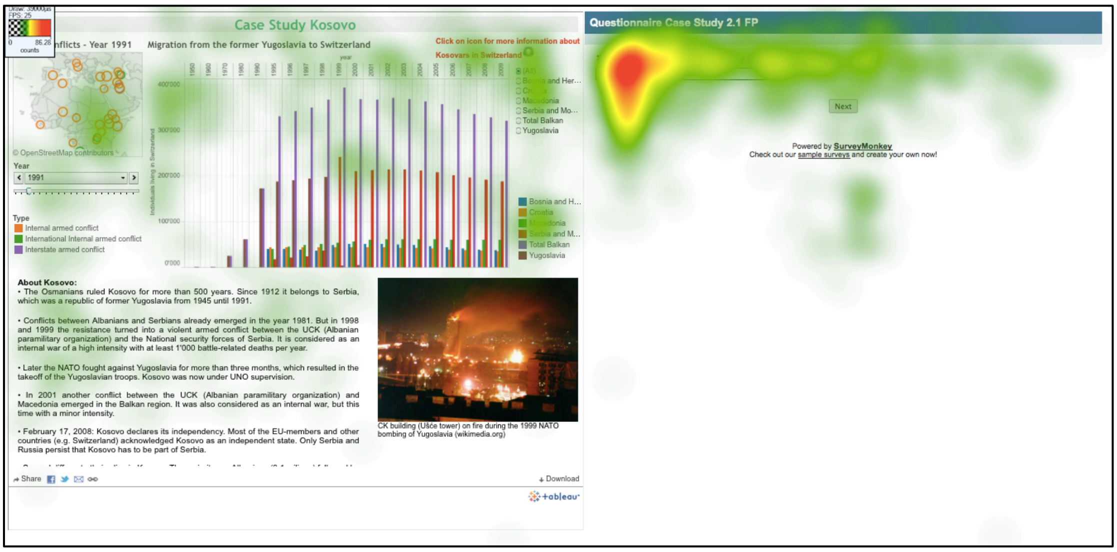


Figure 46: Density map of the mixed visualization type of all participants.

The density maps of this case study show more or less the same patterns of fixation counts for the mixed visualization system (see Figure 46).

5.9.7 Summary

The two performance variables “Average Response Time” and “Accuracy” have been analyzed. This case study has not revealed any statistically significant differences in these variables. It seems that the qualitative visualization system performs better in this case study and therefore the previously detected differences are no longer significant. Participants need more or less the same amount of time in order to answer the questions, uninfluenced by the type of visualization display they used.

Furthermore, the educational background as well as the level of experience of the participants did no longer influence their performance with the three different types of displays.

Due to the small number of wrong answers, no statement about the accuracy of the three visualization types can be made.

The analysis of the relative fixation time of each AOI revealed that generally more time was spend on the qualitative AOI compared to the first case study. Between 35-45% of the recording time was spent looking at objects in the qualitative AOI. This time a difference between participants of different education background could be found. Participants with a social science background tend to spend more time looking at the qualitative type of information compared to participants with natural science background.

6 Discussion

The goal of this project is (1) to compare the performance of mixed methods visualizations compared to the performance of qualitative methods as well as quantitative methods visualizations. Furthermore, (2) exploration possibilities using mixed methods visualizations should be worked out and (3) pros and cons of each approach should be shown. In order to reach these goals, two case studies with three different visualizations have been implemented and tested. The variables “System Usability Scale (SUS)”, “Average Response Time” and “Accuracy” serve as performance indicators, whereas “Total Fixation Time” and the density maps have been used to gather detailed information about the participants’ behavior.

In this chapter the results will be discussed and the limitations of this project will be explained. Finally, future research possibilities will be proposed.

6.1 Discussion of the General Results

The results of the analysis of the variable “SUS” show statistically significant differences between the qualitative methods visualization and the mixed methods visualization. Participants show a higher satisfaction and rate the usability higher when using the quantitative or the mixed visualization type. These findings support the results of (Colaso et al., 2002) which identified a dissatisfaction of participants using text only. Similar to their implications the mixed methods visualization seems to perform relatively well. Furthermore, the results of the preference questionnaire show clearly that nobody, not even one participant preferred the qualitative methods visualization (text). About half of the participants have chosen the quantitative, the other half the mixed version to be their favorite display type. The theory of *visual thinking* by Arnheim (1969) suggests that language is not the formal prototype of knowledge. Rather the sensory knowledge, upon which all our experience is based, creates the possibilities of language. It also includes mental images and prior knowledge based on experience (Arnheim, 1969). Arnheim's theory supports our results of a relatively unattractive text-based visualization type. Participants seem to prefer working with illustrations rather than with text. Textual information is only used in situations of difficulties or emerging problems. Additionally, some participants might prefer the purely quantitative display type to the mixed display type due to redundant information showed in the mixed version. According to Eilam and Poyas (2008), redundant information can lead to an unintended processing overload and thus, participants are not able to identify the important data any longer.

The education background of the participants seems to have an impact on the satisfaction/usability using the different visualizations. Participants with a natural science education rated the mixed methods visualization significantly higher than the qualitative method. On the other hand, for participants with a social science background, this difference could not be found implementing a relatively higher satisfaction/usability of the qualitative visualization type. Even though it was expected that natural scientists are more satisfied working with quantitative data, this hypothesis could not be confirmed. Participants with social science background also like the interactive illustrations, and maybe even a bit more than the natural science based participants. This effect may be explained with the findings of Eilam and Poyas (2008), reporting an increase of motivation of participants working with interactive quantitative data. This novelty effect could be more pronounced for participants with less daily experience with quantitative data, like social scientists who might use primarily qualitative data and methods.

Participants' satisfaction and usability (SUS) ratings match with their preferred visualization type. This means that participants did not answer the preference question naively. Once participants work with a display, they can identify what works best for them. Participants that were most satisfied with the mixed display also showed higher SUS-values for this type of visualization compared to the quantitative visualization, and vise versa. According to Hegarty et al. (2009), the participants' preference alone is not a good indicator of the effectiveness of a display. Often users do not entirely know which kind of display works best for themselves, what is also called *naïve cartography*. Objective measurements are necessary in order to say more about the performance of a system (Hegarty et al., 2009). Hence, the matching SUS and preference of this project indicates meaningful results.

The influence of the level of experience on the usability ratings of participants according to previous studies (e.g. Cook, 2006; Patrick et al., 2005; Schnotz et al., 1993; Larkin, 1981) could not be proven entirely. After the classification of the participants into three levels of experience, sample sizes were too small to ensure representative results.

6.2 Discussion of the Results of the Case Studies

In order to gather more information about the performance of the three visualization types, "Average Response Time" and "Accuracy" have both been analyzed.

Results of the first case study (Spain) indicate that in general, participants need significantly more time answering questions with qualitative methods visualizations. It supports the trend of the SUS-analysis above, which describes the performance using a qualitative data display as significantly worse than the performance of the other two display types (quantitative, mixed).

The education background did not influence the average response time of participants. For both education backgrounds, natural science and social science, significant differences between the qualitative methods display and the mixed method display have been found. Thus, the average response time seems to be less sensitive to educational background than the satisfaction and usability rating of a participant for a certain kind of visualization.

Additionally, due to a relatively high rate of correctly answered questions, no significant differences regarding the "Accuracy" of the different visualization types could be found. Therefore, this project's results indicate a equal accuracy for each of the three analyzed display types. Future research is suggested to address more complex questions or task or set a lower time limit for each question.

Participants' eye-movements have been recorded using an eye-tracking device. The computed fixation times show that participants concentrate more on the quantitative part of the mixed visualizations than on the qualitative half. On average about 65% of the total time, participants were scanning areas with quantitative data visualizations in order to find an answer to their questions. This finding applies to all participants, regardless of their education or their prior knowledge. However, the outcome of Schmidt-Weigand's et al. (2010) study was different. In their experiments, participants spent more time with reading text than with the illustrations. The high level of interactivity in our project could have contributed to the high motivation of using graphics instead of text. As Eilam and Poyas (2008) report, the novelty effect as well as curiosity about interactive visualizations may lead to a higher motivation for using those displays. This phenomenon might be responsible for the high part of time spent with quantitative data in our project.

The case study about migration from Kosovo to Switzerland does not fully support the findings resulted from the first case study. Apparently, in this case participants needed less time in order to respond to the questions when using the qualitative methods visualization. The differences of the average response time between the qualitative and the mixed display are no longer significant. Two different reasons might be responsible for this finding: 1) The representation of the textual information differs. For the case study of Kosovo, subtitles and paragraphs have been implemented more frequently than in the first case study. This higher level of structure of text information might have lead to a more efficient information extraction from the qualitative part of the visualization. 2) The relatively small sample size could be responsible for the marginal different results, which then lead to the non-significant findings.

Another major difference between the case studies can be found when analyzing the fixation durations. In the case study about Kosovo, participants spend more time using the qualitative data part in the mixed methods displays. Now, almost 45% of the total time has been spent looking at qualitative data. This fact could be related to the different design of the two case studies' quantitative visualizations. While the Kosovo case study contains two interactive maps and one bar chart, the first case study only consists of line, bar, and pie charts. In order to extract information from the maps, participants have to interact deeper with the system than when hovering over a bar chart to activate the tooltip in the case study of Spain. The more steps are necessary, the more time a participant spends on an item. Additionally, maps are representations of real-world phenomena. In order to process the information of such representations, participants have to make mental relationships between the map and the actual phenomenon, which again takes additional time.

All results of the experiment have to be interpreted with caution. According to Schnotz and Bannert (2003), results of studies with questionnaires are always task dependent. Decisions of participants concerning the choice of data for example are influenced by the type of task addressed.

6.3 Summary of the Findings

The evaluation of three different display types and two case studies has revealed three major findings. First, nobody, not even one person prefers the qualitative methods visualization type, which is based on text and pictures. However, about half of the participants prefer the quantitative, half the mixed methods visualization. Furthermore, participants' preferences match respectable well the performance, measured in response time, as well as the satisfaction, represented by SUS-scores of the three visualization types. Thus, it can be said that participants were able to successfully identify which display type works best for them. Finally, participants like working with interactive quantitative visualizations, regardless of their educational background. Participants with social science background may like the illustrations even a bit more compared to participants with a natural science background.

The results of this project confirm hypothesis one and two (H1 and H2) about different performances of the three visualization types regarding the two variables "SUS" and "Average Response Time", even though the results were not always statistically significant. Hypothesis three (H3) assuming an influence of the educational background on the performance can be confirmed carefully due to the small sample size and the differences in the case study designs. The influence of different levels of experience (H4) was definitely not analyzable since the classification of participants resulted in extremely small sample sizes.

6.4 Limitations

Possible limitations of this project can be found in the design of the experiment, the technology for measuring the dependent variables, the design of the stimuli and the limited sample size.

Since a within-subject design experiment has been used, learning effect may occur (Martin, 2007). Participants can learn from previous experiment parts. A randomization of questions, visualization types and case studies minimizes this phenomenon (Duchowski, 2007; Martin, 2007). However, learning may still affect the results marginal.

In order to measure the independent variable "Fixation Time", the *eye-tracker* Tobii TX300 has been used. According to Tobii Technology (2010), the ideal distance between the participant and the eye-tracking device is 65cm. This distance can impossibly be kept constant during all recordings. However, the TX300 eye-tracker is able to compensate automatically for distances between 50cm and 80cm. The binocular accuracy of the device at ideal conditions is supposed to be 0.4°, which corresponds to only a few millimeters on the screen. Imprecisions may lead to an inaccurate classification of fixations when using AOIs.

As already mentioned, the design of the stimuli influences the performance. For both case studies different types of representations (e.g. bar charts, maps, tables) were used as well as textual information was structured unequally. This effect has been taken into account and has been discussed in the previous section.

The sample size (N=15) may be a statistically limiting factor of the project and could lead to uncertainties. Most of the data was normally distributed, thus a one-way

ANOVA could be performed. Jacob and Karn (2003) have summarized the results of 21 eye-tracking studies. These studies worked with an average sample size of 15, thus the sample size of our project is comparable.

Some minor uncertainties are related to the sample size as well. In order to evaluate the performance of participants with different levels of experience, a classification was necessary. This clustering of participants into three groups resulted, naturally, in even smaller sample sizes. In turn, the smaller samples lead to even more uncertainties regarding the results.

6.5 Outlook

This experiment could be extended in different ways. First of all, a bigger sample size would allow more representative results. Secondly, the characterization of participants' experience could be done in a more detailed manner in order to gain more insights to prior knowledge. Additionally, the design of the two case studies should be adopted to grant inequality of circumstances. This way, the two case studies could be compared in-depth.

Against the background of the *multimedia learning theory* and the *dual channel theory*, future research exploring the performance using audio information, as it may couple well with visuals, would be interesting.

Furthermore, more research to explore the expert-novice continuum using multimedia displays regarding participants' performances and satisfaction is necessary in order to understand the influence of prior knowledge.

It would also be desirable to understand the magnitude of the motivational effect on the behavior of participants. Therefore, questionnaires about the motivation of participants are required.

7 Conclusion

The qualitative-quantitative debate has a long history in research. While earlier researchers primarily worked with their preferred methods and criticized the other party's approaches, nowadays most scientists pronounce the possibilities of combining qualitative and quantitative research methods. This project investigated on the influence of the debate in the specific field of information visualization systems. Although combining qualitative and quantitative methods is widely accepted, not much exploration about the performance of the different methods in visualization systems has been done so far. Textual and pictorial information is processed differently in the human cognitive system and thus, displays with equal quantity of information can still differ in their usefulness.

In this project, the influence of different data types on the basis of the subject of migration visualizations have been explored. An evaluation of existing approaches of migration visualizations showed that so far, most of the interactive displays are based on quantitative methods, even though the subject of migration would be suitable for a combination of qualitative and quantitative methods in order to show all of its dimensions. Today's approaches using quantitative display types have the advantage of high interactivity compared to qualitative methods approaches. Further, visualizations based on qualitative methods are more useful for learning about background information, individual stories or reasons of migration. Moreover, the evaluation showed that maps, interactive tooltips, filtering and highlighting options, a chronological order of the data as well as linked views are the most common representation methods and tools to display migration globally and regionally. Although quantitative methods visualizations are dominating, due to the social aspect of migration we suggest implementing additional qualitative data towards a better understanding of migration triggers.

