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Exploring Affective Design Techniques in Augmented Reality Data Visualizations: a Case Study with Situated Real Estate Data

Work presented in partial fulfillment of the requirements for the degree of Bachelor in Computer Science

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ABSTRACT

The incorporation of advanced spatial tracking to modern smartphones and the development of new technologies such as Mixed Reality headsets allow us to create new experiences leveraging Virtual and Augmented Realities. Such advances have been explored in the Data Visualization research field in recent years, leading to the development of so-called *Immersive Analytics* approaches, which take advantage of 3D display and interaction to offer users new perspectives on relevant data. Our work seeks to combine the use of Augmented Reality visualizations with *Affective Design*, a common technique in the User Experience area that tries to leverage human emotions to increase people's engagement and recall. We explore how Affective Design choices can affect people's emotions and which choices could be more helpful in showing what data designers intend. Also, this work collects and evaluates people's feelings through an AR data visualization app. The proof-of-concept application we developed displays real estate data from the city of Porto Alegre, Brazil, through a conventional bar chart and an alternative version implementing some Affective Design techniques. The quantitative and qualitative data collected from a study with eleven participants suggests that some of these techniques increased user interest and engagement even in AR environments.

Keywords: Data visualization. augmented reality. affective design.

Explorando Técnicas de Design Afetivo em Visualizações de Dados em Realidade Aumentada: Um estudo de caso com dados imobiliários

RESUMO

A incorporação de rastreamento espacial avançado aos smartphones modernos e o desenvolvimento de novas tecnologias, como os headsets de Realidade Mista, permitem-nos criar novas experiências aproveitando as Realidades Virtuais e Aumentadas. Tais avanços têm sido explorados no campo de pesquisa de Visualização de Dados nos últimos anos, levando ao desenvolvimento das chamadas abordagens *Immersive Analytics*, que aproveitam a exibição e interação 3D para oferecer aos usuários novas perspectivas sobre dados relevantes. Nosso trabalho busca combinar o uso de visualizações de Realidade Aumentada com *Design Afetivo*, uma técnica comum na área de Experiência do Usuário que tenta alavancar as emoções humanas para aumentar o engajamento e a lembrança das pessoas. Exploramos como as escolhas do Design Afetivo podem afetar as emoções das pessoas e quais escolhas poderiam ser mais úteis para mostrar o que os designers de dados pretendem. Além disso, este trabalho coleta e avalia os sentimentos das pessoas por meio de um aplicativo de visualização de dados AR. A aplicação de prova de conceito que desenvolvemos exibe dados imobiliários da cidade de Porto Alegre, Brasil, através de um gráfico de barras convencional e uma versão alternativa implementando algumas técnicas de Design Afetivo. Os dados quantitativos e qualitativos coletados de um estudo com onze participantes sugerem que algumas dessas técnicas aumentaram o interesse e o envolvimento do usuário mesmo em ambientes de realidade aumentada.

Palavras-chave: visualização de dados, realidade aumentada, design afetivo.

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LIST OF ABBREVIATIONS AND ACRONYMS

AR	Augmented Reality
VR	Virtual Reality
MR	Mixed Reality
US	United States
SV	Situated Visualization
UX	User Experience
HCI	Human-Computer Interaction
SQM	Square meter
GPS	Global Positioning System
SUS	System Usability Scale
PANAS	Positive and Negative Affect Scale

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1 INTRODUCTION

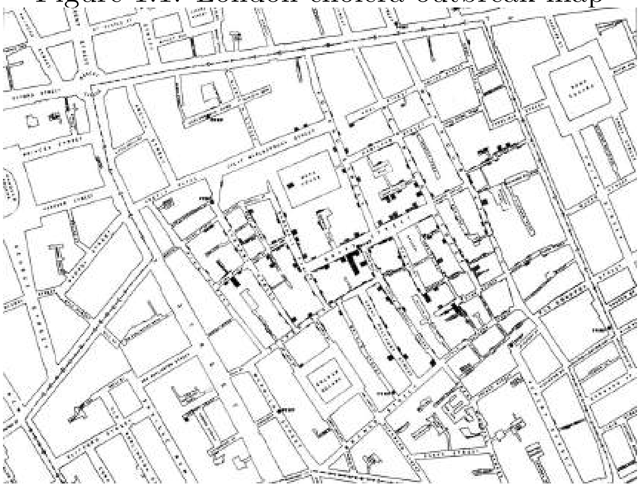
Visual representations are powerful tools that aid human cognition, learning, and communication by enhancing our ability to understand complex information and relationships. They often provide an interactive approach that enables people to ask and answer questions, facilitating a deeper understanding of the subject matter. For instance, sea maps are visualizations that assist sailors in navigating the deep blue sea, helping them to plan their journey, avoid hazards, and arrive safely at their destination.

As the challenges in fields like economy, technology, and science grew more complex over the years, advanced tools were developed to tackle them. In 1786, William Playfair published in Playfair (1801) a series of innovative visualizations, such as the pie chart, to represent England's balance of trade. Another remarkable example of visualization is Snow's map of the cholera outbreak in London in 1854, which is shown in Fig. 1.1. Dr. John Snow, a British physician, plotted individual cases of cholera as dots on a map of London, showing that the majority of cases could be traced to a water pump on Broad Street. As the pump was removed, the disease outbreak also was contained. This example also shows how the use of visualizations not only helps to answer questions but can solve important and daily life problems, like the source of a disease.

The development of technologies since the late 90's with the introduction of the personal computer, the world wide web, smartphones, and sensors created new ways to generate data. The huge amount of data being generated daily, also known as Big Data, has introduced new challenges for data visualization. These include displaying vast quantities of information and time constraints for decision-making. To address these challenges, a new wave of data visualization focused on minimalist dashboards with pastel colors and large annotations to mitigate the Big Data vastness.

On the other hand, researchers and developers are exploring various technologies for data visualizations. One such technology is Virtual Reality (VR), which aims to create an immersive experience for users by simulating a three-dimensional environment that can be explored and interacted with. In personal computers, this experience is created by rendering a 3D virtual world on a regular display. However, Head Mounted Displays (HMDs) were created to user immersion. For instance, a

Figure 1.1: London cholera outbreak map

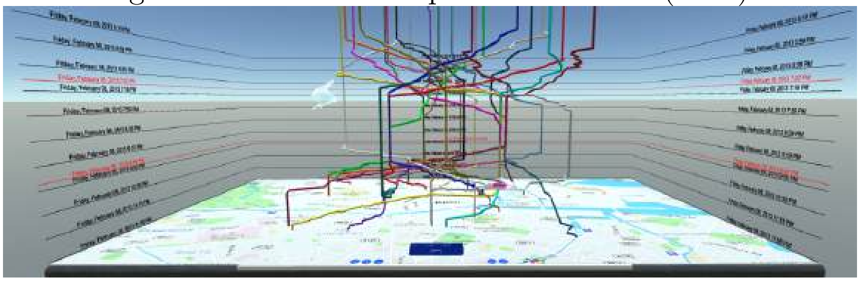


Source: Willett, Jansen and Dragicevic (2017)

study by Lee et al. (2021) created an immersive virtual environment to help users compare and understand data. They used VR to display a virtual Olympic Men's 100m trial and compared it to the default Olympic Men's 100m time chart. Wagner Filho, Stuerzlinger and Nedel (2020) conducted an assessment of the Space-Time Cube (STC) representation for immersive environments, such as virtual reality (VR) for head-mounted displays (HMDs). They created a STC visualization that displays people's trajectories, as depicted in Fig. 1.2, and evaluated the STC on both desktop and HMD platforms. Among their findings, the STC using HMDs resulted in a lower mental workload and higher usability score.

Another technology is Augmented Reality (AR), which displays virtual elements on top of the real world, often used to enhance or create an overall experience, such as providing real-time information about a product or enhancing a museum exhibit (Gong, Wang and Xia, 2022). In journalism, for example, during the pandemic of Covid-19, Bartzokas Mika Gröndahl and Syam (2021) created an AR visualization to simulate how the airflow inside a school room can reduce the spread of the virus. These new technologies and techniques offer new ways to display data to a broader audience, beyond just businesspeople or data analysts. Besides that, many works on AR and VR data visualization aim to enhance the user experience by exploring new techniques and tools as cited by Bressa et al. (2022). However, they rely on default data charts as a basis and the focus is primarily on improving work efficiency, such as comparing values or finding specific information. Given this context, there is a gap between when or where custom data charts are more suitable than default data visualizations in AR environments.

Figure 1.2: Immersive Space-Time Cube (STC)



Source: Wagner Filho, Stuerzlinger and Nedel (2020)

Usually, when developing e-commerce or educational applications, the developers should aim to connect with their respective audience. To achieve this, they can apply various methodologies such as creating personas and using *Affective Design* techniques. Some of these techniques include storytelling, using imagery, and colors that seek to evoke emotions in users. These same methodologies could also improve how data visualizations communicate with their target audiences, encouraging users to explore and analyze even if they lack domain expertise.

This research investigates data visualizations for AR environments that utilize design techniques presented in the state of the art. As a result, we created a proof-of-concept data visualization application for smartphones to conduct user tests to identify contexts of use and assess the impact of these techniques on the user experience and emotion. To achieve this, we compared this data visualization to a baseline AR chart that uses none of the design techniques.

This work is presented in the following chapters. In Chapter 2, we explore the current state of data visualization that relates to this project. In Chapter 3, we provide details on the problem, motivation, and case study. Chapter 4 shows the development of the data visualization application and how *Affective Design* techniques were implemented. In Chapter 5, we discuss the application testing, in Chapter 6, the data collected from the test, and, in Chapter 7, we assess the findings based on previous chapter. Finally, Chapter 8 concludes the work and proposes future directions.

2 BACKGROUND

In this chapter, we review prior work within the Data Visualization literature that informed our research. Section 2.1 explores research works that categorize data visualization as creating or defining development techniques. Then, Section 2.2 expands the previous section, presenting the understanding of situatedness in the state of the art. Finally, Section 2.3 discusses a design techniques overview used in data visualization in different contexts like journalism, art, and entertainment.

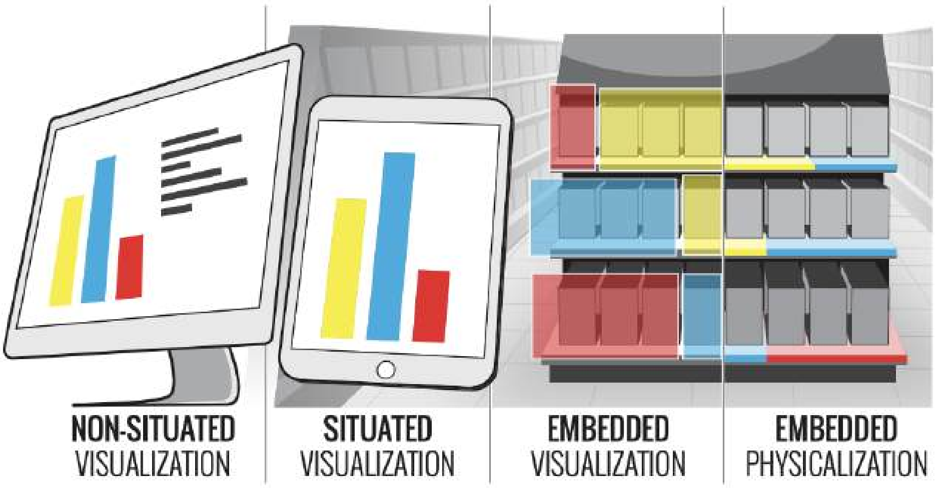
2.1 Categories of Situated Data Visualizations

The continuous technology improvements in sensors and networking increased the amount of data generated about locations, people, and objects. While the data refers to the physical world, most part of the analytics and visualization take place through computers far apart from where the data generation is. In contrast, the growing access to devices like smartphones and smartwatches could provide new opportunities to display and interact with data where it is generated (Willett, Jansen and Dragicevic, 2017).

