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Fill the map: Integrating objective data and citizen knowledge for Participatory Urban Planning

A Superblock project in Vienna

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Fill the map: Integrating objective data and citizen knowledge for Participatory Urban Planning

A Superblock project in Vienna

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Statement of Authorship

Herewith, I declare that I am the sole author of the submitted Master's thesis entitled:

"Fill the map: Integrating objective data and citizen knowledge for Participatory Urban Planning."

I have fully referenced the ideas and work of others, whether published or unpublished. Literal or analogous citations are clearly marked as such.

Vienna, September 2023 Camila, Narbaitz Sarsur

Abstract

The cartographic visualization of urban data is a powerful tool for decision-making processes in participatory urban planning. In these processes, visualizations should enable stakeholders to explore, create hypotheses, make sense of, and interpret patterns in the data. By merging objective data with citizen knowledge, such visualizations can ensure the incorporation of the voices and experiences of residents and community members, making the visualizations more inclusive and accurate. However, a significant challenge remains: designing visualizations that enable both stakeholders with expertise (technical experts such as urban planners, geographers, and architects) and those without (neighborhood experts, such as residents) to effectively make connections between layers and interpret patterns in urban data to enhance decision-making processes.

This study aimed to identify optimal cartographic visualization strategies that combine objective data and citizen knowledge, thereby serving as decision-making tools within the framework of participatory urban planning. The research focused on comparing the understanding and preferences among diverse stakeholders of different urban visualizations, merging the two data types to achieve this goal. These visualizations included varying complexity, granularity, and generalization levels. A methodology using good practices as references was developed for creating the visualizations. The Lichtental Superblock project in Vienna served as the case study, and the evaluation process involved technical experts and residents.

This thesis had three main outcomes. Firstly, a catalog including a structured compilation of visualization strategies, providing valuable references to streamline the process and avoid potential errors in representation. Secondly, a workflow to visualize citizen knowledge and objective data together. Thirdly, a comprehensive set of recommendations based on the analysis of the case study results. These recommendations include general guidelines for creating urban data visualizations depending on their complexity level, aiming to increase the visualizations' effectiveness in the context of participatory urban planning.

Keywords: *urban data visualization, Cartographic visualization, participatory urban planning, stakeholder engagement, citizen knowledge, objective data, subjective data.*

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Contents

1 Introduction **1**
1.1 Motivation and problem statement 1
1.2 Research objectives 2
1.3 Research questions 3
1.4 Thesis Structure 5
2 Literature review **7**
2.1 Mapping cities throughout history 7
2.2 Urban data classification 11
2.3 Urban data visualization analysis 19
3 Methodology **27**
3.1 Framework development 27
3.2 Map analysis 28
3.3 Map design process 34
3.3.1 Data collection 35
3.4 User testing and interpretation 41
4 Case study **43**
4.1 Case study definition 43
4.2 Map design process 46
4.3 User testing and interpretation 68
5 Discussions **79**
5.1 Discussions 79
5.2 Limitations 83
5.3 Recommendations 81
5.4 Future work 84
6 Conclusions **86**
7 References **87**
8 Appendixes **91**

List of Figures

Figure 1: (a) Map of yellow fever on the left (Valentine Seaman, 1798). Retrieved from Wikimedia Commons and (b) map of cholera (John Snow, 1854). Retrieved from Wikimedia Commons. 8
Figure 2: Distribution of sex workers in Paris (Alexandre Jean-Baptiste, 1836). Retrieved from Wikimedia Commons 8
Figure 3: An example of an objective data map. Screenshot of Near Green, Far Green map (Einsemann et al., 2021). Retrieved from https://uclab.fh-potsdam.de/mapping/nahesgruen/. 13
Figure 4: An example of a map with citizen knowledge. Malleshwaram Memoirs (Nagpal Prachi, 2015). Retrieved from https://www.cityvis.io/ 14
Figure 5: Mental map derived from interviews and sketch maps. (Lynch, 1960, p. 147). 15
Figure 6: Map displaying citizen knowledge and objective data. Narratives of displacements and evictions map (Anti-Eviction Mapping Project, 2016). Retrieved from http://www.antievictionmappingproject.net/narratives.html 17
Figure 7: Map displaying citizen knowledge and objective data. Desirable streets in Boston map (Desirable streets project). 18
Figure 8: An example of Point-based visualization. Screenshot of Mapping ethnic communities in Brussels map (University of Leuven, 2016). Retrieved from https://www.cityvis.io/ 20
Figure 9: An example of Line-based visualization. Screenshot of City Flux (University of Applied Sciences Potsdam, 2018). Retrieved from https://city-in-flux.netlify.app/ 20
Figure 10: An example of Point-based visualization. Screenshot of Crashes in DC map (Mapbox, 2017). 21
Figure 11: Visual variables. 23
Figure 12: Conceptual generalization. From a point-based visualization to a region-based visualization. Screenshots of Crashes in DC map (Mapbox, 2017). Retrieved from https://labs.mapbox.com/bites/00379/#10.5/38.8994/-77.0134/0/40 24
Figure 13: Graph representing the methodology used in the research. 27
Figure 14: Graph representing the Map analysis stage. 29
Figure 15: Screenshot from the catalog. 30
Figure 16: Example of low complexity static map. Amor SP map (Maycon Sedrez, 2018). 31
Figure 17: (a) Example of medium complexity map, Haltestelle main map. (b) A view of the map when selecting a route. Screenshot of Haltestelle map (Tagesspiegel, 2016). Retrieved from https://interaktiv.tagesspiegel.de/archiv/haltestelle/ 32
Figure 18: Example of high complexity map, layer "to sleep". Turistification (300.000km/s, 2017). Retrieved from http://turistificacion.300000kms.net/ 33
Figure 19: Graph of the four steps within the Map design process stage 35
Figure 20: Graph explaining the data collection step. Starting with the data collection from the chosen data sources, the digitization step when necessary, and, as an outcome, the digitized objective data and citizen knowledge data. 36
Figure 21: Graphical representation of the three requirements for the selection of the layer combination. 38
Figure 22: Graph explaining a method to use the catalog. On the left is the raw layer. In the middle, the catalog highlights the identification of a matching layer reference. 39
Figure 23: Graph showing the selection of the visual strategy and its subsequent application 40
Figure 24: Current model vs. Superblock model 44
Figure 25: Map of Lichtental showing some critical points, the superblock area (black), and an inset map showing the location of Lichtental within Vienna. 45
Figure 26: Stakeholders involved in the participatory process of the Lichtental Superblock project. 46
Figure 27: Screenshot from QuickOSM plugin showing how the data was retrieved by using tags. 48
Figure 28: (a) Cool and hot Lichtental places. Result from the survey. Klimafittes Lichtenthal (Gebietsbetreuung Stadterneuerung, 2020). 49

Figure 29: Photos taken during the Mental Mapping workshop. 50
Figure 30: Basemap made for the workshop and the scanned results map from the workshop. 50
Figure 31: Attribute Table screenshot from the day paths layer. On yellow, the counts are highlighted. 51
Figure 32: Graph showing the available data and the chosen layer combinations. 51
Figure 33: The invisible forest map (Density Design Research Lab, 2017). 53
Figure 34: Activity map. A sense of place report (SPIN unit, 2015). 54
Figure 35: Turku traffic map. A sense of place report (SPIN unit, 2015). 55
Figure 36: Graph describing the generated visualizations. 56
Figure 37: Residents' temperature perception and green infrastructure map. 57
Figure 38: Screenshot from the trees layer properties configuration 58
Figure 39: Chosen color palette map A, Pattern 1. 58
Figure 40: Diagram showing the process of creating the symbology of the residents' temperature perception layer. 59
Figure 41: Residents' temperature perception and green infrastructure generalized map 60
Figure 42: Heatmap chosen configuration. 60
Figure 43: Chosen color palette map B, Pattern 1. 61
Figure 44: Day pedestrians' movement frequency and activity patterns fine-granularity map. 62
Figure 45: Chosen color palette map A, Pattern 2. 63
Figure 46: Depiction of the line symbology change between QGIS and Adobe Illustrator 64
Figure 47: Three options for the symbology of the activity's layers. 64
Figure 48: Day pedestrians' movement frequency and activity patterns generalized map. 65
Figure 49: Screenshot of the attribute table of the merged layer with the necessary columns 66
Figure 50: Heatmap chosen configuration. 67
Figure 51: Four options showing different radius configurations for the heatmap. 67
Figure 52: Chosen color palette map A, Pattern 2. 67
Figure 53: Diagram showing the survey design, and the questions to be unveiled, and the addressed RQ. 69
Figure 54: Graph showing the three sections of the survey 69
Figure 55: Participants of the survey. 71
Figure 56: Results of the question "Can you find any connection between layers?". 71
Figure 57: Results of the question "Can you find any connection between layers?" divided by stakeholders 72
Figure 58: Results Q3 from Pattern 1. 73
Figure 59: Results Q3 from Pattern 2. 74
Figure 60: Comparison of Q1, Q2, and Q3 in Pattern 1 74
Figure 61: Comparison of Q1, Q2, and Q3 in Pattern 1. 75
Figure 62: Results of Q4, Q5 and Q6 in Pattern 1 76
Figure 63: Results of Q4, Q5 and Q6 in Pattern 2 77

List of Tables

Table 1: Table showing analyzed visualization parameters used on "AMOR SP" map. 31
Table 2: Table showing analyzed visualization parameters used on Haltestelle map. 32
Table 3: Table showing analyzed visualization parameters used on the "to sleep" map. 34
Table 4: Data layers used and their sources. 47
Table 5: Table showing analyzed visualization parameters used on The invisible forest map. 53
Table 6: Table showing analyzed visualization parameters used on the Activity map by SPIN UNIT. 55
Table 7: Table showing analyzed visualization parameters used on GPS traces map by SPIN UNIT. 55

List of acronyms

AIT: Austrian Institute of Technology

GIS: Geographical Information Systems

GPS: Global Positioning System

GSV: Google Street View

GVI: Green View Index

IoT: Internet of Things

KDE: Kernel Density Estimation

OSM: Open Street Maps.

PGIS: Participatory GIS

POI: Points Of Interest

PPGIS: Public Participatory GIS

PUP: Participatory Urban Planning

SVG: Scalable Vector Graphics

1 Introduction

1.1 Motivation and problem statement

For thousands of years, maps have been an essential tool for urban planners to understand urban environments. Initially, they served practical purposes to lay out cities, streets, and landmarks. However, it was not until the 18^{th} century that maps became a tool for statistical analysis (Vaughan, 2018).

In the mid-20th century, participatory urban planning gained prominence alongside movements to rethink cities (Guldi, 2017). This approach marked a turning point, allowing citizens to actively participate in local governance and voice their community's experiences and needs. In participatory urban planning, maps acquired a new role, supporting cross-city analysis, facilitating collaboration, and fostering dialogues that emphasized local priorities in urban projects (Goodwin et al., 2021). Cartography as a discipline started introducing citizen knowledge data into a spatial format. This data included the qualitative and experiential insights of communities, enabling visualizations to capture data that had not been previously charted (Genz & Lucas-Drogan, 2017).

In the last 20 years, as urban objective data proliferated, new opportunities for advanced data collection and analysis have improved the understanding of urban environments (Goodwin et al., 2021). Urban data has moved beyond static representations to real-time, dynamic visualizations (Ratti & Claudel, 2016). Urban data visualization has emerged as a new field, confirming visualizations as critical tools for understanding cities. This field has proven the combined power of objective data and citizen knowledge to reveal new patterns and foster a deeper, more accurate understanding of places, ensuring that the voices and experiences of residents and community members are firmly integrated into the urban narrative (Godwin & Stasko, 2017; Knigge & Cope, 2006; Sauter et al., 2021; Sayegh et al., 2016).

However, a significant challenge remains: designing visualizations that enable stakeholders with expertise (technical experts such as urban planners, geographers, and architects) and those without (neighborhood experts, such as residents) to effectively interpret patterns and connections between layers of urban data. These visualizations must also represent the experiential and qualitative knowledge of those who experience the urban environment (Billger et al., 2017). Overcoming this challenge is crucial for effectively communicating urban issues and engaging diverse stakeholders in the decision-making process (Godwin & Stasko, 2017; Sauter et al., 2021). Cartography emerges as a powerful solution due to its visual and spatial nature, providing a unique opportunity to balance the complex demands of urban data representation.

In summary, recognizing the inherent benefits of combining citizen knowledge with objective data in visualizations, along with the need to create accessible and understandable visualizations for diverse stakeholders, is critical to advancing participatory urban planning. This integration is key to unlocking urban data's full potential in the decision-making process and fostering a more informed and inclusive urban future.

1.2 Research objectives

The primary goal of this thesis is to identify optimal cartographic visualization strategies that combine objective data and citizen knowledge, thereby serving as decision-making tools within the framework of participatory urban planning.

This work does not focus on how this data is gathered or analyzed but on how these two data types (citizen knowledge and objective data) can be merged and integrated visually to enable diverse stakeholders to explore, create hypotheses, make sense of, and interpret patterns in urban data.

The results of this work are intended to assist urban stakeholders, such as urban planners, municipalities, architects, urban developers, citizens, etc. It aims to enrich participatory decision-making processes by communicating data equally for different kinds of stakeholders. Firstly, by combining objective data and citizen knowledge. Secondly, by understanding the differences in the interpretation of cartographic visualizations by stakeholders with expertise and those without. It will also benefit cartographers who would like to better communicate the complexity of urban areas with data of different natures.

The main objective has been divided into three sub-objectives to achieve this research goal.

Sub-objective 1: To analyze and create a catalog of urban data visualizations. As different types of urban data demand different visualization and analysis methods, this objective will analyze current state-of-the-art visualizations, focusing on which visual variables and design elements are used to show different objective data and citizen knowledge layers.

This catalog will serve as a resource for designing visualizations in the case study.

Sub-objective 2: To create a more suitable visualization strategy to combine citizen knowledge and objective data. This sub-objective concerns combining and using visual strategies from the catalog to integrate both data types in a specific case study. The aim is to create different visual combinations showing the same data patterns to later test them.

Sub-objective 3: To understand the effectiveness of the created cartographic visualizations, making diverse stakeholders interpret, make connections, and make sense of different data types. This objective aims to identify the differences in interpreting the combined data layers by stakeholders with and without expertise and their preferred visualizations.

1.3 Research questions

To achieve the three sub-objectives and, consequently, the main, the following research questions must be answered:

RQ1: What are the current state-of-the-art cartographic methods employed for visualizing objective data and citizen knowledge, and what are their challenges and benefits?

A literature review must be carried out to understand already done projects and visualizations to achieve the first sub-objective. These sub-questions will act as a focus during the study:

- RQ1a: What elements and categorizations, such as visual variables and design elements stated by Jacques Bertin (1967), have been used and can be included as parameters for analyzing the visualizations?

- RQ1b: How are urban visualizations, those integrating objective data and citizen knowledge and those visualizing them separately, aligned with the selected analysis parameters?

RQ2: How can citizen knowledge and objective data be visualized using suitable visual variables, design elements, and cartographic generalization techniques to facilitate meaningful connections and pattern identification when interpreting urban data visualizations?

To achieve sub-objective 2, the following three sub-questions must be answered:

- RQ2a: Which visual variables and design elements are suitable to show the selected data? Should objective data and citizen knowledge be visually differentiated?

- RQ2b: How can cartographic generalization techniques be employed to create a simplified visualization that still conveys the underlying data patterns?

Finally, to achieve sub-objective three, an evaluation of the visualizations has to be carried out. An online survey will be undertaken with stakeholders with and without expertise. The aim is to understand the differences in interpreting the combined data layers and their preferred visualizations. The following questions must be answered:

RQ3: How do stakeholders' expertise levels influence their assumptions and preferences regarding visualizations, and are additional features required to effectively interpret and understand the data patterns in the identified case study?

To achieve sub-objective 3, the following three sub-questions must be answered:

- RQ3a: Is there a difference in the assumptions made by stakeholders with and without expertise? Do stakeholders without expertise need other kinds of features more than map symbology (texts, pop-ups, graphs) to interpret and make sense of data?

- RQ3b: Does modifying the symbology improve the intuitive interpretation of data patterns?

- RQ3c: Are there distinct visualization preferences among experts with expertise and non-experts without expertise?

The evaluation will determine and give hints about how biases in data interpretation can be reduced to create urban data visualizations where the understanding and analysis of urban areas can engage diverse stakeholders in the decision-making process.

1.4 Thesis Structure

1. **Introduction:** The first chapter gives a general overview of the thesis research, the motivation, the problem, and the identified research gap. It outlines research objectives, research questions, hypotheses, and the intended contribution of this research to cartography and urban data visualization.

2. **Literature review:** This chapter details the theoretical framework of this thesis research. The Literature review examines the change in the role of maps alongside urban planning. It explains their evolution from simply conventional graphic tools to powerful instruments to convey a comprehensive understanding of urban environments. Moreover, this review explores the different data types they can represent along with their classifications, emphasizing the importance of merging various data types to identify patterns within urban contexts. Finally, it addresses the theoretical frameworks behind the visual representation of spatial information.

3. **Methodology:** The methodology explains the designed workflow for creating the catalog and the visualizations. It elaborates on the four sub-sections (Framework development, Map analysis, Map design process, and User testing) and addresses the research questions each step aims to answer.

4. **Case Study:** The case study chapter defines the chosen project with its area, its topic, and the involved stakeholders. Subsequently, this chapter applies the suggested methodology

to the selected case study. This chapter also presents the survey and its results, offering insight into the participants, the survey design, its results, and the conclusions.

5. **Discussion:** This chapter relates the results to the research objectives, questions, and hypotheses. It also compares the results with existing research. Additionally, the chapter presents recommendations based on the findings, acknowledges research limitations, and outlines possible directions for future research.

6. **Conclusion:** This chapter concisely summarizes the thesis's key insights and contributions.

2 Literature review

Maps are an essential tool in urban planning, providing spatial arrangements and conveying urban dynamics. This literature review comprehensively examines the change in the role of maps alongside urban planning. It explains their evolution from conventional graphic tools to powerful instruments to comprehensively understand urban environments. Moreover, this review explores the different data types they can represent along with their classifications, emphasizing the importance of merging various data types to identify patterns within urban contexts. Finally, it addresses the theoretical frameworks behind the visual representation of spatial information.

2.1 Mapping cities throughout history

For thousands of years, maps have been an essential tool for urban planners to understand urban environments, encompassing their spatial, temporal, social, and material aspects (Arieff, 2014). However, its use has changed over time. Initially, maps served practical purposes, such as organizing and structuring urban spaces. They were graphical tools to lay out cities, streets, and landmarks (Arieff, 2014). It was not until the 18th century that cartography, the art and science of mapmaking, became a tool for statistical analysis (Vaughan, 2018). In this section, I look at the different uses of cartography and maps in urban planning from the 18th century to the present.

2.1.1 Maps for statistical analysis

At the end of the 18th century, cartography became an increasingly popular form of statistical analysis and communication of urban realities. This growth in popularity was facilitated by the expansion of social statistics (censuses, surveys, and other forms of population study) and the developments in statistical graphics and maps (Friendly and D.J. Denis, 2001; Vaughan, 2018).

The period from 1835 to 1855 is often referred to as the "golden age" of cartography, characterized by a flourishing interest in statistical and population representation, including factors such as population numbers, distribution, density, and movement (Robinson, 1955; Friendly et al., 2001; Vaughan, 2018). During this period, cartography shifted from primarily geographic mapping to a tool for statistical analysis, initially applied to the study of pandemic disease. Notable examples include Valentine Seaman's 1795 map of yellow fever cases in New York, which compared fever cases with local waste sites to identify the origin of the disease (Figure 1a) (Friendly et al., 2001; Vaughan, 2018). In 1854, John Snow used maps to track cholera clusters in London, disproving the miasma theory of disease spread (Figure 1b) (Friendly et al., 2001; Vaughan, 2018). This shift towards mapping statistics extended to other social issues such as crime and poverty. For example, Alexandre Parent du Châtelet's 1836 study used choropleth maps to analyze the link between prostitution and public health in Paris, shedding light on the "social topography of the city" and the historical regulation of sex work in relation to poor areas (Figure 2) (Vaughan, 2018).

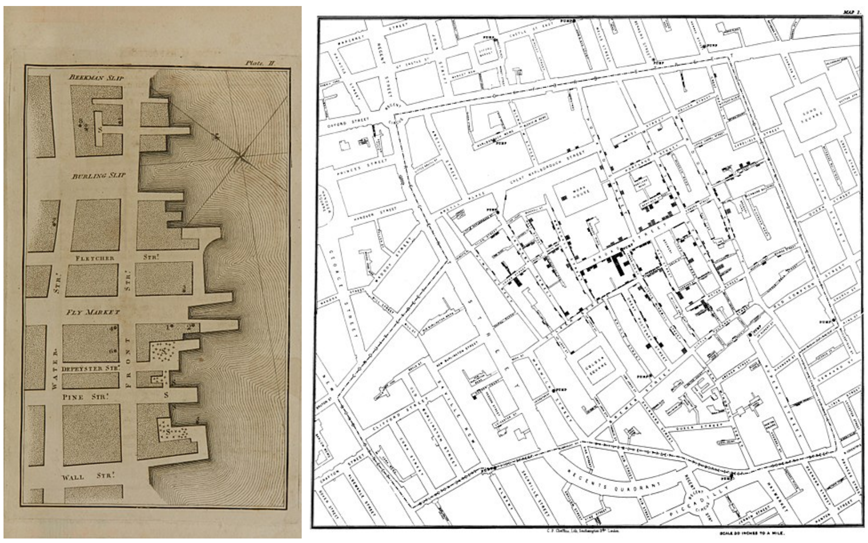

Figure 1: (a) Map of yellow fever on the left (Valentine Seaman, 1798). Retrieved from Wikimedia Commons and (b) map of cholera (John Snow, 1854). Retrieved from Wikimedia Commons.

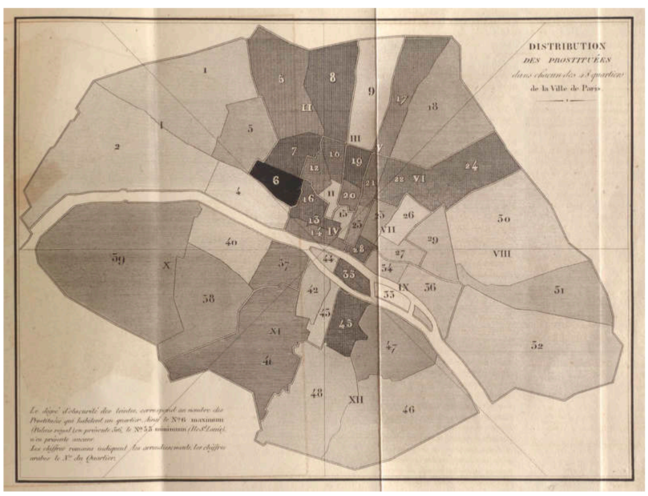

Figure 2: Distribution of sex workers in Paris (Alexandre Jean-Baptiste, 1836). Retrieved from Wikimedia Commons.

With the recognition of the growing importance of numerical information for urban planning, industrialization, and other fields, mapping reached its peak as an investigative tool in the 1880s (Friendly et al., 2001; Vaughan, 2018). Throughout the 18^{th} and 19^{th} centuries, maps began to focus on social inquiry rather than simply data records. Thus, cartographers had to consider not only the map's purpose as a social investigation but also the level of detail and scale of results needed to understand the urban life of the city (Vaughan, 2018).