After three different visualization types (qualitative, quantitative, mixed) for two case studies of important migration flows to Switzerland (from Spain and from Kosovo) were been implemented, a statistical evaluation with 15 participants has been conducted. The comparisons of mixed methods visualizations and qualitative, and mixed methods and quantitative visualizations respectively have revealed major deficits in performance of the qualitative display type. Both variables “System Usability Scale” and “Average Response Time” show significant shortcomings. However, no differences in performance could be proven between the quantitative and the combined methods visualizations. Participants seem to like interactive visualizations even when both data types are available simultaneously, as is the case for the combined display type. Thus, it comes at no surprise that all participants have chosen either the quantitative or the mixed display type to be their favorite. Overall, mixed methods visualization types can be identified as suitable representations of complex phenomena. With enough prior knowledge, most participants seem to work with quantitative data visualizations, but in challenging situations textual information can serve as an alternative source of information.

Since the usability of different data types and their combinations have rarely been explored so far, the outcomes of this study provide insights into this issue. The overall solid performance of the implemented mixed methods visualizations of this project supports nowadays trend of combining different methods, which seemed to be irreconcilable in the past.

8 Bibliography

Al-Kodmany, K. (2000). Extending Geographic Information Systems to Meet Neighborhood Planning Needs: The Case of Three Chicago Communities. *Urisa Journal, 12*(3), 19–37.

Andrews, K. (2008). Evaluation Comes in Many Guises. *AVI Workshop on BEyond time and errors (BELIV) Position Paper*, 8–10.

Arnheim, R. (1969). *Visual Thinking*. Berkeley: U of California P.

Atkinson, R. C., & Shiffrin, R. M. (1968). Human memory: A proposed system and its control processes. In: Spence, K. W. eds. *The psychology of learning and motivation*. New York: Academic Press, 89-195.

Baddeley, A. D. (1986). *Working memory*. Oxford England: Oxford University Press.

Bell, S., & Reed, M. (2004). Adapting to the machine. Cartographica: *The International Journal for Geographic Information and Geovisualization, 39*(1), 55–66.

Bertin, J. (1967). *Sémiologie graphique*. Paris: Mouton/Gauthier-Villars.

Brannen, J., & Coram, T., eds. (1992). *Mixing methods: qualitative and quantitative research*. Aldershot: Avebury.

Bräuniger, D., & Majowski, C., Böttcher, B., & Mayer, T. (2011). Labour mobility in the euro area. Deutsche Bank Research, *Reports on European integration EU Monitor*, 85.

Brooke, J. (1996). SUS-A quick and dirty usability scale. *Usability Evaluation in Industry*, 189.

Bryman, A. (2006). Integrating quantitative and qualitative research: how is it done? *Qualitative Research, 6*(1), 97–113.

Bryman, A. (2012). *Social Research Methods*. Oxford university press.

Buckley, A. (2012). *Make Maps People Want to Look At*. Retrieved from http://www.esri.com/news/arcuser/0112/files/design-principles.pdf (Accessed: 11.09.2014).

Burgen, S. (2013). *Spain youth unemployment reaches record 56.1%*. The Guradian Online. Retrieved from http://www.theguardian.com/business/2013/aug/30/spain-youth-unemployment-record-high (Accessed: 11.09.2014).

Colaso, V., Kamal, A., Saraiya, P., North, C., McCrickard, S., & Shaffer, C. (2002). *Learning and retention in data structures: A comparison of visualization, text, and combined methods*. Proc. ED-MEDIA.

Cook, M. P. (2006). Visual Representations in Science Education: The Influence of Prior Knowledge and Cognitive Load Theory on Instructional Design Principles. *Science education, 90*(6), 1073-1091.

Corbett, J. (N.N.). *Charles Joseph Minard: Mapping Napoleon's March, 1861*. Center for Spatially Integrated Social Science. Retrieved from http://www.csiss.org/classics/content/58 (Accessed: 11.09.2014).

Creswell, J. W. (2013). *Research design: Qualitative, quantitative, and mixed methods approaches*. Sage.

Dolado, J. J., Jansen, M., Felgueroso, F., Fuentes, A., & Wölfl, A. (2013). *Youth Labour Market Performance in Spain and its Determinants*. OECD. Retrieved from http://www.oecd-ilibrary.org/docserver/download/5k487n5bfz5c.pdf?expires=1410599341&id=id&accname=guest&checksum=7D1099CC1BAA345741D385C11BB1C1E6 (Accessed: 13.09.2014).

Duchowski, A. (2007). *Eye tracking methodology: Theory and practice*. Vol. 373. Springer.

Eilam, B., & Poyas, Y. (2008). Learning with multiple representations: Extending multimedia learning beyond the lab. *Learning and Instruction, 18*(4), 368–378.

Elwood, S. (2010). Thinking Outside the Box: Engaging Critical Geographic Information Systems Theory, Practice and Politics in Human Geography. *Geography Compass, 4*(1), 45–60.

Evergreen, S., & Emery, A. K. (2014). *Data Visualization Checklist*. Retrieved from http://stephanieevergreen.com/wp-content/uploads/2014/05/DataVizChecklist_May2014.pdf (Accessed: 11.09.2014).

Field, A. (2009). *Discovering Statistics Using SPSS*. Sage publications.

Hegarty, M., Smallman, H. S., Stull, A. T., & Canham, M. S. (2009). Naïve Cartography: How Intuitions about Display Configuration Can Hurt Performance. Cartographica: *The International Journal for Geographic Information and Geovisualization, 44*(3), 171-186.

Howe, K. (1992). Getting Over the Quantitative-Qualitative Debate. *American Journal of Education, 100*(2), 236–256.

ILO, International Labour Organization (2013). *Global Employment Trends for Youth 2013: A generation at risk*. International Labour Office, Geneva.

Jacob, R. J. K., & Karn, K. S. (2003). Eye Tracking in Human-Computer Interaction and Usability Research. In: Hyona, J., Radach, R., & Deubel, H., eds. *The Mind's Eye: Cognitive and Applied Aspects of Eye Movement Research*. Amsterdam: Elsevier Science. 573-605.

Keim, D. A., Kohlhammer, J., Ellis, G., & Mansmann, F., eds. (2010). *Mastering the Information Age Solving Problems with Visual Analytics*. Florian Mansmann.

Knigge, L., & Cope, M. (2006). Grounded visualization: integrating the analysis of qualitative and quantitative data through grounded theory and visualization. *Environment and Planning A, 38*(11), 2021–2037.

Kuhn, T. S. (2012). *The structure of scientific revolutions*. University of Chicago press.

Kwan, M.-P. (2002). Feminist Visualization: Re-envisioning GIS as a Method in Feminist Geographic Research. *Annals of the Association of American Geographers, 92*(4), 645-661.

Kwan, M.-P. (2004). Beyond difference: From canonical geography to hybrid geographies. *Annals of the Association of American Geographers, 94*(4), 756–763.

Kwan, M.-P., & Lee, J. (2004). Geovisualization of human activity patterns using 3D GIS: a time-geographic approach. *Spatially Integrated Social Science 27*.

Kwan, M.-P., & Knigge, L. (2006). Doing qualitative research using GIS: an oxymoronic endeavor? *Environment and Planning A, 38*(11), 1999–2002.

Kwan, M.-P., & Ding, G. (2008). Geo-Narrative: Extending Geographic Information Systems for Narrative Analysis in Qualitative and Mixed-Method Research. *The Professional Geographer, 60*(4), 443–465.

Larkin, J. (1981). *The Role of Problem Representation in Physics*. Pittsburgh, PA: Carnegie-Mellon University, Department of Psychology.

Levie, W. H., & Lentz, R. (1982). Effects of Text Illustrations: A Review of Research. *Educational Communication and Technology, 30*(4), 195–232.

Lincoln, Y. S., & Guba, E. G. (1985). *Naturalist inquiry*. Beverly Hills, CA: Sage.

MacEachren, A. M., & Taylor, D. R. F., eds. (1994). *Visualization in modern cartography*. Vol. 2. Pergamon Press.

Martin, D. (2007). *Doing psychology experiments*. Cengage Learning.

Mayer, R. E. (2005). Cognitive Theory of Multimedia Learning. *The Cambridge handbook of multimedia learning*, 31-48.

McLafferty, S. (2002). Mapping Women's Worlds: Knowledge, power and the bounds of GIS. *Gender, Place & Culture, 9*(3), 263–269.

Mihi-Ramirez, A., Metelski, D., & Rudzionis, A. (2013). INFLUENCE OF EARNINGS AND UNEMPLOYMENT ON ECONOMIC MIGRATION FLOW. ANALYSIS OF LITHUANIA AND SPAIN. *WHITHER OUR ECONOMIES-2013*, 94-102.

Moreno, R., & Mayer, R. E. (1999). Cognitive principles of multimedia learning: The role of modality and contiguity. *Journal of Educational Psychology, 91*(2), 358–368.

Morgan, D. L. (2007). Paradigms Lost and Pragmatism Regained: Methodological Implications of Combining Qualitative and Quantitative Methods. *Journal of Mixed Methods Research, 1*(1), 48–76.

Paivio, A. D. (1986). *Mental representations: A dual coding approach*. New York: Oxford University Press.

Patrick, M. D., Carter, G., & Wiebe, E. N. (2005). Visual Representations of DNA Replication: Middle Grades Students' Perceptions and Interpretations. *Journal of Science Education and Technology, 14*(3), 353–365.

Pavlovskaya, M. (2002). Mapping Urban Change and Changing GIS: Other views of economic restructuring. Gender, Place & Culture: *A Journal of Feminist Geography, 9*(3), 281-289.

Pinker, S. (1990). A Theory of Graph Comprehension. *Artificial intelligence and the future of testing*, 73-126.

Poole, A., & Ball, L. J. (2005). Eye Tracking in Human--Computer Interaction and Usability Research: Current Status and Future Prospects. *Encyclopedia of Human Computer Interaction*. Vol. 10, 211–219.

Rieber, L. P. (1990). Using Computer Animated Graphics in Science Instruction with Children. *Journal of educational psychology, 82*(1), 135-140.

Sale, J., Lohfeld, L., & Brazil, K. (2002). Revisiting the quantitative-qualitative debate: Implications for mixed-methods research. *Quality and Quantity, 36*(1), 43–53.

Schmidt-Weigand, F., Kohnert, A., & Glowalla, U. (2010). A closer look at split visual attention in system- and self-paced instruction in multimedia learning. *Learning and Instruction, 20*(2), 100–110.

Schnotz, W. (2002). Commentary: Towards an Integrated View of Learning From Text and Visual Displays. *Educational Psychology Review, 14*(1), 101–120.

Schnotz, W., & Bannert, M. (2003). Construction and interference in learning from multiple representation. *Learning and Instruction, 13*(2), 141–156.

Schnotz, W., Picard, E., & Hron, A. (1993). How do successful and unsuccessful learners use texts and graphics? *Learning and Instruction, 3*(3), 181–199.

Schuurman, N. C. (2000). *Critical GIS: Theorizing an emerging science*. ProQuest Dissertations and Theses. Retrieved from https://circle.ubc.ca/handle/2429/10899 (Accessed: 11.09.2014).

Sharani, B. B., Efionayi-mäder, D., Hammer, S., Pecoraro, M., Soland, B., Tsaka, A., & Wyssmüller, C. (2010). *Die kosovarische Bevölkerung in der Schweiz.* Bundesamt für Migration BFM. Retrieved from https://www.bfm.admin.ch/content/dam/data/bfm/publiservice/publikationen/diaspora/diasporastudie-kosovo-d.pdf (Accessed: 11.09.2014).

Shiffer, M. J. (2002). Spatial multimedia representations to support community participation. *Community Participation and Geographic Information Systems.* London: Taylor and Francis. 309-319.

Shneiderman, B. (1996). The eyes have it: a task by data type taxonomy for information visualizations. *Proc. 1996 IEEE Symposium on Visual Languages.*

Shneiderman, B. (2003). *Designing the user interface*. Pearson Education India.

Slocum, T. A. (1999). *Thematic cartography and visualization*. Upper Saddle River, NJ: Prentice hall.

Slocum, T. A., McMaster, R. B., Kessler, F. C., & Howard, H. H. (2009). *Thematic cartography and geovisualization*. New Jersey, NJ: Prentice hall.

Sui, D., & DeLyser, D. (2012). Crossing the qualitative-quantitative chasm I: Hybrid geographies, the spatial turn, and volunteered geographic information (VGI). *Progress in Human Geography, 36*(1), 111–124.

Sweller, J. (2003). Evolution of human cognitive architecture. *Psychology of Learning and Motivation, 43*, 216-266.

Tagesschau (2013). *Schwarzarbeit, Uni oder Deutschland*. ARD. Retrieved from http://www.tagesschau.de/wirtschaft/jugendarbeitslosigkeit-spanien100.html (Accessed: 11.09.2014).

Tashakkori, A., & Teddlie, C., eds. (2010). *Sage Handbook of Mixed Methods in Social & Behavioral Research*. Sage.

Thieme, S., & Wyss, S. (2005). Migration Patterns and Remittance Transfer in Nepal: A Case Study of Sainik Basti in Western Nepal. *International Migration, 43*(5), 59-98.

Tobii Technology (2010). *Tobii TX300 Eye Tracker*. Retrieved from: http://www.tobii.com/Global/Analysis/Downloads/Product_Descriptions/Tobii_TX300_EyeTracker_Product_Description.pdf (Accessed: 11.09.2014).

Tobii Technology (2012). *Determining the Tobii I-VT Fixation Filter's Default Values. Method description and results discussion*. Retrieved from http://www.tobii.com/Global/Analysis/Training/WhitePapers/Tobii_WhitePaper_DeterminingtheTobiiI-VTFixationFilter’sDefaultValues.pdf (Accessed: 11.09.2014).

Tobler, W. R. (2003). *Movement Mapping*. Retrieved from http://www.csiss.org/clearinghouse/FlowMapper/MovementMapping.pdf (Accessed: 11.09.2014).

Tufte, E. R. (2001). *The Visual Display of Quantitative Information*. Graphic Press Cheshire.

Wood, J., Dykes, J., & Slingsby, A. (2002). Visualisation of origins, destinations and flows with OD maps. *The Cartographic Journal, 47*(2), 117-129.

Wottreng, W. (2000). *Ein einzig Volk von Immigranten. Die Geschichte der Einwanderung in die Schweiz.* Zürich.

Wyly, E. K. (1998). Containment and Mismatch: Gender Differences in Commuting in Metropolitan Labor Markets. *Urban Geography, 19*(5), 395–430.