Willett, Jansen and Dragicevic (2017) suggest a framework to describe and compare different visualization types based on how the data visualization is integrated to the data's physical referent, i.e., the object, environment, and/or entity which the data refers to. As shown in Fig. 2.1, there are four classes of how linked a data-visualization can be with the data referent. Non-situated visualizations, the most traditional ones, are when the visualization is not in the same context of the data, like data charts about product sales shown through a computer screen at the financial office. Situated visualization is a data visualization displayed in the same physical context as the data, a product sales chart can be situated if shown through a smartphone or tablet near the product itself. Also, data visualizations that use projections and other techniques to juxtapose the data representation to its physical referent are called embedded visualization.

Usually, data is mapped from the real world to values, colors, and formats, but when "physical artifact whose geometry or material properties encode data" is called data physicalization (Jansen et al., 2015). As shown in Fig. 2.2, data visualizations can be non-situated or situated, and situated visualizations can be embedded

Figure 2.1: From left to right: A desktop setting with non-situated visualization. A situated visualization of the same data on a tablet in the store itself. An embedded visualization overlays the data on top of individual products as a heat map. An embedded physicalization displays data by changing properties of the shelves themselves



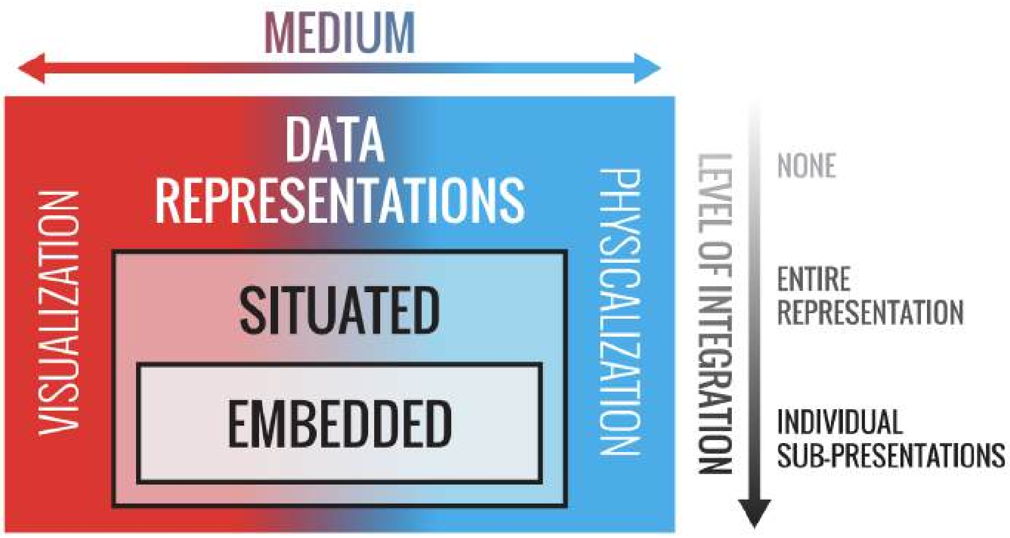
Source: Willett, Jansen and Dragicevic (2017)

or not. Also, any data visualization can be a mix of traditional data visualization and physicalization, since the physicalization can vary in the continuum. Each type has its trade-offs, and one may be more appropriate given the determined context. Since not every data has a physical referent, or maybe the use case is not convenient because of its scale or availability.

Sometimes, data visualization developers can create specific experiences based on data context and the developers' objective. Lee et al. (2021) coined the term *Data Visceralization* where data visualizations "evoke visceral feelings to facilitate understanding measurements and quantities". In the same paper, the authors developed six experiences using different physical measures and quantities, showed in Table 2.1, and conducted an experiment. The experiment was conducted with twelve participants that receive the original charts for E1, E3, and E6, and the respective VR experience, shown in Fig. 2.3.

The authors collected quantitative and qualitative feedback. One of the findings is that this type of visualization has its challenges because when values are too close to each other, it's difficult to make comparisons. One tested solution is making annotations to help users understand the data and round up the overall experience. As the objective of data visualization is to share information and generate data insights, "this type of experience may convey a different understanding that is more

Figure 2.2: Data Representation Classes



Source: Willett, Jansen and Dragicevic (2017)

grounded in reality" (Lee et al., 2021), like information or entertainment.

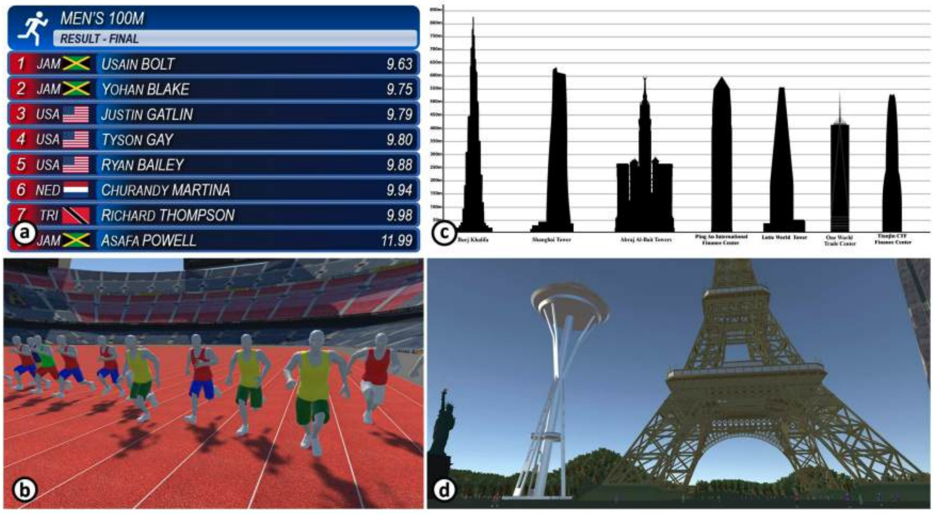
In contrast, Aseniero et al. (2022) proposed the name *Delightful Visualization* for "nonconventional datavis that elicit pleasant emotions through aesthetic appeal and provide enjoyable experiences overall". Fig. 2.4 shows a pipeline example to create delightful visualizations. The authors also suggest that typical data visualizations are task-oriented or focused on work contexts, but non-conventional representations can be used in different contexts "where aesthetics and engagement may take precedence over task efficiency", like journalism or entertainment.

In fact, introducing visual embellishment, complexity, and uncertainty can improve curiosity, engagement, and memorability and motivate the user to explore the data (Bateman et al., 2010). These techniques are also mentioned by Lupi (2017), who criticizes the indiscriminate use of default charts and calls for data analysts and developers to create more humane visualizations that embrace data complexity and human context.

2.2 Surveys of Situatedness Perspectives

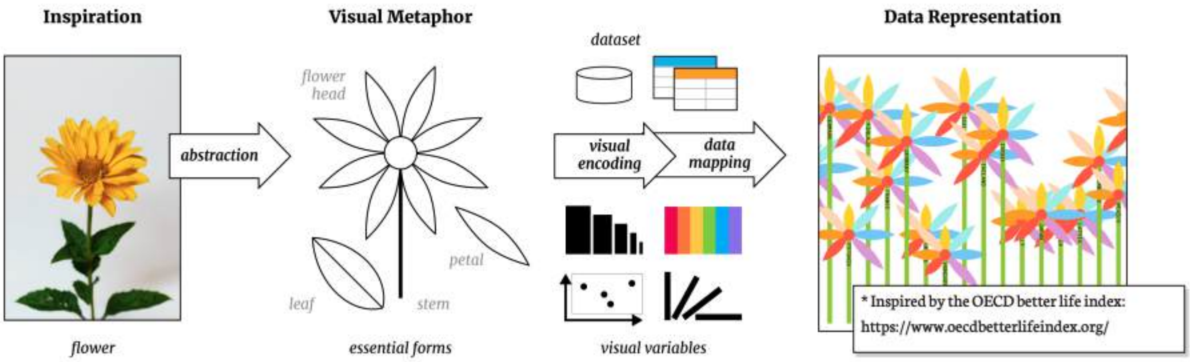
Prior work has reviewed situated data visualization applications to analyze trends, summarize techniques, create insights, and raise questions about research areas. Bressa et al. (2022), for example, reviewed 44 papers about situated vi-

Figure 2.3: (a) Scorecard of results in seconds from Olympic Men's 100 m. (b) Data visceralization equivalent to experience Olympic sprint speeds. (c) Comparison diagram of tall skyscrapers. (d) Data visceralization equivalent to experience and compare tall skyscrapers.



Source: Lee et al. (2021)

Figure 2.4: Delightful Visualization Pipeline



Source: Aseniero et al. (2022)

sualization, comparing used technologies, data type, visualization type, and other characteristics. Some findings show that most papers use standard visualizations like scatter and bar charts. The authors also pointed out that Augmented Reality is the dominant technology used, possibly influenced by the examples provided by Willett, Jansen and Dragicevic (2017), the most cited reference as the definition of situatedness.

Taking the reviewed papers, the authors elaborate that the situatedness of data visualization can take five perspectives or ways of looking. The Spatial perspective refers to the proximity between data representations and physical referents. The time perspective emphasizes the relationship between when the data was recorded

Table 2.1: Data Visceralization's Experiences

Experience	*Measurement*	*Description*
E1	Speed	A comparison of Usain Bolt and other Olympic champions at the Olympic Men's 100m since 1986.
E2	Distance	Comparison between the champions of Olympic Men's Long Jump.
E3	Height	Comparison between comparing skycrapers and landmarks.
E4	Scale	An intent to see other planets fitting the space between the the Earth and Moon.
E5	Discrete Quantities	The number of protester at Hong Kong street marches.
E6	Abstract Measures	Compare the US Debt as money towers.

Source: Lee et al. (2021)

and its presentation. The Place perspective is when the data is relatable to the history, identity, or meaning of the place where the data visualization is displayed. The Activity perspective is when the data visualization connects to another set of human activities, like taking care of hospital patients, where technology, placement, and interaction are affected by environmental aspects. Taking a Community perspective emphasizes the community of people who are the audience for visualizations centered around local issues and shared concerns, complementing place and activity perspectives. In the end, these different perspectives clarify and engage the community to create situated visualizations that are driven by their context beyond the spatial aspect.

Martins et al. (2022) expanded the perspective model above adding the Content perspective, which relies on how developers elaborate and implement the data visualization. Martins et al. (2023) proposed the Ethics perspective, which takes into account ethical "considerations and implications related to the principles, values, rights, and interests of all parties involved in a given space, time, place, activity, community, or content to which the data refers" (Martins et al., 2023). The same paper refines perspective into categories, where each category represents a perspective's characteristic.

In conclusion, the authors describe some challenges addressed by the situated visualizations, like data overload, and visual interference caused by the environment that can distract the user. Another challenge is the lack of guidelines to develop efficient and fresh situated visualizations focused on analytics, even if situated visualizations take a less formal implementation.