In the early 20^{th} century, there were few graphical advances in mapping. By the 1930s, the popularity of formal models and quantification in the social sciences had overtaken the enthusiasm for visualization. However, it is reasonable to see this as a period of basic application, popularization, and dormancy rather than one of creativity and innovation (Friendly and D.J. Denis, 2001).

2.1.2 Maps for Participatory Urban Planning

In the 1950s, participatory urban planning gained prominence alongside movements to rethink cities (Guldi, 2017). This approach represented a paradigm shift in urban planning, as it involved the entire community in the planning process. The emergence of participatory planning was a reaction to earlier urban planning methodologies characterized by centralized and rationalist perspectives. Subsequently, the involvement of citizens in local governance has proven to be essential for the effective functioning of cities even nowadays. Thus, urban programs that adopt a paternalistic approach and disregard the insights and expertise of citizens run the risk of being misguided at best and potentially manipulative at worst (Godwin & Stasko, 2017). Within participatory urban planning, participatory cartography (also known as participatory mapping) has been recognized as a crucial component as it includes and represents the community's needs and preferences. It introduces qualitative and experiential knowledge of the communities in a spatial format. It maps, analyzes, and visualizes different perspectives on the same issues and includes all stakeholders in the decision-making process (Denwood, 2022; Hemmersam et al., 2016). Participatory mapping has changed the relationship between experts (e.g., researchers) and participants (e.g., community) by narrowing the division between them (International Fund for Agricultural Development, 2009).

Participatory cartography is the broadest term that could be used to subsume strategies such as sketch mapping, mental mapping, community mapping, participatory GIS (PGIS), and public participatory GIS (PPGIS), among others (Denwood, 2022). Denwood (2022) proposes a high-level and simple classification for participatory cartography. She divides the categories into "paper-based approaches" and "digital approaches". Paper-based strategies are typically referred to as "sketch mapping" or "mental mapping" (Boschmann & Cubbon, 2014). Sketch mapping uses a base map to perform contextualized mapping.

On the other hand, mental mapping uses freehand drawing to create spatial perceptions without any spatial context (Green et al., 2005). Digital approaches (PGIS) include public participation GIS (PPGIS), which allows the general public to take part rather than being limited to specific stakeholder groups. In this approach, traditionally produced by professionals, cartography becomes more democratic as everybody can be involved in mapping. Individuals can create maps that meet their needs by using platforms such as Google Maps and Mapbox and by taking advantage of the increasing amount of data available on the internet. OpenStreetMap, a collaborative mapping website, has become a real competitor to official institutions (Picon & Ratti, 2017; Crampton & Krygier, n.d.).

2.1.3 Maps for smart cities.

In the last 20 years, a new domain of digitally integrated urban space has come to be known as the smart city. Every piece of information is instantly revealed, and urban digital tools can control and optimize the urban analysis (Ratti & Claudel, 2016). These digital tools have revolutionized cartography and have given rise to dedicated communities, such as "CityVis" (Goodwin et al., 2021). CityVis, launched at the UN conference Habitat III in Quito, Ecuador, in 2016, promotes collaboration, knowledge exchange, and innovation in urban data analysis and visualization. CityVis focuses research on the technologies used to develop new visualization ideas and on the human-centric perspective in urban data visualizations. This perspective considers how people experience cities and how this insight can improve visualizations (CityVis.Io, n.d.).

Nowadays, cities generate increasingly large data volumes, allowing an unparalleled range of spatial analysis and visualizations. The analysis can cover environmental factors, such as pollution levels and the condition of vehicle traffic, to city-wide fine-grained urban population distribution at the building level (Goodwin et al., 2021; Picon & Ratti, 2017; Yao Yao et al., 2017). The visualizations can take multiple formats, ranging from static to digital interactive maps (Friendly et al., 2001; Knigge & Cope, 2006; Picon & Ratti, 2017). Static maps often function as visual evidence to convey a particular point of view and are placed intentionally into a larger narrative by an author. Two factors remain constant: the resolution of the underlying data and the size of the canvas where it is displayed. Static maps are limited to constructing complex visualizations where time, space, and scale work interdependently (Sauter et al., 2021). In contrast, dynamic maps have been created to allow users to explore, manipulate, and interactively display (real-time) data. Maps can be mixed with different graphics, texts, and sound, facilitating collaboration and dissemination.

Both static and interactive maps facilitate participatory urban planning by engaging diverse stakeholders and effectively communicating data, plans, and concepts. These tools serve as a bridge among stakeholders with different levels of expertise, including those with technical knowledge (such as members of academic and institutional bodies) and those with neighborhood expertise (such as citizens participating in the participatory process) (Sauter et al., 2021). While stakeholders may have varying levels of knowledge and engagement, establishing a common visual language is essential to reconcile their different viewpoints. Whether they are experts in the subject matter or in the local neighborhood dynamics. Creating an integrated visualization and structuring a network of spatial relationships stands out as one of the most critical challenges for cartographers creating urban visualizations for participatory urban planning (Hemmersam et al., 2016; Sauter et al., 2021).

2.2 Urban data classification

The transformation of cartography in the era of smart cities has revolutionized urban data analysis and visualization, accommodating a diverse range of data types and sources. Different urban data types demand different visualization and analysis methods. Therefore, it is crucial to comprehensively understand what data types can appear in the urban context and what visualization strategies can be applied to them.

Zheng et al. (2016) have categorized the urban data types frequently used in the urban visualization field by data's nature and usage. They have created five categories:

- Human Mobility Data facilitates the study of social and community dynamics and can be sub-categorized into traffic data, commuting data, mobile phone data, and geo-tagged social media data.
- Social Network Data includes all user-generated social media data, such as texts, photos, and videos, which contain rich information about a user's interests and characteristics, all the relationships among different people, and the social structure of a specific community.
- Geographical Data provides the basic structure and semantic information for urban computing scenarios. In the visualization field, frequently used data of this type are road network data, transportation network data, and POI data (point of interest).
- Environmental data includes environment monitoring data, such as meteorological data (e.g., temperature, humidity, sunshine duration, weather conditions), air pollution data, water quality, and satellite remote sensing data. It also includes energy consumption data, such as records of electricity, gas, etc.
- Other related data: health care data, public utility service data, economy data, education data, manufacturing data, and sports data.

Regardless of the data's nature, another urban data classification can be based on the data source. Data can be broadly classified by its source as objective and citizen knowledge data. From the IoT (Internet of Things) perspective, objective data can be obtained from sensors, GPS receivers, and smartphones, while citizen knowledge is collected directly from humans (Erhan et al., 2019).

2.2.1 Objective data

Objective data refers to information about a place or community based on verifiable facts and figures, such as population density and land use. Objective data requires a top-down approach to data collection, where official sources typically generate the data, and the data presents a standard and consistent urban information (Godwin & Stasko, 2017; Sayegh et al., 2016).

Objective data provides a reliable and impartial basis for planning decision-making processes. As an example, the Berlin map "Nahes Grün, Fernes Grün" ("Near Green, Far Green") created by Eisemann et al. (2021) (see Figure 3) uses 100% objective data. The map shows differences in the distribution and accessibility of green spaces in Berlin. For the creation, the authors used freely available objective datasets, including geographical, environmental, human mobility, and population data. The geographical data includes the green spaces polygons, and the environmental data has noise pollution, vegetation amount, and available facilities. The human mobility data consists of routing data to calculate travel time areas. Finally, population data carries the number and percentage of Berlin residents who can reach a green space under certain conditions.

Figure 3: An example of an objective data map. Screenshot of Near Green, Far Green map (Einsemann et al., 2021). Retrieved from https://uclab.fh-potsdam.de/mapping/nahesgruen/.

2.2.2 Citizen knowledge data

> The people who inhabit the territory are the ones who can really create and transform the space; they shape those spaces every day by inhabiting them, going through them, perceiving, and creating them (Ares & Risler, 2013, p. 10).

On the other hand, citizen knowledge data refers to information and insights about a place or community based on personal experiences and perspectives. This data type is often (but not always) subjective and can include the perception of safety, feelings of attachment to a place, and knowledge of local customs and practices (Erhan et al., 2019). Citizen knowledge data provides valuable insights for a holistic understanding of urban spaces. As an example, the map "Malleshwaram Memoirs" created by Nagpal Prachi (2015) (see Figure 4) uses citizen knowledge data. The map visualizes the rhythmicity of the city by representing human perceptions and experiences of its urban fabric. The visualization contains objective data comprising the geographical location of points of interest. These points were divided into nine categories depending on their use: religious, cultural, etc. On this map, citizen knowledge data consists of perceptions and experiences of individuals in these points of interest. This data consists of "emotional feeling of the place", "sense of pace and temporality", and "social rhythm" (see Figure 4). The "emotional feeling of the place" could be described as "calm and harmonious" or "stressed and restless". The "sense of pace and temporality" could be described as "intermittent" or "continuous" and "slow" or "fast" and their combinations. In the case of "social rhythm", two categories were provided: "societal", pertaining to communal social activities, and "cultural", arising from shared meanings of codes, gestures, and more.

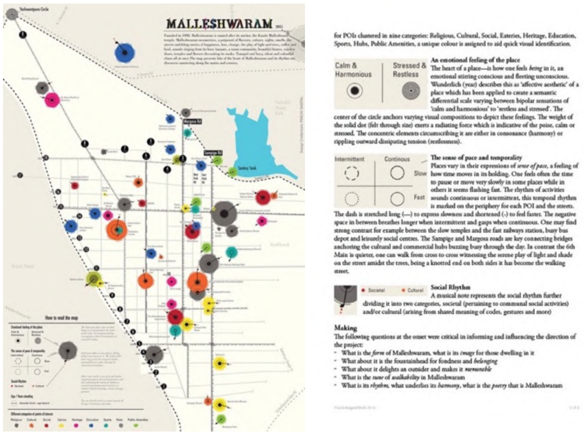

Figure 4: An example of a map with citizen knowledge. Malleshwaram Memoirs (Nagpal Prachi, 2015). Retrieved from https://www.cityvis.io/

In summary, the map "Malleshwaram Memoirs" vividly exemplifies the use of citizen knowledge data to capture the intricate nuances of urban life, shedding light on emotional landscapes, temporal rhythms, and social dynamics within the cityscape. This form of data requires a bottom-up approach to be collected. The collection can be done through participatory methods, such as surveys and participatory cartography (see Section 2.1.1) (Hemmersam et al., 2016; Sayegh et al., 2016). In recent years, there has been an increase in the significance of participatory cartography for integrating personal experiences and perceptions to create, maintain, and legitimate social, economic, and political processes (Knigge & Cope, 2006). One of the biggest challenges of participatory mapping is translating the intangible and fleeting nature of personal experiences and perceptions into a tangible form.

Most of the time, participatory mapping methods require researchers to conduct a series of workshops to document the values, ideas, and opinions of citizens (Godwin & Stasko, 2017). Each method has different objectives and requires different process time and resources. One of the most used and known approaches is mental mapping. This approach uses the advantages of paper map techniques, integrating rapid sketch representations that improve simplicity and communication during the workshops. Moreover, as mental mapping does not rely on advanced technology, it is accessible for individuals, making it easy for more people to comprehend and engage in (Al-Kodmany, 2002; Godwin & Stasko, 2017).

Mental mapping has been used to capture people's perceptions of places (Jung, 2014). Kevin Lynch (1960), a renowned urban planner, was one of its early developers. In his influential book The Image of the City (1960), Lynch asked people to share their feelings about landmarks, routes, and areas they often used while driving around. Later, he sketched a general image of the city by pinpointing the essential elements and feelings shared by participants. He identified three main elements: nodes (areas of heightened activity and interaction), paths (channels that people take to move around the city), and edges (barriers that divide regions). For example, Figure 5 shows a map of Boston derived from the consensus of verbal interviews with a sample of citizens regarding their image of the environment. Participants made sketch maps describing several trips through the city, highlighting the most distinctive or memorable elements in their minds. Additionally, trained observers made a systematic field examination of the environment. These methods provide urban planners with invaluable data to create more inclusive and effective cityscapes and empower individuals to contribute to urban planning.

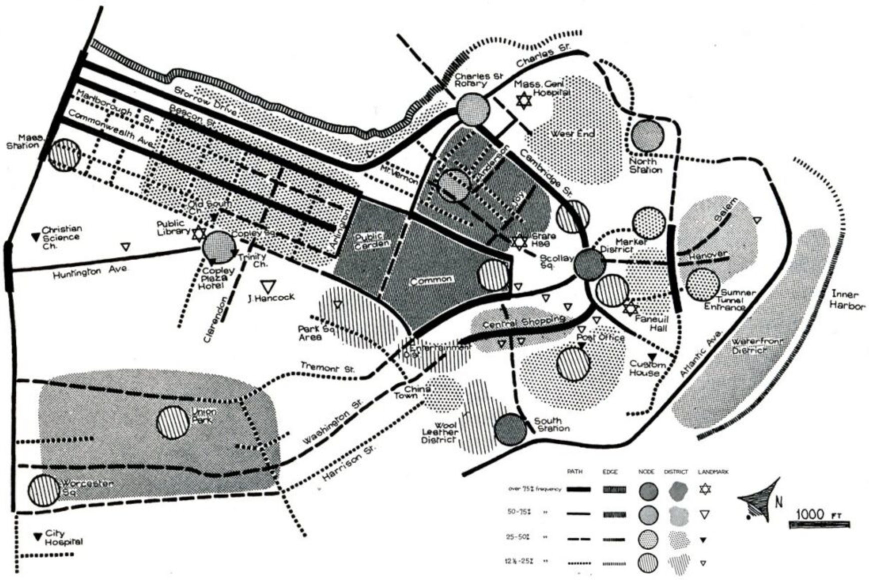

Figure 5: Mental map derived from interviews and sketch maps. (Lynch, 1960, p. 147).
Retrieved from the book "The Image of the City" by Kevin Lynch. Publisher: MIT Press.

2.2.3 Merging citizen knowledge and objective data

Representing multiple types of data can improve interpretations of the world and encourage diverse views of reality. Firstly, different data types can complement each other to fill information gaps and enrich insights. Secondly, multiple interpretations can coexist, even when they appear contradictory, each offering a valid perspective. These discrepancies can represent new areas for exploration (Knigge & Cope, 2006).

Visualizing and analyzing objective data through various techniques in urban planning can reveal patterns and correlations. However, it is essential to recognize that citizen knowledge data can provide deep insights from the experiences of real people living in specific conditions, even if their explanations and perceptions might appear to differ from other data sources (Knigge & Cope, 2006). Relying solely on objective data or citizen knowledge in isolation may result in an incomplete understanding of the urban environment (Godwin & Stasko, 2017; Sayegh et al., 2016).

Moere & Hill (2012) emphasize that effective participatory urban planning practices require a fusion of existing objective data and citizen knowledge data. Incorporating citizen knowledge into objective data ensures that the voices and experiences of residents and community members are considered. This inclusive approach leads to more equitable and people-centered decision-making processes, addressing the needs and concerns of the urban population. This approach includes giving a voice to under-represented citizens and understanding biases (Goodwin et al., 2021). Figure 6 shows the Anti-Eviction Mapping, an exemplary participatory mapping project giving voice to the under-represented. This project maps the housing crisis in the San Francisco Bay Area and documents the landscapes, lives, and sites of resistance and dispossession (CityVis, n.d.). The map presents a stark reality demonstrating the magnitude of ongoing displacements by using red points to visualize the precise geographical locations of evictions. However, it goes beyond statistical data by incorporating real stories from people in audio and pop-up formats, offering a more profound understanding of the human experience of eviction. This combination of visual and narrative elements provides a more accurate and empathetic portrayal of the impact and implications of being evicted. It directly connects society and space, showing that an urban phenomenon, such as segregation, is not only a product of social structures but also of urban configurations (Vaughan, 2018).

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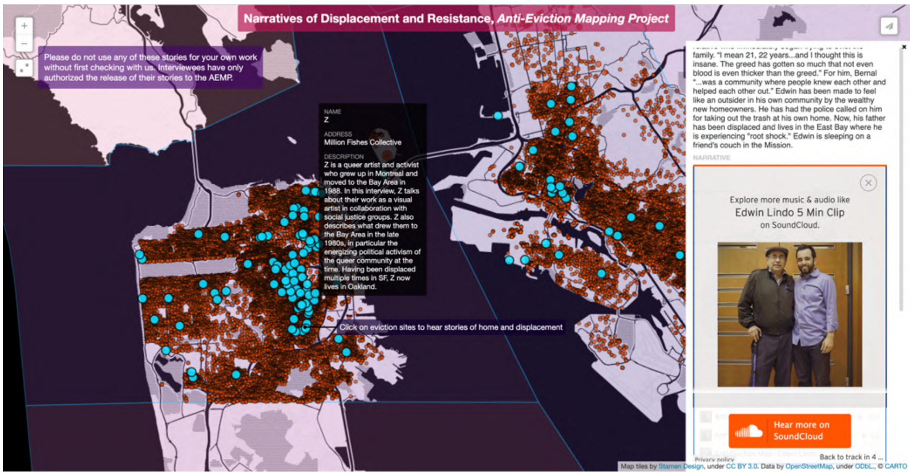

Figure 6: Map displaying citizen knowledge and objective data. Narratives of displacements and evictions map (Anti-Eviction Mapping Project, 2016). Retrieved from http://www.antievictionmappingproject.net/narratives.html

Citizen knowledge also helps to contextualize objective data. Residents can provide context-specific information about cultural practices, community dynamics, and local nuances that may not be evident from objective data alone. This contextualization improves the accuracy and relevance of the data analysis (Erhan et al., 2019; Sayegh et al., 2016). One of the most prevalent visualization types, the visualization dashboard, has found many applications in monitoring and controlling urban infrastructure. Understanding how the actual physical location of a city space and the user's sense of place interact presents an even greater challenge (Goodwin et al., 2021). For example, the project "Desirable Cities" (see Figure 7) visualizes the shortest routes and compares them with the most desirable routes, where people prefer to walk. For this analysis, objective data was employed to create the shortest route. Then, citizen knowledge data represented by people's deviations from the shortest path in more than 120,000 trips showed the most desirable streets in Boston. Finally, the characteristics of the built environment were analyzed to understand what the most desirable street segments had in common. In this case, community dynamics data was vital to understand the wider community's preferences.

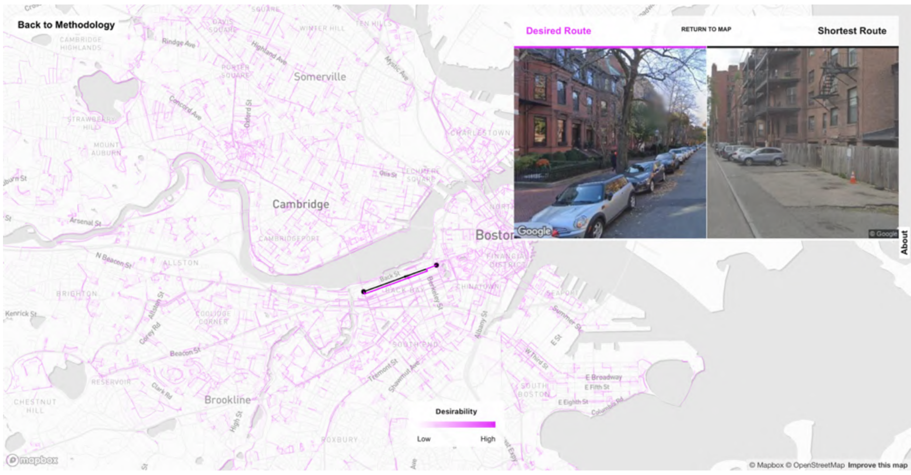

Figure 7: Map displaying citizen knowledge and objective data. Desirable streets in Boston map (Desirable streets project). Retrieve from https://senseable.mit.edu/desirable-streets/.

Citizens may possess valuable information about urban issues that traditional data sources may not capture. Engaging with citizen knowledge can help identify data gaps and areas where additional data collection may be needed (Erhan et al., 2019; Goodwin et al., 2021; Klettner & Huang, 2013). For example, in a study by Dennis (2006), local youths were interviewed and requested to generate sketches depicting their perceptions of the qualitative aspects of the environment. These sketches included how problematic intersections affected their intended routes within the neighborhood. Combining these mental maps with the official police data about the spatial distribution of crimes, greater accuracy was achieved. If these maps had been created based solely on authoritative data, they would not have captured the insights of the workshop attendees (Godwin & Stasko, 2017).

In summary, a comprehensive understanding of the urban environment requires the integration of objective data and citizen knowledge data. While objective data reveals patterns, citizen knowledge provides valuable insights from residents' experiences. Relying on either source alone can lead to an incomplete understanding. Effective participatory urban planning involves combining these types of data to ensure that community voices are considered, to contextualize objective data, and to identify data gaps. This integration leads to more equitable and people-centered decision-making processes.

2.3 Urban data visualization analysis

Visualizing integrated objective data and citizen knowledge has already shown promise in enhancing the accurate comprehension of urban environments (Erhan et al., 2019; Goodwin et al., 2021; Klettner & Huang, 2013). However, effectively visualizing this combined data to understand patterns among different stakeholders remains a challenge (Goodwin et al., 2021). This section presents and explains the parameters to analyze different urban data visualizations. These parameters include visual variables, design elements, generalization techniques, and complexity levels.

2.3.1 Visual variables

Jacques Bertin (1967) analyses the map as an ordered network where geographic elements can take the form of POINTS, without dimensions (geodetic points, junctions, crossroads); LINES, also without dimensions (coastlines, river axes, natural or human boundaries); or AREAS, which do have perceptible dimensions (cities, lakes). Zheng et al. (2016) introduce the visualization techniques for these three types of geographic elements: point-based, region-based, and line-based visualization.

- Point-based visualization is a straightforward and intuitive method for presenting and analyzing locations. It involves placing points or special symbols on their geographical coordinates' location. This technique allows users to easily observe individual data points. However, as data points increase, visual clutter can make the visualization unclear and challenging to interpret. Heatmaps with kernel density estimation (KDE) are commonly employed to address this issue. Figure 8 shows an example of a point-based visualization.