A Appendix

A.1 Evaluation of Existing Approaches

Evaluator 1:

	Interactivity			**Layout**			**Content**				**Total**	**Comments**
	Level of Interactivity	Linked view	Tooltip	Text & Labels	Colors	Design	Magnitude	Triggers	Spatial	Temporal		
Interactivethings.com	1	1	1	2	1	2	2	0	1	0	**11**	clean design
Migrationsmap.net	1	0	2	2	1	1	1	1	2	0	**11**	dark colors
Visualizing.org	2	1	2	2	2	1	0	0	1	1	**12**	OD map would be better
Nytimes.com	2	0	2	2	1	1	2	0	0	1	**11**	
Contakt-spuren.ch	0	0	0	2	1	1	0	2	0	1	**7**	no interaction
Theoage.com.au	0	0	0	2	1	2	0	2	0	0	**7**	no interaction
Books & Videos	0	0	0	2	1	1	1	2	0	1	**8**	no interaction
Statistics.gov.uk	1	2	0	1	1	2	2	2	1	2	**14**	Migration and triggers visible, missing tooltip

Evaluator 2:

	Interactivity			**Layout**			**Content**				**Total**	**Comments**
	Level of Interactivity	Linked view	Tooltip	Text & Labels	Colors	Design	Magnitude	Triggers	Spatial	Temporal		
Interactivethings.com	1	0	0	2	2	2	2	0	2	0	**11**	modern appearance
Migrationsmap.net	2	1	2	1	0	0	0	1	2	0	**9**	
Visualizing.org	2	2	1	1	1	2	1	0	1	1	**12**	temporal comparison would be interesting
Nytimes.com	1	1	1	1	0	1	2	0	1	1	**9**	adjustable circle size is good
Contakt-spuren.ch	0	0	0	1	0	1	0	2	0	2	**6**	classification into "epochen" good
Theoage.com.au	1	0	0	1	1	1	0	2	0	1	**7**	person stories
Books & Videos	0	0	0	1	1	1	1	2	0	1	**7**	interaction missing
Statistics.gov.uk	2	2	0	0	1	2	2	2	1	2	**14**	qual.+quant information, not very hierarchical

Evaluator 3:

	Interactivity			Layout			Content				Total	Comments
	Level of Interactivity	Linked view	Tooltip	Text & Labels	Colors	Design	Magnitude	Triggers	Spatial	Temporal		
Interactivethings.com	2	0	1	1	2	2	2	0	2	0	**12**	
Migrationsmap.net	2	2	1	1	1	1	1	0	2	0	**11**	
Visualizing.org	2	2	2	1	0	1	1	0	2	2	**13**	colors
Nytimes.com	2	1	1	1	1	1	2	0	2	2	**13**	
Contakt-spuren.ch	0	0	0	1	1	1	1	2	0	2	**8**	pictures
Theoage.com.au	1	1	0	1	1	0	0	2	1	0	**7**	videos, audio
Books & Videos	0	0	0	0	1	1	1	2	0	0	**5**	
Statistics.gov.uk	2	1	0	1	2	2	2	1	1	2	**14**	spatial information missing

A.2 Questionnaires

A.2.1 Pre-Questionnaire

Pre-experiment questionnaire

***1. Participant No: (to be filled by the experimenter)**

***2. Date and Time: (experimenter)**

***3. Age**

- under 20 years
- 20 - 30 years
- 30 - 40 years
- over 40 years

***4. Gender:**

- female
- male

5. Which description fits best to your educational background?

- Scientific education (e.g. BSc, MSc, technical education...)
- Social education (e.g. BA, MA...)
- Other (please specify)

***6. Do you have migrational background? (Have you, your parents or your grandparents migrated to Switzerland?)**

- Yes
- No
- No answer

***7. Do you use prescription glasses or contact lenses?**

- yes
- no

***8. If yes, are you wearing them now?**

- yes
- no

Pre-experiment questionnaire

***9. Have you ever been told by a professional that you have imperfect color vision?**

- yes
- no

If you do specifically know, what kind?

Please rate your level of training in the following categories.

***10. Cartography and/or Geographic Information Systems**

0 No training	1	2	3	4 Proficient

***11. Computer Graphics**

0 No experience	1	2	3	4 Everyday use

***12. Graphic Design, Fine Arts**

0 No experience	1	2	3	4 Extensive experience

***13. User Interface Design**

0 No experience	1	2	3	4 Extensive experience

Please rate your level of experience in the following categories.

***14. Graphics of any kind (maps, charts, graphs, photos, etc.)**

0 No experience	1	2	3	4 Everyday use

***15. Spatial data of any kind (maps, digital elevation models, remotely sensed images, etc.)**

0 No experience	1	2	3	4 Everyday use

***16. The Internet**

0 No experience	1	2	3	4 Everyday use

***17. Microsoft Windows**

0 No experience	1	2	3	4 Everyday use

***18. Mozilla Firefox Internet Browser**

0 No experience	1	2	3	4 Everyday use

Pre-experiment questionnaire

***19. Tableau**

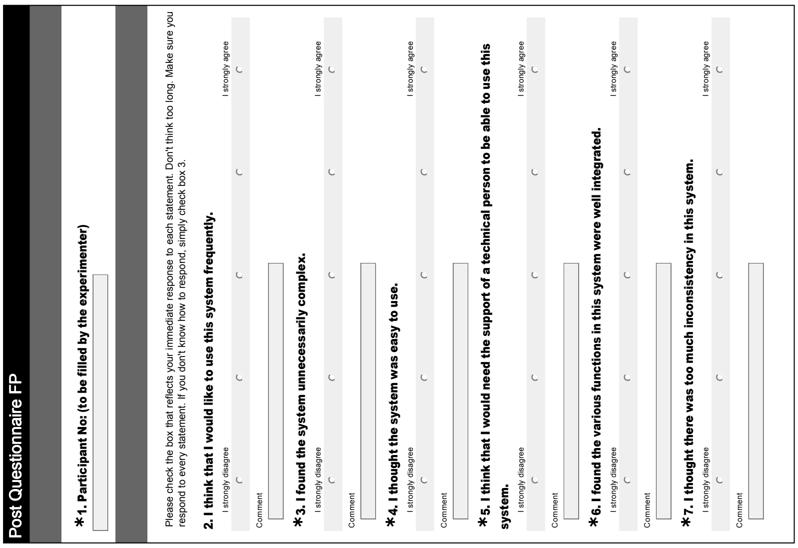
0 No experience	1	2	3	4 Everyday use

***20. English language**

0 No experience	1	2	3	4 Everyday use

Thank you for the answers.

A.2.2 Post-Questionnaire


Post Questionnaire FP

*1. Participant No: (to be filled by the experimenter)

Please check the box that reflects your immediate response to each statement. Don't think too long. Make sure you respond to every statement. If you don't know how to respond, simply check box 3.

2. I think that I would like to use this system frequently.
I strongly disagree / I strongly agree
Comment

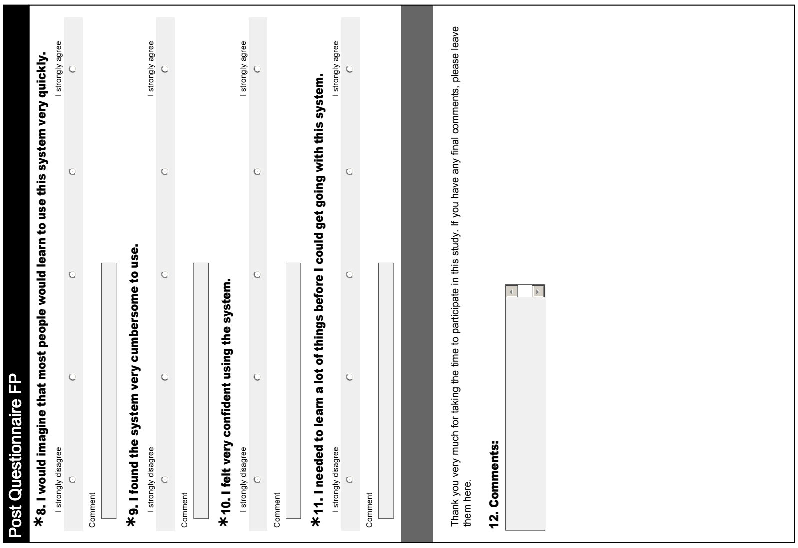
*3. I found the system unnecessarily complex.
I strongly disagree / I strongly agree
Comment

*4. I thought the system was easy to use.
I strongly disagree / I strongly agree
Comment

*5. I think that I would need the support of a technical person to be able to use this system.
I strongly disagree / I strongly agree
Comment

*6. I found the various functions in this system were well integrated.
I strongly disagree / I strongly agree
Comment

*7. I thought there was too much inconsistency in this system.
I strongly disagree / I strongly agree
Comment


Post Questionnaire FP

*8. I would imagine that most people would learn to use this system very quickly.
I strongly disagree / I strongly agree
Comment

*9. I found the system very cumbersome to use.
I strongly disagree / I strongly agree
Comment

*10. I felt very confident using the system.
I strongly disagree / I strongly agree
Comment

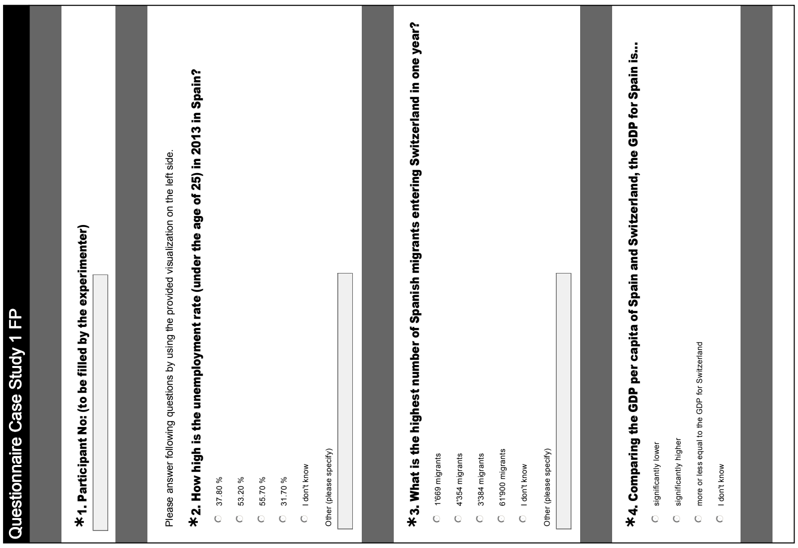
*11. I needed to learn a lot of things before I could get going with this system.
I strongly disagree / I strongly agree
Comment

Thank you very much for taking the time to participate in this study. If you have any final comments, please leave them here.

12. Comments:

A.2.3 Preference Question

A.2.4 Questionnaires Case Study Spain


Questionnaire Case Study 1 FP

*1. Participant No: (to be filled by the experimenter)

Please answer following questions by using the provided visualization on the left side.

*2. How high is the unemployment rate (under the age of 25) in 2013 in Spain?

- 37.80 %
- 53.20 %
- 55.70 %
- 31.70 %
- I don't know

Other (please specify)

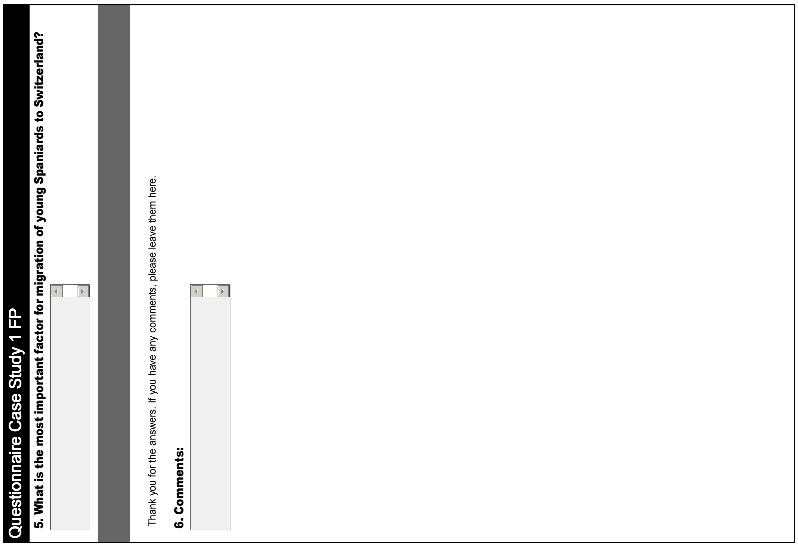
*3. What is the highest number of Spanish migrants entering Switzerland in one year?

- 1'669 migrants
- 4'354 migrants
- 3'384 migrants
- 61'900 migrants
- I don't know

Other (please specify)

*4. Comparing the GDP per capita of Spain and Switzerland, the GDP for Spain is...

- significantly lower
- significantly higher
- more or less equal to the GDP for Switzerland
- I don't know


Questionnaire Case Study 1 FP

5. What is the most important factor for migration of young Spaniards to Switzerland?

Thank you for the answers. If you have any comments, please leave them here.

6. Comments:

Questionnaire Case Study 1.1 FP

*1. Participant No: (to be filled by the experimenter)**

Please answer following questions by using the provided visualization on the left side.

***2. How high is the unemployment rate (under the age of 25) in 2013 in Switzerland?**

- 37.80 %
- 6.000 %
- 6.695 %
- 31.70 %
- I don't know

Other (please specify)

***3. How high was the GDP per capita in Spain in 2008?**

- 23'500 Euro
- 24'900 Euro
- 23'900 Euro
- I don't know

Other (please specify)

***4. How many Spanish migrants were living in Germany in 2011?**

- 69'220 migrants
- 169'550 migrants
- 4'354 migrants
- 3'384 migrants
- I don't know

Other (please specify)

Questionnaire Case Study 1.1 FP

5. What is the most important factor for migration of young Spaniards to Switzerland?

Thank you for the answers. If you have any comments, please leave them here.

6. Comments:

Questionnaire Case Study 1.2 FP

***1. Participant No: (to be filled by the experimenter)**

Please answer following questions by using the provided visualization on the left side.

***2. In which year was the unemployment rate (under the age of 25) in Spain the highest?**

- 2009
- 2013
- 2011
- I don't know

Other (please specify)

***3. What is the number of Spanish migrants entering Switzerland in 2009?**

- 1'669 migrants
- 2'139 migrants
- 2'622 migrants
- 61'900 migrants
- I don't know

Other (please specify)

***4. How high is the income share of the first quintile (poorest) in Spain?**

- 40.80%
- 5.70%
- 28.7%
- I don't know

Other (please specify)

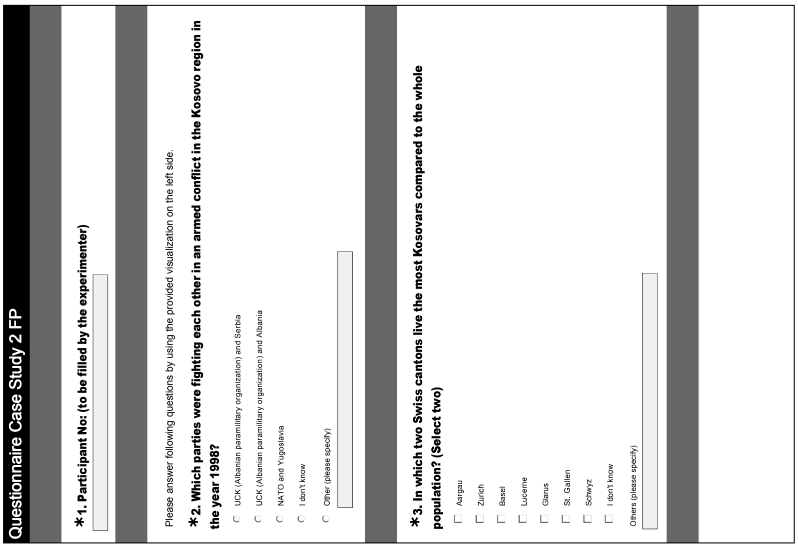
Questionnaire Case Study 1.2 FP

5. What is the most important factor for migration of young Spaniards to Switzerland?

Thank you for the answers. If you have any comments, please leave them here.