2.3 Affective Design and Data Visualization

In general, Emotional Design “is the concept of how to create designs that evoke emotions which result in positive user experiences” (Norman, 2004). In HCI, the concept became popular with affective computing, the study of how to develop technologies that correspond to human emotions. Affective design or emotional design was embraced by the HCI community to develop user interfaces or applications. The use of affective design in datavis is recent since data visualization applications usually try to facilitate understanding complex data and generate data-driven insights.

Since the emerging use of affective design in data visualization, Lan, Wu and Cao (2024) reviewed 109 existing researches, applications, experiences, and practices on affective visualization design. Using the What-Why-How framework (Munzner, 2014), the review aims to answer three questions: why emotion is important for visualization design, what tasks the design can undertake, and how to develop the design.

The authors summarize some of the arguments found in the corpus to justify the use of affective designs and separate them into five perspectives. From the Application perspective, some of the data visualizations belong to a domain where emotion is important like journalism, art, and entertainment. “For example, during the COVID-19 pandemic, many data stories were created to evoke shock, fear, or grief for deaths” (Lan, Wu and Cao, 2024). From the Usefulness perspective, many researches convey that rational thinking can co-exist with emotion and even bring benefits, like engagement, enjoyment, and interest. The Rhetorical perspective discusses that even standard charts with simple shapes, colors, and labels, are not impartial because someone has chosen their characteristics. From the perspective of sociology, the importance and use of emotion in different areas is a social phenomenon with highs and lows. Humanism perspective, the last one, observes that standard charts can be considered cruel or cold when showing delicate data like traffic accidents or birth rates.

Data visualization experiments typically focus on work tasks like comparing data and seeking determined information where the aim is to evaluate the tasks' difficulty. However, looking at the research's corpus, the authors distinguished 10 different tasks that have a high abstraction level, inform, engage, experiment, provoke, advocate, socialize, heal, empower, commemorate, and archive. These tasks are based on the data developer's intent, and as discussed in the previous sections, there are contexts where the intention is more important than how fast the user has an insight or searches for something.

The design techniques used in the applications were categorized into four strategies. Sensation strategy uses shapes, colors, glyphs, realist or metaphorical imagery, and other low-level techniques to influence viewers' emotions. The Narrative strategy tries to evoke some emotion using storytelling methods like word phrasing and narrative structure. Behavior strategy utilizes different ways viewers interact with data aiming to engage emotionally. The final strategy, Context, brings the user close to data, for example with immersive VR technologies or situated visualizations.

Also, some research opportunities are suggested as an outcome of their research. Experiment replications in diverse scenarios to cross-validate research and application findings. Conduct studies with more diverse and larger sample sizes, and the main opportunity that motivates this work, is to evaluate how design techniques affect emotion.

3 SELECTED CASE STUDY: SITUATED REAL ESTATE DATA

This chapter introduces the specific case study we selected for investigation in the present work, addressing the motivation and the selected data. By doing so, we aim to provide a clear overview of the project's objectives and significance.

3.1 Motivation

In the last chapter, we discussed some of the previous works with data visualization applications in AR and VR. Most of them focused on established chart styles, like scatterplots, that are present in most traditional spreadsheet applications, with limited exploration of the new design possibilities opened up by novel AR devices. Our goal is to design and evaluate a more tailored data-driven experience in an AR environment.

The creation of customized data-driven experiences can take into account the audience's preferences, behaviors, and needs, permitting users to have immersive and personalized encounters that align with their unique interests and requirements. The delivery of relevant and engaging content can provide a more in-depth understanding of a particular topic or new perspectives that users were not previously aware of.

Many methodologies can be employed to model or create applications such as the Double Diamond framework described in Council (2007), and depending on the development stage other methodologies can be applied. In the data visualization area, especially in business, a more popular approach is Data Storytelling which "is the ability to effectively communicate insights from a dataset using narratives and visualizations" (Cote, 2021). It utilizes storytelling elements to guide the target audience through data, making it easier to comprehend and draw conclusions. Nonetheless, businesspeople usually have some expertise in comprehending data charts. Bringing to a wider audience, Data Storytelling may need more tools, like affective design techniques, to communicate the right message.

As elaborated in related work section, many data visualizations that use affective design techniques are already being developed. Also, the use of these techniques begins to appear in different areas like journalism, entertainment, and social impact. The audience of these areas is often diverse, and not everyone may have experience with data visualizations. The objective of data visualization in nonbusiness areas can be slightly different, as they aim to grab the readers' attention to tell a story. In contrast to the already discussed papers on AR and VR, the works using affective design almost do not use neither of these two technologies.

This work aims to fill some of the gap between affective design and AR technologies for data visualization. The first goal is to explore affective design in data visualization applications for AR environments. For this objective, we develop an AR application that implements the affective design techniques cited in (Lan, Wu and Cao, 2024) that will be more detailed in the next sections. The second goal is to conduct a user experiment to investigate the differences between default data charts and more custom charts that use affective techniques, both in the AR environment.

This research contributes to the state of the art elucidating some of the contexts of use for custom and default data visualizations in AR, like when and where the user would prefer one over another. Additionally, the study also aims to determine how applying affective design strategies can alter user emotions, and to identify which technique could have the most significant effect.

3.2 Selected Data

This work proposes a data visualization to evaluate some hypotheses, but to develop the visualization we used the What-Why-How framework. Given time concerns and other restrictions we opted to develop a single visualization that will already have different features based on the affective design strategies.

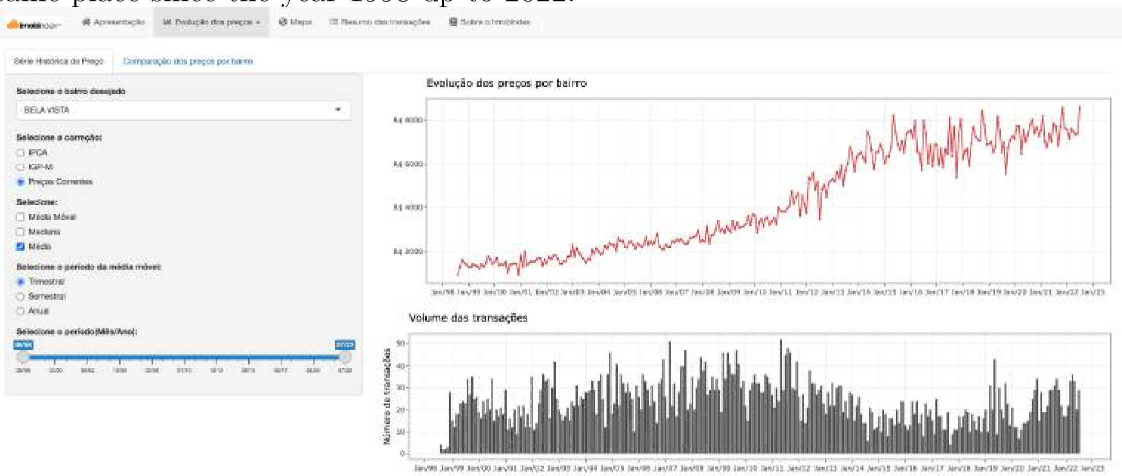
Selecting a dataset that most of the experiment participants will have an interest in is very challenging since people have different preferences. So, different affective strategies could not affect the user's interest if the data is displaced from the user context. For instance, displaying financial statistics to a user who has no interest or understanding of business. Another data aspect taken into consideration is how easy it is to situate, embed, and physicalize in the AR environment.

In recent years, there has been a growing interest in Open Government Data[1] (OGD), which is data collected and distributed by public bodies. This data often relates to areas such as the environment, health, and mobility. The Open Data

[1]https://www.oecd.org/gov/digital-government/open-government-data.htm

movement[2] aims to increase transparency and access to information. Open Data has many benefits, including improving public services and encouraging citizen participation and collaboration.

Figure 3.1: IMOBIndex dashboard showing a line chart about Bela Vista neighborhood square meter evolution and a bar chart with the number of sold houses in the same place since the year 1998 up to 2022.



Source: IMOBIndex (2022)

As the majority of the experiment participants reside in Porto Alegre, we chose to use one of the datasets provided by the city hall - the price per square meter (SQM) for each neighborhood. The data is available through IMOBIndex[3], a web-based public tool that allows access to the mean, median, and mode of SQM based on sold properties in each month. Fig. 3.1 shows the tool dashboard used to collect the data. The created dataset is the max price of all neighborhoods in each year from 1999 up to 2021 and was collected manually.

[2]https://data.europa.eu/en/dataeuropa-academy/what-open-data
[3]https://imobindex.procempa.com.br/

4 PROTOTYPE DESIGN AND IMPLEMENTATION

To evaluate how affective design technique could influence the user's emotions, this work develops a smartphone app that displays the price per SQM in Porto Alegre through different experiences. This chapter describes how the application was developed making an overview of technologies and the baseline experience in Section 4.1, and the next sections will explain how each technique was implemented.

4.1 Proposed Application Design

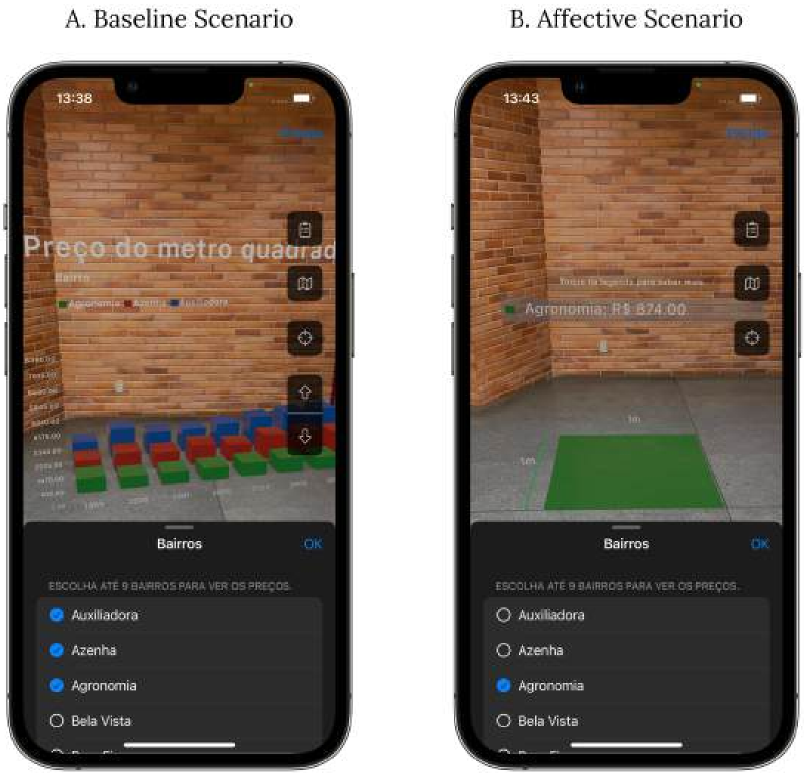
The purpose of this work is to assess the difference of data visualization design techniques, so it is important to define "How" the data will be presented as cited in Munzner (2014). As well, defining the set of technologies used is important, as they can have an impact on users. So, nowadays, there are "1,2 smartphones per inhabitant" (Meirelles, 2023) in Brazil, becoming one of the most accessible platforms for creating applications. Moreover, smartphones come equipped with sensors such as cameras, gyroscopes, and GPS, making them a complete platform for immersive experiences using AR.