Figure 8: An example of Point-based visualization. Screenshot of Mapping ethnic communities in Brussels map (University of Leuven, 2016). Retrieved from https://www.cityvis.io/

- Line-Based Visualization represents locations based on road maps or traffic networks, commonly known as linear referencing. It can also depict locations based on trajectories, such as paths or routes taken by objects over time. Trajectories can be represented as lines or curves on a map, connecting the initial and final points in sequence. To uncover hidden patterns, trajectories can be transformed and visualized using topological or geometric algorithms. Figure 9 shows an example of a line-based visualization.
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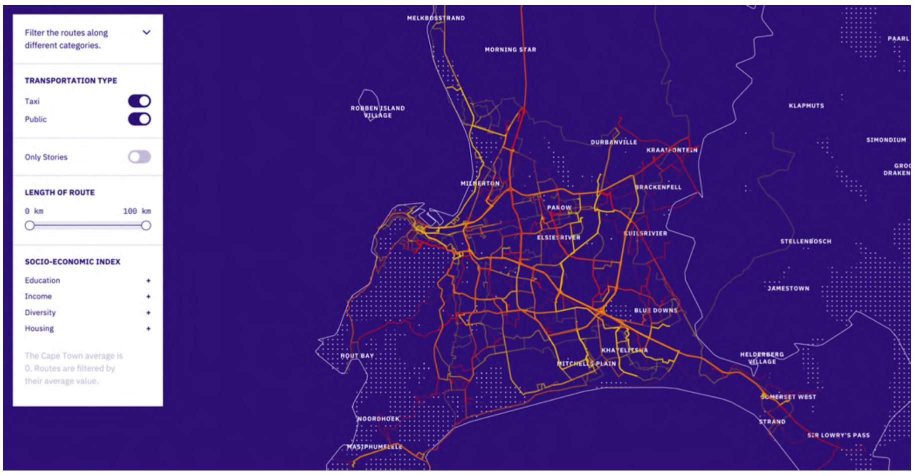

Figure 9: An example of Line-based visualization. Screenshot of City Flux (University of Applied Sciences Potsdam, 2018). Retrieved from https://city-in-flux.netlify.app/

- Region-Based Visualization focuses on displaying aggregated information based on predefined regions. A typical example is the choropleth map, where regions are shown as colored areas with colors representing specific attributes. Region-based visualization is excellent for revealing broader patterns, such as flows among regions, but may not be suitable for analyzing individual behavior in detail. It is often combined with other techniques to provide a comprehensive analysis with varying levels of detail. Figure 10 shows an example of a region-based visualization.
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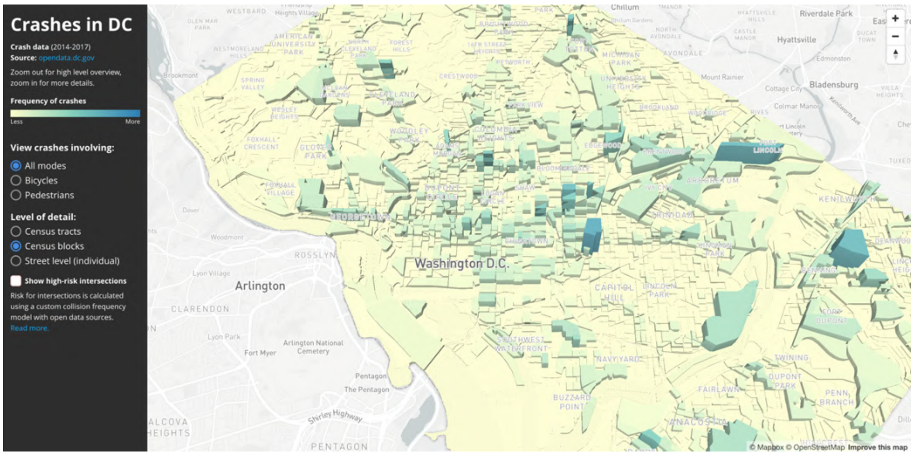


Figure 10: An example of Point-based visualization. Screenshot of Crashes in DC map (Mapbox, 2017).
Retrieved from https://labs.mapbox.com/bites/00379/#10.5/38.8994/-77.0134/0/40

Other types of properties, such as textual properties, may require different techniques for visualization. These specific methods cater to the unique characteristics of the data being visualized, ensuring clear and meaningful presentations for various types of information. In summary, visual variables serve as the foundational elements for visualizing data, but the mere spatial placement of map symbols is not enough to convey the richness of data. Incorporating design elements is crucial to move beyond the spatial location representation of data.

2.3.2 Design elements

A map can only be perceived as a single image when two or more data layers are involved (Bertin, 1967). To make these two layers readable, they must be represented by an ordered “retinal variable”. These retinal variables, known as design elements, are divided into the following (see Figure 11):

- Location: describes the position of the map symbol relative to a coordinate frame. It is considered an ‘indispensable’ visual variable and takes visual primacy over the others.
- Size: describes the amount of space occupied by the map symbol. It is the primary visual variable manipulated in proportional symbol maps.
- Shape describes the symbol's external form and can vary from highly abstract, such as circles, to highly iconic.
- Color hue: describes the specific color we see, such as red, blue, or green.
- Color value: refers to how bright or dark a color appears in a map symbol. Accordingly, color value is sometimes referred to as ‘lightness’ in color theory.
- Orientation: describes the direction or rotation of the map symbol from “normal”. Orientation is also manipulated in flow maps to represent the directionality of flow.
- Texture: refers to how rough or fine the pattern inside the symbol looks.

Bertin’s set of visual variables was extended by Morrison (1974) to include two additional variables employed in the cartographic design (Roth, 2015):

- Color saturation: describes the intensity of the color employed in a map symbol. It goes from bold or saturated colors to pastel or desaturated ones.
- Arrangement: refers to how the graphic marks are organized to constitute a map symbol. The visual variable arrangement can range from regular to irregular.
-

Finally, MacEachren (1995) identified three additional visual variables that are easier to manipulate using digital production methods (Roth, 2015):

- Crispness: describes the sharpness of the boundary of the map symbol. Crispness is also called ‘depth-of-field’ and ‘fuzziness’ in Information Visualization.
- Resolution: refers to the level of spatial precision at which the map symbol is displayed. It is related to the concept of generalization, which involves simplifying the map to fit a smaller scale, and removing some details while keeping meaningful information.

- Transparency: describes the amount of graphic blending between a map symbol and the background or underlying map symbols.

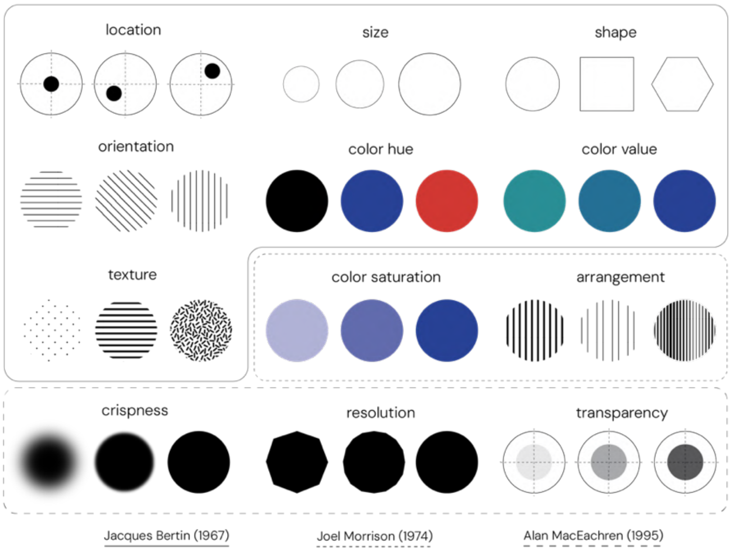


Figure 11: Visual variables.

In summary, design elements, or retinal variables, are pivotal to comprehending a map's intricate relationships among multiple data layers. These attributes allow the user to differentiate and grasp the presented data. Sometimes, displaying individual data points becomes impractical due to data volume or excessive detail. This is when generalization techniques are crucial for enhancing the accessibility and clarity of complex spatial data in cartography.

2.3.3 Generalization

Generalization is the spatial equivalent of simplification (Bertin, 1967). It involves identifying common concepts among available data points within a specific area to distinguish it from neighboring regions. Bertin (1967) classifies generalization in two:

- Conceptual Generalization: It involves changing how something is represented on the map. For example, individual points can be adjusted to be shown as a whole area, such as transforming "accident locations" into "number of accidents per area" (see Figure 12). This requires new information beyond what is already available.

- Structural Generalization: In this case, a consistent approach depicting something, such as the arrangement and shape of the phenomenon, is maintained, but the distribution on the map must be simplified. It involves reducing map details while keeping it comprehensive with the available information.

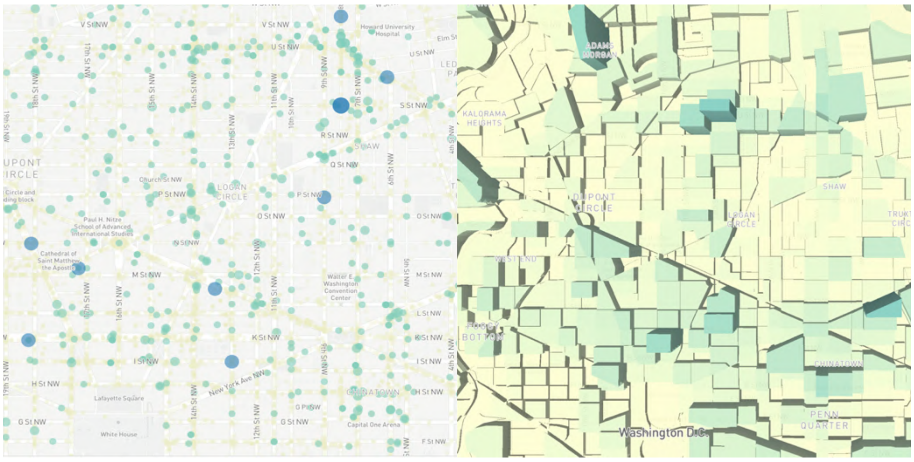


Figure 12: Conceptual generalization. From a point-based visualization to a region-based visualization. Screenshots of Crashes in DC map (Mapbox, 2017). Retrieved from https://labs.mapbox.com/bites/00379/#10.5/38.8994/-77.0134/0/40

Generalization is crucial, especially in non-interactive maps, which cannot be dynamically rescaled. The heatmap is one of the most common conceptual generalizations employed in urban planning. In heatmaps, Kernel Density Estimation or Point/Line Density Estimation are employed to transition from source data to surfaces. However, it is essential to recognize that generalizing information can potentially lead to misinterpretation or loss of critical details. While heat maps and similar techniques offer valuable simplifications, they may not capture the nuanced intricacies of specific data points. As a result, urban planners must be cautious about relying solely on generalized representations and consider their limitations to ensure that important insights are not overlooked in the pursuit of simplicity and clarity.

2.3.4 Complexity levels

Urban data is characterized by complexity and interconnectivity. These two characteristics are due to the growth and diversity of the data and the intricate interconnections that can be done between different datasets and analytical methods (Goodwin et al., 2021). By overlapping different datasets, more significant insights can be gained when examining their intersections (Ratti & Claudel, 2016).

Even though the complexity of urban data, the use of visual variables, design elements, and generalization techniques can be helpful in making data readable by simplifying and organizing the complex geospatial intersections and avoiding visual outputs to cognitively overwhelming the viewer (Sauter et al., 2021).

Jacques Bertin (1967) describes the complexity of visualizations by the number and type of components employed. A component is based on its nature and characteristics. He identifies four main types of components in cartography: the Geographic Component (GEO) represents the spatial dimension of the data, including points, lines, and areas on the map. The GEO involves mapping the locations of landmarks (points), road networks (lines), and administrative regions (areas); the Qualitative Component (≠) involves categorical or qualitative data, where items are grouped into distinct classes or categories. It categorizes land cover types or classifies neighborhoods by socioeconomic status; the Quantitative Component (Q) deals with numerical data and involves measures or quantities associated with geographic locations. These data are ordered in categories, and these categories can manifest at variable distances. The Q visualizes population density, crime rates, or traffic volume; the Ordered Component (O) also involves numerical data. However, the distances between categories are accepted as equal (because of universally acknowledged sequence or accepted a priori). In other words, even if O and Q represent numerical data and have an order, O represents equal intervals, while Q manifests variable distances between intervals.

Bertin then categorizes map complexity into three forms: maps involving one component (GEO); maps involving two components when the information relates a geographic component to a single additional component (GEO+≠, GEO+Q, or GEO+O); and maps involving more than two components (GEO+≠+Q, and all the possible combinations). He suggests an image can handle up to three components but must be visually ordered. The visual arrangement enhances map comprehension using visual variables, design elements, and generalizations.

In conclusion, effectively visualizing integrated objective data and citizen knowledge is a promising way to improve our understanding of complex urban environments. The complexity of urban data requires a thoughtful and balanced approach to visualization, where the right choice of visual variables, design elements, and generalization techniques play a critical role. These techniques must work harmoniously to enable meaningful analysis and informed decision-making, ensuring that essential insights are not lost in the pursuit of clarity.

3 Methodology

The research objectives are addressed by implementing the following general stages: Framework development, Map analysis, Map design process, and User testing (see Figure 13). I elaborate on these four stages by comprehensively describing their precise steps and the research questions each step aims to answer. Additionally, the source materials created and used during the process and the outcomes of each step are presented.

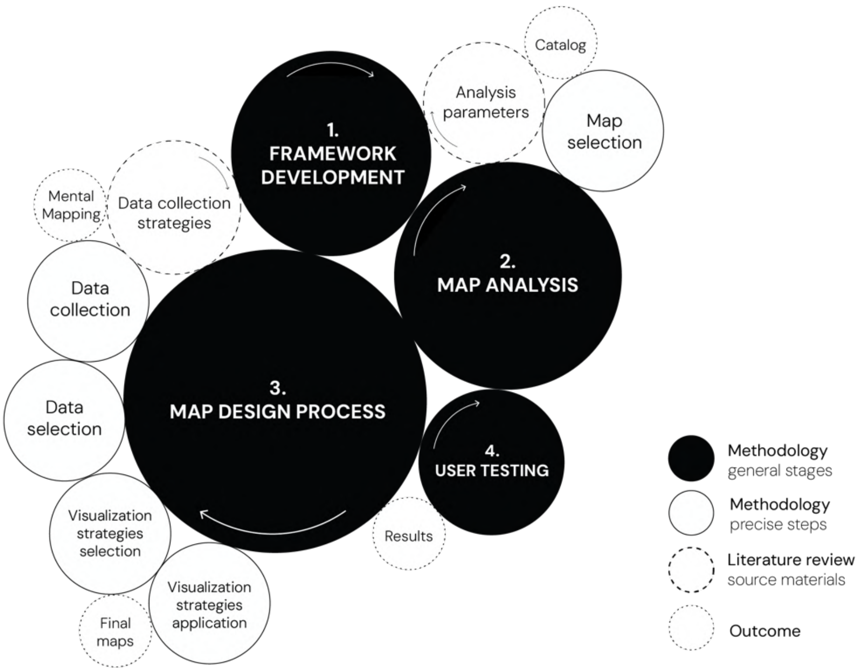


Figure 13: Graph representing the methodology used in the research.

3.1 Framework development

The framework development was conducted for two primary objectives: parameter establishment to use during the map analysis stage and data collection strategy for using during the map design process stage. These two objectives are represented in Figure 13 by a dashed circle. The first objective focused on answering RQ1A, creating a set of parameters to comprehensively analyze existing urban data visualizations. The parameters adopted were the following: data classification by type and origin, visual variables, design elements, use of generalization, and complexity of the visualization. These parameters are explained in Sections 2.2 and 2.3 of the Literature Review chapter, along with their significance and relevance to the study. The second objective focused on finding a data collection strategy for gathering missing citizen knowledge data later applied to the Map design process stage. Diving into various methodologies, the review culminated in selecting the Mental Mapping approach as the most fitting strategy for this study's specific case. Section 3.3.1 explains the approach and the reasons behind its selection.

3.2 Map analysis

The map analysis stage addressed RQ1b, aiming to identify visualization strategies employed in urban data visualization design. This stage was subdivided into two steps. Firstly, maps were selected from the CityVis repository, and then the selected maps were analyzed by applying the analysis parameters. The outcome of this step was the catalog, compilating the selected maps and their associated analyzed parameters (see Figure 14 with a graph of the Map analysis steps). The catalog serves as a structured compilation of visualization strategies employed in the urban visualization domain, helping to identify best practices in urban data representation.

For creating the catalog, a categorization of complexity levels in urban data visualizations was designed. For categorizing these levels of complexities, the concepts of components outlined by Bertin (see Section 2.3.4) were considered. The categorization is divided into low, medium, and high complexity levels.

- Low Complexity (Simple Visualizations): refers to what Bertin called “maps involving two components” and consists of simply a geographical component and one of the other categories. This enables a limited number of visual variables and design elements. In the case of interactive visualizations, basic representations of data without sophisticated interactions are used. The level of interaction with the data must be low, and viewers can explore basic details but not deeply analyze or manipulate the visualization.

- Medium Complexity (Moderately Complex Visualizations): consists of three components. A simple data categorization exists to differentiate data points or elements. It is necessary to employ multiple colors, shapes, or sizes to convey information; these visual variables enhance hierarchy and understanding. The level of interaction can be moderate, and viewers can explore data with some drill-down capabilities or filtering options for deeper analysis.

- High Complexity (Highly Complex Visualizations): consists of 3 components and encompasses a wide range of data interactions and connections. It can include extensive data categorization and organization for in-depth analysis, intricate data visualizations with complex relationships, and advanced use of visual elements and design principles. It has a high level of interaction; viewers can engage in advanced exploration, filtering, and data manipulation for detailed insights and complex data connections.

As already stated, the CityVis (n.d.) platform was chosen as a repository for the visualization selection. CityVis is an accessible repository where urban data visualization projects can be showcased and shared with a broader audience through a straightforward application process. This allows the designer to learn and be inspired by diverse urban data visualizations. All of the visualizations of the website were applicable to the analysis. However, a selection process was implemented due to time constraints. Visualizations related to the case study, regarding the data used and their topics, were primarily included. Additionally, various visualizations were incorporated to showcase different parameters, such as varied data types, visual variables, design elements, generalization techniques, and complexity levels.

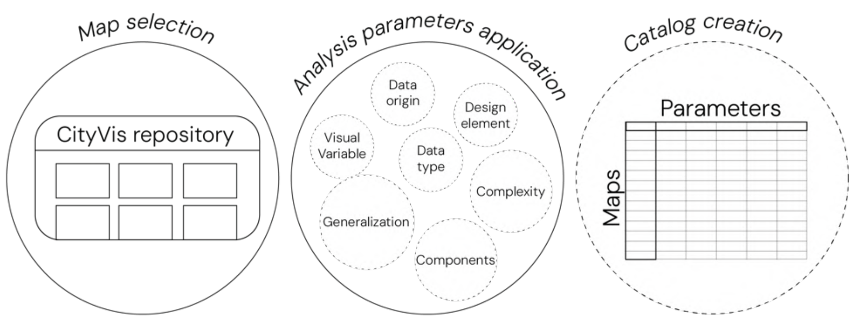


Figure 14: Graph representing the Map analysis stage.

The selection process yielded an Excel catalog with 18 urban data visualizations (see Figure 15). These visualizations were analyzed using the predetermined parameters (elaborated in Sections 2.2

and 2.3): data origin, data type, visual variable, design element, applied generalization technique, components, and visualization complexity. Additionally, the catalog integrates other pertinent details such as visualization name, data detail, author, geographic area, publication year, and source link. Each detail represents a distinct column within the Excel file. This structured approach ensures a thorough and systematic evaluation of the visualizations' characteristics and qualities.

1	Name of the visualization	Data by origin	Data by type	Data detail	Visual variable	Design element	Symbology detail	Generalization	Component	Complexity	Author	Area	Year	Source link
13		objective data	geographical	Green spaces	area	colour	green polygons							
14		objective data	environmental	noise pollution	area	value	orange polygon+G13:H17s opacity							
15	Nahes Grün, Fernes Grün	objective data	environmental	vegetation amount	area	value	orange polygons opacity			medium	Ella Eisemann Ester Scheck Henning Oskamp Jona Pomerance	Berlin	2021	tsdam.de/ma
16		objective data	human mobility	Routing data	area	size	green buffer (+ travel time, bigger)							
17		objective data	other	Population	graph		Extra graph with text + percentage							
18		objective data	geographical	Base map				no	geographical					
19	visitmyorbit	objective data	geographical	Artist	point	location	gray points for all, blue point when selected	no	geographical	low	nie Neumann, Alsino Skov	Berlin	2021	t.vercel.app/gr
20		citizen knowled	geographical	Artist relations	point	location	black points when selecting an artist	no	qualitative					
21		objective data	human mobility	Public transport	line	value	more transparency, less traffic							
22	City in Flux	objective data	human mobility	Shared taxis	line	value	more transparency, less traffic			high	Fabian Dinklage, Caroline Doyé, Fabian Ehmel, Valentina Tröndle	Cape Town	2018	ity-in-flux.net
23		objective data	other	Census data	graph		pops ups a graph showing the connection between demographic statistics through ou							
24		citizen knowled	other	random stories	text		a point on the graph leads to a text with local stories							
25		objective data	geographical	Base map					geographical					
26	AMOR SP	citizen knowled	social network	feeling of love	point	size	bigger the point, more love posts	no	ordered	medium				https://mrsedr
27		citizen knowled	social network	feeling of hate	point	size	bigger the point, more hate posts	no	ordered		Maycon Sedrez	Sao Paulo	2018	
28		objective data	other	Criminality	point	size	the map is divided in a grid, the bigger the circle in the	no	ordered					
29		objective data	geographical	Base map	point			no	geographical					
30		objective data	other	Superficie de vivienda segun catastro	point	size	bigger the circle, more residential surface	no	quantitative					
31	Turistificación - Dormir	objective data	other	Proporción de población por m2 de vivie	point	size	bigger the circle, more dense the area	no	quantitative	high				
32		objective data	social network	Numero de ofertas de alojamiento en Airl	line	size	thicker the line, more airbnb publications	no	ordered					
33		objective data	social network	Ofertas de alojamiento p2p que han aloja	line	size	thicker the line, more tourist hosted	no	ordered					
34		objective data	other	Superficie de hoteles según catastro	line	size	thicker the line, more hotels	no	quantitative					
35		citizen knowled	social network	Number of pictures taken by locals	point	size	bigger the circle, more pictures taken by locals	no	ordered					
36		citizen knowled	social network	Number of pictures taken by tourists	point	size	bigger the circle, more pictures taken by tourists	no	ordered					
37	Turistificación - Pasear	citizen knowled	social network	Increase of taken pictures in the last 4 ye	point	size	bigger the circle, more pictures taken in the last 4 year:	no	ordered	medium	300.000km/s, la casa encendida de Fundacion Montemadrid	Madrid	2017	ificacion.300
38		citizen knowled	social network	Percentage of pictures taken by tourists i	point	size	bigger the circle, more pictures taken by tourists than	no	ordered					
39		objective data	other	Museums and number of visitors	point	size	bigger the circle, more visitors in the museum	no	quantitative					
40		objective data	geographical	Heritage	area	location	yellow area where the heritage is located	no	geographical					
41		objective data	other	Area of low commercial density	point	size	bigger the circle, lower commercial density							
42		objective data	other	Number of supermarkets	point	size	bigger the circle, more supermarkets							
43	Turistificación - Servicios	objective data	other	Number of shops specialed on fresh foo	point	size	bigger the circle, more shops selling fresh food							
44		objective data	other	Number of educational institutions	point	size	bigger the circle, more schools							
45		objective data	other	Bars and restaurants most visited by Trip	point	value	thicker the polygon, more restaurants visited							
46		objective data	geographical	Base map				no	geographical					
47	Haltestelle	objective data	geographical	public transport network	line	colour	different colors, different lines	no	qualitative	medium				
48		objective data	human mobility	public transport line punctuality	point	graph	pie charts along the line showing percentage of how e	no	ordered		Tagesspiegel	Berlin	2016	agesspiegel.de
49		objective data	geographical	Bike crashes	point	location								
50	Visualising fatalities in Washington DC	objective data	geographical	Pedestrian crashes	point	location								
51		objective data	human mobility	Severity of the crash	point	colour	Color depends on the severity of the crash							
52		objective data	human mobility	Bike crashes	area	value	More crashes, higher the area			medium	Mapbox	Washington	2017	es/00379/#12
53	Visualising fatalities in Washington DC	objective data	human mobility	Pedestrian crashes	area	value	More crashes, higher the area							
54		objective data	human mobility	Severity of the crash	area	colour	Color depends on the severity of the crash							
55	Rionow.org	objective data	other	Urban projects constructed from 2009 t	area	value	The higher the mountain the more projects that where constructed in that area			low	Universidade Católica do	Rio de Janeiro	2016	
56		citizen knowled	social network	Ethnicity	point	colour	Different colors, different ethnic							
57	Mapping Ethnic Communities in Bruss	citizen knowled	social network	Languages	point	colour	Different colors, different languages			medium	t of Architecture, Universi	Brussels	2016	roject/mappin
58		objective data	geographical	Specific nodes	point		number + reference							
59		objective data	other	Space: building reach, FAR, Pedestrian acc	area	colour	Heatmap, from pink to blue (easy access-non access)							
60	Turku Open Platform and the 15min ci	objective data	other	Activities: consumption, mobility, necess	area	colour	Heatmap, from pink to blue (easy access-non access)			high	SPIN	Turku	2018	pinunit.gitlab.
61		objective data	other	Values: indoor activity, lively places, popular indoor, popul		colour	Heatmap, from pink to blue (easy access-non access)							
62		objective data	geographical	Position	graph		Popup shows the mean of each category for a particular POI one places							
63	A sense of place - activity patterns	objective data	geographical	Activities	point	color hue	Magenta, yellow and blue depending on the type of ac	no		low				

Figure 15: Screenshot from the catalog.