6. Comments:

A.2.4 Questionnaires Case Study Kosovo



Questionnaire Case Study 2 FP

*1. Participant No: (to be filled by the experimenter)

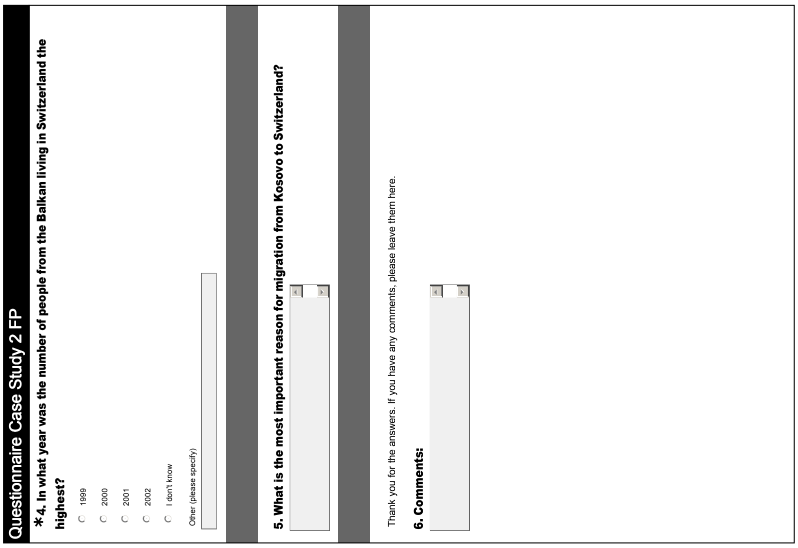
Please answer following questions by using the provided visualization on the left side.

*2. Which parties were fighting each other in an armed conflict in the Kosovo region in the year 1998?

- UCK (Albanian paramilitary organization) and Serbia
- UCK (Albanian paramilitary organization) and Albania
- NATO and Yugoslavia
- I don't know
- Other (please specify)

*3. In which two Swiss cantons live the most Kosovars compared to the whole population? (Select two)

- Aargau
- Zurich
- Basel
- Lucerne
- Glarus
- St. Gallen
- Schwyz
- I don't know
- Others (please specify)



Questionnaire Case Study 2 FP

*4. In what year was the number of people from the Balkan living in Switzerland the highest?

- 1999
- 2000
- 2001
- 2002
- I don't know
- Other (please specify)

5. What is the most important reason for migration from Kosovo to Switzerland?

Thank you for the answers. If you have any comments, please leave them here.

6. Comments:

Questionnaire Case Study 2.1 FP

***1. Participant No: (to be filled by the experimenter)**

Please answer following questions by using the provided visualization on the left side.

***2. Which parties were fighting each other in an armed conflict in the Balkan region in the year 2001?**

- UCK (Albanian paramilitary organization) and Serbia
- UCK (Albanian paramilitary organization) and Macedonia
- NATO and Yugoslavia
- I don't know
- Other (please specify)

***3. In which two Swiss cantons live the most Kosovars (absolute)? (Select two)**

- Aargau
- Zurich
- Basel
- Lucerne
- Glarus
- St. Gallen
- Schwyz
- I don't know

Others (please specify)

Questionnaire Case Study 2.1 FP

***4. In what year was the number of people from Serbia and Montenegro living in Switzerland the highest?**

- 1999
- 2000
- 2001
- 2002
- I don't know

Other (please specify)

5. What is the most important reason for migration from Kosovo to Switzerland?

Thank you for the answers. If you have any comments, please leave them here.

6. Comments:

Questionnaire Case Study 2.2 FP

*1. Participant No: (to be filled by the experimenter)

Please answer following questions by using the provided visualization on the left side.

*2. Which parties were fighting each other in an armed conflict in the Kosovo region in the year 1999?

- UCK (Albanian paramilitary organization) and Serbia
- UCK (Albanian paramilitary organization) and Albania
- NATO and Yugoslavia
- I don't know
- Other (please specify)

*3. In which two Swiss cantons live the least Kosovars compared to the whole population? (Select two)

- Appenzell
- Zurich
- Basel
- Lucerne
- Glarus
- Uri
- Schwyz
- I don't know

Others (please specify)

Questionnaire Case Study 2.2 FP

*4. How many people from the Balkan region were living in Switzerland in 1999?

- 241'976
- 367'243
- 390'000
- 393'781
- I don't know

Other (please specify)

5. What is the most important reason for migration from Kosovo to Switzerland?

Thank you for the answers. If you have any comments, please leave them here.

6. Comments:

A.3 Participant Consent Form

The University of Zurich - **Participant Information Statement and Consent Form**
Evaluating Interface Design for Interactive Geovisualizations: A Case Study with Eye Movement Analysis

June, 2014

Participant No:

Purpose of study

You are invited to participate in a study regarding an evaluation of quantitative and qualitative data visualizations. We hope to learn more about the use of different data types.

Description of study and risks

If you decide to participate, we will ask you to begin by filling out a short background questionnaire including demographic information. This will be followed by a session at the computer where you will be asked to use an information visualization system. During this process we will record your interactions with the computer using a webcam, audio recorder and eye tracking. The eye tracking device is non-contact, uses near infrared light and should not cause any discomfort. After the experiment we will ask you to fill out a second questionnaire.

The whole procedure should take approximately 60 minutes and there are no particular risks or benefits to you from participating in this experiment.

Confidentiality and disclosure of information

Any information and that can be identified with you in connection with this study will remain confidential and will be disclosed only with your permission. If you give us permission by signing this document, we plan to publish the results of this research in scientific publications. In any publication, information will be provided in such a way that you cannot be identified.

Compensation

You will get a coffee voucher for your participation in this experiment. There are no costs for you for your participation.

Feedback to participants

If you would like to be kept informed about the results of this research, please leave your name and contact details with the experiment leader. A copy of publications resulting from this research will be sent to you when available.

Your consent

Your decision whether or not to participate will not prejudice your future relations with University of Zurich. If you decide to participate, you are free to withdraw your consent and to discontinue participation at any time without prejudice.

If you have any questions, please feel free to ask me. If you have any additional questions later, Dr. Arzu Coltekin (044 6355440, arzu@geo.uzh.ch) will be happy to answer them.

You will be given a copy of this form to keep.

Page 1 of 2

The University of Zurich - **Participant Information Statement and Consent Form (continued)**
Evaluating Interface Design for Interactive Geovisualizations: A Case Study with Eye Movement Analysis

June, 2014

Participant No:

You are making a decision whether or not to participate. Your signature indicates that, having read the information provided above, you have decided to participate.

……………………………………… ………………………………

Signature of Research Participant Signature of Experimenter

……………………………………… ………………………………

Please PRINT name Please PRINT name

………………………………………

Date and Place

The University of Zurich - **Participant Information Statement and Consent Form (continued)**
Evaluating Interface Design for Interactive Geovisualizations: A Case Study with Eye Movement Analysis

June, 2014

Participant No:

REVOCATION OF CONSENT

Evaluating Quantitative and Qualitative Information Visualizations: A Case Study with Eye Movement Analysis

I hereby wish to WITHDRAW my consent to participate in the research proposal described above and understand that such withdrawal WILL NOT jeopardize any treatment or my relationship with The University of Zurich.

……………………………………… ………………………………

Signature Date

………………………………………

Please PRINT name

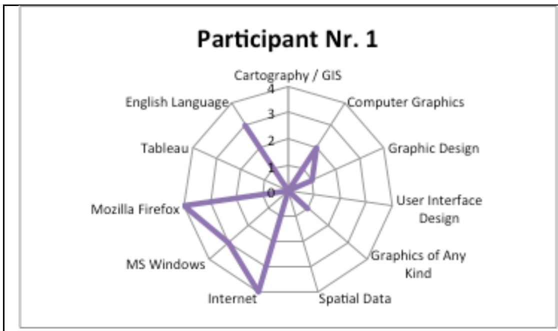
This section of Revocation of Consent should be forwarded to Dr. Arzu Coltekin, Geographic Information Visualization and Analysis, Dept. of Geography, University of Zurich, CH-8057, Zurich.

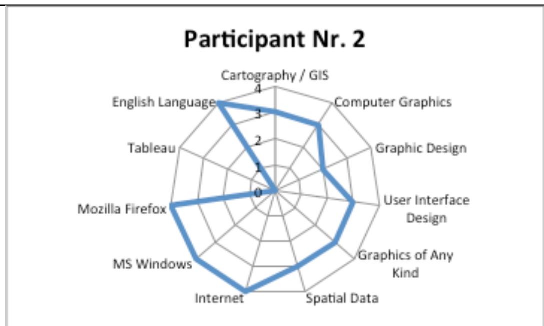
Page 2 of 2

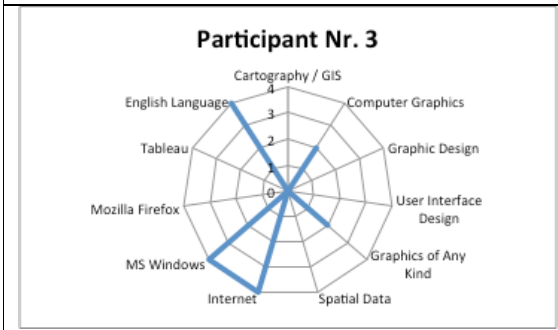
A.4 Participants

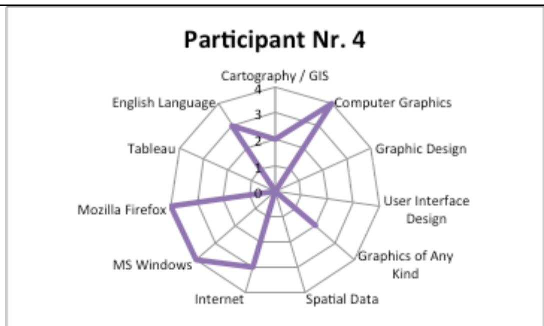
A.4.1 Spider Diagrams

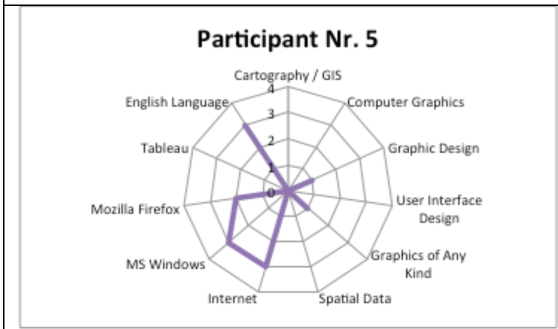
Colors: Blue indicates a male participant, violet indicates a female participant.