Also, considering the previous discussion about situatedness in Subsection 2.2 and the price per SQM for the neighborhoods, anywhere in the city can be a physical referent. Therefore, displaying this dataset anywhere within the city can be considered a situated visualization. Furthermore, if we make use of AR technologies, we can create an embedded visualization that enhances the overall experience. Finally, regarding the authors' background and device availability, the application was developed using *Swift*[1], the language for Apple platforms like iPhone, Apple Watch, and Vision Pro. Also, utilizes the latest AR frameworks such as ARKit, and RealityKit to build up the different experiences.

As discussed, affective design techniques can be used alongside each other, so combining the four strategies, *Context*, *Anthropomorphism*, *Narrative*, and *Sensation* generates sixteen experiment scenarios, considering a scenario where none of the strategies are used. Considering time constraints, repetition, and comparison between the strategies, we limited the experiment to two scenarios, *Baseline* where do not use any of strategies, and *Affective*.

[1]https://www.swift.org/

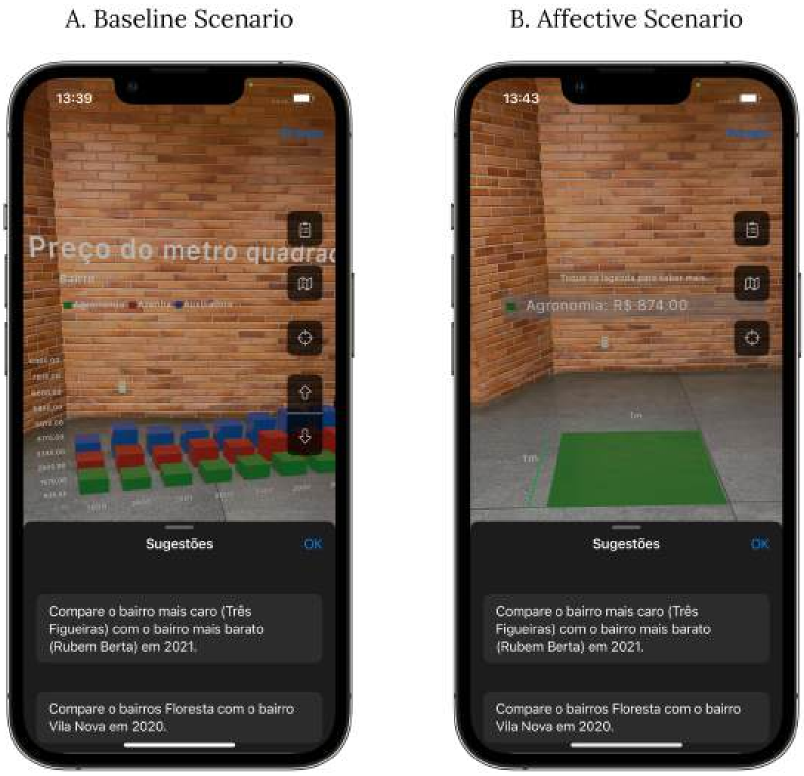
Figure 4.1: Neighborhood Selection



The application also gathers some device metrics such as chart position and scale, as well as device position. As for user data, the device records the interactions that the user had with the application, such as which neighborhoods were selected and how many times the buttons were tapped and time. This data can be analyzed to understand user preferences, like most used scale and y-axis position and other behaviors.

In both scenarios, there were some common usability features, such as neighborhood selection. To choose different neighborhoods, the user can tap the map button on the right, and a list of neighborhoods will appear in a sheet as shown in Fig. 4.1. By tapping on a neighborhood in the list, the application will add the neighborhood information to the chart, and a round checkbox will appear checked in blue. To remove a neighborhood, the user can tap on a neighborhood that has already been added to the chart, and it will be removed. Also, we provide some task suggestions for the user like comparing the most expensive and less expensive neighborhoods, the full list is in Table 5.1. These tasks could be accessed by the user tapping the right clipboard button, and doing so, opens up a sheet with the task list, this feature is shown in Fig. 4.2.

Figure 4.2: Suggested Tasks

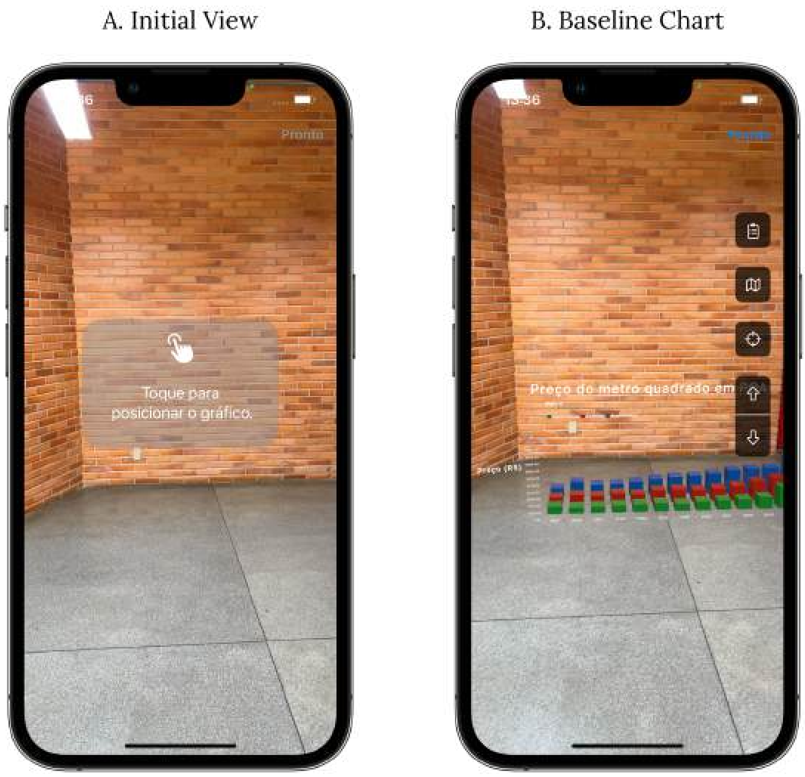


4.2 Proposed Baseline Features

In the *Baseline* scenario, no affective strategies are implemented and have the objective to be used in contrast with the scenario *Affective*, where all of the strategies are implemented. The AR experience for this scenario is shown in Fig. 4.3, where Fig. 4.3A is the initial view that informs the user to tap on the screen where they wish to add the chart. After the user taps the desired location, a default bar chart will be placed in AR, where the horizontal denotes the years, the height price per SQM, and the colors represent different neighborhoods (see Fig. 4.3B). The chart provides default annotations such as tick markers, axis titles, and legends to assist users in better understanding the data. Initially, the chart shows the first three neighborhoods in alphabetical order, but the user can select nine neighborhoods.

As shown in Fig. 4.4A, the user can interact with the chart using the drag gesture to move around and rotate through the default rotation gesture. On the right side of the screen, there are arrow buttons that allow the user to adjust the positioning of the chart up or down, whether it's on a table or the ground. Additionally, Fig. 4.4B shows other ways to facilitate the user to compare values, the

Figure 4.3: Baseline Scenario



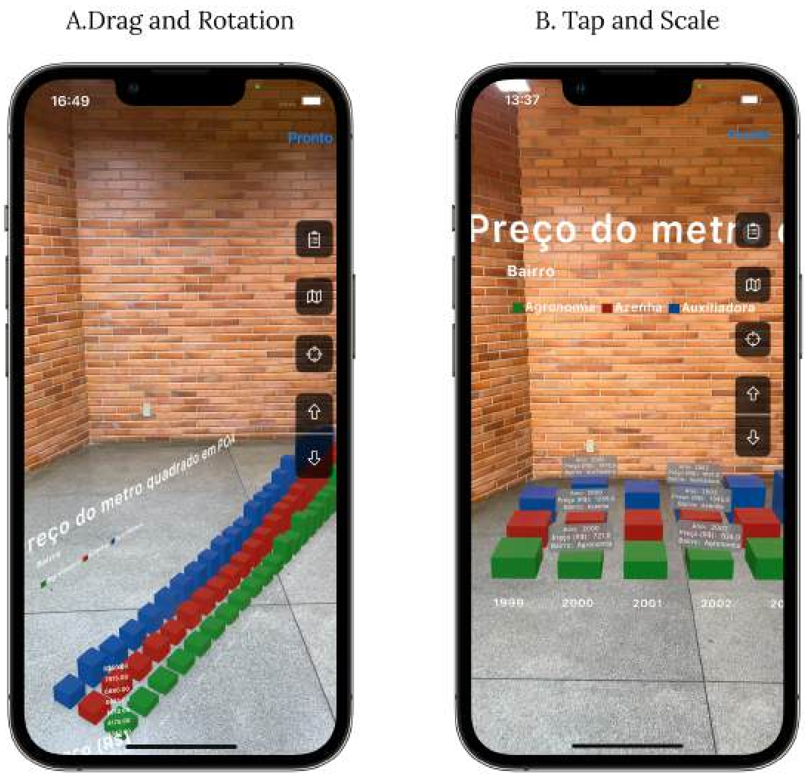
user can tap on a bar to view the exact information such as value, neighborhood, and year. Also, the user can scale the chart with the pinch gesture, as shown in Fig. 4.4B as well.

4.3 Proposed Narrative Features

The Narrative technique is an affective design approach that gives more context for the user using storytelling or other narrative structures. Using this technique, an initial screen (Fig. 4.5A) is shown to the user, containing word-phrasing and call-to-action texts such as the title “How much is your slice worth?”. This feature should instigate the application use and the data context and significance.

In this particular case, the narrative screen highlights some of the differences between the most and least expensive neighborhoods in the city as described in AIRES (2024) and WEBER (2024). By presenting this information, is the first step to the user explore the data further and think about such discrepancies. This approach could lead to valuable insights but also makes the data more engaging for the user.

Figure 4.4: Baseline Interaction



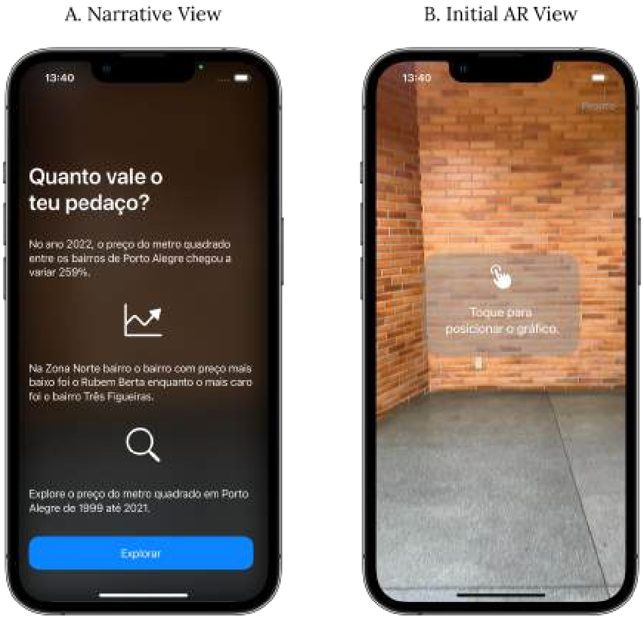
The button *Explore* at the bottom of the screen invites the user to investigate not only the data but the app itself. When the users tap the button it will lead to the AR environment as shown in Fig. 4.5B, where a centered *bento* card tells the user to tap the screen to add the chart.