Regarding the analysis of the visualizations, it is important to highlight that this study focuses on the urban data layers and components beyond the constant base map. Consequently, the analysis did not extend to examine the layers incorporated within the base map. Next, selected examples detailing the established parameters to illustrate the analysis process are showcased. To access the entire catalog and a detailed breakdown of the analyzed parameters concerning this visualization of the below examples, please refer to Appendix A.

Example 1: Mixing citizen knowledge and objective data in crime analysis in low complexity visualization - AMOR SP (2018) by Maycon Sedrez.

"Amor SP" is a static map visualization (see Figure 16) that tries to establish spatial correlations between feelings of love and hate within the city and crime hotspots in Sao Paulo. This map employs a point-based visualization, which is of low complexity since it employs two types of components:

geographical and ordered. In “Amor SP” feelings were mapped using social media geolocated tags, while criminality data was sourced from official data repositories.

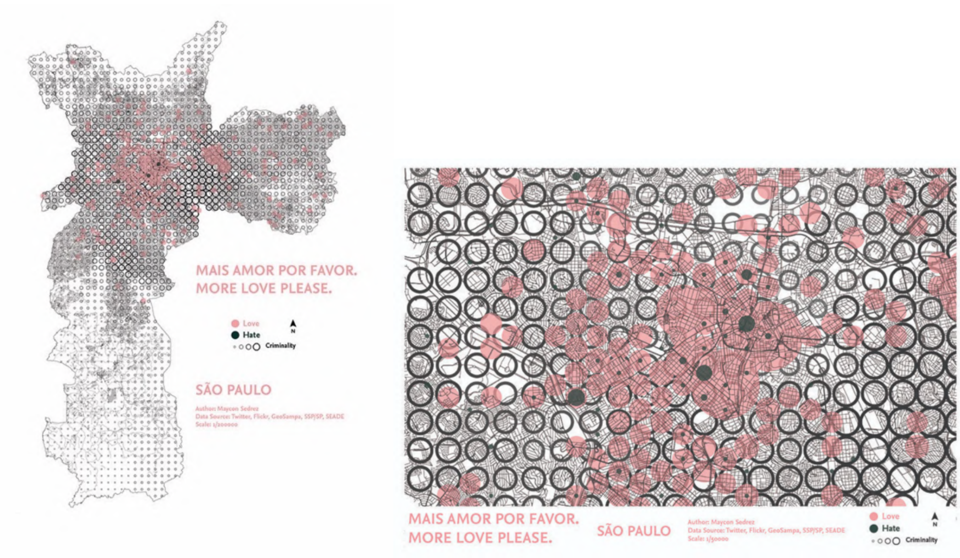


Figure 16: Example of low complexity static map. Amor SP map (Maycon Sedrez, 2018). Retrieved from https://mrsedrez.com/portfolio/amor-sp/

Table 1: Table showing analyzed visualization parameters used on “AMOR SP” map.

Data by origin	Data by type	Data detail	Visual variable	Design element	Symbology detail	Generalization	Bertin component	Complexity
objective data	geographical	Base map	-	-	-	-	geographical	low
citizen knowledge	social network	feeling of love	point	size	bigger the point, more love posts	no	ordered	
citizen knowledge	social network	feeling of hate	point	size	bigger the point, more hate posts	no	ordered	
objective data	other	Criminality	point	size	the map is divided in a grid, the bigger the circle in the gid the more criminality	no	ordered	

Example 2: Objective data for assessing public transport efficiency in medium complexity visualization - Haltestelle (2016) by Tagesspiegel.

"Haltestelle" is an interactive map visualization (see Figure 17a). It presents the punctuality of Berlin's most frequently employed public transport lines. As stated on the website, the visualization could be used by transportation authorities and commuters to assess the overall performance of the public transport system. This interactive map employs a line-based visualization, primarily employed in transportation network visualizations. It is of medium complexity since it uses three components: geographical, qualitative, and ordered.

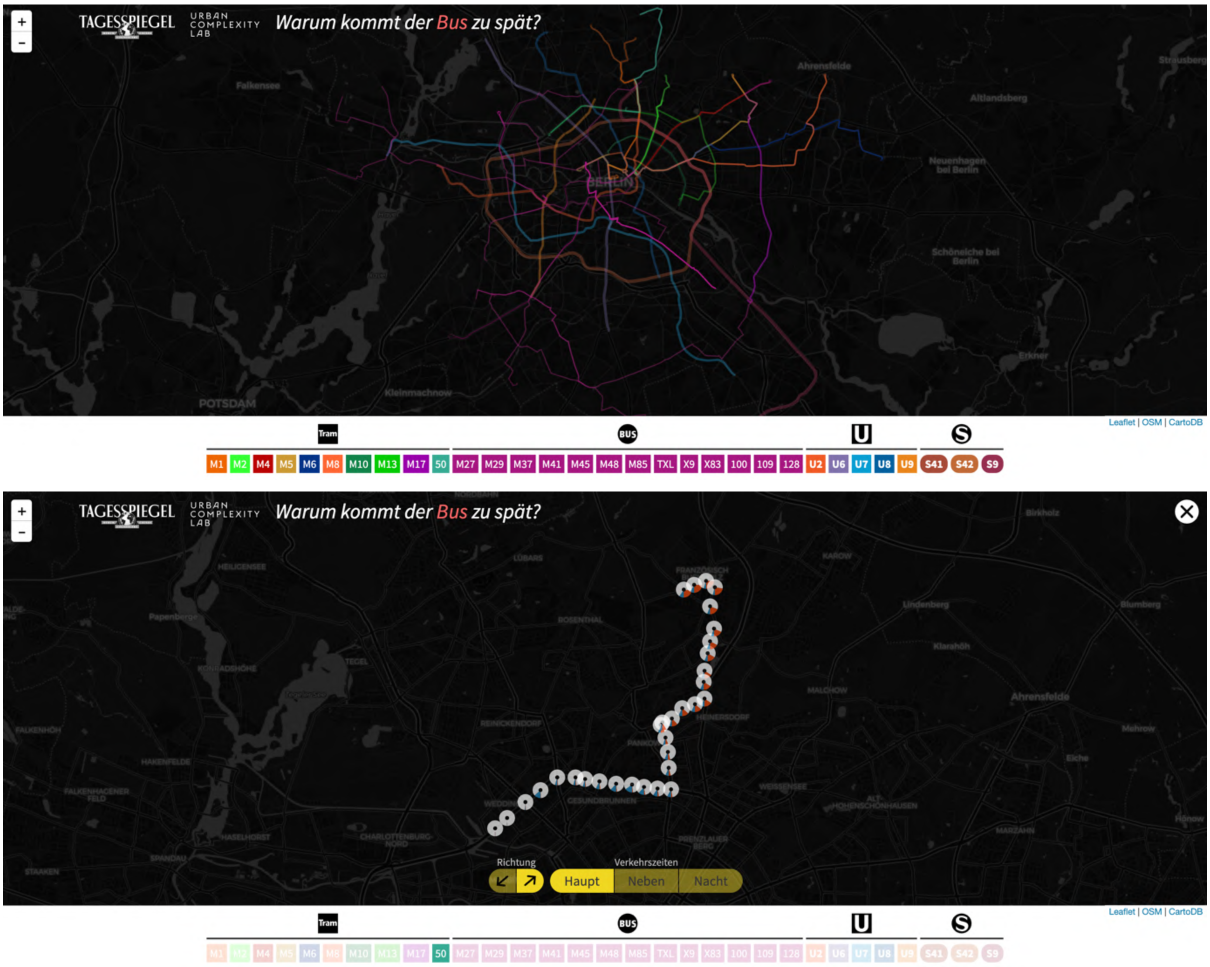


Figure 17: (a) Example of medium complexity map, Haltestelle main map. (b) A view of the map when selecting a route. Screenshot of Haltestelle map (Tagesspiegel, 2016). Retrieved from https://interaktiv.tagesspiegel.de/archiv/haltestelle/

"Haltestelle" map only represents objective data. By clicking on a route, represented by a colored line, the map displays pie charts at different stops along the selected route (see Figure 17b). These pie charts show the punctuality of the chosen public transport line at each stop. Using graphs as visual variables allows users to compare the punctuality percentages at various stops along the selected route. Furthermore, users can choose between high-traffic, low-traffic, and night-time hours.

Table 2: Table showing analyzed visualization parameters used on Haltestelle map.

Data by origin	Data by type	Data detail	Visual variable	Design element	Symbology detail	Generalization	Bertin component	Complexity
objective data	geographical	Base map	-	-	-	-	geographical	
objective data	geographical	Public transport network	line	colour	different colors, different routes	no	qualitative	medium
objective data	human mobility	Public transport line punctuality	point	graph	pie charts showing percentage of punctuality	no	ordered	

Example 3: Visualization with high complexity and interactivity - Turistification (2017) by 300.000km/s.

As a last example, Turistification was chosen. It is a website that employs data to show the impact of tourism in Madrid. It has three different sections, and the third one is an atlas showing five different topic maps: to walk, to sleep, services, land market competition, and displacement. Figure 18 shows the "to sleep" map. The map is interactive, and it employs a point-based visualization approach. It shows five different layers of data concerning the disparities in accommodation between tourists and locals. This includes factors such as housing area, percentage of population per m^2 of housing, and number of accommodations on Airbnb, among others.

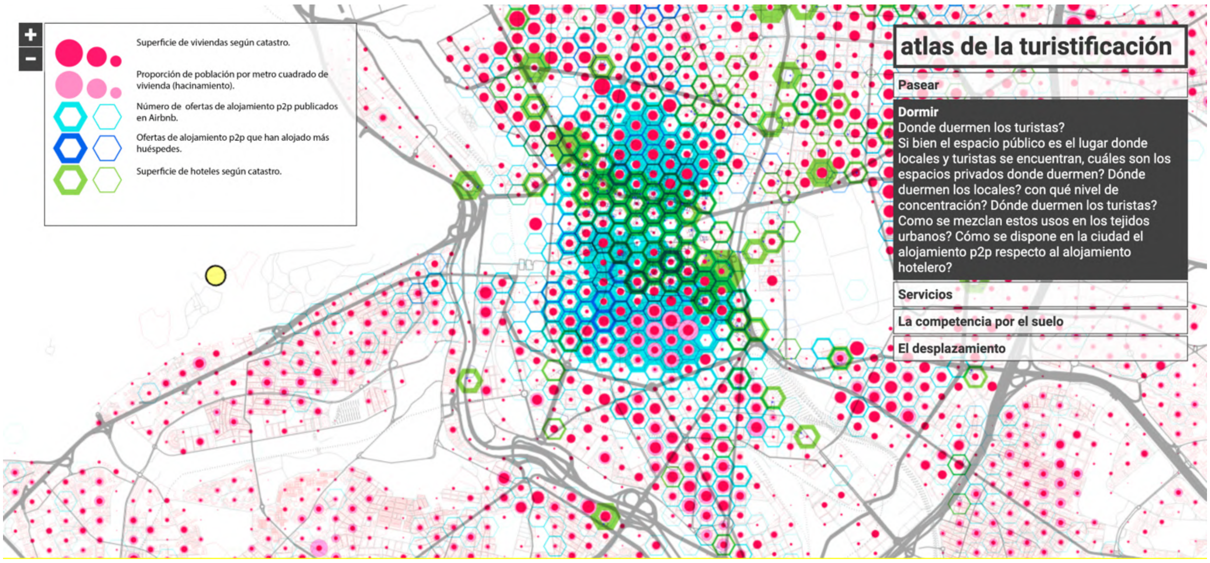


Figure 18: Example of high complexity map, layer "to sleep". Turistification (300.000km/s, 2017). Retrieved from http://turistificacion.300000kms.net/

The map is of medium complexity as it presents three components: geographical, quantitative, and ordered components. This visualization employs a consistent visual variable and design element to represent different components and data types. A key technique employed is transparency manipulation, allowing the different components to be discernible while coexisting within the visualization.

Table 3: Table showing analyzed visualization parameters used on the "to sleep" map.

Data by origin	Data by type	Data detail	Visual variable	Design element	Symbology detail	Generalization	Bertin component	Complexity
objective data	geographical	Base map	-	-	-	-	geographical	high
objective data	other	Housing density according to cadastre	point	size	bigger the circle, more residential surface	no	quantitative	
objective data	other	Population density per m2 of housing (overcrowding)	point	size	bigger the circle, more dense the area	no	quantitative	
objective data	social network	Number of Airbnb accommodation listings	point	size	thicker the line, more airbnb publications	no	ordered	
objective data	social network	P2p number of Airbnb accommodation listings with the highest guest count.	point	size	thicker the line, more tourist hosted	no	ordered	
objective data	other	Hotel square footage reported by cadastre	point	size	thicker the line, more hotels	no	quantitative	

In summary, this subsection provides insights into four visualizations to demonstrate the methodology used to analyze the maps. The result of this analysis was the creation of the catalog. The catalog serves as a well-structured repository of visualization strategies employed in urban visualization. Its significance extends beyond this case study, as it provides a valuable resource of good practices for future work in the field. The catalog aims to streamline the research process and minimize potential errors in urban visualization projects.

3.3 Map design process

After analyzing different urban data visualizations and creating the catalog, the Map Design process was the next step. This step was employed to answer RQ2, which primarily concerns identifying and applying precise visualization strategies for the specific collected data. This procedure had four stages (see Figure 19):

- **Data collection**: During this stage, the actual data was gathered.
- **Layer selection**: In this stage, the curation of layers to be visualized on the maps was done.
- **Visualization strategies selection**: In this stage, references from the catalog to be applied to the selected layers were chosen. These selections dictated the way the data would be presented visually.
- **Visualization strategies application**: This final stage involved the application of the selected strategies and the final creation of the maps.

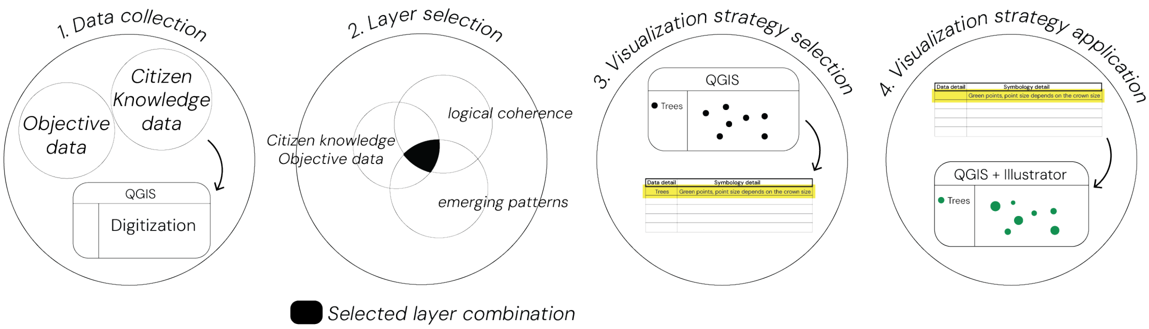


Figure 19: Graph of the four steps within the Map design process stage

3.3.1 Data collection

During the data collection step, an important goal was to combine objective data and citizen knowledge. As stated in Section 2.2.3, incorporating citizen knowledge into objective data ensures that the voices and experiences of residents and community members are considered, which is crucial in participatory urban planning strategies to engage citizens in the decision-making process. This inclusive approach leads to more equitable and people-centered decision-making processes, addressing the needs and concerns of the urban population (see Figure 20 for a graphical representation of this step). Two distinct sources were employed to combine objective data and citizen knowledge data: open data sources (official and non-official) and participatory mapping strategies.

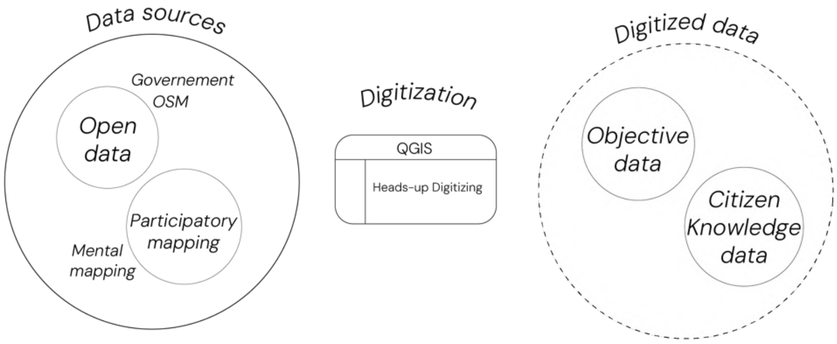


Figure 20: Graph explaining the data collection step. Starting with the data collection from the chosen data sources, the digitization step when necessary, and, as an outcome, the digitized objective data and citizen knowledge data.

Open data sources are openly accessible, exploitable, editable, and shared by anyone for any purpose, even commercially. Open data is licensed under an open license. These sources, commonly provided by city administrations or organizations, host a range of information encompassing various urban attributes such as infrastructure, transportation networks, and land use. These sources encourage data sharing by providing a repository that is open to the public. A prominent example is OpenStreetMap (OSM), an open-source mapping project that relies on contributions from individuals worldwide. OSM allows individuals to collaboratively create, update, and share spatial information, including details about streets, buildings, amenities, and geographical features. This collective effort results in a rich and detailed map that can be employed for diverse purposes, including urban analysis. Using open data sources, researchers can access reliable datasets that form the basis of data-driven analyses and visualizations. There are many options for getting OSM data, especially for one-time use. For example, in the QGIS software, QuickOSM and OSM Downloader are the most popular plugins for directly downloading OpenStreetMap data for a specific area of interest. These plugins, however, can only retrieve specified data for smaller areas. QuickOSM and the city administration's open data platform were selected for this study.

Participatory mapping strategies are used to gather on-site citizen knowledge data. The chosen approach for this study was mental mapping (see Section 2.1.2). In mental mapping, participants were encouraged to mark, draw, or annotate directly on the paper maps. This interactivity enabled them to express their knowledge and perceptions of the city's spatial patterns, landmarks, and urban features. This method was carefully selected for its simplicity and accessibility, as it requires minimal technical resources and organizational efforts. Paper-printed maps made the process easily transportable and convenient to conduct on the streets, making it accessible to the general public. The open and inclusive nature of the mental mapping technique allowed individuals from diverse backgrounds and demographics to contribute their perspectives and insights to the urban analysis.

After data collection, some of the layers were not in the correct format, so digitization of the data was necessary. Digitizing is converting coordinates from a map, image, or other sources into a digital format in a GIS. Digitization is a fundamental task frequently undertaken by GIS Specialists to accomplish spatial analysis and visualization. There are different ways of digitizing geographic information. The Heads-up Digitizing method was selected (Bolstad, 2016, p. 157). This method requires first scanning the map or image into a computer. Then, the digitizer traces the points, lines, and polygons using digitizing software, in this case, QGIS. This method of digitizing has been named "heads-up" digitizing because the user focuses on the screen rather than down on a digitizing tablet. The accuracy is limited to using scans of high-quality maps and images. Since the tracing is done on a computer, lines can be set to snap together, and polygons can be programmed to share an edge, thus removing accidental sliver polygons.

In summary, the data collection step involved compiling existing objective and citizen knowledge data, including collecting and digitizing data where needed. This multifaceted process served as a central means of understanding the data landscape and identifying available and missing data points. It also harmonized the disparate data sets into a cohesive digital format, laying the groundwork for subsequent stages, including layer selection and meticulous pattern creation.

3.3.2 Layer selection

There were three main requirements for the Layer selection step: the selection should combine citizen knowledge layers and objective data layers, ensure the logical coherence of combined layers, and unveil emerging patterns (see Figure 21 for a graphical representation of this step). Combining citizen knowledge and objective data achieves a more prosperous and more diverse perspective on urban dynamics. Ensuring logical coherence guarantees credible insights, preventing misinterpretations. Unveiling emerging patterns offers deeper understanding, guiding predictions, and informed decision-making for effective urban planning and interventions.

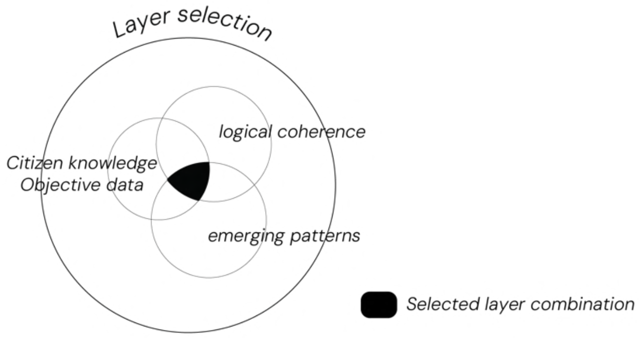


Figure 21: Graphical representation of the three requirements for the selection of the layer combination

For the Layer Selection, a combination of citizen knowledge and objective data layers was required since it can improve interpretations and encourage diverse views of reality, as discussed in Section 2.2.3. This choice was guided by the principle of logical coherence, ensuring that the combination of layers would make sense logically. As demonstrated in the case of Dennis (2006), it is reasonable to combine crime locations with citizens' perceptions of safety around a neighborhood because this combination can help to find relationships between where crime happens and where people feel safe or unsafe. On the contrary, merging crime locations with citizens' perceptions of temperature would lack logical coherence due to the absence of an inherent relationship between these two variables. In a practical scenario, such as the one exemplified by Dennis (2006), combining crime locations with citizens' perceptions of safety could lead to more accurate decision-making. For example, it could influence decisions such as streetlight placement, which would be informed by crime locations and areas where individuals feel unsafe, thereby enhancing public safety.

The logical coherence is directly related to the requirement of unveiling emerging patterns. A pattern is a recognizable and repeated arrangement of elements, characteristics, or data points with a certain relationship or similarity that occurs more than once and can be identified amidst data. In the case demonstrated by Dennis (2006), an identified pattern was the concentration crime incidents at street intersections. This pattern could also influence decisions related to streetlight placement by locating streetlights not only at crime locations but also at every street corner. Patterns help to understand and predict things based on what is observed in the data. Patterns are related to what Bertin (1967) calls "combinational elements". He stated, "discovering combinational elements which are less numerous than the initial elements yet capable of describing all the information in a simpler form”. In this sense, a pattern in data is a structure formed by multiple elements, but it can be described without enumerating these elements (Andrienko et al., 2021).