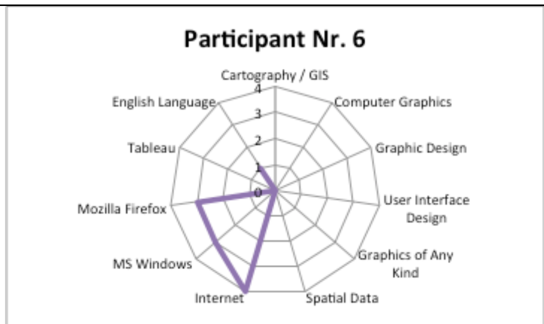


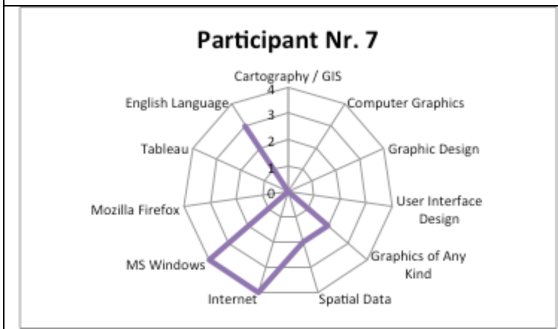


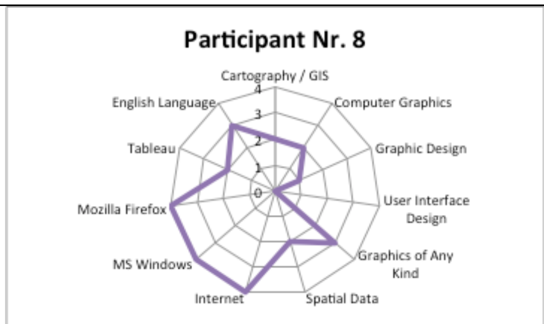


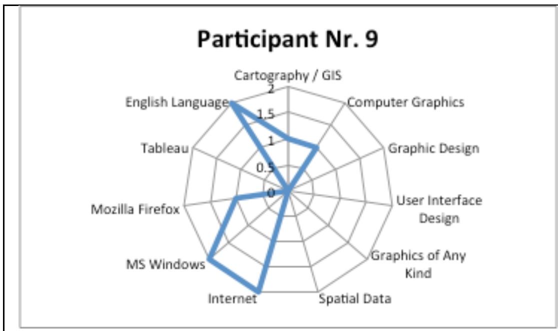


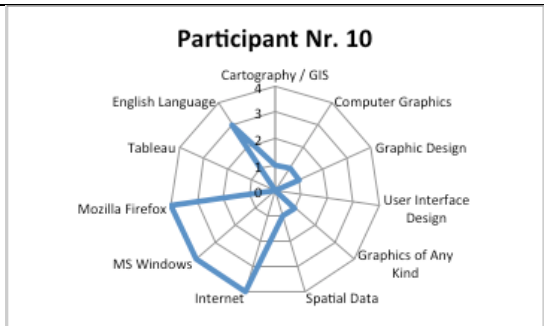


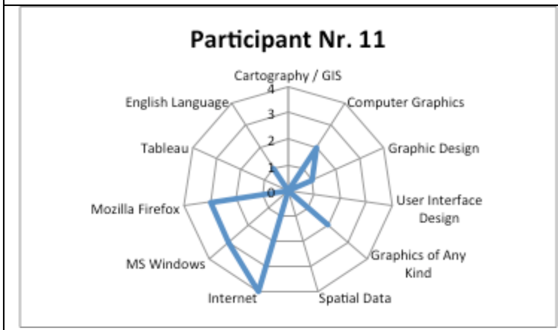


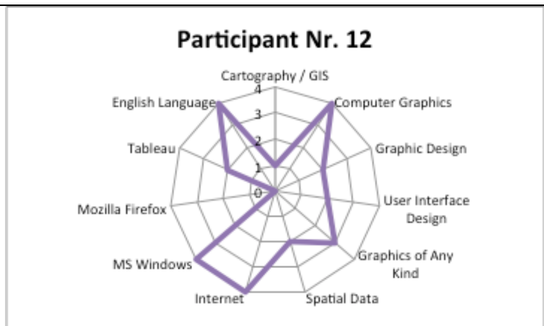


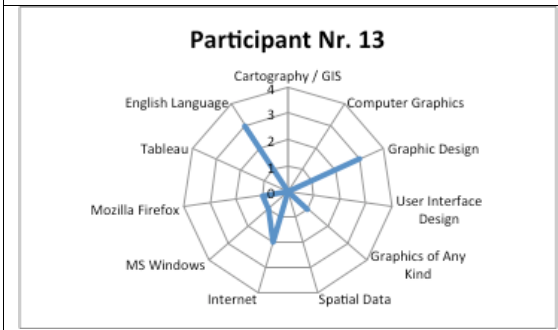


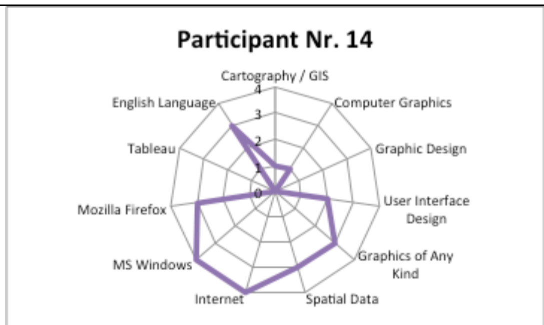

Participant Nr. 9
Cartography / GIS
Computer Graphics
Graphic Design
User Interface Design
Graphics of Any Kind
Spatial Data
Internet
MS Windows
Mozilla Firefox
Tableau
English Language
2
1.5
1
0.5
0

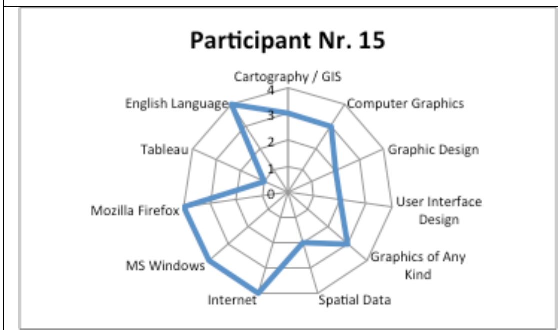

Participant Nr. 10
Cartography / GIS
Computer Graphics
Graphic Design
User Interface Design
Graphics of Any Kind
Spatial Data
Internet
MS Windows
Mozilla Firefox
Tableau
English Language
4
3
2
1
0


Participant Nr. 11
Cartography / GIS
Computer Graphics
Graphic Design
User Interface Design
Graphics of Any Kind
Spatial Data
Internet
MS Windows
Mozilla Firefox
Tableau
English Language
4
3
2
1
0


Participant Nr. 12
Cartography / GIS
Computer Graphics
Graphic Design
User Interface Design
Graphics of Any Kind
Spatial Data
Internet
MS Windows
Mozilla Firefox
Tableau
English Language
4
3
2
1
0


Participant Nr. 13
Cartography / GIS
Computer Graphics
Graphic Design
User Interface Design
Graphics of Any Kind
Spatial Data
Internet
MS Windows
Mozilla Firefox
Tableau
English Language
4
3
2
1
0


Participant Nr. 14
Cartography / GIS
Computer Graphics
Graphic Design
User Interface Design
Graphics of Any Kind
Spatial Data
Internet
MS Windows
Mozilla Firefox
Tableau
English Language
4
3
2
1
0


Participant Nr. 15
Cartography / GIS
Computer Graphics
Graphic Design
User Interface Design
Graphics of Any Kind
Spatial Data
Internet
MS Windows
Mozilla Firefox
Tableau
English Language
4
3
2
1
0

A.4.2 Clustering of Participants (k-means, 3 cluster)

Initial Cluster Centers

	Cluster		
	1	2	3
Cartography / GIS	2.00	1.00	.00
Computer Graphics	4.00	4.00	.00
Graphic Design	.00	2.00	3.00
User Interface Design	.00	2.00	.00
Graphics of Any Kind	2.00	3.00	1.00
Spatial Data	.00	2.00	.00
Internet	3.00	4.00	2.00
MS Windows	4.00	4.00	1.00
Mozilla Firefox	4.00	.00	1.00
Tableau	.00	2.00	.00
English Language	3.00	4.00	3.00

Iteration History[a]

Iteration	Change in Cluster Centers		
	1	2	3
1	2.839	2.345	3.033
2	.000	.000	.000

a. Convergence achieved due to no or small change in cluster centers. The maximum absolute coordinate change for any center is .000. The current iteration is 2. The minimum distance between initial centers is 6.000.

Cluster Membership

Case Number	Participant Nr.	Cluster	Distance
1	1	1	2.704
7	2	1	3.579
13	3	2	2.345
19	4	1	2.839
25	5	3	1.095
31	6	3	2.683
37	7	3	3.162
43	8	1	2.194
49	9	3	2.098
55	10	1	2.136
61	11	1	3.211
67	12	2	2.345
73	13	3	3.033
79	14	1	2.839
85	15	1	2.750

A.5 Statistical Tests (SPSS 22.0.0.0)

A.5.1 General Results

SUS

Descriptive Statistics:

	Visualization Type			Statistic	Std. Error
SUS Score	Quantitative	Mean		84.833	2.9324
		95% Confidence Interval for Mean	Lower Bound	78.544	
			Upper Bound	91.123	
		5% Trimmed Mean		85.231	
		Median		90.000	
		Variance		128.988	
		Std. Deviation		11.3573	
		Minimum		62.5	
		Maximum		100.0	
		Range		37.5	
		Interquartile Range		20.0	
		Skewness		-.641	.580
		Kurtosis		-.728	1.121
	Qualitative	Mean		56.333	4.5830
		95% Confidence Interval for Mean	Lower Bound	46.504	
			Upper Bound	66.163	
		5% Trimmed Mean		56.065	
		Median		57.500	
		Variance		315.060	
		Std. Deviation		17.7499	
		Minimum		25.0	
		Maximum		92.5	
		Range		67.5	
		Interquartile Range		22.5	
		Skewness		.284	.580
		Kurtosis		-.038	1.121
	Mixed	Mean		81.500	3.6580
		95% Confidence Interval for Mean	Lower Bound	73.654	
			Upper Bound	89.346	
		5% Trimmed Mean		81.528	
		Median		82.500	
		Variance		200.714	
		Std. Deviation		14.1674	
		Minimum		62.5	
		Maximum		100.0	
		Range		37.5	
		Interquartile Range		30.0	
		Skewness		-.185	.580
		Kurtosis		-1.731	1.121

Tests of Normality:

	Visualization Type	Kolmogorov-Smirnov[a]			Shapiro-Wilk		
		Statistic	df	Sig.	Statistic	df	Sig.
SUS Score	Quantitative	.209	15	.078	.914	15	.154
	Qualitative	.091	15	.200*	.988	15	.998
	Mixed	.181	15	.199	.875	15	.040

*. This is a lower bound of the true significance.

a. Lilliefors Significance Correction

ANOVA:

SUS Score

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	7283.611	2	3641.806	16.945	.000
Within Groups	9026.667	42	214.921		
Total	16310.278	44			

Post Hoc:

Dependent Variable: SUS Score
Tukey HSD

(I) Visualization Type	(J) Visualization Type	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval	
					Lower Bound	Upper Bound
Quantitative	Qualitative	28.5000*	5.3531	.000	15.495	41.505
	Mixed	3.3333	5.3531	.809	-9.672	16.339
Qualitative	Quantitative	-28.5000*	5.3531	.000	-41.505	-15.495
	Mixed	-25.1667*	5.3531	.000	-38.172	-12.161
Mixed	Quantitative	-3.3333	5.3531	.809	-16.339	9.672
	Qualitative	25.1667*	5.3531	.000	12.161	38.172

*. The mean difference is significant at the 0.05 level.

Natural Science Education

Descriptive Statistics:

	Visualization Type			Statistic	Std. Error
SUS Score	Quantitative	Mean		88.438	3.3051
		95% Confidence Interval for Mean	Lower Bound	80.622	
			Upper Bound	96.253	
		5% Trimmed Mean		88.542	
		Median		91.250	
		Variance		87.388	
		Std. Deviation		9.3482	
		Minimum		75.0	
		Maximum		100.0	
		Range		25.0	
		Interquartile Range		17.5	
		Skewness		-.632	.752
		Kurtosis		-.985	1.481
	Qualitative	Mean		49.063	4.7231
		95% Confidence Interval for Mean	Lower Bound	37.894	
			Upper Bound	60.231	
		5% Trimmed Mean		49.514	
		Median		50.000	
		Variance		178.460	
		Std. Deviation		13.3589	
		Minimum		25.0	
		Maximum		65.0	
		Range		40.0	
		Interquartile Range		21.9	
		Skewness		-.674	.752
		Kurtosis		.006	1.481
	Mixed	Mean		84.375	5.2557
		95% Confidence Interval for Mean	Lower Bound	71.947	
			Upper Bound	96.803	
		5% Trimmed Mean		84.722	
		Median		90.000	
		Variance		220.982	
		Std. Deviation		14.8655	
		Minimum		62.5	
		Maximum		100.0	
		Range		37.5	
		Interquartile Range		29.4	
		Skewness		-.622	.752
		Kurtosis		-1.501	1.481

Test of Normality:

	Visualization Type	Kolmogorov-Smirnov[a]			Shapiro-Wilk		
		Statistic	df	Sig.	Statistic	df	Sig.
SUS Score	Quantitative	.191	8	.200*	.891	8	.239
	Qualitative	.131	8	.200*	.957	8	.784
	Mixed	.208	8	.200*	.873	8	.162

*. This is a lower bound of the true significance.

a. Lilliefors Significance Correction

ANOVA:

SUS Score

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	7503.646	2	3751.823	23.120	.000
Within Groups	3407.813	21	162.277		
Total	10911.458	23			

Post Hoc:

Dependent Variable: SUS Score

Tukey HSD

(I) Visualization Type	(J) Visualization Type	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval	
					Lower Bound	Upper Bound
Quantitative	Qualitative	39.3750*	6.3694	.000	23.320	55.430
	Mixed	4.0625	6.3694	.801	-11.992	20.117
Qualitative	Quantitative	-39.3750*	6.3694	.000	-55.430	-23.320
	Mixed	-35.3125*	6.3694	.000	-51.367	-19.258
Mixed	Quantitative	-4.0625	6.3694	.801	-20.117	11.992
	Qualitative	35.3125*	6.3694	.000	19.258	51.367

*. The mean difference is significant at the 0.05 level.

Social Science Education / Humanities

Descriptive Statistics:

	Visualization Type			Statistic	Std. Error
SUS Score	Quantitative	Mean		80.000	6.5192
		95% Confidence Interval for Mean	Lower Bound	61.900	
			Upper Bound	98.100	
		5% Trimmed Mean		80.139	
		Median		82.500	
		Variance		212.500	
		Std. Deviation		14.5774	
		Minimum		62.5	
		Maximum		95.0	
		Range		32.5	
		Interquartile Range		28.8	
		Skewness		-.265	.913
		Kurtosis		-2.650	2.000
	Qualitative	Mean		67.000	9.4340
		95% Confidence Interval for Mean	Lower Bound	40.807	
			Upper Bound	93.193	
		5% Trimmed Mean		67.222	
		Median		67.500	
		Variance		445.000	
		Std. Deviation		21.0950	
		Minimum		37.5	
		Maximum		92.5	
		Range		55.0	
		Interquartile Range		38.8	
		Skewness		-.344	.913
		Kurtosis		-.319	2.000
	Mixed	Mean		71.500	4.0774
		95% Confidence Interval for Mean	Lower Bound	60.179	
			Upper Bound	82.821	
		5% Trimmed Mean		71.389	
		Median		67.500	
		Variance		83.125	
		Std. Deviation		9.1173	
		Minimum		62.5	
		Maximum		82.5	
		Range		20.0	
		Interquartile Range		17.5	
		Skewness		.482	.913
		Kurtosis		-2.851	2.000

Test of Normality:

	Visualization Type	Kolmogorov-Smirnov[a]			Shapiro-Wilk		
		Statistic	df	Sig.	Statistic	df	Sig.
SUS Score	Quantitative	.204	5	.200*	.898	5	.401
	Qualitative	.131	5	.200*	.990	5	.981
	Mixed	.270	5	.200*	.860	5	.229

*. This is a lower bound of the true significance.

a. Lilliefors Significance Correction

ANOVA:

SUS Score

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	435.833	2	217.917	.883	.439
Within Groups	2962.500	12	246.875		
Total	3398.333	14			

Post Hoc:

Dependent Variable: SUS Score
Tukey HSD

(I) Visualization Type	(J) Visualization Type	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval	
					Lower Bound	Upper Bound
Quantitative	Qualitative	13.0000	9.9373	.418	-13.511	39.511
	Mixed	8.5000	9.9373	.677	-18.011	35.011
Qualitative	Quantitative	-13.0000	9.9373	.418	-39.511	13.511
	Mixed	-4.5000	9.9373	.894	-31.011	22.011
Mixed	Quantitative	-8.5000	9.9373	.677	-35.011	18.011
	Qualitative	4.5000	9.9373	.894	-22.011	31.011

Low Level of Experience

Descriptive Statistics:

	Visualization Type			Statistic	Std. Error
SUS Score	Quantitative	Mean		89.688	3.3553
		95% Confidence Interval for Mean	Lower Bound	81.753	
			Upper Bound	97.622	
		5% Trimmed Mean		89.931	
		Median		93.750	
		Variance		90.067	
		Std. Deviation		9.4904	
		Minimum		75.0	
		Maximum		100.0	
		Range		25.0	
		Interquartile Range		16.3	
		Skewness		-1.063	.752
		Kurtosis		-.385	1.481
	Qualitative	Mean		51.875	6.0826
		95% Confidence Interval for Mean	Lower Bound	37.492	
			Upper Bound	66.258	
		5% Trimmed Mean		51.806	
		Median		50.000	
		Variance		295.982	
		Std. Deviation		17.2041	
		Minimum		25.0	
		Maximum		80.0	
		Range		55.0	
		Interquartile Range		25.0	
		Skewness		.109	.752
		Kurtosis		-.066	1.481
	Mixed	Mean		82.813	5.8523
		95% Confidence Interval for Mean	Lower Bound	68.974	
			Upper Bound	96.651	
		5% Trimmed Mean		82.986	
		Median		90.000	
		Variance		273.996	
		Std. Deviation		16.5528	
		Minimum		62.5	
		Maximum		100.0	
		Range		37.5	
		Interquartile Range		33.8	
		Skewness		-.476	.752
		Kurtosis		-2.131	1.481

Test of Normality:

	Visualization Type	Kolmogorov-Smirnov[a]			Shapiro-Wilk		
		Statistic	df	Sig.	Statistic	df	Sig.
SUS Score	Quantitative	.263	8	.109	.801	8	.029
	Qualitative	.111	8	.200*	.991	8	.997
	Mixed	.236	8	.200*	.805	8	.032

*. This is a lower bound of the true significance.

a. Lilliefors Significance Correction

ANOVA:

SUS Score

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	6491.146	2	3245.573	14.752	.000
Within Groups	4620.313	21	220.015		
Total	11111.458	23			

Post Hoc:

Dependent Variable: SUS Score
Tukey HSD

(I) Visualization Type	(J) Visualization Type	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval	
					Lower Bound	Upper Bound
Quantitative	Qualitative	37.8125*	7.4164	.000	19.119	56.506
	Mixed	6.8750	7.4164	.630	-11.819	25.569
Qualitative	Quantitative	-37.8125*	7.4164	.000	-56.506	-19.119
	Mixed	-30.9375*	7.4164	.001	-49.631	-12.244
Mixed	Quantitative	-6.8750	7.4164	.630	-25.569	11.819
	Qualitative	30.9375*	7.4164	.001	12.244	49.631

*. The mean difference is significant at the 0.05 level.