4.4 Proposed Sensation Features

The Sensation strategy illustrated in Fig. 4.6 involves somewhat physicalizing the data. So, in this case, the application displays a colored square meter on the ground, representing the most expensive neighborhood selected by the user. Other neighborhoods are displayed as smaller squares with other colors, indicating their proportional values in comparison to the most expensive neighborhood. In this case, Fig. 4.6B shows that the neighborhood Auxiliadora in red is the most expensive, followed by Bom Fim in blue, Camaquã in yellow, and Agronomia in green. The green square, for example, represents the area in the Auxiliadora neighborhood that a person could buy with the same price of Agronomia SQM.

To improve the understanding of the data, this data visualization also counts

Figure 4.5: Affective Scenario



with annotations like a legend that displays the color of each neighborhood, names, and respective values, as verified in Lee et al. (2021). As well as *Baseline*, the user can move the data visualization around with the drag gesture, but it is important to note that the user cannot scale, as the biggest square should always represent 1 SQM.

Additionally, the user can only view one year at a time, making it challenging to compare the price per SQM between years. In contrast to the *Baseline*, which should be easier to compare. However, the primary purpose of the data visualization is to compare prices between neighborhoods. The user can select the year of interest by scrolling the ticked timeline at the bottom of the screen. Actually, in Fig. 4.6B, the selected year is 1999, but in Fig. 4.6C the selected year is 2020. As shown, the chart updates with the new area proportions and the legend with the values, we can perceive that the Auxiliadora neighborhood increased in value compared with the other neighborhoods.

4.5 Proposed Context Features

On the *Context* technique, instead of displaying the first three neighborhoods as the *Baseline* scenario, the application utilizes the smartphone's location service to identify the user's current neighborhood. This technique is already presented in

Figure 4.6: Affective AR chart

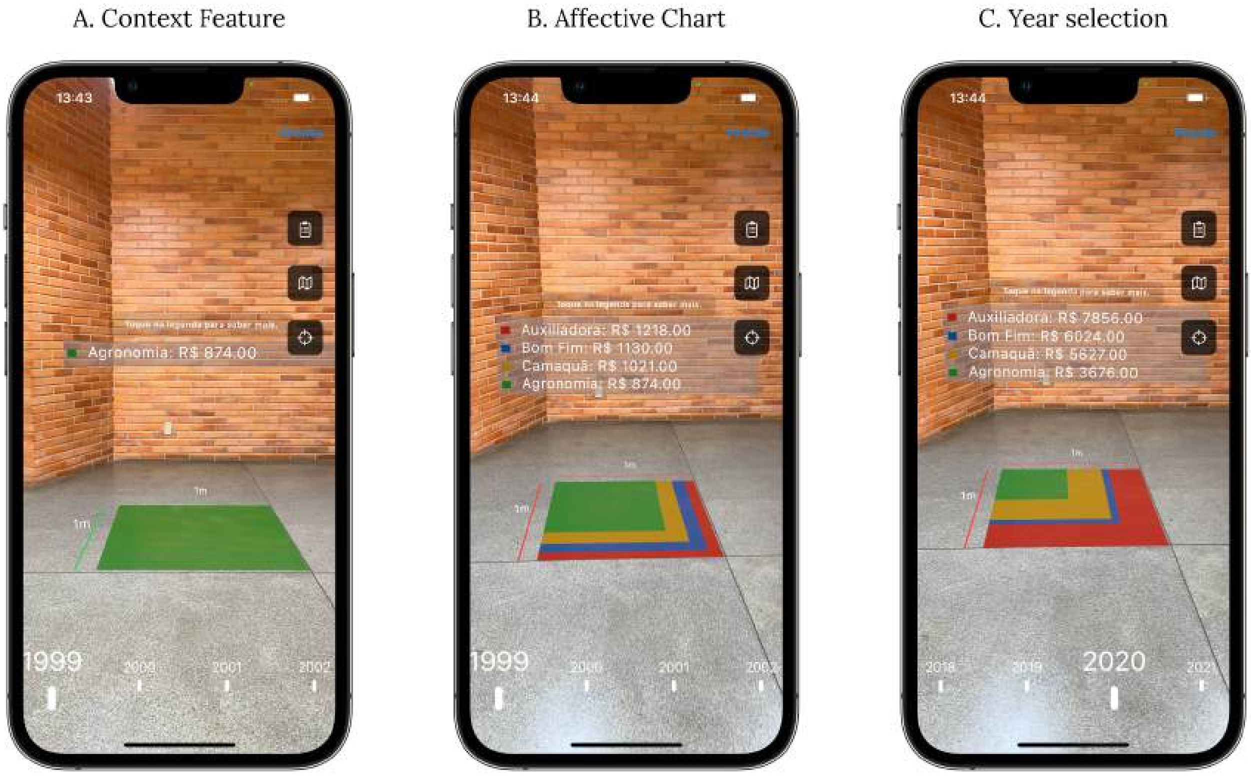


Fig. 4.6A, but it's only noticeable in the context of use. So, in this case, when we captured this image, we were in the Agronomia neighborhood, the same neighborhood in the legend.

Using this technique results in a situated visualization since it's closely related to its physical referent, the user's location. This approach can enhance the user's experience by providing more relevant and personalized information based on their current location.

4.6 Proposed Anthropomorphism Features

The anthropomorphism technique seeks to portray data in a more relatable and humane way by using abstract characteristics such as human traits, history, and emotion. The strategy was implemented to aid users in learning more about the neighborhood.

The objective is to provide a more interactive approach to data visualization and to make it easier for users to learn about the various neighborhoods. To achieve this, users are encouraged to tap the neighborhoods' names in the legend. By doing

Figure 4.7: Anthropomorphism Feature

A. Anthropomorphism for Agronomia

B. Anthropomorphism for Bom Fim

so, a panel will appear that gives more information about the specific neighborhood that the user selected. The panel will display the neighborhood's location on a map, as well as provide a brief history of the area collected from Franco (2018). As depicted in the Fig. 4.7A, on the left side of the panel there is a map of Porto Alegre city where the neighborhood is colored in red. The right side displays the neighborhood's name, Agronomia, and a text with some information and curiosities about the neighborhood. In Fig. 4.7B, the same feature is shown but for the Bom Fim neighborhood.

This should allow users to gain a better understanding of the neighborhood's context and significance. Overall, by providing this extra layer of information, it is hoped that users will be able to gain a deeper appreciation for the neighborhoods and the city as a whole.

5 EXPLORATORY USER INTERVIEWS

The experiments were conducted using an iPhone 13 Pro which provides a better AR experience using the LiDAR sensor. LiDAR sensors capture the environment by sending and receiving light pulses, using time-of-flight (ToF). In other words, the time difference between sending and receiving the light calculates the distance between the sensor and environment objects. This method creates a point data cloud with location and time as a geospatial map of the environment.

In the experiment, the participants will test the two scenarios, *Baseline* and *Affective*. These scenarios are shuffled for each user to mitigate incremental complexity or learning effect from influencing the test. Before each scenario, clear instructions were provided on how the participant can interact with the data visualization through gestures. Also, the participants are informed that they are allowed to move around during the experiment, can ask questions to the interviewer, and have the freedom to stop the experiment at any time without any prejudice. The tests were in different environments, so some participants were at home and work, so we didn't have much control over how large or cluttered the environment was.

In addition, suggested tasks, detailed in Table 5.1, are provided to guide the participant in exploring both scenarios. The first task aims for the user to compare two neighborhoods (n = 2) with a considerable price difference. The second task is for the user to compare two neighborhoods (n = 2) with a close price difference. The third one suggests that the user compare more than two neighborhoods (n > 2). The last one is for the user to compare their living neighborhoods with another one through the city. Besides that, participant did not receive any context of use, such as a user story, to allow them to explore the application as they intended.

Each scenario is followed by two questionnaires, a Portuguese version of the System-Usability-Scale (SUS) questionnaire provided by Lourenço, Carmona and Lopes (2022), and the Positive and Negative Affect Scale (PANAS), both of them developed within the app (see Fig. 5.1). The SUS questionnaire can be used to evaluate products, services, and applications in three different aspects. Effectiveness, as "the ability of users to complete tasks using the system, and the quality of the output of those tasks" (Brooke, 1995). Efficiency, as "the level of resource consumed in performing task" (Brooke, 1995), and satisfaction, "users' subjective reactions to using the system" (Brooke, 1995). The questionnaire is composed of ten questions

Table 5.1: Suggested Tasks

Task
1. Compare the most expensive neighborhood with the cheapest neighborhood in 2021.
2. Compare the Floresta neighborhoods with the Vila Nova neighborhood in 2020.
3. Choose more than 3 neighborhoods to see the difference between them.
4. Compare your neighborhood with other neighborhoods in the city.

Figure 5.1: SUS and PANAS questionnaires in the app.

with five response options varying from zero for strongly disagree to four for strongly agree, providing the SUS score. The score has a range between 0 and 100, and above 68 is considered greater than the average as mentioned by Brooke (2013).

After the SUS questionnaire, it is followed by the PANAS questionnaire provided by Watson, Clark and Tellegen (1988). Only the instructions were changed to ask how the user felt when exploring the data visualization application. This questionnaire provides positive and negative scores ranging from 10 to 50, that will be evaluated the difference between these scores for each scenario in Chapter 6.

The experiment session concludes with a semi-structured interview that allows the user to comment pros and cons of each scenario, use cases, improvements, and opinions that are explored in the next chapter.

Table 5.2: Interview Questions

Question
Which scenario was more difficult to understand?
Can you elaborate what do you liked about in each scenario?
Can you elaborate what do not liked about in each scenario?
Do you see any specific use case or local of use for each scenario?
Do you have any suggestion for improvements?
Do you have any additional comment about this study?

5.1 Interview Protocol

In the interview stage, we asked the participants the questions contained in Table 5.2. The aim of this approach was to create a more informal conversational atmosphere, allowing the user to freely express their emotions, preferences, and concerns regarding the experience. These questions were crafted to acquire comprehensive insights into the application, prompting the user to consider different usage scenarios, evaluate the user interface, and contemplate the worth and drawbacks of the application. Furthermore, following the user testing phase, more tailored questions may arise, delving into specific topics such as the reasons behind the user's choice to walk or not during the test.

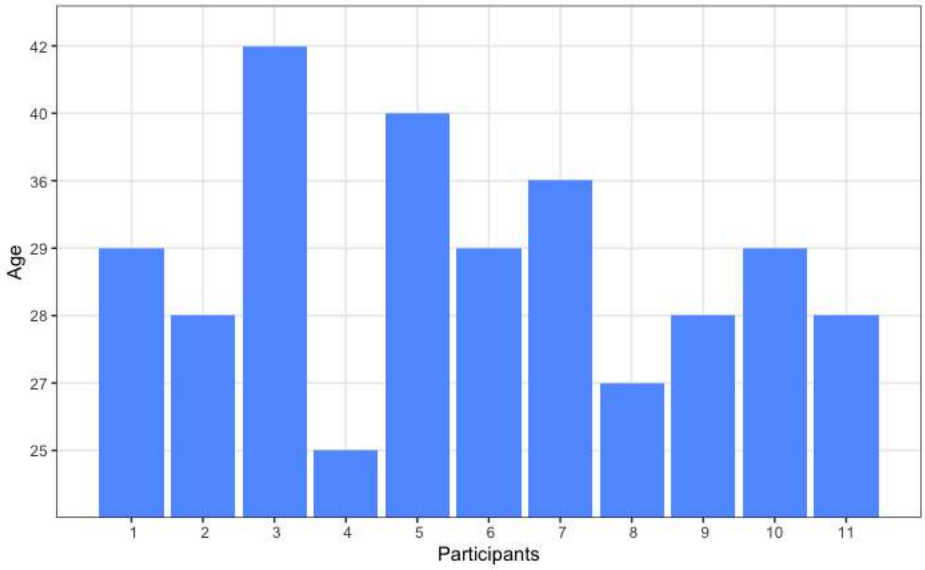
5.2 Participants

In our study, we examined the impact of design techniques on user experience by recruiting eleven participants aged 25 to 42, as seen in Fig. 5.2, where the y-axis means the age and the x-axis the participants. The participants follow the gender distribution shown in Fig. 5.3, revealing that the majority of participants were male, followed by females and individuals who opted not to declare their gender. It's important to note that none of the participants received any form of compensation for their involvement in the study.