3.3.3 Selection of visualization strategies

Once the layers were selected, the next step was the visualization strategy selection. This step was necessary to choose from the catalog those visualization strategies that could be integrated into the map design (see Figure 22). Visualization strategies refer to the parameter’s combination used in the visualizations (see Sections 2.2 and 2.3 to understand the parameters). For example, one visualization strategy could be using different colored lines to depict different public transport lines, or different point sizes could be used to depict the number of visits to a museum. The catalog was valuable for exploring how similar layers were presented in other visualizations. By incorporating pre-existing visualizations as references during the design process, time can be saved, and potential errors can be avoided. This practice increases the likelihood of success in the current project by choosing strategies that have already demonstrated their utility and effectiveness in similar contexts. The use of references not only inspires new creative approaches but also facilitates informed decision-making.

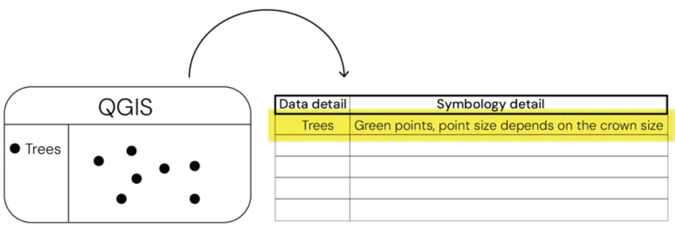


Figure 22: Graph explaining a method to use the catalog. On the left is the raw layer. In the middle, the catalog highlights the identification of a matching layer reference.

The visualization strategy selection can be quickly done by navigating the catalog. The catalog is an organized list of urban data visualizations and helps the user find visualization strategies in different ways. After pinpointing a specific urban data layer, the designer accesses the catalog to locate analogous layers based on the various parameters (represented in columns), such as data origin, type, visual variables, etc. Ideally, a matching layer can be found by searching the "data detail" column. For instance, if the user needs to visualize a "Trees" layer, a similar entry can be found under "data detail" column in the catalog. Once the entry is identified, the "symbology detail" column explains the visualization representation used (see Figure 22). Users can later directly apply or adapt this symbology representation as needed. While aligning with "data detail" results in more accurate matches, references can also be explored based on data type, origin, and visual variables, among other parameters. The proposed method serves as a guide for navigating the catalog, however, users are encouraged to tailor the method to their preferences. It is essential to note that the catalog serves as inspiration within the map design process by using tried-and-tested visualization strategies. Experimenting with diverse symbologies and visual variables from the catalog can refine the layer's visualization, ensuring effective communication of insights and patterns.

3.3.4 Application of Visualization Strategies

After selecting the visualization strategies that could be applied to the data, the next step was the application of those strategies (see Figure 23). However, it is worth noting that only some datasets were aligned with an existing visualization strategy. In such cases, creativity became key for adapting strategies used for other types of data or for developing entirely new approaches. This flexibility allows the visualization designer to craft innovative solutions that effectively communicate the message, even when a direct fit is not readily available.

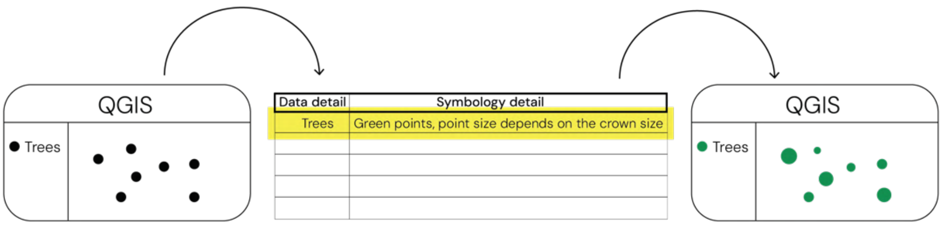


Figure 23: Graph showing the selection of the visual strategy and its subsequent application

During this step, two different software were used: QGIS 3.30 for data manipulation and initial visualization and Adobe Illustrator (2022) for fine-tuning and refining the visualizations. These two software were chosen for their distinct capabilities in handling different aspects of the visualization design process, each contributing to the overall effectiveness and aesthetic appeal of the desired final output, and for personal familiarity and expertise. The collaborative utilization of QGIS and

Adobe Illustrator maximized the potential to create informative and visually engaging urban data visualizations that effectively conveyed the insights derived from the study.

QGIS, a geospatial tool, was employed for pre-processing, data analysis, layer ordering, and initial layout. Pre-processing refers to a set of techniques and procedures used to prepare and clean raw geographical data before it is ready for analysis. In the case of this research, the methods used were cleaning, filtering, and clipping, among others. Data analysis was the following step to pre-processing. This step involves geospatial analysis, such as identifying clusters of data points, calculating distances between points, or performing statistical analyses on spatial attributes. Once the spatial analysis was finished, the last steps were layer ordering and creating the initial map layout to export in SVG format to use in Adobe Illustrator.

On the other hand, Adobe Illustrator, a graphic design software, was instrumental in refining the visual appearance of the maps. It allowed for the careful design of the visual variables, manipulation of design elements (colors and styles), and the addition of annotations and labels to enhance the clarity and communicative value of the visualizations. Adobe Illustrator served as the canvas for crafting the final layout of the maps.

3.4 User testing and interpretation

Once all the necessary visualizations were created, the user testing stage was done to answer RQ3 about the interpretation of patterns and preferences of the different visualizations by stakeholders with and without expertise. A comparative visualization evaluation was conducted using Google Forms questionnaires to evaluate the created visualizations. The questionnaire predominantly consisted of quantitative analysis with multiple-choice and multiple-selection options. A qualitative analysis with open questions was used to understand more accurate stakeholders' interpretations. The interpretation of the quantitative analysis involved quantifying responses for statistical assessment in Excel and its subsequent graphical visualization. The quantitative analysis allowed for a structured examination of patterns and trends among participants' choices, enabling the identification of prevailing preferences and relationships among different visualization strategies and stakeholder groups. On the other hand, qualitative analysis delved into the underlying meanings of participants' responses. A manual reviewing achieved this analysis. Although the questionnaire leaned towards quantitative analysis, the qualitative data from open-ended questions provided more specific insights that complemented and enriched the understanding of stakeholder perspectives.

4 Case study

This section describes the implementation of the proposed methodology on a particular case study located in Lichtental, Vienna. As such, it explains the study and the significant milestones of the methodology. Firstly, I present the chosen case study, describing its location, the urban project, and the involved stakeholders. Secondly, I address the map design process detailing the data collection method application, the map analysis considering the specific visualizations chosen as references, and the application of the visualization strategies and their results. Lastly, I discuss the user testing step and the approach to analyzing the outcomes.

4.1 Case study definition

Specific requirements guided the selection of the case study. The case had to be part of the Austrian Institute of Technology (AIT) projects. This was essential because AIT would facilitate my access to their contacts and relevant data for the study. Secondly, the requirement was to work on a project with available data, as the focus was on visualization, not data collection. Although the presence of data was one of the criteria for selecting the case study, it is worth noting that some additional data had to be collected to fill in the gaps during the process. Finally, selecting an ongoing participatory urban project in Vienna was preferred. Practical considerations primarily drove this preference. My physical presence in Vienna offered the advantage of direct engagement with the project group, facilitating the data collection process and allowing for immediate feedback on the generated visualizations.

The case study chosen was the Lichtenthal Superblock project. Superblock is an urban planning design concept to calm traffic in residential neighborhoods. Several consecutive blocks are designated in practice, and traffic is restricted on the inner streets (see Figure 24). This change creates an inner area that allows for redesign and alternative uses, such as for pedestrians and cyclists. The superblock concept originated in Barcelona, where large blocks have dominated the cityscape for decades. This urban design has now caught the attention of many other cities. Streets comprise a large part of a city's total area (between 15 and 25 percent of the land). By transforming them into superblocks, streets can be used for other purposes, making cities more livable (Lischer, 2021). The Lichtental Superblock project is part of the TuneOurBlock project by AIT, which aims to expand the superblock concept as a policy and planning strategy for transformative urban adaptation in Vienna 9/7/23 4:10:00 PMSuperblocks offer a reorientation of the use and design of public street spaces in the context of climate change. To this end, such an urban planning design combines decision-making in mobility and traffic, climate adaptation, public space, participation, and neighborhood development so that the densely populated existing city continues to offer everyone a high quality of life. The superblock is a concept for urban areas larger than a building block and smaller than a district. Road safety is improved by converting traffic roads into pedestrian roads. Thus, kindergarten and school children, pedestrians, cyclists, and older people are safer in the superblock. The transformation of a neighborhood into a superblock is promoted together with the population (Stadt Wien, 2022)9/7/23 4:10:00 PM.

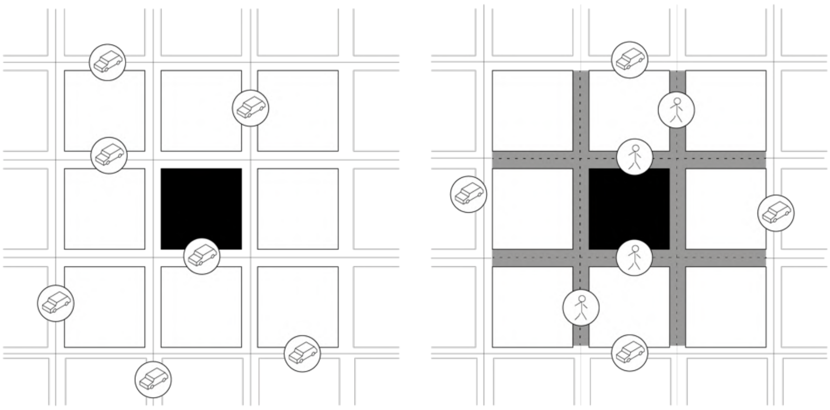


Figure 24: Current model vs. Superblock model

The Lichtenthal Superblock project is located in Lichtental, on the borders between Liechtensteinstraße (west), Althanstraße (east), and Alserbachstraße (south), offering a promising setting for the implementation of a superblock concept. The Lichtental Park in the middle provides a natural nucleus, surrounded by an elementary school, youth center, and church (see Figure 25). In addition, Lichtental is characterized by its striking stairs, dense municipal housing, and proximity to the Franz Joseph train station. The neighborhood, densely inhabited and dynamic, maximizes the use of the available public spaces. The small Lichtental Park is bustling in summer. However, it is encircled by roads with parking lots on both sides. Expanding the park emerges as an important step toward an equitable redistribution of the limited space, and it resonates with the transformation of the rest of the district (Agenda Alsergrund, n.d.).

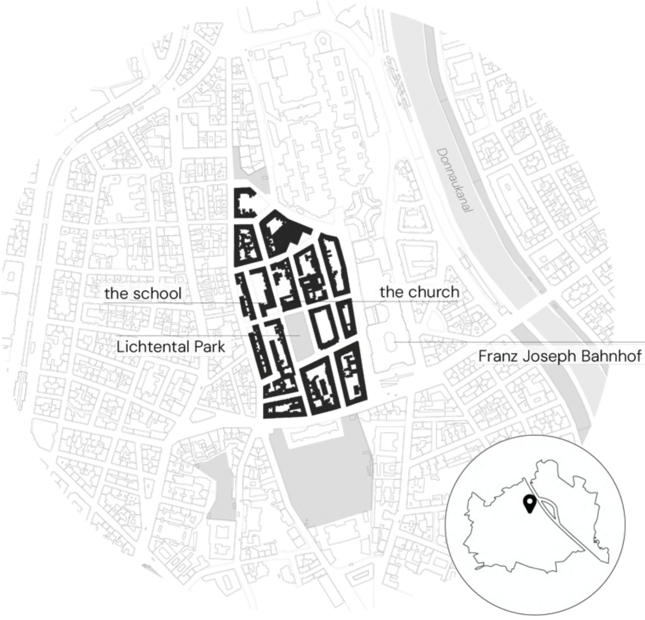


Figure 25: Map of Lichtental showing some critical points, the superblock area (black), and an inset map showing the location of Lichtental within Vienna.

The Superblock Lichtental is a project "by the people in the neighborhood for the people in the neighborhood", as highlighted in the document provided by the Agenda Group Lichtental (Agenda Alsergrund, n.d., p. 4). While the Agenda group is the primary driving force for the initiative, a constellation of stakeholders collectively contributes (see Figure 26). The Agenda group is an open group that carries out activations in the public space and takes a leading part in the decision-making process of the superblock. Its members live in the neighborhood or use it regularly, and their commitment is voluntary. Technical implementation is supported by the research collective Tune Our Block (ToB). ToB groups, municipal planners, practitioners, researchers, and NGOs to co-create practical and transferrable guidelines, policy options, and tools for implementing superblocks in varied urban contexts. One of the ToB members is the Austrian Institute of Technology (AIT). The Agenda group has also established close contacts with the most important institutions in the neighborhood. Equally important is the support and knowledge of neighborhood experts, in short, the residents and users of the neighborhood. Through active information, exchange, and participation, the idea is to bring together residents and experts to co-creatively design the Superblock Lichtental (Agenda Alsergrund, n.d.).

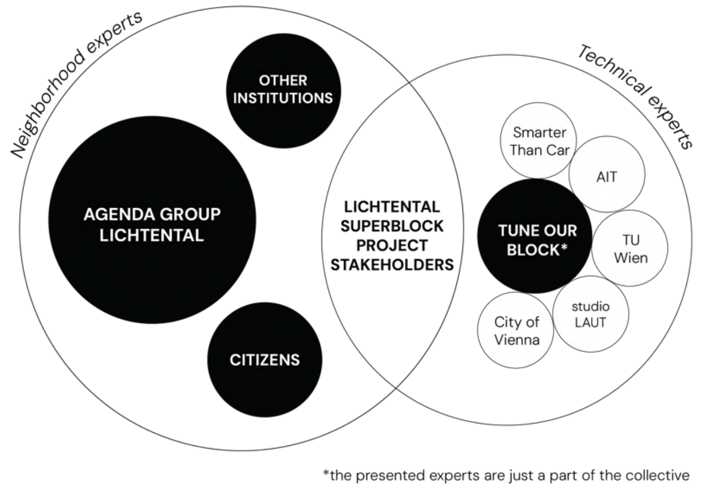


Figure 26: Stakeholders involved in the participatory process of the Lichtental Superblock project.

4.2 Map design process

This section describes the process of creating different maps of Lichtental representing two different patterns: residents' temperature perception and green infrastructure and day pedestrians' movement frequency and activity patterns. For each pattern, two different maps using different visualization strategies were created. Finally, these maps were tested among two groups of stakeholders (with and without expertise) to discern which visualization strategies were more understandable and preferred in the context of participatory urban processes. The goal was to identify optimal cartographic visualization strategies that combine objective data and citizen knowledge, which can serve as decision-making tools within the framework of participatory urban planning.

4.2.1 Data collection

One of the objectives of the thesis was to combine objective data with citizen knowledge. Therefore, different main sources of data were used. The objective data was collected from the Stadt Wien Open Data platform, and AIT shared data. A part of the citizen knowledge data was taken from the official brochures Klimafittes Lichtental (2021) analysis made by the Gebietsbetreuung

Stadterneuerung (Urban Renewal office) for the City of Vienna. The missing layers were gathered with a mental mapping workshop. Table xxx presents the data layers used and their sources.

Table 4: Data layers used and their sources.

Layer name	Source
Blocks cadastre	Stadt Wien Open Data - https://data.wien.gv.at
Buildings cadastre	Stadt Wien Open Data - https://data.wien.gv.at
Water bodies	Stadt Wien Open Data - https://data.wien.gv.at
Green spaces	Stadt Wien Open Data - https://data.wien.gv.at
Trees locations	Stadt Wien Open Data - https://data.wien.gv.at
Streets	Stadt Wien Open Data - https://data.wien.gv.at
Pedestrian shortcuts	Infopaket Supergrätzl Lichtental – Agenda Gruppe Lichtental
Amenities	Open Street Maps
Public transport stops	Stadt Wien Open Data - https://data.wien.gv.at
Residents‘ temperature perception	Klimafittes Lichtental – Gebietsbetreuung Stadterneuerung
Day pedestrians‘ movement frequency	Mental mapping workshop
Evening pedestrians‘ movement frequency	Mental mapping workshop

The distinct data sources required different methodologies to retrieve, download, and process the data. Further details on the specific methods used for each data source is provided.

- Data downloaded from the Stadt Wien Open Data platform.

Most of the layers used in this study were sourced directly from the Stadt Wien Open Data platform (https://data.wien.gv.at), which provides open and free access to a wide array of urban data. This platform serves as a comprehensive repository for various datasets relevant to Vienna. Leveraging this resource allowed for collection of diverse objective data, encompassing details such as street layouts, building footprints, land use classifications, green spaces, and more. It is important to note that the data from the Stadt Wien platform was predominantly in the shapefile format, which inherently required no preprocessing. This facilitated the seamless data integration into the study, ensuring that the layers were readily available for visualization.

- Data collection from OSM

The Activities layer was obtained using the QuickOSM plugin on QGIS. The plugin is a tool that enables users to easily extract specific types of geographic data from the OSM database directly within the QGIS environment. Using the quick query function, different OSM tags were used to retrieve relevant data points associated with various amenities, such as public facilities, services, and points of interest (see Figure 27).

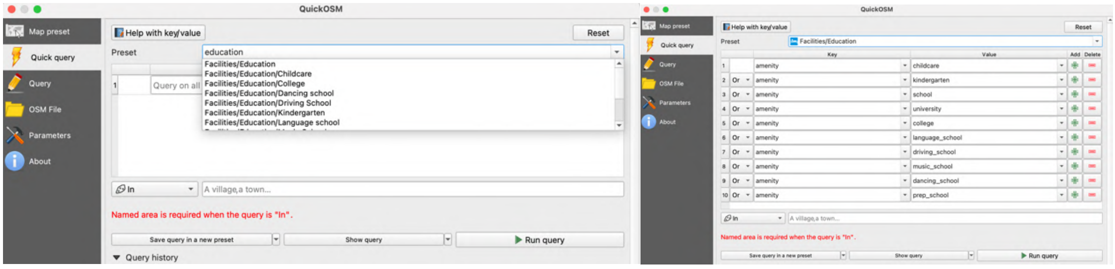
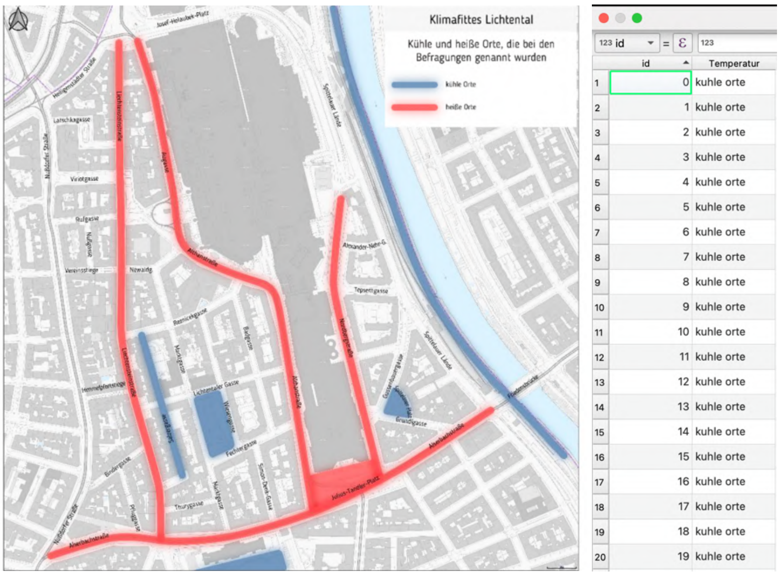


Figure 27: Screenshot from QuickOSM plugin showing how the data was retrieved by using tags.

- Digitization of data from official brochures.

The Residents' temperature perception layer was digitized from a map appearing in the Klimafittes Lichtental brochure made by the Gebietsbetreuung Stadterneuerung (Urban Renewal office). The map (see Figure 28a) was one of the results of a survey where residents were asked to provide their perceptions of different aspects of the neighborhood, including areas they perceived as particularly cool or hot. Since the initial data was only available in a PDF format, digitization was essential for incorporation into my visualizations. The digitization was pursued on QGIS, using the “heads-up“ method. After georeferencing the map in QGIS and creating a new vector layer, the PDF information was manually traced onto the new layer. The data was attributed by introducing a new column in the attribute table to accommodate "hot" or "cold" perceptions (see Figure 28b). This procedure resulted in a spatial representation of the temperature perception layer. The same digitization process was made with the pedestrian shortcuts layer, also derived from a PDF brochure.



	id	Temperatur
1	0	kuhle orte
2	1	kuhle orte
3	2	kuhle orte
4	3	kuhle orte
5	4	kuhle orte
6	5	kuhle orte
7	6	kuhle orte
8	7	kuhle orte
9	8	kuhle orte
10	9	kuhle orte
11	10	kuhle orte
12	11	kuhle orte
13	12	kuhle orte
14	13	kuhle orte
15	14	kuhle orte
16	15	kuhle orte
17	16	kuhle orte
18	17	kuhle orte
19	18	kuhle orte
20	19	kuhle orte

Figure 28: (a) Cool and hot Lichtental places. Result from the survey. Klimafittes Lichtenthal (Gebietsbetreuung Stadterneuerung, 2020). (b) Attribute table of the Temperature Perception layer showing the added column.

- Data gathered with a Mental Mapping workshop.

The pedestrians' movement frecuency layers were gathered with a Mental Mapping workshop organized within the context of the festival "Spielfest im Lichtentalerpark" on June 16th, 2023, from 2 p.m. to 8 p.m (see pictures from the activity on Figure 29). The festival is a traditional event happening every year in the neighborhood, and it was organized by the Agenda Group Lichtental and the Youth Center z9, among others. Two streets around the park were transformed into a playground street, and the program had different activities, primarily, for children and young people.

The Mental Mapping workshop was designed to capture participants' movement patterns within the Lichtental neighborhood. Passersby were invited to sketch their routes in response to the question, "How do you move around Lichtental?". These routes were differentiated based on morning, afternoon, and evening timeframes. To facilitate the process, an A1-sized map of Lichtental (see Figure 30 showing the base map and the map with results), with legends, was printed and placed on a table next to the Agenda Gruppe space. It is noteworthy that the experience went beyond mere drawing, it also included verbal narration and discussions about their chosen routes.

Figure 29: Photos taken during the Mental Mapping workshop.

Figure 30: Basemap made for the workshop and the scanned results map from the workshop.

While the Mental Mapping data might have not be exhaustive, given the relatively small number of participants (20 passersby), the data still offered the potential for uncovering connections and patterns between datasets.

After data collection, digitalization was necessary. A street shapefile from Vienna Open Data was acquired, opened on QGIS and the streets used during the mental mapping were segmented into sections, going from one corner to another. Subsequently, the number of lines within each section on the paper map was counted and incorporated the total as an attribute on a column called "count" on the attribute table (see Figure 31). As the number of afternoon pedestrians' movements was small, two layers were created: one for the day, which compressed morning and afternoon pedestrians' movements (depicted in blue and green on the paper map, figure 30), and one for the evening (depicted in red, figure 30).