Medium Level of Experience

Descriptive Statistics:

	Visualization Type			Statistic	Std. Error
SUS Score	Quantitative	Mean		73.750	11.2500
		95% Confidence Interval for Mean	Lower Bound	-69.195	
			Upper Bound	216.695	
		5% Trimmed Mean		.	
		Median		73.750	
		Variance		253.125	
		Std. Deviation		15.9099	
		Minimum		62.5	
		Maximum		85.0	
		Range		22.5	
		Interquartile Range		.	
		Skewness		.	.
		Kurtosis		.	.
	Qualitative	Mean		62.500	5.0000
		95% Confidence Interval for Mean	Lower Bound	-1.031	
			Upper Bound	126.031	
		5% Trimmed Mean		.	
		Median		62.500	
		Variance		50.000	
		Std. Deviation		7.0711	
		Minimum		57.5	
		Maximum		67.5	
		Range		10.0	
		Interquartile Range		.	
		Skewness		.	.
		Kurtosis		.	.
	Mixed	Mean		71.250	3.7500
		95% Confidence Interval for Mean	Lower Bound	23.602	
			Upper Bound	118.898	
		5% Trimmed Mean		.	
		Median		71.250	
		Variance		28.125	
		Std. Deviation		5.3033	
		Minimum		67.5	
		Maximum		75.0	
		Range		7.5	
		Interquartile Range		.	
		Skewness		.	.
		Kurtosis		.	.

Test of Normality:

	Visualization Type	Kolmogorov-Smirnov[a]		
		Statistic	df	Sig.
SUS Score	Quantitative	.260	2	.
	Qualitative	.260	2	.
	Mixed	.260	2	.

a. Lilliefors Significance Correction

ANOVA:

SUS Score

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	139.583	2	69.792	.632	.590
Within Groups	331.250	3	110.417		
Total	470.833	5			

Post Hoc:

Dependent Variable: SUS Score
Tukey HSD

(I) Visualization Type	(J) Visualization Type	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval	
					Lower Bound	Upper Bound
Quantitative	Qualitative	11.2500	10.5079	.591	-32.660	55.160
	Mixed	2.5000	10.5079	.970	-41.410	46.410
Qualitative	Quantitative	-11.2500	10.5079	.591	-55.160	32.660
	Mixed	-8.7500	10.5079	.712	-52.660	35.160
Mixed	Quantitative	-2.5000	10.5079	.970	-46.410	41.410
	Qualitative	8.7500	10.5079	.712	-35.160	52.660

High Level of Experience

Descriptive Statistics:

	Visualization Type			Statistic	Std. Error
SUS Score	Quantitative	Mean		81.500	4.6503
		95% Confidence Interval for Mean	Lower Bound	68.589	
			Upper Bound	94.411	
		5% Trimmed Mean		81.667	
		Median		82.500	
		Variance		108.125	
		Std. Deviation		10.3983	
		Minimum		67.5	
		Maximum		92.5	
		Range		25.0	
		Interquartile Range		20.0	
		Skewness		-.397	.913
		Kurtosis		-1.578	2.000
	Qualitative	Mean		61.000	9.8615
		95% Confidence Interval for Mean	Lower Bound	33.620	
			Upper Bound	88.380	
		5% Trimmed Mean		60.556	
		Median		57.500	
		Variance		486.250	
		Std. Deviation		22.0511	
		Minimum		37.5	
		Maximum		92.5	
		Range		55.0	
		Interquartile Range		41.3	
		Skewness		.609	.913
		Kurtosis		-.743	2.000
	Mixed	Mean		83.500	5.5678
		95% Confidence Interval for Mean	Lower Bound	68.041	
			Upper Bound	98.959	
		5% Trimmed Mean		83.889	
		Median		82.500	
		Variance		155.000	
		Std. Deviation		12.4499	
		Minimum		65.0	
		Maximum		95.0	
		Range		30.0	
		Interquartile Range		22.5	
		Skewness		-.720	.913
		Kurtosis		-.078	2.000

Test of Normality:

	Visualization Type	Kolmogorov-Smirnov[a]			Shapiro-Wilk		
		Statistic	df	Sig.	Statistic	df	Sig.
SUS Score	Quantitative	.193	5	.200*	.947	5	.715
	Qualitative	.166	5	.200*	.959	5	.802
	Mixed	.222	5	.200*	.895	5	.384

*. This is a lower bound of the true significance.

a. Lilliefors Significance Correction

ANOVA:

SUS Score

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	1550.833	2	775.417	3.104	.082
Within Groups	2997.500	12	249.792		
Total	4548.333	14			

Post Hoc:

Dependent Variable: SUS Score
Tukey HSD

(I) Visualization Type	(J) Visualization Type	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound
Quantitative	Qualitative	20.5000	9.9958	.142	-6.168	47.168
	Mixed	-2.0000	9.9958	.978	-28.668	24.668
Qualitative	Quantitative	-20.5000	9.9958	.142	-47.168	6.168
	Mixed	-22.5000	9.9958	.102	-49.168	4.168
Mixed	Quantitative	2.0000	9.9958	.978	-24.668	28.668
	Qualitative	22.5000	9.9958	.102	-4.168	49.168

Quantitative Preferred

Descriptive Statistics:

	Visualization Type			Statistic	Std. Error
SUS Score	Quantitative	Mean		86.875	3.0891
		95% Confidence Interval for Mean	Lower Bound	79.570	
			Upper Bound	94.180	
		5% Trimmed Mean		87.083	
		Median		88.750	
		Variance		76.339	
		Std. Deviation		8.7372	
		Minimum		75.0	
		Maximum		95.0	
		Range		20.0	
		Interquartile Range		18.1	
		Skewness		-.472	.752
		Kurtosis		-1.710	1.481
	Qualitative	Mean		54.688	7.7982
		95% Confidence Interval for Mean	Lower Bound	36.248	
			Upper Bound	73.127	
		5% Trimmed Mean		54.236	
		Median		50.000	
		Variance		486.496	
		Std. Deviation		22.0566	
		Minimum		25.0	
		Maximum		92.5	
		Range		67.5	
		Interquartile Range		35.0	
		Skewness		.670	.752
		Kurtosis		-.075	1.481
	Mixed	Mean		75.313	4.9425
		95% Confidence Interval for Mean	Lower Bound	63.625	
			Upper Bound	87.000	
		5% Trimmed Mean		74.931	
		Median		70.000	
		Variance		195.424	
		Std. Deviation		13.9794	
		Minimum		62.5	
		Maximum		95.0	
		Range		32.5	
		Interquartile Range		28.8	
		Skewness		.644	.752
		Kurtosis		-1.492	1.481

Test of Normality:

	Visualization Type	Kolmogorov-Smirnov[a] Statistic	df	Sig.	Shapiro-Wilk Statistic	df	Sig.
SUS Score	Quantitative	.240	8	.195	.828	8	.057
	Qualitative	.199	8	.200*	.946	8	.670
	Mixed	.270	8	.090	.824	8	.051

*. This is a lower bound of the true significance.

a. Lilliefors Significance Correction

ANOVA:

SUS Score

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	4253.646	2	2126.823	8.415	.002
Within Groups	5307.813	21	252.753		
Total	9561.458	23			

Post Hoc:

Dependent Variable: SUS Score
Tukey HSD

(I) Visualization Type	(J) Visualization Type	Mean Difference (I–J)	Std. Error	Sig.	95% Confidence Interval	
					Lower Bound	Upper Bound
Quantitative	Qualitative	32.1875*	7.9491	.002	12.151	52.224
	Mixed	11.5625	7.9491	.332	-8.474	31.599
Qualitative	Quantitative	-32.1875*	7.9491	.002	-52.224	-12.151
	Mixed	-20.6250*	7.9491	.043	-40.661	-.589
Mixed	Quantitative	-11.5625	7.9491	.332	-31.599	8.474
	Qualitative	20.6250*	7.9491	.043	.589	40.661

*. The mean difference is significant at the 0.05 level.

Mixed Preferred

Descriptive Statistics:

	Visualization Type			Statistic	Std. Error
SUS Score	Quantitative	Mean		82.500	5.3452
		95% Confidence Interval for Mean	Lower Bound	69.421	
			Upper Bound	95.579	
		5% Trimmed Mean		82.639	
		Median		90.000	
		Variance		200.000	
		Std. Deviation		14.1421	
		Minimum		62.5	
		Maximum		100.0	
		Range		37.5	
		Interquartile Range		25.0	
		Skewness		-.379	.794
		Kurtosis		-1.621	1.587
	Qualitative	Mean		58.214	4.7782
		95% Confidence Interval for Mean	Lower Bound	46.522	
			Upper Bound	69.906	
		5% Trimmed Mean		58.571	
		Median		62.500	
		Variance		159.821	
		Std. Deviation		12.6421	
		Minimum		37.5	
		Maximum		72.5	
		Range		35.0	
		Interquartile Range		22.5	
		Skewness		-.819	.794
		Kurtosis		-.538	1.587
	Mixed	Mean		88.571	4.3252
		95% Confidence Interval for Mean	Lower Bound	77.988	
			Upper Bound	99.155	
		5% Trimmed Mean		89.107	
		Median		92.500	
		Variance		130.952	
		Std. Deviation		11.4434	
		Minimum		67.5	
		Maximum		100.0	
		Range		32.5	
		Interquartile Range		17.5	
		Skewness		-1.161	.794
		Kurtosis		.802	1.587

Test of Normality:

	Visualization Type	Kolmogorov-Smirnov[a]			Shapiro-Wilk		
		Statistic	df	Sig.	Statistic	df	Sig.
SUS Score	Quantitative	.273	7	.122	.911	7	.401
	Qualitative	.204	7	.200*	.919	7	.461
	Mixed	.206	7	.200*	.901	7	.339

*. This is a lower bound of the true significance.

a. Lilliefors Significance Correction

ANOVA:

SUS Score

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	3612.500	2	1806.250	11.041	.001
Within Groups	2944.643	18	163.591		
Total	6557.143	20			

Post Hoc:

Dependent Variable: SUS Score
Tukey HSD

(I) Visualization Type	(J) Visualization Type	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval	
					Lower Bound	Upper Bound
Quantitative	Qualitative	24.2857*	6.8367	.006	6.837	41.734
	Mixed	-6.0714	6.8367	.654	-23.520	11.377
Qualitative	Quantitative	-24.2857*	6.8367	.006	-41.734	-6.837
	Mixed	-30.3571*	6.8367	.001	-47.805	-12.909
Mixed	Quantitative	6.0714	6.8367	.654	-11.377	23.520
	Qualitative	30.3571*	6.8367	.001	12.909	47.805

*. The mean difference is significant at the 0.05 level.

A.5.2 Case Study Spain

Response Time

Descriptive Statistics:

	Visualization Type			Statistic	Std. Error
Average Response Time (s)	Quantitative	Mean		32.2333	1.86373
		95% Confidence Interval for Mean	Lower Bound	28.2360	
			Upper Bound	36.2306	
		5% Trimmed Mean		32.1343	
		Median		30.5000	
		Variance		52.102	
		Std. Deviation		7.21820	
		Minimum		21.75	
		Maximum		44.50	
		Range		22.75	
		Interquartile Range		13.00	
		Skewness		.284	.580
		Kurtosis		-.950	1.121
	Qualitative	Mean		42.5667	2.50041
		95% Confidence Interval for Mean	Lower Bound	37.2038	
			Upper Bound	47.9295	
		5% Trimmed Mean		42.4907	
		Median		41.7500	
		Variance		93.781	
		Std. Deviation		9.68406	
		Minimum		27.25	
		Maximum		59.25	
		Range		32.00	
		Interquartile Range		17.50	
		Skewness		-.045	.580
		Kurtosis		-.855	1.121
	Mixed	Mean		25.1429	1.89195
		95% Confidence Interval for Mean	Lower Bound	21.0555	
			Upper Bound	29.2302	
		5% Trimmed Mean		24.8532	
		Median		22.2500	
		Variance		50.113	
		Std. Deviation		7.07903	
		Minimum		16.50	
		Maximum		39.00	
		Range		22.50	
		Interquartile Range		10.44	
		Skewness		.782	.597
		Kurtosis		-.466	1.154

Test of Normality:

	Visualization Type	Kolmogorov-Smirnov[a]			Shapiro-Wilk		
		Statistic	df	Sig.	Statistic	df	Sig.
Average Response Time (s)	Quantitative	.128	15	.200*	.951	15	.537
	Qualitative	.114	15	.200*	.966	15	.801
	Mixed	.197	14	.148	.901	14	.117

*. This is a lower bound of the true significance.

a. Lilliefors Significance Correction

ANOVA:

Average Response Time (s)

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	2234.919	2	1117.460	17.008	.000
Within Groups	2693.831	41	65.703		
Total	4928.750	43			

Post Hoc:

Dependent Variable: Average Response Time (s)
Tukey HSD

(I) Visualization Type	(J) Visualization Type	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval	
					Lower Bound	Upper Bound
Quantitative	Qualitative	-10.33333*	2.95980	.003	-17.5305	-3.1361
	Mixed	7.09048	3.01219	.060	-.2341	14.4151
Qualitative	Quantitative	10.33333*	2.95980	.003	3.1361	17.5305
	Mixed	17.42381*	3.01219	.000	10.0992	24.7484
Mixed	Quantitative	-7.09048	3.01219	.060	-14.4151	.2341
	Qualitative	-17.42381*	3.01219	.000	-24.7484	-10.0992

*. The mean difference is significant at the 0.05 level.