The educational background of the participants varied, with a majority having completed their education and others still pursuing undergraduate degrees, as shown in as shown in Fig. 5.4. Their fields of study range between diverse disciplines such as law, language teaching, economics, and predominantly computer science.

We also asked the participants about their experience using smartphones and about their familiarity with AR. The chart presented in Fig. 5.5 illustrates that

Figure 5.2: Participants by age.



most of the participants are very habituated to using smartphones in their daily lives. Besides that, as shown in Fig. 5.5, most of the participants are a little familiar with using AR. Interestingly, the distribution of responses to these two questions was nearly opposite, besides that participants were not expected to face any usability issues during the tests.

Figure 5.3: Participants distributed by gender.

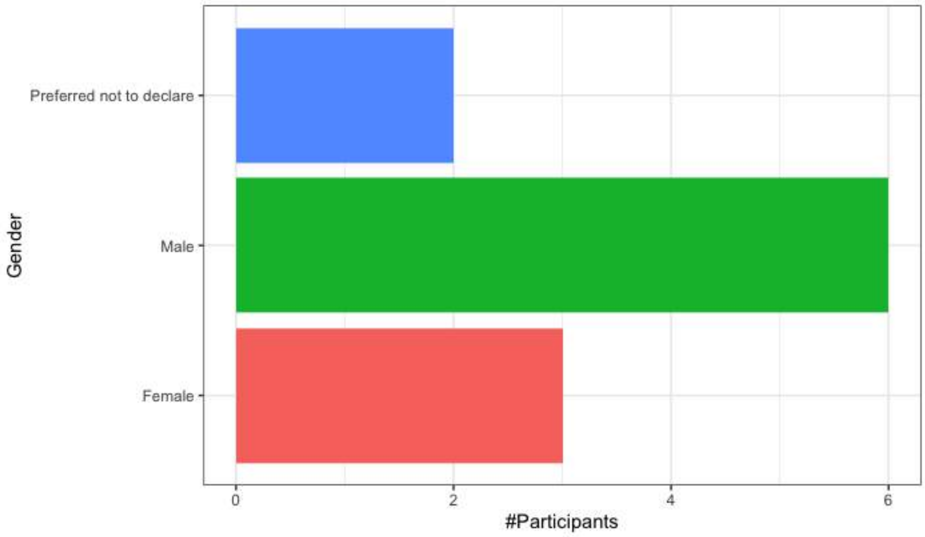


Figure 5.4: Participants distributed by education.

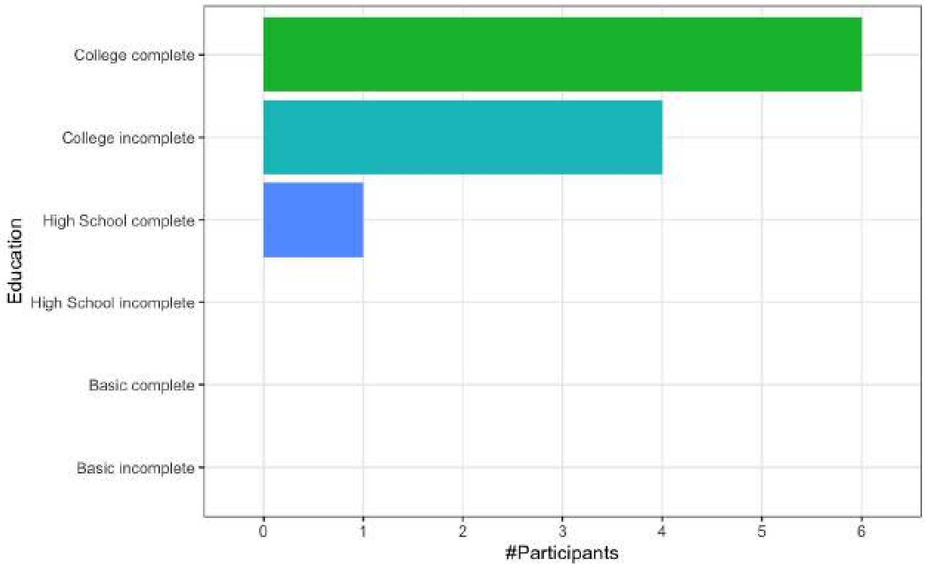
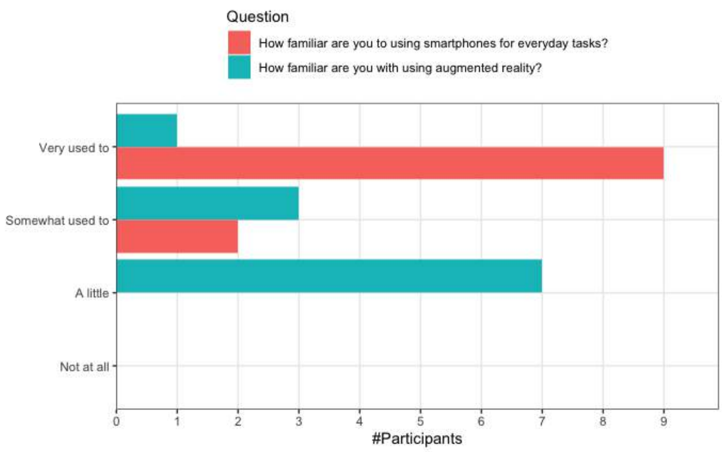


Figure 5.5: Participants distributed by their experience with smartphones and AR.



6 RESULTS

In this chapter, we dive into the data collected during the experiments. In the first subsection, the quantitative data is analyzed such as the SUS and PANAS scores, as well as other metrics like device movement and time usage for each scenario. In the Section 6.2, we analyze the qualitative data obtained from interviews with users.

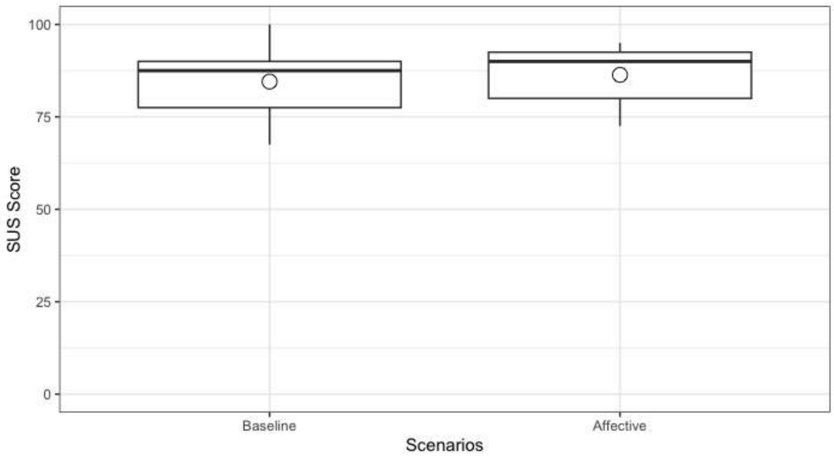
6.1 Quantitative Analysis

The SUS score evaluates the efficiency, effectiveness, and satisfaction of the user while using applications, products, and features. As depicted in Fig. 6.1, both scenarios received high SUS Scores. The average score, represented by the circles in the box plot, were approximately 84.54 and 86.36 for *Baseline* and *Affective*, respectively. A considerable value taken 68 is considered the median value. Upon initial review, it seems that these values are similar, even though the two scenarios involve different features. This would indicate that these features do not impact usability, and usability should not affect other quantitative analyses. However, we performed a t-test with a 95% confidence interval to determine if there was a significant difference in the SUS Score between the scenarios. The test resulted in a p-value of 0.6514, indicating that the difference between the scenarios cannot be assumed to be significant.

At the PANAS score, the average of each scenario for the Negative Affect Score was very low, which is good, (*Baseline* = 12.27, *Affective* = 10.9), with three outliers represented by dots, as depicted in Fig. 6.2A. We also performed a t-test, which yielded no significant difference between each scenario (p-value = 0.5154). For the Positive Affect Score (refer to Fig. 6.2B), we observed fewer outliers, and an average score of 30.36 for *Baseline* and 28.72 for *Affective* scenario. However, the t-test produced similar result to the Negative Affect Score with p-value = 0.6292.

Considering the time usage, shown in Fig. 6.3, there is a noticeable difference between the hard users of the *Affective* scenario and the hard users of the *Baseline*. In other words, the top two quartiles represent the individuals who use each scenario the most, and those who use the *Affective* scenario the most surpass those who use the *Baseline* scenario the most. However, as the SUS and PANAS scores, we

Figure 6.1: Boxplot chart for SUS score for each scenario. Higher the better.

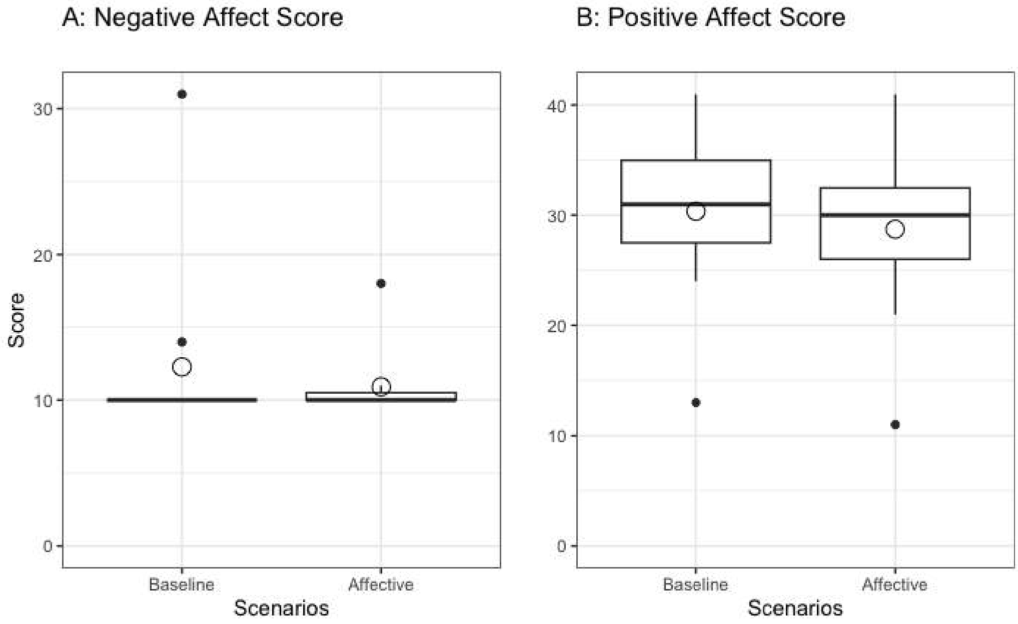


conducted a t-test that proved no difference between the usage times with a p-value of 0.41.