	OBJECTID	MAINNAME_O	FEATURENAM	REG_STRNAM	EDGECATEGO	EDGECATEG0	Direction	count
1	4963177,000...	10002815,99...	Lichtentaler ...	NULL	G	Gemeindestr...	2	7
2	4964555,00...	10002815,99...	Lichtentaler ...	NULL	G	Gemeindestr...	-1	7
3	4963707,000...	10000316,00...	Badgasse	NULL	G	Gemeindestr...	1	5
4	4952168,00...	10000316,00...	Badgasse	NULL	G	Gemeindestr...	2	5
5	4948644,00...	10002826,0...	Liechtenstein...	NULL	L	Hauptstraße ...	2	4
6	4950787,000...	10002826,0...	Liechtenstein...	NULL	L	Hauptstraße ...	2	4
7	4956050,00...	10003855,0...	Reznicekgasse	NULL	G	Gemeindestr...	2	4
8	4940081,00...	10002815,99...	Lichtentaler ...	NULL	G	Gemeindestr...	2	3
9	4941634,00...	10000095,0...	Althanstraße	NULL	L	Hauptstraße ...	2	3
10	4941905,00...	10002826,0...	Liechtenstein...	NULL	L	Hauptstraße ...	2	3
11	4943944,00...	10000095,0...	Althanstraße	NULL	L	Hauptstraße ...	2	3

Figure 31: Attribute Table screenshot from the day paths layer. On yellow, the counts are highlighted.

4.2.2 Layer selection

Selecting layers for visualizations required a thoughtful combination of citizen knowledge data and objective data layers. The combination had to ensure logical coherence and unveil emerging patterns. Figure 32 illustrates the selected layers divided into objective and citizen knowledge data and the chosen combinations. The combination was guided by the citizen knowledge data due to its limited number of layers.

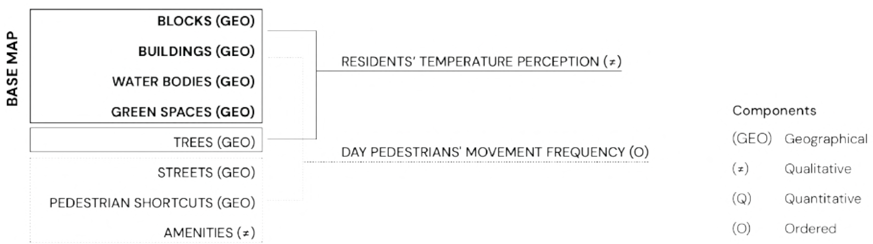


Figure 32: Graph showing the available data and the chosen layer combinations.

Two layer combinations, which hereafter are refered to as “Patterns”, were selected:

- Pattern 1: Residents’ temperature perception and green infrastructure.
- Pattern 2: Day pedestrians' movement frequency and activity patterns.

In addition to the layer combinations, a base map was necessary to provide the urban context. The base map consisted of four geographical components: blocks, buildings, water bodies, and green spaces. Figure 32 shows these layers along with their component type.

As stated in the Methodology chapter (see Section 3.3.2), the layer selection required logical coherence of the layer combinations to facilitate pattern identification. The following explanation details how the chosen layer combinations fulfill these requirements:

- Pattern 1: Residents’ temperature perception and green infrastructure:

A clear and direct connection exists between these two elements. Urban trees and green spaces (green infrastructure) contribute to lowering urban temperatures by shading and transpiration. Shading prevents direct shortwave radiation, reducing the surface temperature, and transpiration cools the air with evaporated water (Li et al., 2015; Vincenzo Costanzo et al., 2021). When these layers are overlapped, a discernible pattern emerges: areas with green infrastructure correlate with a perception of cool temperatures, while the absence of trees or vegetation is associated with a perception of hotter temperatures.

- Pattern 2: Day pedestrians' movement frequency and activity patterns:

Studying pedestrians' movement frequency and activity patterns helps to understand how and where individuals move and which are the activity hotspots. This aids in optimizing infrastructure design, such as the placement of pedestrian crossings, public transportation stops, and amenities (Cerrone et al., 2015). When the pedestrians' movement frequency and activity layers are overlapped, a discernible pattern emerges: high movement frequency aligns with areas featuring major transportation infrastructure and a dense concentration of activities.

4.2.3 Selection of visualization strategies

Once the layers were selected, the next step was the visualization strategy selection. This step was necessary to select from the catalog those visualization strategies that could be integrated into the map design. The selection either replicates visualization strategies from the catalog or closely aligns with them according to the needs of the map design. The following presents a selection of visualizations along with their visualization strategies.

Strategy 1: Generalized heatmap visualization – The Invisible Forest (2017) by Density Design Research Lab.

Strategy 1, "Generalized heatmap visualization", is from Density Design Research Lab (2017). The Invisible Forest is a static map (see Figure 33) that experiments with a poetic and rhetorical dimension in the visual representation. It creates a heatmap representing the distribution of more than one million Wi-Fi access points within Milan. The heatmap is made of five density degrees, and standard visual models of a woodland forest were used as a design element. The same heatmap style divided into density degrees was used for the case study.

Figure 33: The invisible forest map (Density Design Research Lab, 2017). Retrieved from https://www.cityvis.io/collection/project/the-invisible-forest/

Table 5: The analyzed visualization parameters used on The invisible forest map.

<table>
<tr><th>Data by origin</th><th>Data by type</th><th>Data detail</th><th>Visual variable</th><th>Design element</th><th>Symbology detail</th><th>Generalization</th><th>Complexity</th></tr>
<tr><td>objective data</td><td>geographical</td><td>Base map</td><td></td><td></td><td rowspan="2">More wifi signals, darker green</td><td>no</td><td rowspan="2">Low</td></tr>
<tr><td>objective data</td><td>geographical</td><td>Wifi signals</td><td>area</td><td>color value</td><td>yes</td></tr>
</table>

Strategy 2: Activity categorization and Strategy 3: Traffic-based line variation - A sense of place (2015) by SPIN unit.

Strategy 2 and 3 are part of the A Sense of Place (2015) research project. It explores the potential and possible uses of Location Based Social Network Data for urban and transportation planning in Turku City Centre. It presents different types of analysis maps, but for this thesis, the analysis concentrated on the “Activity map” (see Figure 34) and “GPS Traces map” (see Figure 35).

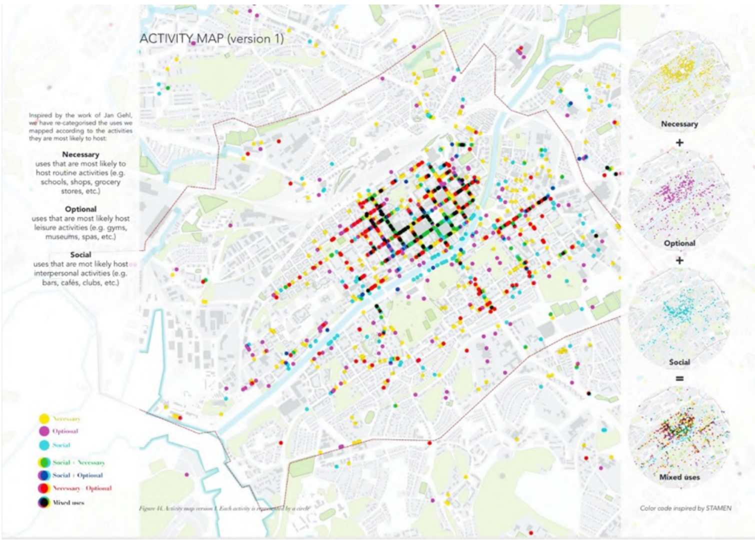


Figure 34: Activity map. A sense of place report (SPIN unit, 2015).

The activity map in this study employs Jan Gehl's methodology to study the complexity of people’s behavior in public spaces. Gehl's approach categorizes human activities into Necessary, Optional, and Social activities. "Necessary" activities include routine tasks such as commuting, shopping, and grocery shopping; "Optional" activities include leisure activities such as walking the dog, jogging, or visiting cultural sites; "Social" activities involve social interactions such as meeting friends or cultural events. This study aimed to analyze the interactions occurring along streets by looking at the activities happening at street level, remotely, within a one-week timeframe. Researchers used OpenStreetMap (OSM) and Google Street View to identify and map visible street-level uses such as shops, bars, restaurants, and offices. Following Gehl's methodology, activities were categorized as Necessary, Optional, or Social and were visualized on the map to provide insights into street-level dynamics. The same activity categorization, which is explained in Section 4.2.4, was used.

Table 6: Table showing analyzed visualization parameters used on the Activity map by SPIN UNIT.

Data by origin	Data by type	Data detail	Visual variable	Design element	Symbology detail	Generalization	Complexity
objective data	geographical	Activities	point	color hue	Magenta, yellow and blue depending on the type of activity (necessary, optional or social)	no	low

The Turku traffic map depicts mobility patterns around Turku. It presents the average estimated traffic intensity derived from actual measurements. This map was used to visualize the pedestrian's movement frequency layer.

Figure 35: Turku traffic map. A sense of place report (SPIN unit, 2015).

Table 7: Table showing analyzed visualization parameters used on GPS traces map by SPIN UNIT.

Data by origin	Data by type	Data detail	Visual variable	Design element	Symbology detail	Generalization	Complexity
Objective data	human mobility	Mobility data	line	color hue and value	From bright to dark and thick to thin. The darker and thicker, the more traffic	no	low

4.2.4 Application of visualization strategies

For the creation of the visualizations, QGIS and Adobe Illustrator played a pivotal role in applying the visualization strategies. An explanation of their capabilities and use can be found in Section 3.3.4. As this research aimed to evaluate and test the effectiveness of different visualization approaches, two maps using different visualization strategies were created to depict each pattern. This was essential to assess and test the understanding and preferences of different stakeholders. The visualizations were based on two patterns (1 and 2) to achieve this. Pattern 1 was visualized as a low-complexity map, while Pattern 2 as a medium-complexity map. For each pattern, two maps were generated: Map A featured a detailed representation, and Map B underwent a generalization process. In Figure 36, a graph detailing these two patterns and the outcome can be seen.

Figure 36: Graph describing the generated visualizations.

In this section, I elaborate on the diverse tools used from QGIS and Adobe Illustrator for creating the final visualizations.

Pattern 1: Residents’ temperature perception and green infrastructure.

Map A: Fine-granularity map.

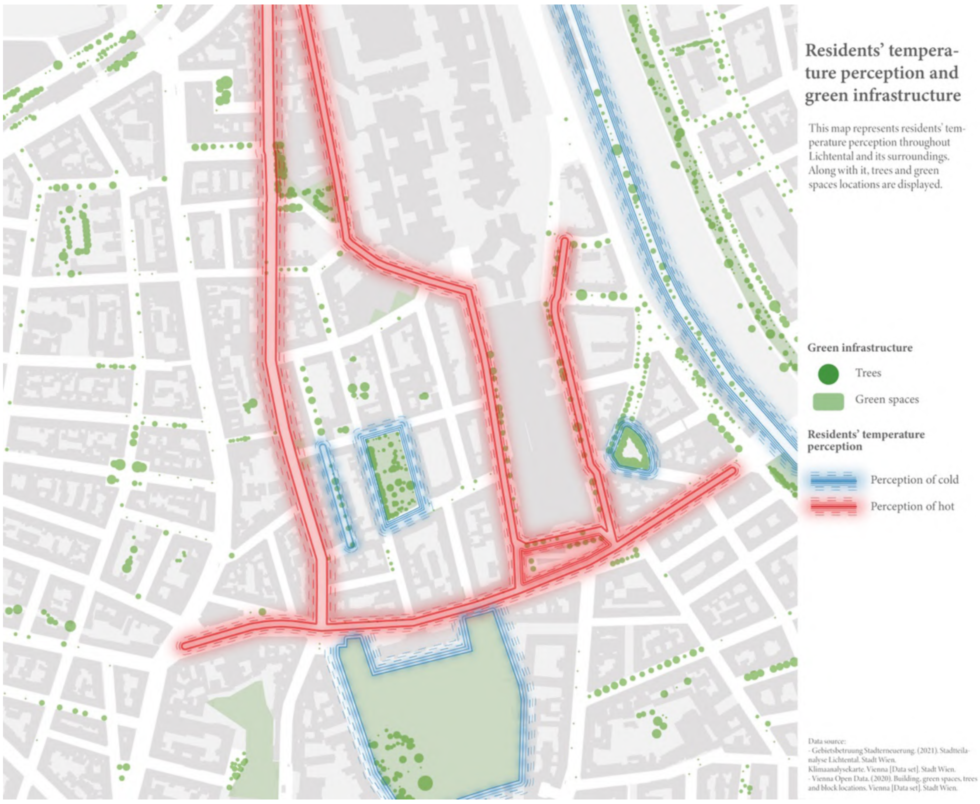


Figure 37: Residents’ temperature perception and green infrastructure map.

To demonstrate the visualization strategy application of the "Residents’ temperature perception and green infrastructure" map, I break it down into its three primary items: the base map (geographic component), the green infrastructure layer displaying trees and green spaces (geographic component), and the residents' temperature perception layer (qualitative component). Firstly, I explain the steps pursued on QGIS. The base map for this visualization is relatively straightforward, portraying blocks and buildings differentiated by distinct values of gray. For the trees layer, a preliminary step involved clipping it to the relevant area, as the original layer contained all Vienna's trees. Employing the “single symbol“ symbology method, was chosen to symbolize the tree layer based on crown size, utilizing one of the attribute columns that contained crown size to dictate the symbol's dimensions (see Figure 38). This approach imparts a dynamic, realistic feel to the map by representing individual trees with varying sizes. Lastly, the chosen colors were applied to the green spaces and temperature perception layers. After ensuring all layers were configured correctly, the map was exported to SVG format to refine it in Adobe Illustrator.

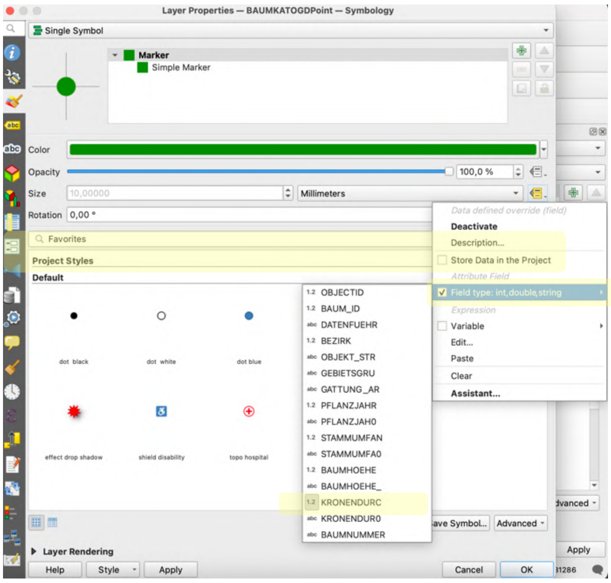


Figure 38: Screenshot from the trees layer properties configuration

Figure 39: Chosen color palette map A, Pattern 1.

Within Adobe Illustrator, the focus was on refining details and selecting the final color palette. Figure 39 showcases the chosen color palette, with colors thoughtfully selected to foster intuitive connections with their represented attributes: green for green infrastructure, blue for cold, and red for hot areas. In Adobe Illustrator, the chosen colors for the base map and green spaces were applied. For the trees layer, transparency was employed to reveal the trees' density, denoted by the superposition of green color. The residents' temperature perception layer posed the most intricate symbology task. This layer included polylines defining streets and polygons outlining green spaces (see Figure 40). In this case, the aim was to represent polygons (green spaces) and lines (streets) with the same visual variable. To achieve this, multiple offsets were applied to the polygons and lines, which transformed lines into polygons. Then, various line widths and dash patterns were tested, going from thicker, solid lines closely spaced to thinner, dashed lines widely separated. This process is represented in Figure 40. Once a satisfying outcome was achieved, a 'Gaussian blur' effect was applied to the middle lines to underscore the subjective aspect of the layer.

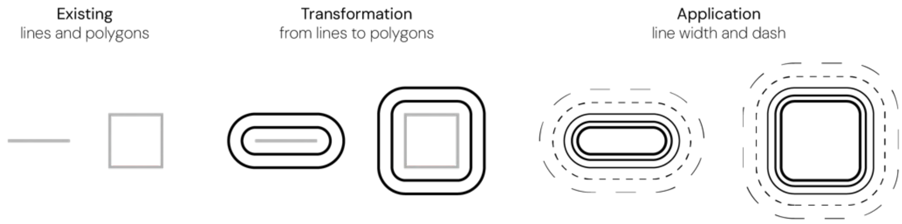


Figure 40: Diagram showing the process of creating the symbology of the residents' temperature perception layer.

Finally, the map layout was completed by properly ordering the layers, adding references, the title, and necessary additional information.

Pattern 1: Residents' temperature perception and green infrastructure.

Map B: Generalized map

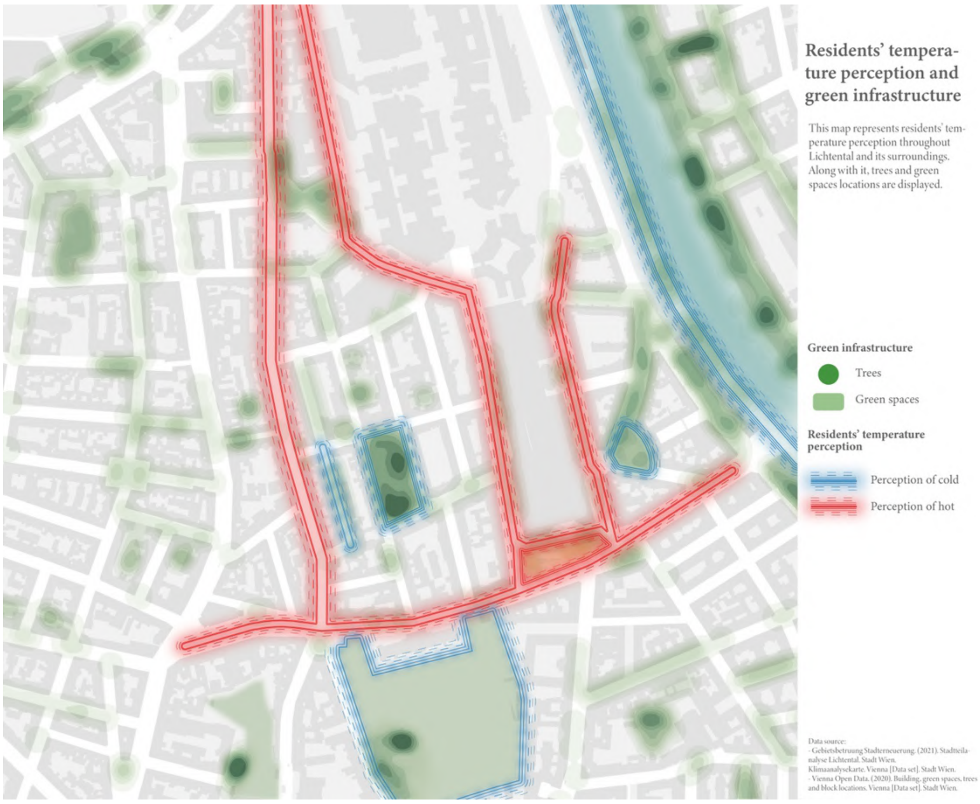


Figure 41: Residents' temperature perception and green infrastructure generalized map.

The subsequent map serves to illustrate the same pattern as map A. However, a generalization was applied to the tree layer in this iteration. Given that the visualization strategy application aligns with that of map A, only the creation of the tree map's generalization is addressed. In QGIS, the 'heatmap' symbology was chosen for the layer (see Figure 42). A color ramp was created selecting a gradient from white to a darker green hue. A radius of 10 was chosen to enhance map legibility by highlighting visible "hot spots". After ensuring all layers were configured correctly, the map was exported to SVG format to refine it in Adobe Illustrator.

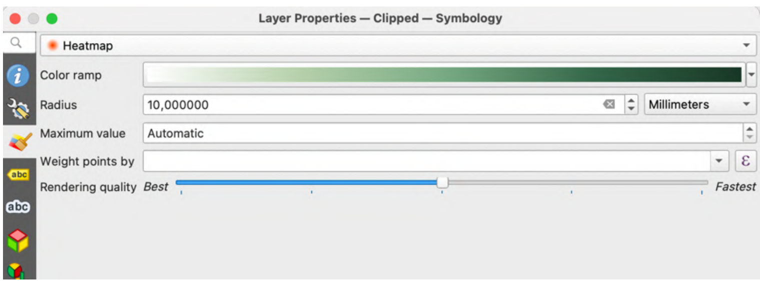


Figure 42: Heatmap chosen configuration.

Figure 43: Chosen color palette map B, Pattern 1.

Within Adobe Illustrator, the focus was on refining details and selecting the final color palette. Figure 43 showcases the chosen color palette. The color scheme remained consistent, except for a deliberate adjustment to the value of green infrastructure. This modification achieved better visual harmony when combined with the other layers. The heatmap contained the entire extent of the tree layers, resulting in unnecessary white space where no trees were present. To address this, the '16 colors' option within the 'image tracing' function was used. This function converts a bitmap into a vector image using a palette of up to 16 colors. The '16 colors' option was selected because it simplified the heatmap the least, allowing for a more accurate representation. Subsequently, the 'expand' feature was employed to transform each color into distinct vector shapes. This transformation allowed an easier manipulation of the layer with Adobe Illustrator's tools. This maneuver enabled removing the white area, revealing the underlying layers, such as the base map and green spaces. Finally, the map layout was completed by properly ordering the layers, adding references, the title, and necessary additional information.

Pattern 2: Day pedestrians' movement frequency and activity patterns.

Map A: Fine-granularity map.

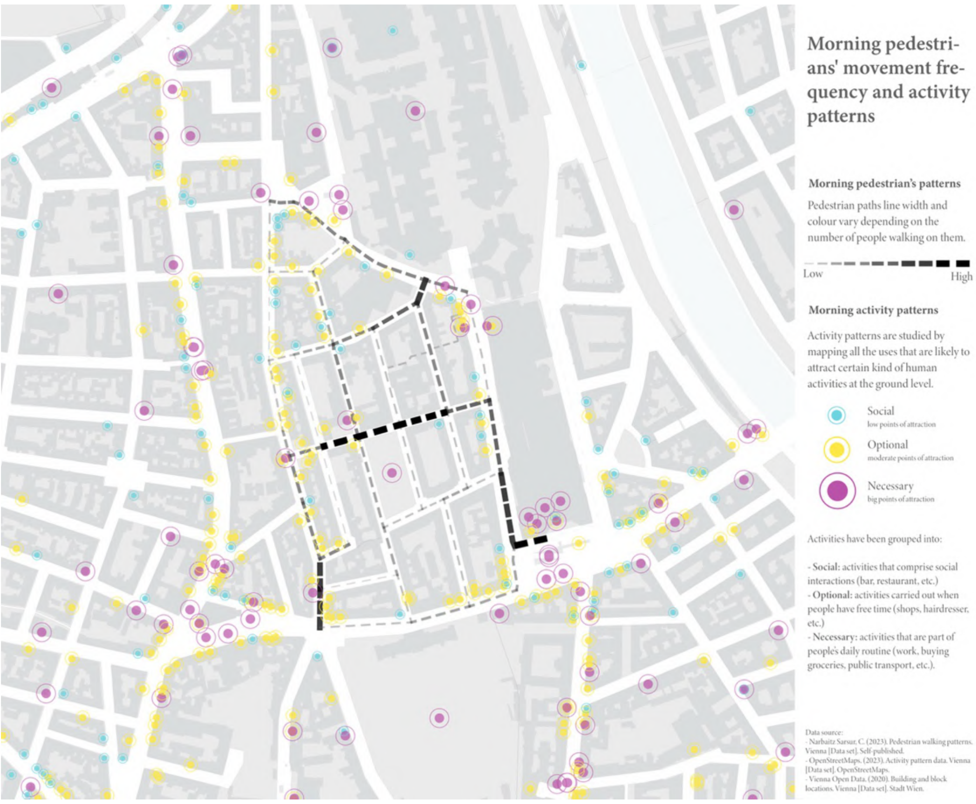


Figure 44: Day pedestrians' movement frequency and activity patterns fine-granularity map.