Natural Science Education

Descriptive Statistics:

	Visualization Type			Statistic	Std. Error
Average Response Time (s)	Quantitative	Mean		34.1875	2.30040
		95% Confidence Interval for Mean	Lower Bound	28.7479	
			Upper Bound	39.6271	
		5% Trimmed Mean		33.9861	
		Median		32.5000	
		Variance		42.335	
		Std. Deviation		6.50652	
		Minimum		27.50	
		Maximum		44.50	
		Range		17.00	
		Interquartile Range		12.38	
		Skewness		.795	.752
		Kurtosis		-.868	1.481
	Qualitative	Mean		42.6563	3.48560
		95% Confidence Interval for Mean	Lower Bound	34.4141	
			Upper Bound	50.8984	
		5% Trimmed Mean		42.5347	
		Median		41.5000	
		Variance		97.195	
		Std. Deviation		9.85877	
		Minimum		28.25	
		Maximum		59.25	
		Range		31.00	
		Interquartile Range		15.19	
		Skewness		.463	.752
		Kurtosis		.053	1.481
	Mixed	Mean		22.6786	1.70932
		95% Confidence Interval for Mean	Lower Bound	18.4960	
			Upper Bound	26.8611	
		5% Trimmed Mean		22.4623	
		Median		20.5000	
		Variance		20.452	
		Std. Deviation		4.52243	
		Minimum		18.50	
		Maximum		30.75	
		Range		12.25	
		Interquartile Range		7.25	
		Skewness		1.269	.794
		Kurtosis		.286	1.587

Test of Normality:

	Visualization Type	Kolmogorov-Smirnov[a]			Shapiro-Wilk		
		Statistic	df	Sig.	Statistic	df	Sig.
Average Response Time (s)	Quantitative	.215	8	.200*	.874	8	.166
	Qualitative	.206	8	.200*	.960	8	.810
	Mixed	.317	7	.032	.816	7	.059

Kruskal-Wallis Test:

	Average Response Time (s)
Chi-Square	13.189
df	2
Asymp. Sig.	.001

a. Kruskal Wallis Test

b. Grouping Variable: Visualization Type

Post Hoc:

Sample1-Sample2	Test Statistic	Std. Error	Std. Test Statistic	Sig.	Adj.Sig.
Mixed-Quantitative	8.348	3.509	2.379	.017	.052
Mixed-Qualitative	12.598	3.509	3.590	.000	.001
Quantitative-Qualitative	-4.250	3.390	-1.254	.210	.630

Each row tests the null hypothesis that the Sample 1 and Sample 2 distributions are the same.
Asymptotic significances (2-sided tests) are displayed. The significance level is .05.

Social Science Education Background

Descriptive Statistics:

	Visualization Type			Statistic	Std. Error
Average Response Time (s)	Quantitative	Mean		29.7000	3.26286
		95% Confidence Interval for Mean	Lower Bound	20.6409	
			Upper Bound	38.7591	
		5% Trimmed Mean		29.5417	
		Median		26.5000	
		Variance		53.231	
		Std. Deviation		7.29597	
		Minimum		21.75	
		Maximum		40.50	
		Range		18.75	
		Interquartile Range		12.75	
		Skewness		.790	.913
		Kurtosis		-.074	2.000
	Qualitative	Mean		44.8500	4.25265
		95% Confidence Interval for Mean	Lower Bound	33.0428	
			Upper Bound	56.6572	
		5% Trimmed Mean		45.2083	
		Median		49.0000	
		Variance		90.425	
		Std. Deviation		9.50921	
		Minimum		30.75	
		Maximum		52.50	
		Range		21.75	
		Interquartile Range		17.38	
		Skewness		-.964	.913
		Kurtosis		-.740	2.000
	Mixed	Mean		30.2500	3.95917
		95% Confidence Interval for Mean	Lower Bound	19.2576	
			Upper Bound	41.2424	
		5% Trimmed Mean		30.5278	
		Median		30.0000	
		Variance		78.375	
		Std. Deviation		8.85297	
		Minimum		16.50	
		Maximum		39.00	
		Range		22.50	
		Interquartile Range		15.38	
		Skewness		-.976	.913
		Kurtosis		.890	2.000

Test of Normality:

	Visualization Type	Kolmogorov-Smirnov[a]			Shapiro-Wilk		
		Statistic	df	Sig.	Statistic	df	Sig.
Average Response Time (s)	Quantitative	.270	5	.200*	.933	5	.614
	Qualitative	.269	5	.200*	.856	5	.213
	Mixed	.233	5	.200*	.916	5	.504

*. This is a lower bound of the true significance.

a. Lilliefors Significance Correction

ANOVA:

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	738.308	2	369.154	4.988	.027
Within Groups	888.125	12	74.010		
Total	1626.433	14			

Post Hoc:

Dependent Variable: Average Response Time (s)
Tukey HSD

(I) Visualization Type	(J) Visualization Type	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval	
					Lower Bound	Upper Bound
Quantitative	Qualitative	-15.15000*	5.44097	.041	-29.6658	-.6342
	Mixed	-.55000	5.44097	.994	-15.0658	13.9658
Qualitative	Quantitative	15.15000*	5.44097	.041	.6342	29.6658
	Mixed	14.60000*	5.44097	.049	.0842	29.1158
Mixed	Quantitative	.55000	5.44097	.994	-13.9658	15.0658
	Qualitative	-14.60000*	5.44097	.049	-29.1158	-.0842

*. The mean difference is significant at the 0.05 level.

Low Level of Experience

Descriptive Statistics:

	Visualization Type			Statistic	Std. Error
Average Response Time (s)	Quantitative	Mean		34.0625	2.35506
		95% Confidence Interval for Mean	Lower Bound	28.4937	
			Upper Bound	39.6313	
		5% Trimmed Mean		33.9028	
		Median		32.5000	
		Variance		44.371	
		Std. Deviation		6.66112	
		Minimum		26.50	
		Maximum		44.50	
		Range		18.00	
		Interquartile Range		12.38	
		Skewness		.716	.752
		Kurtosis		-.878	1.481
	Qualitative	Mean		41.3438	3.79466
		95% Confidence Interval for Mean	Lower Bound	32.3708	
			Upper Bound	50.3167	
		5% Trimmed Mean		41.0764	
		Median		40.1250	
		Variance		115.195	
		Std. Deviation		10.73291	
		Minimum		28.25	
		Maximum		59.25	
		Range		31.00	
		Interquartile Range		19.25	
		Skewness		.592	.752
		Kurtosis		-.550	1.481
	Mixed	Mean		25.3214	2.49506
		95% Confidence Interval for Mean	Lower Bound	19.2162	
			Upper Bound	31.4266	
		5% Trimmed Mean		24.9683	
		Median		21.5000	
		Variance		43.577	
		Std. Deviation		6.60132	
		Minimum		20.00	
		Maximum		37.00	
		Range		17.00	
		Interquartile Range		10.50	
		Skewness		1.063	.794
		Kurtosis		-.067	1.587

Test of Normality:

	Visualization Type	Kolmogorov-Smirnov[a]			Shapiro-Wilk		
		Statistic	df	Sig.	Statistic	df	Sig.
Average Response Time (s)	Quantitative	.204	8	.200*	.898	8	.278
	Qualitative	.161	8	.200*	.949	8	.705
	Mixed	.290	7	.077	.830	7	.079

*. This is a lower bound of the true significance.

a. Lilliefors Significance Correction

ANOVA:

Average Response Time (s)

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	958.602	2	479.301	6.954	.005
Within Groups	1378.425	20	68.921		
Total	2337.027	22			

Post Hoc:

Dependent Variable: Average Response Time (s)
Tukey HSD

(I) Visualization Type	(J) Visualization Type	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval	
					Lower Bound	Upper Bound
Quantitative	Qualitative	-7.28125	4.15094	.210	-17.7831	3.2206
	Mixed	8.74107	4.29663	.130	-2.1293	19.6115
Qualitative	Quantitative	7.28125	4.15094	.210	-3.2206	17.7831
	Mixed	16.02232*	4.29663	.004	5.1519	26.8927
Mixed	Quantitative	-8.74107	4.29663	.130	-19.6115	2.1293
	Qualitative	-16.02232*	4.29663	.004	-26.8927	-5.1519

*. The mean difference is significant at the 0.05 level.

Medium Level of Experience

Descriptive Statistics:

	Visualization Type			Statistic	Std. Error
Average Response Time (s)	Quantitative	Mean		27.0000	.50000
		95% Confidence Interval for Mean	Lower Bound	20.6469	
			Upper Bound	33.3531	
		5% Trimmed Mean		.	
		Median		27.0000	
		Variance		.500	
		Std. Deviation		.70711	
		Minimum		26.50	
		Maximum		27.50	
		Range		1.00	
		Interquartile Range		.	
		Skewness		.	.
		Kurtosis		.	.
	Qualitative	Mean		40.3750	.87500
		95% Confidence Interval for Mean	Lower Bound	29.2571	
			Upper Bound	51.4929	
		5% Trimmed Mean		.	
		Median		40.3750	
		Variance		1.531	
		Std. Deviation		1.23744	
		Minimum		39.50	
		Maximum		41.25	
		Range		1.75	
		Interquartile Range		.	
		Skewness		.	.
		Kurtosis		.	.
	Mixed	Mean		17.5000	1.00000
		95% Confidence Interval for Mean	Lower Bound	4.7938	
			Upper Bound	30.2062	
		5% Trimmed Mean		.	
		Median		17.5000	
		Variance		2.000	
		Std. Deviation		1.41421	
		Minimum		16.50	
		Maximum		18.50	
		Range		2.00	
		Interquartile Range		.	
		Skewness		.	.
		Kurtosis		.	.

Test of Normality:

	Visualization Type	Kolmogorov-Smirnov[a]		
		Statistic	df	Sig.
Average Response Time (s)	Quantitative	.260	2	.
	Qualitative	.260	2	.
	Mixed	.260	2	.

a. Lilliefors Significance Correction

High Level of Experience

Descriptive Statistics:

	Visualization Type			Statistic	Std. Error
Average Response Time (s)	Quantitative	Mean		31.4000	4.08243
		95% Confidence Interval for Mean	Lower Bound	20.0654	
			Upper Bound	42.7346	
		5% Trimmed Mean		31.4306	
		Median		33.2500	
		Variance		83.331	
		Std. Deviation		9.12860	
		Minimum		21.75	
		Maximum		40.50	
		Range		18.75	
		Interquartile Range		18.13	
		Skewness		-.240	.913
		Kurtosis		-3.022	2.000
	Qualitative	Mean		45.4000	4.70810
		95% Confidence Interval for Mean	Lower Bound	32.3282	
			Upper Bound	58.4718	
		5% Trimmed Mean		46.0139	
		Median		49.0000	
		Variance		110.831	
		Std. Deviation		10.52764	
		Minimum		27.25	
		Maximum		52.50	
		Range		25.25	
		Interquartile Range		16.00	
		Skewness		-1.863	.913
		Kurtosis		3.577	2.000
	Mixed	Mean		27.9500	3.40257
		95% Confidence Interval for Mean	Lower Bound	18.5029	
			Upper Bound	37.3971	
		5% Trimmed Mean		27.8333	
		Median		28.7500	
		Variance		57.888	
		Std. Deviation		7.60838	
		Minimum		19.00	
		Maximum		39.00	
		Range		20.00	
		Interquartile Range		13.50	
		Skewness		.492	.913
		Kurtosis		.186	2.000

Test of Normality:

	Visualization Type	Kolmogorov-Smirnov[a]			Shapiro-Wilk		
		Statistic	df	Sig.	Statistic	df	Sig.
Average Response Time (s)	Quantitative	.248	5	.200*	.835	5	.152
	Qualitative	.313	5	.122	.765	5	.040
	Mixed	.194	5	.200*	.969	5	.872

*. This is a lower bound of the true significance.

a. Lilliefors Significance Correction

ANOVA:

Average Response Time (s)

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	854.008	2	427.004	5.082	.025
Within Groups	1008.200	12	84.017		
Total	1862.208	14			

Post Hoc:

Dependent Variable: Average Response Time (s)
Tukey HSD

(I) Visualization Type	(J) Visualization Type	Mean Difference (I–J)	Std. Error	Sig.	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound
Quantitative	Qualitative	-14.00000	5.79713	.078	-29.4659	1.4659
	Mixed	3.45000	5.79713	.825	-12.0159	18.9159
Qualitative	Quantitative	14.00000	5.79713	.078	-1.4659	29.4659
	Mixed	17.45000*	5.79713	.027	1.9841	32.9159
Mixed	Quantitative	-3.45000	5.79713	.825	-18.9159	12.0159
	Qualitative	-17.45000*	5.79713	.027	-32.9159	-1.9841

*. The mean difference is significant at the 0.05 level.