As said in the Section 4.1, other metrics were collected like how much the participants moves the smartphone through its use and how much they drag the charts. The box plot charts in Fig. 6.4 indicate that participants moved through the environment and dragged charts more in the *Baseline* scenario. This difference could be because the bar chart was too long and did not fit properly on the screen, which is supported by the qualitative analysis in the next section.

Analyzing metrics that are present only in the *Affective* scenario for *Anthropomorphism* and *Narrative* features. As shown in the chart in Fig. 6.5, 7 out 11 (63%) participants used the *Anthropomorphism* feature to explore the story, map, and other information about their neighborhoods of interest. Also, we can perceive that participants 2, 5, and 9 were who most used this feature, while 3, 6, 10 and 11 did not use it at all. Fig. 6.6 shows the percentage of time that each participant used each part of the test. The green color represents the percentage of time that the user spent in the AR on *Baseline* scenario, the blue color represents the percentage of time the user spent in the AR on *Affective* scenario and the coral color represents the time the user spent to read the *Narrative* screen (this feature is present only in the *Affective* scenario). The AR use time starts after the user taps the screen on Fig. 4.3A and Fig. 4.5B to add the chart on the environment, for *Baseline* and *Affective*, respectively, and the chart is fully loaded on the screen. It is noticeable that most participants spent more or less the same time in each scenario, with a few participants spending more time in one over another such as P4 that use more the

Figure 6.2: Boxplot chart for Negative and Positive Affect Score for each scenario based on PANAS questionnaire.



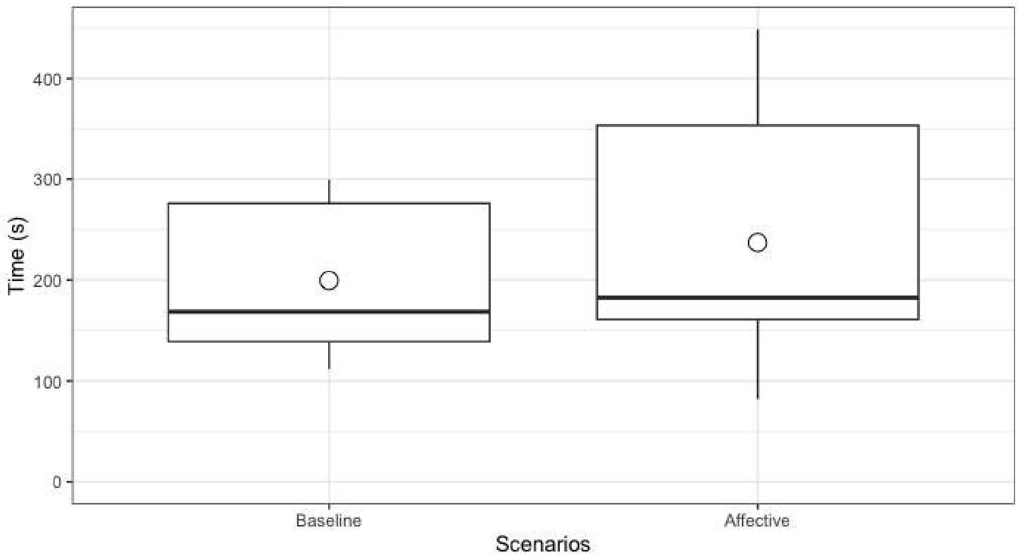
Baseline one. Yet, the *Narrative* feature captured some of the user time compared with the user analyzing the *Affective* AR chart. On average, the participants spent 7.04 s in the *Narrative* feature, which is on average of 7% of their time in the AR environment.

6.2 Qualitative Analysis

Interviewing participants could generate much data about the application, increasing contextual understanding of the participant's behaviors. Also, the interviews focus on a more humane part of the test and allow the participants to share their experiences. Nonetheless, qualitative data is often very complex and challenging to store, organize, and analyze in order to find valuable insights. In this work, first, we divide the answers for each question and annotate the answers that appear the most and the least. Then, a wrap-up was made to summarize some comments. Another important aspect of this research is that the sample is small and the participants' backgrounds were diverse, which means that many of the answers were unique.

We perceived during the test that some users preferred to be stood, seated, or seated after an amount of time. We questioned why they had these preferences,

Figure 6.3: Boxplot chart displaying the time spent by the users when analysing the AR charts in each scenario.

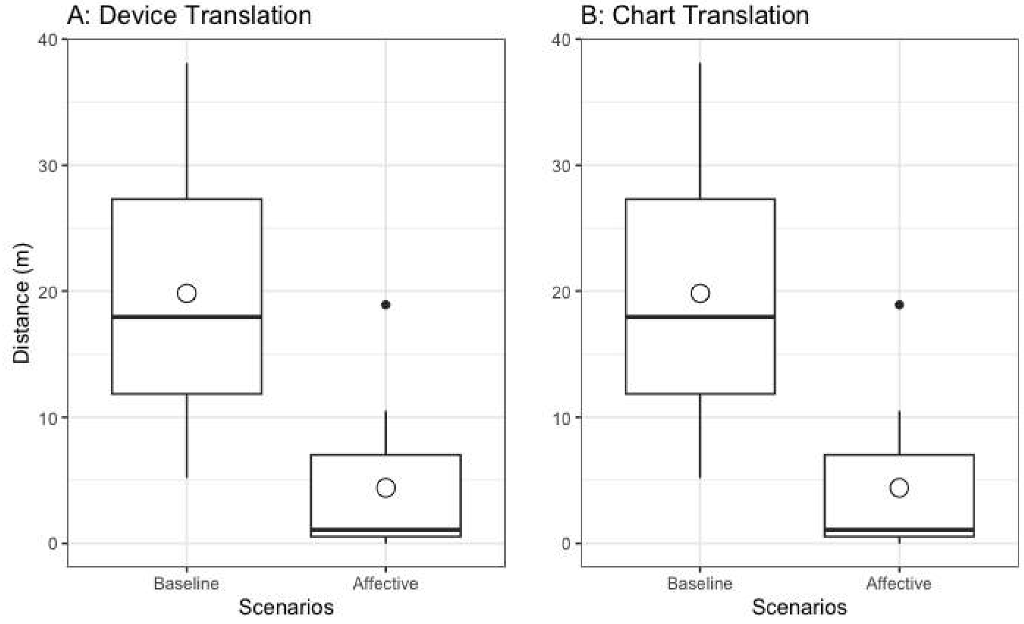


four participants (P4, P5, P9, P10) opted to be seated because they did not see any valuable difference between standing or walking in the environment, and three (P1, P2, P9) participants alleged to be more comfortable. Three participants (P3, P6, P10) moved to see better, while others did so to enhance immersion (P6, P10), fun (P3), and the general experience (P6).

Related to the difficulty of understanding each scenario, three participants (P3, P9, and P10) did not know which was more difficult. Participants P2, P4, P5, P6, and P7 found the *Affective* scenario more complex. Each one gave a different reason for that, P4 had difficulty realizing the difference between the values, and P6 related that was hard to analyze the difference between the years, for example. The *Baseline* scenario was considered the most difficult for three participants (P1, P8, P11). Participant P8, for example, found that rotating, scaling, and moving the bar chart mix up the understanding. Instead, P1 and P11 found that environment occlusion made the overall understanding harder because sometimes the part of the bar chart disappeared. Some users also suggested that if they did not find it too difficult, others, like elderly people, might have a difficult time using it.

The most cited aspect that the user did not like about the *Baseline* scenario was the length i.e. the bar chart was too long (P1, P3, P5, P6, P7, and P11). Additionally, the second most cited aspect was the user interaction for moving, rotating, and scaling (P5, P8, P9, and P10). Also, P9 expressed, “I think the bar

Figure 6.4: Boxplot chart displaying the device and charts translation made by the users for each scenario.

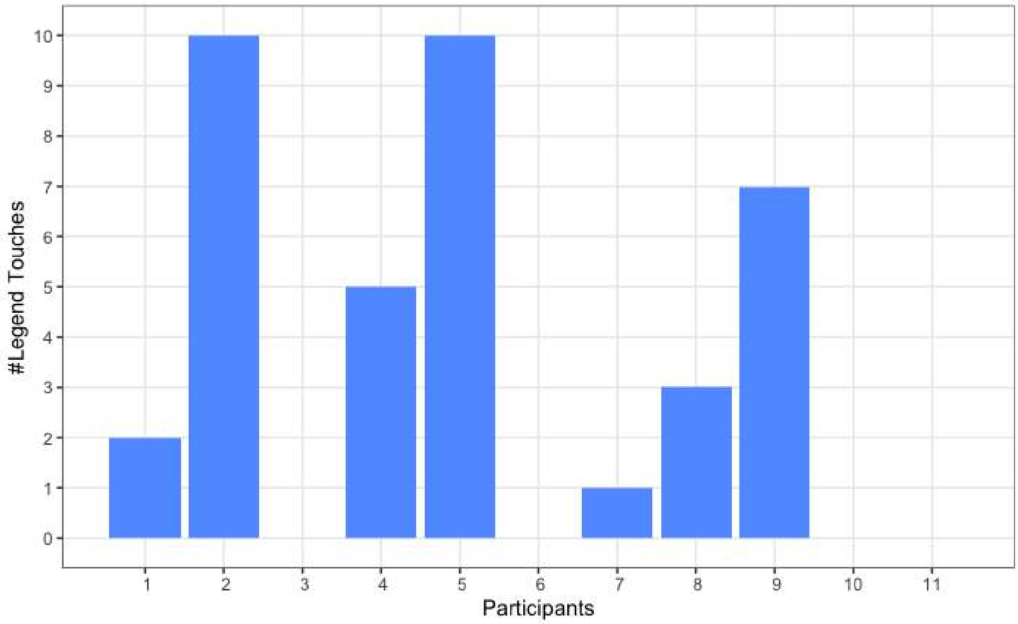


[chart] is cool, the movement of it, but it itself is boring". In the *Affective* scenario, the users provided different aspects that they did not like, including difficulty to understand (P3), the legend was too high and the chart was too low (P11), the colors were sometimes difficult to differentiate (P2, P9). Some users also expressed dissatisfaction with visualizing the price difference only one year at a time (P6) or even found the chart "unecessary" (P5)

Some users related that the most liked thing about the *Baseline* chart was that it's easy to understand (P4, P5, P9). Nonetheless, the most cited characteristic was the ability to compare the price alongside multiple years simultaneously (P1, P4, P5, P6, and P10). On the other hand, P2, P6, and P11 like the easy understanding of the *Affective* chart, and P3, and P11 found it more visually appealing. And, P1, P2, P5, and P9 liked the legend with some story of the neighborhoods. In contrast, those who did not use the *Anthropomorphism* feature alleged the focus on price comparison and had some previous familiarity with the neighborhoods of their interest (P6, P10), P3 and P11 did not comment on why they did not the feature.