To demonstrate the visualization strategy application of the "Day pedestrians' movement frequency and activity patterns " map, I break it down into its three primary items: the base map (geographic component), the morning pedestrian's frequency layer displaying (ordered component), and the morning activity patterns layer (qualitative component).

Firstly, I explain the steps pursued on QGIS. The base map for this visualization is relatively straightforward, portraying blocks and buildings differentiated by distinct values of gray. And the river layer on light blue to contextualize. The 'categorized' symbology method was used for the morning pedestrian frequency layer, and a random color ramp was selected. The colors assigned were determined by the values in the 'count' column of the attribute table, which represented the total number of pedestrians on each street. The color applied to each street was determined by its respective count, generating a varied color distribution on the map. It is important to note that the color ramp was initially random, as adjustments were planned in Adobe Adobe Illustrator for further refinement. For the morning activity layer, all the data was retrieved in QuickOSM and categorized into three different activity layers (necessary, optional, and social). Then, the layers were visualized with different colors. Necessary activities had a higher attraction weight as they happen on a daily base. Therefore, they were depicted with a bigger point. After ensuring all layers were configured correctly, the map was exported to SVG format to refine it in Adobe Illustrator.

Within Adobe Illustrator, the focus was on refining details and selecting the final color palette. Figure 45 showcases the chosen color palette. Different light gray values were deliberately selected to establish the base map as the background. Regarding symbology, a specific approach was taken for the morning pedestrian's frequency layer. Dashed lines were employed to avoid confusion with conventional solid lines frequently used to depict vehicular traffic. Inspired by the “Turku traffic map” example (see Figure 35), varying line widths and color shifts were used to convey the frequency of pedestrian movement along each street. This involved using thicker, darker gray lines for more frequented streets and, conversely, opting for lighter, thinner lines for routes with lower pedestrian traffic. Considering this, the final symbology was created through a sequence of seven steps (see Figure 46, final symbology). Notably, based on pedestrian frequency, the layer's initial QGIS color facilitated a seamless transition in Adobe Illustrator. Using the "selection by color" feature, the style was modified, specifically targeting and adjusting the attributes of interest using the “eyedropper” tool. For example, all the lines with the same blue value were selected and then the defined symbology was applied. To visually comprehend the transformation from the preliminary symbology established in QGIS to the final symbology within Adobe Illustrator, refer to Figure xxx.

Figure 45: Chosen color palette map A, Pattern 2.

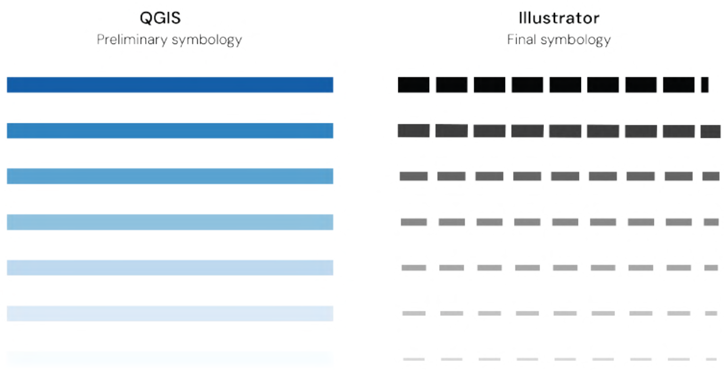


Figure 46: Depiction of the line symbology change between QGIS and Adobe Illustrator.

For the activity layer, I selected the classification and color hues from the "Activity map" (Cerrone et al., 2015) (see section 4.3.3, Figure 34). For the symbology, three options were created (see Figure 47). The first iteration was simple and it employed small points. However, this approach resulted in too small points to be easily perceptible. Subsequently, an option with larger points was created, which unfortunately overlapped with specific segments of the pedestrian path lines and made it hard to see some of them. Finally, the third option emerged, presenting a design of a filled circle within an outlined circle, a synthesis of the previous alternatives. This last symbol stood out as the most fitting choice. To ensure optimal visibility of overlapping points, transparency was applied to the symbols. Notably, the variation in size among different categories was kept.

Figure 47: Three options for the symbology of the activity's layers.

Finally, the map layout was completed by properly ordering the layers, adding references, the title, and necessary additional information.

Pattern 2: Day pedestrians' movement frequency and activity patterns.

Map B: Generalized map.

Figure 48: Day pedestrians' movement frequency and activity patterns generalized map.

The map in Figure 48 illustrates the same pattern as the previous one. However, a generalization was applied to the activity layer in this iteration. For achieving this heatmap, QGIS was used. Heatmaps can be done when all the necessary points are on the same layer. Therefore, the three activity layers had to be merged. Firstly, two columns were added to the attribute table of each layer. One column with the type of activity (necessary, optional, or social) and another column with a number (3, 2, and 1, respectively) is used later during the heatmap creation. Once the three attribute tables were edited, they were merged using the "Merge Vector Layers" tool from the Processing Toolbox. Once merged, all the unnecessary columns were removed. See Figure 49, showing the final attribute table.

	full_id	osm_id	osm_type	weight	category
1	n76471793	76471793	node	3	necessary
2	n111110224	111110224	node	3	necessary
3	n742643223	742643223	node	3	necessary
4	n1466988216	1466988216	node	3	necessary
5	n1467022527	1467022527	node	3	necessary
6	n1687549406	1687549406	node	3	necessary

Figure 49: Screenshot of the attribute table of the merged layer with the necessary columns

Once the layer was created, the heatmap configurations were implemented, mirroring the approach seen in Map B Pattern 1. For the newly merged layer, the 'heatmap' symbology was chosen (see Figure 50). A color gradient was generated using the pink and yellow from the previous palette. The radius was chosen through trial and error, as documented in Figure 51. Notably, a study conducted by Słomska-Przech et al. (2021) posited that radius sizes of 10 and 20 pixels were the most legible. Intriguingly, the preferences were divided along expertise lines, with novices favoring a 10-pixel radius and experts leaning towards a 20-pixel radius. Larger radius (30 or 40 pixels) were less preferred due to the complexity they introduced, often leading to intricate graphical overlaps that necessitated a certain level of skill for accurate interpretation. These insights were considered, but in practice, a radius of 10 and 20 fell short in adequately highlighting significant "hot spots," while a radius of 40 was excessively generalized in its depiction. Finally, a radius of 30 was used (see Figure 50). The “weight points by” option refers to a feature that allows assigning varying weights or importance to individual data points when creating the heatmap. This option helps to emphasize certain data points over others based on their significance. This attribute column contains values that determine how much influence each point should have on the resulting heatmap. The SQL CASE statement was used within my attribute column "weight," which assigns different weight values to my data points based on their existing "weight" values. This expression creates a new attribute column with adjusted weight values that can be used as the basis for generating a heatmap. My expression “CASE WHEN "weight" = 3 THEN 5, WHEN "weight" = 2 THEN 3, ELSE 1, END” refers that if the original "weight" value is 3, it is being changed to 5. This implies that data points with a "weight" of 3 influence the heatmap's intensity more. If the original "weight" value is 2, it is changed to 3. This means that data points with a "weight" of 2 moderately influence the heatmap. For all other cases (when the original "weight" value is neither 3 nor 2), the new weight value is set to 1. This assigns a lower influence to those data points on the heatmap. This expression was used to adjust the impact of each data point on the heatmap visualization. It gave the necessary activities a higher "weight" than the others. This can help to modify weights faster and choose the best option. After ensuring all layers were configured correctly, the map was exported to SVG format to refine it in Adobe Illustrator.

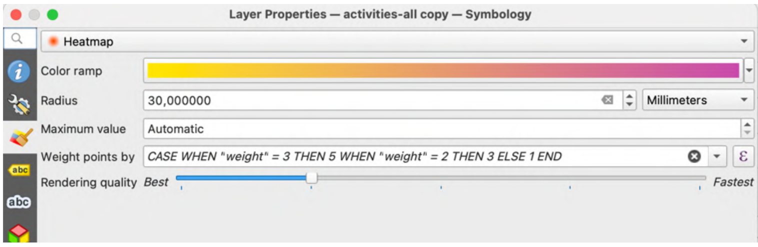


Figure 50: Heatmap chosen configuration.

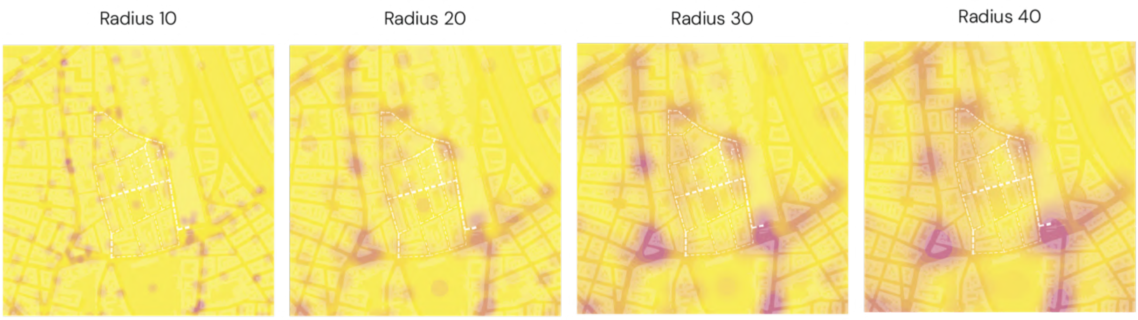


Figure 51: Four options showing different radius configurations for the heatmap.

Figure 52: Chosen color palette map A, Pattern 2.

Within Adobe Illustrator, the focus was on refining details and selecting the final color palette. Figure 52 showcases the chosen color palette. A white color scheme was employed for the other layers to ensure seamless integration with the heatmap. This adjustment led to better visual cohesion when juxtaposed with the heatmap. Aesthetic considerations prompted me to transform the bitmap into a vector image using the '16 colors' option within the 'image tracing' function. This option was chosen as it preserved the original heatmap the most. This decision facilitated a more precise and authentic representation of the original image. For the pedestrian frequency layer, white dashed lines were employed. To enhance prominence, thicker and more opaque lines were used for streets with higher pedestrian traffic. Conversely, more transparent and thinner lines were chosen for routes with less foot traffic, ensuring visual balance. Lastly, adding the block layer was instrumental in providing additional contextual information to the map, enhancing its overall readability. Finally, the map layout was completed by properly ordering the layers, adding references, the title, and necessary additional information.

4.3 User testing and interpretation

Once all the necessary visualizations were created, the next stage was to evaluate the maps to answer RQ3 about the interpretation of patterns and preferences of the different visualizations by stakeholders with and without expertise. According to Roth et al. (2015), there are three different methods for map evaluation:

1. Expert-based methods: Feedback and evaluation are done by consulting experts without any prior knowledge.
2. Theory-based methods: Cartographers reflect on their own map using a scientific framework.
3. User-based methods: Feedback is given by the target group of the map.

For this research, the user-based method was chosen. Google Forms questionnaire was used as a surveying tool. The survey was conducted with stakeholders with and without expertise taking part in the Lichtental Superblock project. They were requested to interpret and compare the created visualizations.

4.3.1 Participants and recruitment

A total of 46 participants were recruited for the study through my personal network with the help of the AIT and the Agenda Gruppe Lichtental. A majority were familiar with the project, while those who lacked knowledge were provided with an explanatory guide at the start of the survey. Of the participants, 25 had expertise in fields such as urban planning, architecture, cartography, and geodata analysis (technical experts), while 21 had no expertise in these fields but most of them lived in Lichtental or the surrounding area (neighborhood experts). Among them, there were 4 participants who were both technical and neighborhood experts.

4.3.2 Design of the survey

The goal of this survey was to understand the differences in the interpretation of urban data visualizations by stakeholders with and without expertise in the context of participatory urban strategies (RQ3). To achieve this goal, the survey was designed around three focal points: interpretation of urban data visualizations (RQ3a), effectiveness in interpretation based on the level of complexity and the map design (RQ3b) and map preferences (RQ3c). Figure 53 shows the survey design graphically.

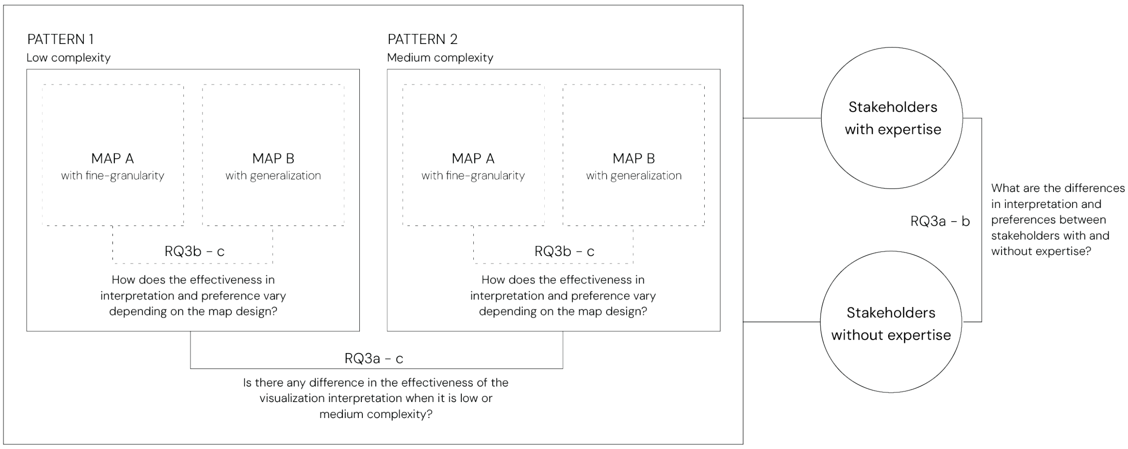


Figure 53: Diagram showing the survey design, and the questions to be unveiled, and the addressed RQ.

The survey included quantitative and qualitative questions. The quantitative questions were multiple-choice, while the qualitative questions were open-ended and related to the participant's understanding of the maps. The survey was split into sections: Introduction, Interpretation and Preferences of Pattern 1, Interpretation and Preferences of Pattern 2, and General Information (see Figure 54). The survey can be seen in Appendix B.

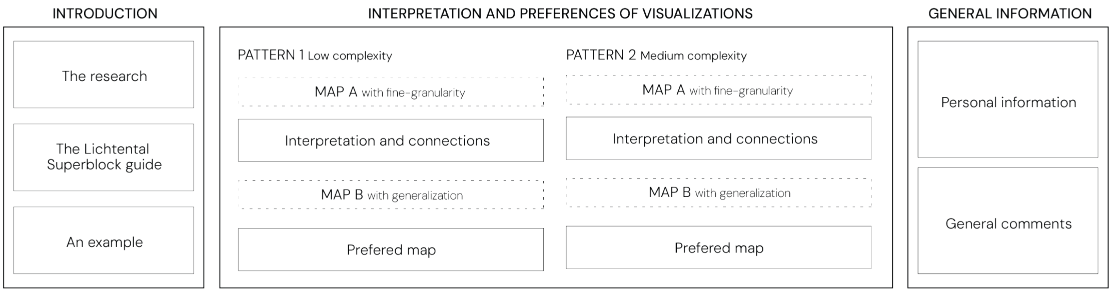


Figure 54: Graph showing the three sections of the survey

- Introduction

This section introduced the research, its objectives, and its purpose. An explanatory guide was created to ensure uniform understanding among all stakeholders regarding the Lichtental Superblock project, and an access link was provided. Additionally, an illustrative map was presented to clarify fundamental concepts that reappeared throughout the survey and that could lead to confusion among participants.

- Interpretation and preferences of visualizations

The subsequent two sections followed an identical structure but with differing visualizations. The first section presented Pattern 1 of low complexity, followed by the second, which presented Pattern 2 of medium complexity (refer to Figure 54 for the survey layout). In both sections, the same set of questions was reiterated. Initially, participants were presented with Map A and asked if they could identify connections between the layers. Response options included "Yes, I do," "No, I don't," or "I am not sure / I don't know". Subsequently, an open-ended question prompted participants to describe any connections they had identified. Expecting that stakeholders might not easily perceive patterns, a checkbox question was also included, listing possible assumptions that could be made when finding connections between the layers. This question included one or two wrong assumptions to assess respondents' ability to distinguish between correct and incorrect options. Following this, Map B was presented. Map B represented Pattern 1 of low complexity but with a change in the visualization strategy used. Participants had to look at it and then answer questions comparing the two maps regarding preferences regarding Aesthetics, Ease of Interpretation, and Data Accuracy and Level of Detail. They were required to select among “Map A“, “Map B“, “Equally“, or “None“. This structure was replicated for Pattern 2 of medium complexity, including two maps (A and B).

- General information

This section asked participants about their expertise as stakeholders and whether they resided in Lichtental. Additionally, participants were allowed to provide any comments regarding the visualizations or suggestions for improvements.

4.3.3 Results

In this section, the results from the survey are going to be described.

- Description of the participants

Figure 55 provides an overview of the participants. Of the 46 participants, 25 had expertise (55.4%), and 21 did not have expertise (44.6%).

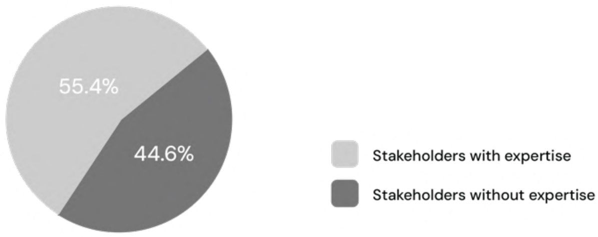


Figure 55: Participants of the survey.

- Interpretation and preferences of visualizations

The first question (Q1) asked if participants could identify connections between the layers in the visualizations. The visualizations presented Map A with fine granularity. Figure 56 shows the results for each pattern.

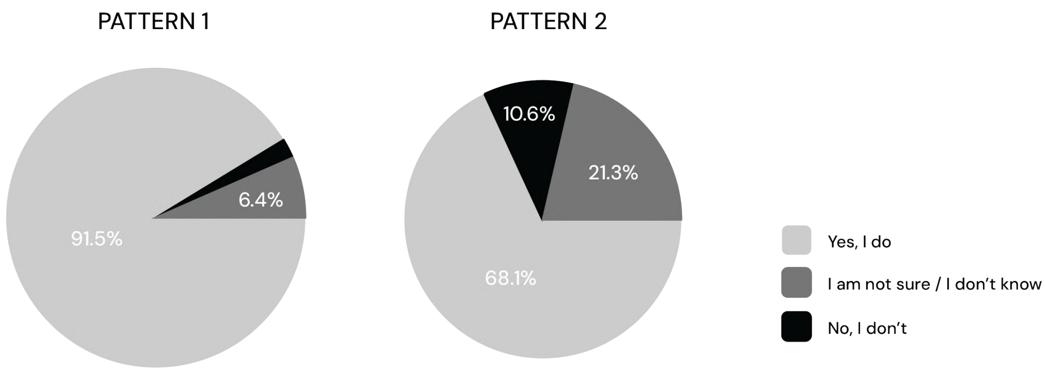


Figure 56: Results of the question "Can you find any connection between layers?".

In general, most participants could find a connection between layers in both patterns. However, the positive results were higher in Pattern 1 of low complexity (91.5%) than in Pattern 2 of medium complexity (68.1%). In Pattern 2, more than 30% of the participants were unsure or could not find connections. These differences between patterns were expected due to the change in complexity. In Figure 57 can be seen how the answers changed between stakeholders with and without expertise.

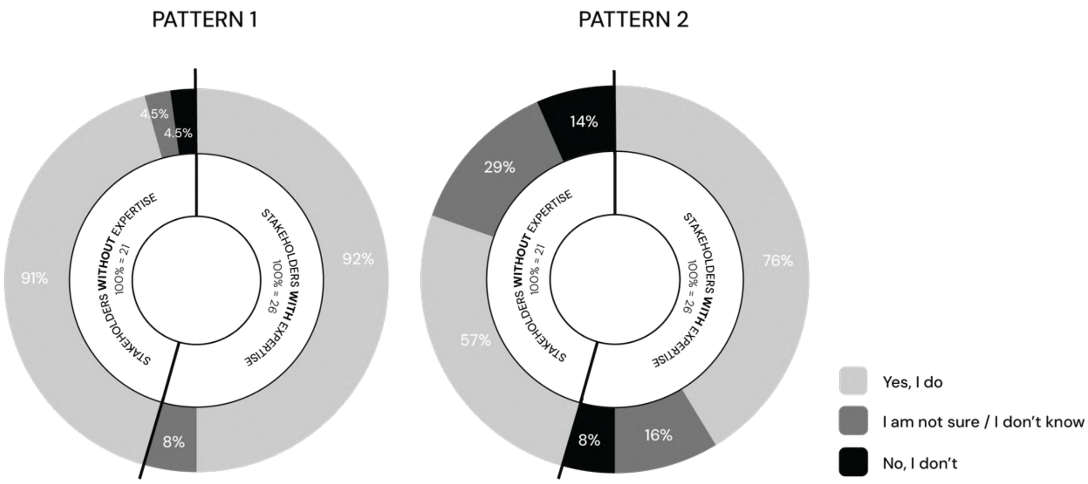


Figure 57: Results of the question "Can you find any connection between layers?" divided by stakeholders.

When comparing stakeholders with and without expertise, a trend emerges in Pattern 2: Stakeholders with expertise tend to answer more confidently, whereas stakeholders without expertise often express uncertainty (29%) or difficulty in identifying connections (14%). In the case of Pattern 1 as almost all the participants answered positively, there are no trends when dividing into the two types of stakeholders.

The second question (Q2) was open-ended to allow participants to write the connection found. It was included to understand if participants found a logical connection between layers and thus to avoid misinterpretations. The analysis of these answers was made individually. Two points were considered: if the explained link had a logical coherence and if they showed some uncertainty with the used words such as "I am not sure" "Could be…", among others. In both Patterns, participants answered with a correct connection, some even wrote more than one. The uncertainty in the answers was not significant.

The third question (Q3) was a multiple choice format that allowed participants to choose from provided assumptions outlining possible connections between layers. This question was included with the expectation that some participants would not be able to identify patterns on their own (Q1 and 2). Thus, it assessed whether participants could identify patterns when given clues. Pattern 1 presented three possible correct and one incorrect assumption. Pattern 2 presented two possible correct and two incorrect assumptions. Participants also had the choice to indicate that none of the given assumptions applied to the map. Figure 58 shows the results from Pattern 1, highlighting in bold the possible correct assumptions. Most participants selected the three options, and there is not much difference between stakeholders with and without expertise.

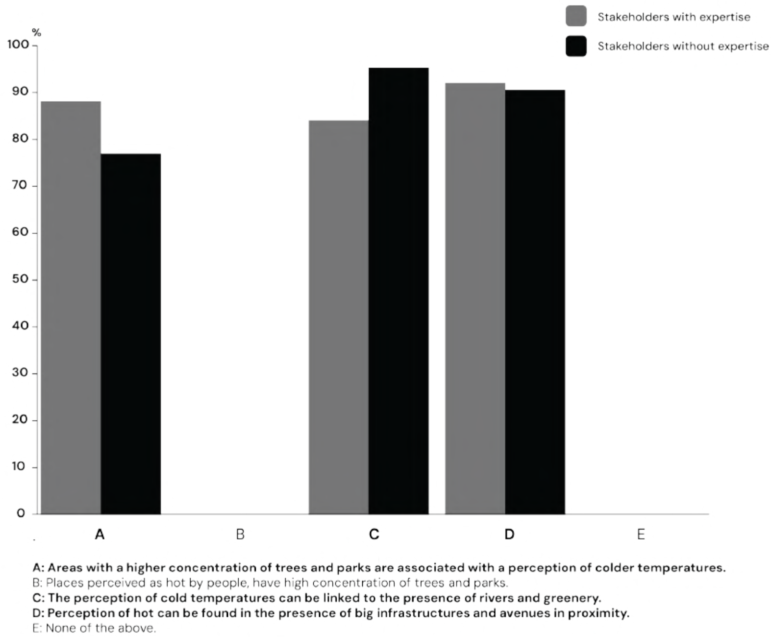


Figure 58: Results Q3 from Pattern 1.