Accuracy

Descriptive Statistics:

	Visualization Type			Statistic	Std. Error
Wrong Answers	Quantitative	Mean		.33	.187
		95% Confidence Interval for Mean	Lower Bound	-.07	
			Upper Bound	.73	
		5% Trimmed Mean		.26	
		Median		.00	
		Variance		.524	
		Std. Deviation		.724	
		Minimum		0	
		Maximum		2	
		Range		2	
		Interquartile Range		0	
		Skewness		1.981	.580
		Kurtosis		2.550	1.121
	Qualitative	Mean		.27	.118
		95% Confidence Interval for Mean	Lower Bound	.01	
			Upper Bound	.52	
		5% Trimmed Mean		.24	
		Median		.00	
		Variance		.210	
		Std. Deviation		.458	
		Minimum		0	
		Maximum		1	
		Range		1	
		Interquartile Range		1	
		Skewness		1.176	.580
		Kurtosis		-.734	1.121
	Mixed	Mean		.13	.091
		95% Confidence Interval for Mean	Lower Bound	-.06	
			Upper Bound	.33	
		5% Trimmed Mean		.09	
		Median		.00	
		Variance		.124	
		Std. Deviation		.352	
		Minimum		0	
		Maximum		1	
		Range		1	
		Interquartile Range		0	
		Skewness		2.405	.580
		Kurtosis		4.349	1.121

Test of Normality:

	Visualization Type	Kolmogorov-Smirnov[a]			Shapiro-Wilk		
		Statistic	df	Sig.	Statistic	df	Sig.
Wrong Answers	Quantitative	.477	15	.000	.514	15	.000
	Qualitative	.453	15	.000	.561	15	.000
	Mixed	.514	15	.000	.413	15	.000

a. Lilliefors Significance Correction

ANOVA:

Wrong Answers

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	.311	2	.156	.544	.584
Within Groups	12.000	42	.286		
Total	12.311	44			

A.5.3 Case Study Kosovo

Response Time

Descriptive Statistics:

	Visualization Type			Statistic	Std. Error
Average Response Time (s)	Quantitative	Mean		38.8333	3.28168
		95% Confidence Interval for Mean	Lower Bound	31.7948	
			Upper Bound	45.8718	
		5% Trimmed Mean		38.4398	
		Median		38.2500	
		Variance		161.542	
		Std. Deviation		12.70990	
		Minimum		21.50	
		Maximum		63.25	
		Range		41.75	
		Interquartile Range		19.75	
		Skewness		.565	.580
		Kurtosis		-.388	1.121
	Qualitative	Mean		38.2667	3.23057
		95% Confidence Interval for Mean	Lower Bound	31.3378	
			Upper Bound	45.1956	
		5% Trimmed Mean		38.0741	
		Median		35.5000	
		Variance		156.549	
		Std. Deviation		12.51195	
		Minimum		21.25	
		Maximum		58.75	
		Range		37.50	
		Interquartile Range		22.00	
		Skewness		.314	.580
		Kurtosis		-1.316	1.121
	Mixed	Mean		28.6923	2.72294
		95% Confidence Interval for Mean	Lower Bound	22.7595	
			Upper Bound	34.6251	
		5% Trimmed Mean		28.4220	
		Median		26.7500	
		Variance		96.387	
		Std. Deviation		9.81769	
		Minimum		17.25	
		Maximum		45.00	
		Range		27.75	
		Interquartile Range		17.13	
		Skewness		.489	.616
		Kurtosis		-1.013	1.191

Test of Normality:

	Visualization Type	Kolmogorov-Smirnov[a]			Shapiro-Wilk		
		Statistic	df	Sig.	Statistic	df	Sig.
Average Response Time (s)	Quantitative	.146	15	.200*	.948	15	.489
	Qualitative	.186	15	.172	.926	15	.238
	Mixed	.143	13	.200*	.910	13	.186

*. This is a lower bound of the true significance.

a. Lilliefors Significance Correction

ANOVA:

Average Response Time (s)

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	883.755	2	441.877	3.151	.054
Within Groups	5609.911	40	140.248		
Total	6493.666	42			

Natural Science Background

Descriptive Statistics:

	Visualization Type			Statistic	Std. Error
Average Response Time (s)	Quantitative	Mean		37.2500	4.50644
		95% Confidence Interval for Mean	Lower Bound	26.5940	
			Upper Bound	47.9060	
		5% Trimmed Mean		36.8333	
		Median		37.0000	
		Variance		162.464	
		Std. Deviation		12.74615	
		Minimum		21.50	
		Maximum		60.50	
		Range		39.00	
		Interquartile Range		20.25	
		Skewness		.714	.752
		Kurtosis		.297	1.481
	Qualitative	Mean		38.5625	4.73417
		95% Confidence Interval for Mean	Lower Bound	27.3680	
			Upper Bound	49.7570	
		5% Trimmed Mean		38.2778	
		Median		33.2500	
		Variance		179.299	
		Std. Deviation		13.39026	
		Minimum		23.50	
		Maximum		58.75	
		Range		35.25	
		Interquartile Range		25.06	
		Skewness		.724	.752
		Kurtosis		-1.125	1.481
	Mixed	Mean		28.8750	3.96167
		95% Confidence Interval for Mean	Lower Bound	18.6912	
			Upper Bound	39.0588	
		5% Trimmed Mean		28.5972	
		Median		26.3750	
		Variance		94.169	
		Std. Deviation		9.70406	
		Minimum		18.00	
		Maximum		44.75	
		Range		26.75	
		Interquartile Range		16.63	
		Skewness		.880	.845
		Kurtosis		.179	1.741

Test of Normality:

	Visualization Type	Kolmogorov-Smirnov[a]			Shapiro-Wilk		
		Statistic	df	Sig.	Statistic	df	Sig.
Average Response Time (s)	Quantitative	.211	8	.200*	.949	8	.702
	Qualitative	.215	8	.200*	.877	8	.177
	Mixed	.253	6	.200*	.935	6	.622

*. This is a lower bound of the true significance.

a. Lilliefors Significance Correction

ANOVA:

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	362.804	2	181.402	1.204	.322
Within Groups	2863.188	19	150.694		
Total	3225.991	21			

Social Science Background

Descriptive Statistics:

	Visualization Type			Statistic	Std. Error
Average Response Time (s)	Quantitative	Mean		42.1000	5.88674
		95% Confidence Interval for Mean	Lower Bound	25.7558	
			Upper Bound	58.4442	
		5% Trimmed Mean		41.6528	
		Median		39.5000	
		Variance		173.269	
		Std. Deviation		13.16316	
		Minimum		29.00	
		Maximum		63.25	
		Range		34.25	
		Interquartile Range		22.25	
		Skewness		1.229	.913
		Kurtosis		1.719	2.000
	Qualitative	Mean		38.3500	4.71010
		95% Confidence Interval for Mean	Lower Bound	25.2727	
			Upper Bound	51.4273	
		5% Trimmed Mean		38.3889	
		Median		43.0000	
		Variance		110.925	
		Std. Deviation		10.53209	
		Minimum		25.50	
		Maximum		50.50	
		Range		25.00	
		Interquartile Range		19.63	
		Skewness		-.301	.913
		Kurtosis		-2.201	2.000
	Mixed	Mean		29.0500	4.90306
		95% Confidence Interval for Mean	Lower Bound	15.4369	
			Upper Bound	42.6631	
		5% Trimmed Mean		28.7917	
		Median		28.0000	
		Variance		120.200	
		Std. Deviation		10.96358	
		Minimum		17.75	
		Maximum		45.00	
		Range		27.25	
		Interquartile Range		20.38	
		Skewness		.667	.913
		Kurtosis		-.476	2.000

Test of Normality:

	Visualization Type	Kolmogorov-Smirnov[a]			Shapiro-Wilk		
		Statistic	df	Sig.	Statistic	df	Sig.
Average Response Time (s)	Quantitative	.228	5	.200*	.919	5	.524
	Qualitative	.271	5	.200*	.907	5	.447
	Mixed	.182	5	.200*	.950	5	.736

ANOVA:

Average Response Time (s)

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	451.425	2	225.713	1.674	.228
Within Groups	1617.575	12	134.798		
Total	2069.000	14			

Low Level of Experience

Descriptive Statistics:

	Visualization Type			Statistic	Std. Error
Average Response Time (s)	Quantitative	Mean		36.7188	4.51669
		95% Confidence Interval for Mean	Lower Bound	26.0385	
			Upper Bound	47.3990	
		5% Trimmed Mean		36.2431	
		Median		35.0000	
		Variance		163.204	
		Std. Deviation		12.77514	
		Minimum		21.50	
		Maximum		60.50	
		Range		39.00	
		Interquartile Range		20.19	
		Skewness		.873	.752
		Kurtosis		.487	1.481
	Qualitative	Mean		41.1563	4.75492
		95% Confidence Interval for Mean	Lower Bound	29.9127	
			Upper Bound	52.3998	
		5% Trimmed Mean		41.1597	
		Median		40.0000	
		Variance		180.874	
		Std. Deviation		13.44894	
		Minimum		23.50	
		Maximum		58.75	
		Range		35.25	
		Interquartile Range		26.25	
		Skewness		.119	.752
		Kurtosis		-1.745	1.481
	Mixed	Mean		29.6071	3.42733
		95% Confidence Interval for Mean	Lower Bound	21.2208	
			Upper Bound	37.9935	
		5% Trimmed Mean		29.4107	
		Median		26.7500	
		Variance		82.226	
		Std. Deviation		9.06787	
		Minimum		18.00	
		Maximum		44.75	
		Range		26.75	
		Interquartile Range		13.25	
		Skewness		.541	.794
		Kurtosis		-.190	1.587

Test of Normality:

	Visualization Type	Kolmogorov-Smirnov[a]			Shapiro-Wilk		
		Statistic	df	Sig.	Statistic	df	Sig.
Average Response Time (s)	Quantitative	.202	8	.200*	.939	8	.602
	Qualitative	.163	8	.200*	.927	8	.492
	Mixed	.195	7	.200*	.964	7	.855

*. This is a lower bound of the true significance.

a. Lilliefors Significance Correction

ANOVA:

Average Response Time (s)

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	502.688	2	251.344	1.732	.202
Within Groups	2901.904	20	145.095		
Total	3404.592	22			

Medium Level of Experience

Descriptive Statistics:

	Visualization Type			Statistic	Std. Error
Average Response Time (s)	Quantitative	Mean		50.8750	12.37500
		95% Confidence Interval for Mean	Lower Bound	-106.3643	
			Upper Bound	208.1143	
		5% Trimmed Mean		.	
		Median		50.8750	
		Variance		306.281	
		Std. Deviation		17.50089	
		Minimum		38.50	
		Maximum		63.25	
		Range		24.75	
		Interquartile Range		.	
		Skewness		.	.
		Kurtosis		.	.
	Qualitative	Mean		29.5000	.25000
		95% Confidence Interval for Mean	Lower Bound	26.3234	
			Upper Bound	32.6766	
		5% Trimmed Mean		.	
		Median		29.5000	
		Variance		.125	
		Std. Deviation		.35355	
		Minimum		29.25	
		Maximum		29.75	
		Range		.50	
		Interquartile Range		.	
		Skewness		.	.
		Kurtosis		.	.

a. Average Response Time (s) is constant when Visualization Type = Mixed. It has been omitted.

Test of Normality:

	Visualization Type	Kolmogorov-Smirnov[a]		
		Statistic	df	Sig.
Average Response Time (s)	Quantitative	.260	2	.
	Qualitative	.260	2	.

a. Lilliefors Significance Correction

b. Average Response Time (s) is constant when Visualization Type = Mixed. It has been omitted.

High Level of Experience

Descriptive Statistics:

	Visualization Type			Statistic	Std. Error
Average Response Time (s)	Quantitative	Mean		37.4000	4.88275
		95% Confidence Interval for Mean	Lower Bound	23.8433	
			Upper Bound	50.9567	
		5% Trimmed Mean		37.4444	
		Median		39.5000	
		Variance		119.206	
		Std. Deviation		10.91816	
		Minimum		23.75	
		Maximum		50.25	
		Range		26.50	
		Interquartile Range		21.00	
		Skewness		-.207	.913
		Kurtosis		-1.885	2.000
	Qualitative	Mean		37.1500	5.91058
		95% Confidence Interval for Mean	Lower Bound	20.7396	
			Upper Bound	53.5604	
		5% Trimmed Mean		37.1806	
		Median		43.0000	
		Variance		174.675	
		Std. Deviation		13.21647	
		Minimum		21.25	
		Maximum		52.50	
		Range		31.25	
		Interquartile Range		24.63	
		Skewness		-.276	.913
		Kurtosis		-2.238	2.000
	Mixed	Mean		29.6000	5.16515
		95% Confidence Interval for Mean	Lower Bound	15.2593	
			Upper Bound	43.9407	
		5% Trimmed Mean		29.4306	
		Median		28.0000	
		Variance		133.394	
		Std. Deviation		11.54962	
		Minimum		17.25	
		Maximum		45.00	
		Range		27.75	
		Interquartile Range		22.25	
		Skewness		.394	.913
		Kurtosis		-1.692	2.000

Test of Normality:

	Visualization Type	Kolmogorov-Smirnov[a]			Shapiro-Wilk		
		Statistic	df	Sig.	Statistic	df	Sig.
Average Response Time (s)	Quantitative	.179	5	.200*	.956	5	.782
	Qualitative	.271	5	.200*	.903	5	.425
	Mixed	.185	5	.200*	.948	5	.720

*. This is a lower bound of the true significance.

a. Lilliefors Significance Correction

ANOVA:

Average Response Time (s)

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	196.508	2	98.254	.690	.520
Within Groups	1709.100	12	142.425		
Total	1905.608	14			

Accuracy

Descriptive Statistics:

Visualization Type				Statistic	Std. Error
Wrong Answers	Quantitative	Mean		.67	.126
		95% Confidence Interval for Mean	Lower Bound	.40	
			Upper Bound	.94	
		5% Trimmed Mean		.69	
		Median		1.00	
		Variance		.238	
		Std. Deviation		.488	
		Minimum		0	
		Maximum		1	
		Range		1	
		Interquartile Range		1	
		Skewness		-.788	.580
		Kurtosis		-1.615	1.121
	Qualitative	Mean		.47	.133
		95% Confidence Interval for Mean	Lower Bound	.18	
			Upper Bound	.75	
		5% Trimmed Mean		.46	
		Median		.00	
		Variance		.267	
		Std. Deviation		.516	
		Minimum		0	
		Maximum		1	
		Range		1	
		Interquartile Range		1	
		Skewness		.149	.580
		Kurtosis		-2.308	1.121
	Mixed	Mean		.27	.118
		95% Confidence Interval for Mean	Lower Bound	.01	
			Upper Bound	.52	
		5% Trimmed Mean		.24	
		Median		.00	
		Variance		.210	
		Std. Deviation		.458	
		Minimum		0	
		Maximum		1	
		Range		1	
		Interquartile Range		1	
		Skewness		1.176	.580
		Kurtosis		-.734	1.121

Test of Normality:

	Visualization Type	Kolmogorov-Smirnov[a]			Shapiro-Wilk		
		Statistic	df	Sig.	Statistic	df	Sig.
Wrong Answers	Quantitative	.419	15	.000	.603	15	.000
	Qualitative	.350	15	.000	.643	15	.000
	Mixed	.453	15	.000	.561	15	.000

a. Lilliefors Significance Correction

ANOVA:

Wrong Answers

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	1.200	2	.600	2.520	.093
Within Groups	10.000	42	.238		
Total	11.200	44			

Personal declaration:

I hereby declare that the submitted thesis is the result of my own, independent, work. All external sources are explicitly acknowledged in the thesis.

Fabian Perler