When questioned about the context of use, most participants (10 out of 11) associated the charts with the housing market either being a buyer looking for a house or a salesperson analyzing the prices in a neighborhood of interest. Considering the context of searching for a place, the users noticed that the *Affective* is useful for displaying the space that a user would buy for a determined value in

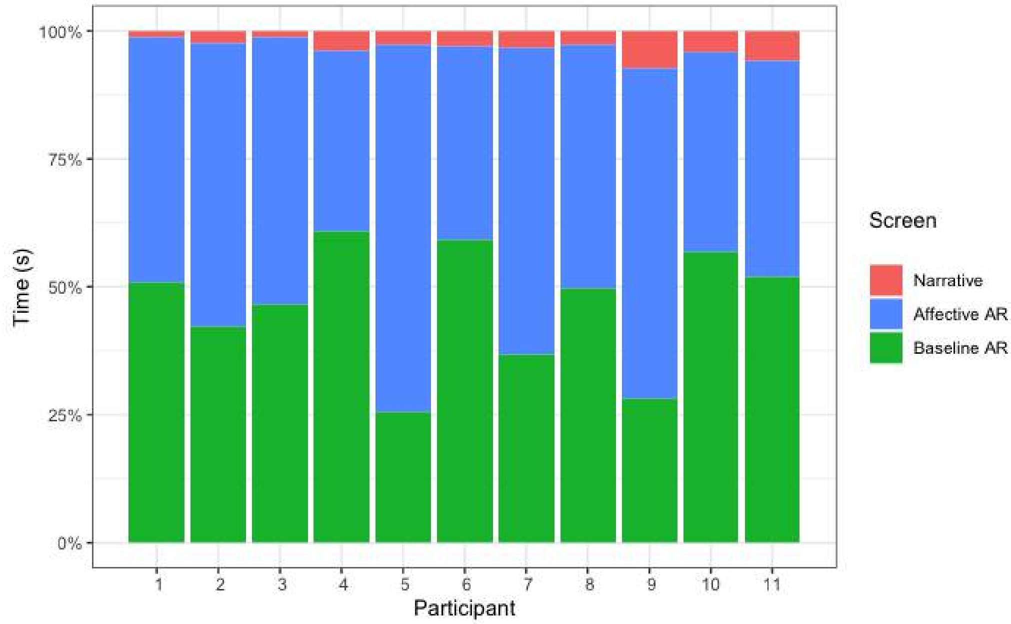
Figure 6.5: Bar chart displaying how much each participant used the *Anthropomorphism* feature.



a specific location (P2, P3, P6, P10, and P11). Some of these users noticed that vendors could benefit from the location aka *Context* feature to display the price and the space *in loco* for a possible buyer (P6, P9, P10, P11). P9 states "If I were a real estate agent and I was showing someone what they want to rent or buy, I think in this case it would be buying for the value of the square meter that is there [on the ground]". In the other scenario, the users (P1, P2, P3, P5, P6, P7, P8, P9) considered that might be useful for analyzing price trends for investments in housing, and so on. "It would be worth it for someone who is looking to invest, for someone who is not, for example, an end customer [...] then they can see how much the region is costing if the value of the region is decreasing in relation to [another], it gives a perspective." (P6) Another important comment about this scenario is that P7 questioned the use of AR and recommending that would be better an *non-AR* version. Fewer participants considered the *Affective* scenario as a tool to learn more about the city or its neighborhoods (P2, P5, and P8): "Maybe neighborhoods that I don't know. And also, I wonder if people who don't live in Porto Alegre get to know the neighborhoods better and also for more curiosities." (P2) Only one participant did not provide any use case for each of the scenario, P4.

In the last questions, the participants were invited to make suggestions about the usability and other aspects of the test like methodology, interview, and time. As expected, many users suggested improving the bar chart, making it shorter, or

Figure 6.6: Stacked bar chart displaying the percentage of time spent by the participants in different areas of the application.



creating a filter to compare only a set of years (P11). P2 and P7 would add or improve the onboarding with how to use and interpret the charts, and P5 would improve how to select neighborhoods. Participant P8 had difficulty with the label colors and suggested changing the label colors based on the environment. P4 and P11 would like a better indication of the difference or the size of each square for the *Affective* scenario. Many users proposed new features like scanning informing an area and providing a price in a determined neighborhood. Additionally, the user inputs how much money they intend to spend and the application shows how the house area will be in the selected neighborhoods.

7 FINDINGS AND DISCUSSION

This section addresses some of the results that were expected and the differences from the collected data. Also, it discusses the insights obtained from the quantitative data in Section 7.1. The Section 7.2 elaborates about the user perception of the implemented *Affective* features. Lastly, in Section 7.3, we propose improvements based on user feedback, learnings, and findings.

7.1 Overall Findings

Despite similar SUS results, many users mentioned during the qualitative interview that the bar chart was too long. As a result, they had to move or drag the chart to analyze the data, as supported by the quantitative analysis in Fig. 6.3. Another side effect is that users preferred this chart to track the price changes over the year, which may not be the most suitable analysis for the other scenario. Therefore, comparing the two scenarios based on analysis tasks may seem unfair. Due to this, we did not attempt to measure user tasks in any way, but instead focused on other metrics.

The main goal of this research was to observe differences in user emotions when using default and affective designs for AR datavis. We anticipated that the SUS score would not show any significant difference, suggesting that despite the different features, neither would have impacted overall usage. On the other hand, we expected that PANAS scores would exhibit a significant difference based on the impact of the implemented *Affective* features. The time usage also would be impacted since with more features and the additional complexity the user should take time to comprehend and explore the application. However, all t-tests showed high p-values, indicating that there is no difference between the scenarios, this result may be due to the low number of participants ($n = 11$).

The small sample size may have impacted the t-tests, but the set of participants was diverse. This is evidenced by the diverse range of expertise among the participants, the significant number of outliers in certain quantitative measures, and the small number of repeated responses in the qualitative interviews. Another aspect to notice is that AR technologies still have a relatively small presence in people's lives. Which becomes evident when comparing the usage of smartphones and AR on Fig. 5.5, however this did not interfere with the usability of the data visualizations.

7.2 Use of Affective Techniques

The *Affective* chart was generally found to be more difficult for users (5 out of 11) to understand in contrast with the bar chart (3 out of 11). This result is expected and arises from *Sensation* feature which provided an uncommon way of visualizing data with some visual complexity introduced, as discussed in Bateman et al. (2010). Additionally, the chart had a certain level of physicalization which may contributed as well, as similar in Lee et al. (2021). Some users found this scenario more personalized and aesthetically pleasing, but the only noticeable difference was that some users liked to see the space with the cost as an application feature. So, the real effect of the *Sensation* technique on the user's emotions remains uncertain.

Some users have commented on the *Context* feature as a helpful tool, particularly noting its benefits in quickly providing accurate pricing based on the user's location. This aligns with similar feedback about the *Sensation* technique, which aims to help users understand the space and associated costs. However, it seems that these features serve more as functional tools rather than aspects that engage or influence the user's perception of the data visualization. In fact, 90.9% of the users commented about the use of the application as a tool for real estate agents or for people who are looking to buy or rent a place. Moreover, some users elaborated on other interesting features if the application was a distributed app, like measuring the area or even evaluating a possible area for a budget in a determined neighborhood. However, these ideas may be connected of the nature of data rather than the focus of this work, user engagement. So, even if the application was in the market, it remains unclear how *Context* technique could improve or enhance the overall experience in data visualization. Another possibility is that the data was already situated enough with the user context, the same city, maybe if the *Baseline* scenario showed the same data about a different location the result would be more perceptible.

In this study, the most remarkable feature was the *Anthropomorphism* technique, which was utilized by 63% of the participants as seen in Fig. 6.5. Additionally, 3 out of 11 participants (27%) indicated this feature as their favorite. The *Narrative* feature captured users' attention for an average of 7% more time, reflecting a substantial increase in engagement. In conclusion, when bringing the data visualization to a broader audience, as the participant sample, the data engineers could benefit from these two features to engage more with their target audience.

7.3 Improvements

Among the improvements for this work, the first one is to conduct a test with a larger sample of testers ($n > 11$) to increase the significance of the t-tests and their confidence. Regardless of the methodology some users related that they had a hard time with the questions of the SUS and PANAS formularies. In the SUS case, maybe implement a better interface that elucidate to the user about the objective of this questionnaire. At the PANAS, we did not find an official Portuguese adaptation during the initial review of the state of the art, so the direct translation of the questions caused some doubts in the participants. After perceiving this issue and revisiting the state of the art, the use of this version created in (Galinha and Pais-Ribeiro, 2005) could avoid those doubts when the user answers the questionnaire. Even more, using other business metrics could bring new ways to evaluate user engagement. The qualitative interview could be enhanced by including more questions about the *Affective* scenario and its usage. In several interviews, participants either did not notice certain features or were unable to provide detailed elaboration on them.

Also, use the participant's suggestions for the application like keeping the legend near the ground in the *Affective* scenario. In this same scenario, annotate the difference between each square area alongside the price and improve the color scheme. Another important suggestion is to make the bar chart shorter or even use the same timeline filter used on the *Affective* scenario. This change would make the chart fit better on the screen and would avoid the difference between the answers in the context of use since the user wouldn't be allowed to see the evolution of the prices over the years as easily. Besides the same timeline being used in the different scenarios and making them closer to each other in terms of usability, it should not impact the tests because the timeline itself has no connection with the any *Affective* features.

8 CONCLUSION & FUTURE WORK

In this work, we reviewed the state of the art with the definitions and examples of data visualizations in VR and AR identifying gaps between the efforts in analysis efficiency and user experience for these environments. Some of these gaps are evaluating *Affective Design* for AR environments and its impact on user emotions through quantitative and qualitative data. Additionally, we aimed to determine when users would prefer a default chart as opposed to a custom one and to identify which affective techniques are more likely to engage the user.

First of all, to evaluate the influence on user emotions we proposed a prototype AR application for smartphones. This application presented a default bar chart called *Baseline* scenario and a customized one. The last one uses different design techniques like *Narrative*, *Context*, *Sensation*, and *Anthropomorfism*, this version was called *Affective* scenario. Both scenarios used the same data source, which was the price of the SQM in the neighborhoods of Porto Alegre. The main hypothesis was that these affective features could lead to a difference in user engagement and emotions, evaluated by different metrics.

We recruited eleven participants to test both scenarios and asses their experience through two questionnaires and an interview. Also, the application collected relevant data like movement, time, and touches to describe how the different scenarios were used. All tests were conducted within the city limits making the data more or less situated depending on the scenario.

The two questionnaires evaluated the usability of the application and its effect in negative and positive ways. Based on these two questionnaires, we did not observe any significant impact, for better or worse, from the developed affective features. Moreover, the increased complexity and the addition of these features did not lead to an increase or decrease in the time usage. Although, it's important to note that these results may be inconclusive because the number of participants was insufficient.

The qualitative interviews revealed interesting insights into the context of the use of each scenario. Eight participants considered that the *Baseline* chart would be more interesting for those who evaluate investing in the housing market, which might require some analytics knowledge. The other scenario was considered more interesting for individuals seeking to rent or buy a residence, as this task can be performed by most people without an analytical background. In essence, users preferred default charts when they needed to analyze data with a certain efficiency and confidence, rather than using a custom chart.

While investigating the user interactions, most users interacted with the *Antropomorphism* feature, suggesting that this feature increases user interest and engagement. Another important feature was the *Narrative* that increased the usage time by 7% on average. In this work and the context of real state data, these were the most effective techniques developed. The other two, *Context* and *Sensation* were recognized by the participants as tools to change the experience, but the real impact on data visualization couldn't be acknowledged.

Given that the implementation of design techniques could be varied, our work did not exhaust all the possibilities for feature development. Also, it's essential to recognize that specific design implementations may affect people differently, and a design that works well for one person may not be as effective for another. There are many opportunities for future work based on this study, such as evaluating the same metrics and other factors using different methodologies, implementing other *Affective* features and comparing them with each other, or using different datasets. In conclusion, this work opens up new possibilities for researching affective designs for data visualizations in AR environments.

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