Pattern 2's results are shown in Figure 59 and exhibit a higher degree of variability. This variation may have arisen because the visualization patterns were not clear enough, which could have confused participants trying to make assumptions.

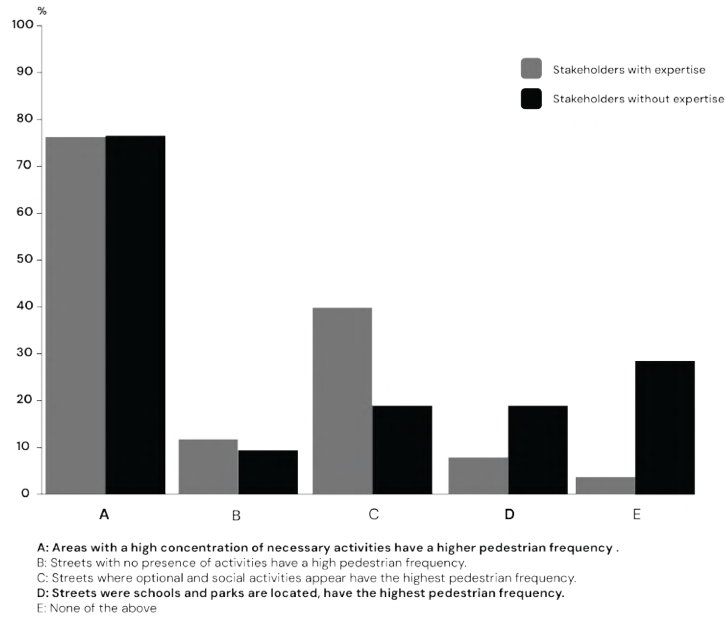


Figure 59: Results Q3 from Pattern 2.

Using the results from the three questions, a comparison was conducted among participants who could identify a pattern between layers right from the start (answering "Yes, I do" to Q1), those who not only identified a pattern but also explained it (Q2), and those who were able to identify a pattern using the multiple-choice assumptions provided (Q3). Figure 60 illustrates this comparison for Pattern 1.

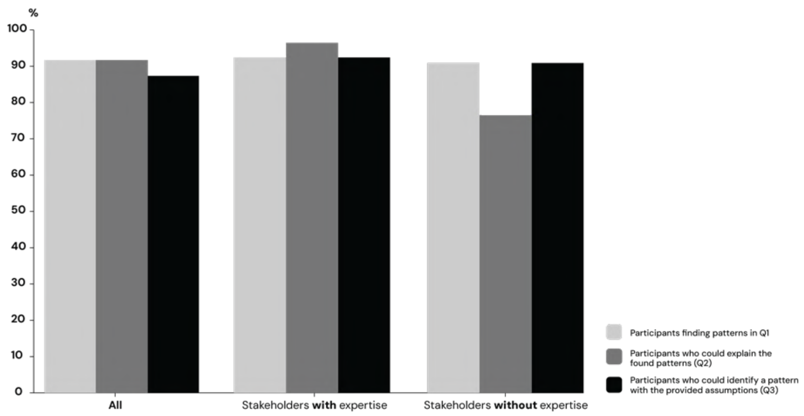


Figure 60: Comparison of Q1, Q2, and Q3 in Pattern 1

Since most participants in Pattern 1 initially responded positively, the graph does not show any significant changes. However, an apparent result is observed in Pattern 2, as shown in Figure 61. In general, the graph shows a noticeable increase in the percentage of pattern recognition when participants were presented with possible assumptions in Q3. Comparatively, participants with expertise showed a higher initial rate of pattern recognition than those without expertise (Q1). However, despite the lower initial rate for the latter group, it steadily increased over time, approaching a level similar to that of their expert counterparts (Q3).

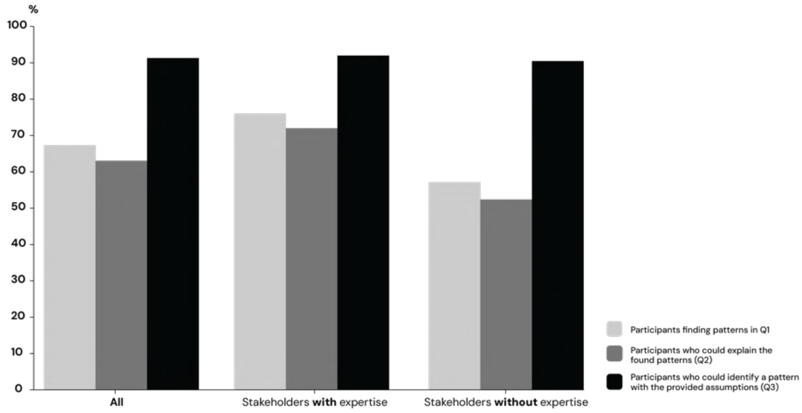


Figure 61: Comparison of Q1, Q2, and Q3 in Pattern 1

Before proceeding to the next set of questions, Map B was presented. In both Pattern 1 and Pattern 2, Map B displayed the same data as Map A but used different visualization strategies. While Map A displayed the data with fine granularity, Map B displayed a heatmap, a generalized data representation (as described in Section 4.2.4, Figure 36). Following the presentation of Map B, three subsequent questions (Q4, Q5, and Q6) were asked to understand preferences in terms of aesthetics (Q4), ease of interpretation (Q5), and data accuracy and level of detail (Q6) between Map A and B. These questions used a multiple-choice format, allowing participants to select one option from "Map A," "Map B," "Equally", and "None." Figure 62 shows the results from Pattern 1. In general, Map A was preferred by both stakeholders with and without expertise. The options "Equally" and "None" did not carry significant weight in the preferences.

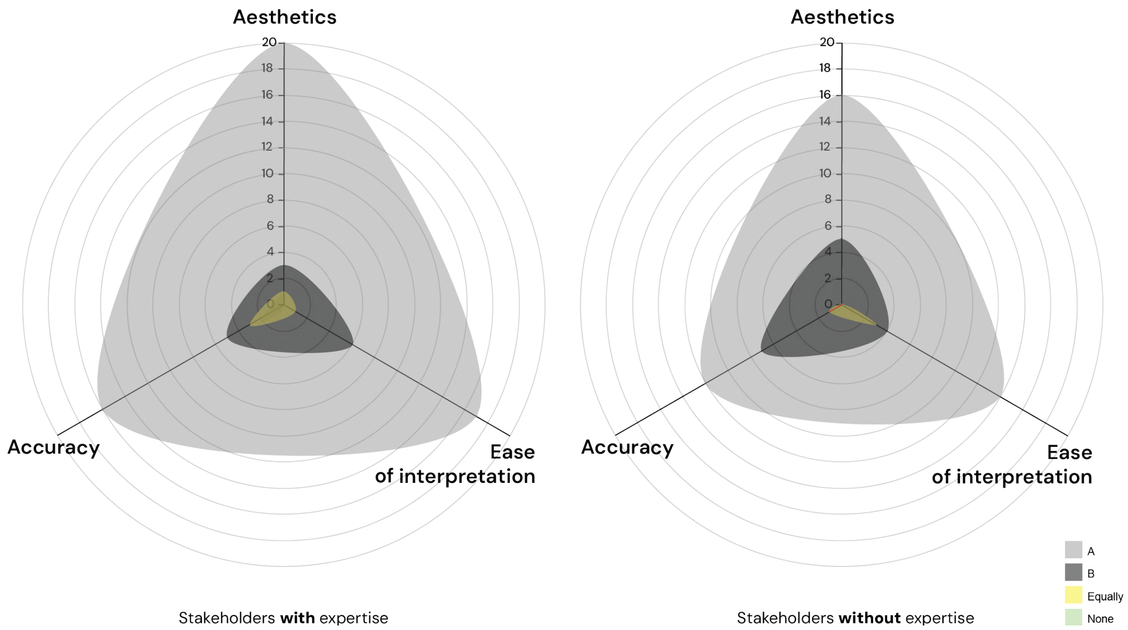


Figure 62: Results of Q4, Q5 and Q6 in Pattern 1

Figure 63 shows the results of Pattern 2, where several preference trends emerge among stakeholders with and without expertise. Without delving into specific criteria, Map A was preferred by stakeholders with expertise, and Map B was preferred by stakeholders without expertise. However, these results change upon closer examination. First, I will analyze the results by differentiating between the two groups of stakeholders. Then, I will break down the results based on specific criteria.

While there was no clear aesthetic trend, Map A was the preferred choice for accuracy and level of detail for stakeholders with expertise. Interestingly, Map B was slightly preferred for ease of interpretation, although the difference was not considered significant. For stakeholders without expertise, Map B showed a clear preference for aesthetics, while Map A regained its prominence for accuracy. Map B was preferred for ease of interpretation.

If we analyze the results from the criteria perspective, both groups preferred Map A in terms of accuracy, a preference likely influenced by the fine granularity of the map. Aesthetically, while experts showed relatively equal preferences, non-experts tended to prefer Map B. Meanwhile, regarding ease of interpretation, both groups tended to prefer Map B despite a slight discrepancy in preference intensity.

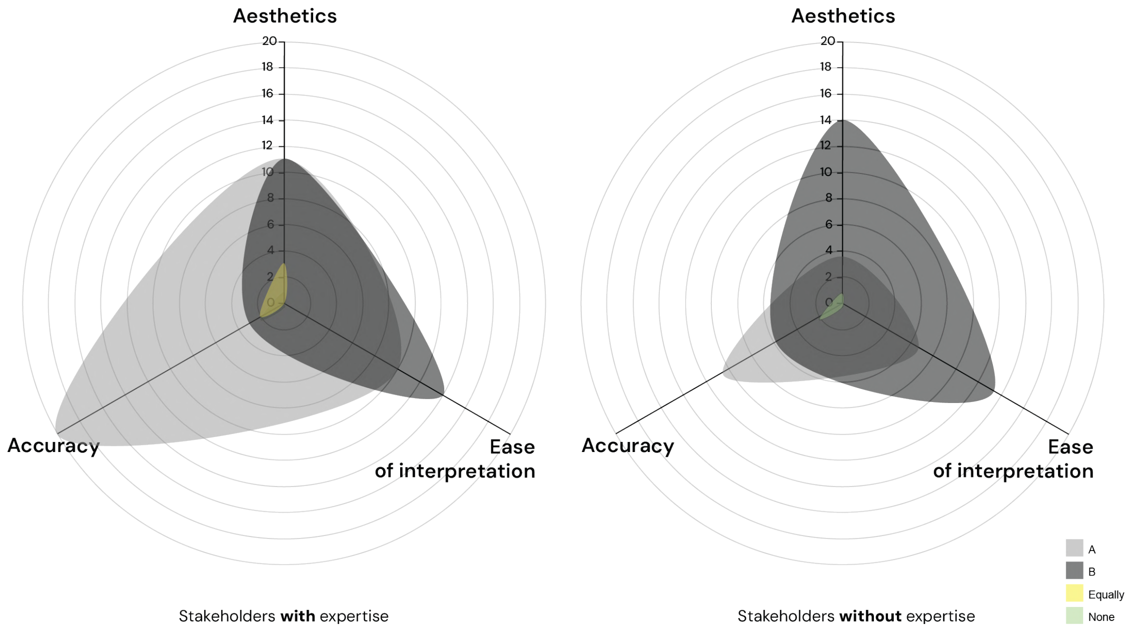


Figure 63: Results of Q4, Q5 and Q6 in Pattern 2

4.3.4 Conclusions

The survey results show a clear divergence in the effectiveness of pattern interpretation and map preferences of the two stakeholder groups depending on the visualization's complexity. It would be premature to conclude that a particular map design is exclusively effective for a particular purpose, as the limitations of this research influence the results of this survey. Nevertheless, the survey provided valuable insights that allowed some conclusions to be drawn.

It becomes evident that in low-complexity visualizations (Pattern 1), participants—both those with and those without expertise—could easily identify connections between layers. Notably, the fine granularity option (Map A) was strongly favored across all criteria. The results displayed greater variability when considering the medium complexity visualizations (Pattern 2). While participants initially encountered challenges in identifying connections between layers, a significant proportion succeeded when provided with assumptions. However, these results displayed variations based on stakeholders' expertise. Participants with expertise demonstrated a greater propensity for initial pattern identification than those without expertise. Yet, both groups exhibited equal capability in identifying connections when assumptions were provided. Regarding preferences, both groups favored Map A in terms of accuracy and Map B in terms of ease of interpretation. Aesthetically, while experts showed relatively equal preferences, non-experts tended to prefer Map B.

In conclusion, both stakeholders with expertise and those without possess the capacity to discern connections between layers. As anticipated, simpler maps yielded more favorable outcomes than their more intricate counterparts. Interestingly, while stakeholders with expertise showed superior ability to identify connections in complex maps, those without expertise achieved comparable results when assumptions were introduced. This indicates the potential for bridging the gap between these two stakeholder groups. Furthermore, it's noteworthy that in the open questions, some experts expressed the need for references related to the urban context. This consideration was not raised by participants living in the neighborhood or surroundings. This underlines the intricate interplay between technical experts and neighborhood experts and effective map comprehension.

5 Discussion

The main objective of this thesis was to identify optimal cartographic visualization strategies that combine objective data and citizen knowledge to serve as decision-making tools in the context of participatory urban planning. This chapter assesses the results by discussing and comparing them with the expected performance to verify that the research objectives have been achieved and that all research questions have been sufficiently answered. Afterward, the limitations of this study are discussed, followed by potential improvements and suggestions for future research.

5.1 Discussion

RO1: To analyze and create a catalog of urban data visualizations.

The catalog of urban data visualizations was created based on the comprehensive literature review in Chapter 2 and the map analysis in Chapter 3.2. The literature review provided the parameters to analyze and categorize the existing urban data visualizations (RQ1a). RQ1b addressed the actual map selection and analysis. This step resulted in a catalog that serves as a structured compilation of visualization strategies employed in the urban visualization domain, not only for this case but also for future work. The catalog aids in identifying best practices in urban data representation, saving time, and preventing errors.

RO2: To create a suitable visualization strategy to combine citizen knowledge and objective data.

Combining citizen knowledge and objective data is essential in urban planning as each type can complement and fill gaps left by the other (Billger et al., 2017; Hemmersam et al., 2016; Knigge & Cope, 2006). A methodological framework was developed to facilitate this combination. The framework focused on using visual references as a source to find better design solutions. RQ2a focused on identifying the design solutions commonly used for visualizing objective data and citizen knowledge. On the other hand, RQ2b explored how cartographic generalization techniques could be employed to simplify visualizations while preserving data patterns. Both visual strategies and generalization techniques were used within the context of the specific case study. However, neither of the questions has a definitive answer due to time constraints and the need for more in-depth research. Nevertheless, general recommendations on when to use generalization techniques can be found in Section 5.3.

RO3: To understand the effectiveness of the created cartographic visualizations by evaluating how stakeholders interpret, make connections, and make sense of different data types.

Field Cepero García & Montané-Jiménez (2020) suggested that the User-Centered Design approach was employed in the survey to achieve RO3. Their suggestion highlighted the need to analyze the decision-maker's profiles and opinions regarding satisfaction, capabilities, and preferences in urban visualizations. The survey results answered the three research questions embedded in RO3 regarding stakeholders' pattern interpretation and preferences.

RQ3a addressed whether there were differences in the effectiveness of pattern interpretation by stakeholders with and without expertise. This RQ was based on the hypothesis that stakeholders with expertise (technical experts) could make connections between layers and achieve more accurate assumptions. In contrast, stakeholders without expertise (neighborhood experts) needed extra help to find connections between layers. This hypothesis was partially overturned. Almost all stakeholders correctly identified connections between layers when working with low-complexity visualizations. On the contrary, in medium complexity visualizations, stakeholders with expertise recognized patterns easier than those without expertise. After providing hints about connections between layers, pattern recognition for the latter group reached a similar level to that of their expert counterparts. This result answered the second part of RQ3a, supporting the hypothesis that all stakeholders could understand the connections between layers when provided hints. This emphasizes the importance of considering users' needs to provide adaptable solutions to improve their understanding of visualizations. For instance, Marras et al. (2018) proposed an adaptable dashboard solution that empowers users to create urban data visualizations that meet their unique needs.

RQ3b aimed to prove whether changing the symbology of the visualization could improve pattern interpretation. RQ3c aimed to determine visualization preferences among stakeholders with and without expertise. To answer these questions, two maps were presented to the respondents: Map A showing a fine-granularity representation, and Map B, depicting a generalized version of Map A. The study results showed that all stakeholders preferred the fine-granularity representation for the low complexity visualization. On the other hand, the results were more complex for medium complexity maps. Both groups preferred the fine granularity map in terms of accuracy and detail. Aesthetic preferences were balanced among stakeholders with expertise, while those without expertise preferred the generalized map. Interestingly, both groups tended to prefer the generalized map (Map B) in terms of ease of interpretation. These results align with the findings made by Kleinmuntz & Schkade (1993), who observed that respondents sought a balance between maximizing accuracy and minimizing effort. Essentially, decision-makers needed a high level of accuracy to support their decisions (choice of Map A for accuracy and level of detail) while striving for minimal effort in the process (selection of Map B for ease of interpretation). Netek et al. (2018) suggest using heatmaps, a form of generalized maps, for the efficient visualization of data and hotspot identification. Nevertheless, their research discourages relying on heatmaps for precise data interpretations.

5.2 Recommendations

This section presents recommendations derived from the analysis of the case study results. They aim to improve the effectiveness of urban data visualizations in the context of participatory urban planning. I would like to emphasize that these recommendations are based on the results of a case study, and further research is needed to support these suggestions.

Recommendation 1: Tailoring visualizations considering their complexity levels.

The main objective of this thesis was to combine objective data and citizen knowledge to identify optimal cartographic visualization strategies, which can serve as decision-making tools in participatory urban planning. Visualizations were created and tested. Based on the results, two main recommendations were formulated regarding visualization complexity levels. These recommendations address accuracy maximization and effort minimization (Kleinmuntz & Schkade 1993).

When working with low-complexity visualizations, it is recommended to prioritize two key aspects: data accuracy and level of detail. This recommendation is consistent with the concept of accuracy maximization (Kleinmuntz & Schkade, 1993). Accuracy maximization suggests that stakeholders tend to make decisions more confidently when including the highest accuracy and the highest level of detail in the data. The nature of low complexity visualizations allows for the inclusion of accurate and fine granularity data without overwhelming users with excessive details.

When working with medium complexity visualizations, the visualization strategy choice should align with the intended goals of the map. There are two main goals for medium complexity visualizations: high data accuracy and level of detail or ease of interpretation. If the primary goal is to achieve high data accuracy and level of detail, it may be advantageous to opt for fine granularity. However, it is essential to avoid excessive detail that may cause overlapping elements, reduce readability, and overwhelm the user. On the other hand, if the goal is to prioritize ease of interpretation, a generalized visualization may prove more effective. This approach is closely related to the concept of effort minimization (Kleinmuntz & Schkade, 1993), which focuses on reducing the time, resources, or cognitive effort required to understand the visualization and make informed decisions. A generalized visualization presents information in a pre-digested form to the user, thereby simplifying the interpretation process. It is worth noting that in such cases, including subtle hints or assumptions can further enhance the intended interpretation.

<u>Recommendation 2: Adapting to Workshop Objectives</u>

This thesis aimed to create visualizations as decision-making tools within the framework of participatory urban planning. A theoretical participatory mapping workshop proposal has been designed to fulfill this aim. The workshops focus on making connections between layers and finding patterns in urban visualizations. Two workshops are proposed: Data Exploration Workshop and Pattern Conveying Workshop. It is important to note that the descriptions of these workshops provide a conceptual framework rather than an exhaustive guide to their execution.

Data Exploration workshops aim to empower participants to actively uncover intricate relationships and hidden patterns within urban data visualizations. Data Exploration workshops emphasize the importance of collective intelligence (Denwood, 2022), allowing stakeholders to contribute their perspectives and expertise to the data analysis process. For instance, technical and neighborhood experts can share knowledge to enrich data understanding and pattern recognition. The preferred visualizations to use in these workshops are dynamic and provide access to diverse datasets. With interactive visualizations, participants can delve deep into the data, ask questions, and generate insights. This workshop allows urban planners and communities to make collaborative city planning decisions that align with the needs and aspirations of all involved.

The Pattern Conveying Workshop is designed to communicate pre-identified patterns to participants. These workshops should ensure that the communication of patterns is as clear and understandable as possible. Interactive elements, such as pop-up annotations and tooltips, are key in highlighting and explaining specific patterns within the data. The workshops can also be integrated with urban planning workshops. In this collaborative approach, patterns serve as both a starting point and a compass, guiding stakeholders in the design process toward more informed and effective urban solutions.

5.3 Limitations

While this research provides an interesting first step in exploring urban data visualization as a tool for participatory urban planning, it has several limitations. Firstly, the results of this study survey are likely influenced by the small participant numbers (N = 46). This was most apparent when comparing stakeholders with and without expertise, with n = 25 and n = 21 participants, respectively. Additionally, the data collected through the Mental Mapping workshop was also limited, given the relatively small number of participants (20 passersby). Matheus et al. (2020) present the relationship between data quality and quantity as one of the challenges in urban data visualizations.

The availability of data and the limited time to collect it, was a notable constraint, particularly concerning citizen knowledge data. The scarcity of this data type determined the layer selection and influenced the direction of the visualizations. As only two layers of this type were available, the objective data layers had to be selected to complement these available layers. Ideally, the selection should have been guided by user needs (Cepero García & Montané-Jiménez, 2020; Zhang et al., 2008).

Moreover, the design of the map was greatly influenced by time limitations. As previously stated, the project timeline did not account for data collection, resulting in a shorter map design timeframe. Creating a map typically involves multiple rounds of expert feedback before conducting the survey, but in this case, only a few rounds could be done. Additionally, the time constraints restricted the amount of data collected. Ideally, workshops for data collection are conducted multiple times to obtain data from a broader range of participants. However, designing the map required time, so only one workshop could be organized.

This research is firmly rooted in one specific case study, so the conclusions should be viewed within this contextual boundary. Urban planning and participatory strategies exhibit a high degree of variability, influenced by diverse factors such as location, culture, and stakeholder dynamics. Consequently, the findings and recommendations derived from this single case study may not seamlessly transfer to every urban planning scenario. Other contexts' unique characteristics and intricacies could lead to different outcomes and requirements.

5.4 Future work

As this research is based on one case study, future efforts could include a broader range of cases to increase the reliability and applicability of the results and recommendations. These case studies could explore different urban contexts, involve different stakeholder groups, and incorporate a more diverse range of data types. By conducting a comprehensive set of case studies, common patterns could be identified, along with best practices and visualization strategies that could be reliably applied to different urban planning scenarios.

Future efforts could also include a practical implementation of the visualizations as dialogue tools in participatory urban processes. This includes refining the visual techniques among diverse groups and ensuring that the visualizations serve as catalysts for informed decision-making. The focus should be on how these visualizations can be integrated into real-world urban planning scenarios to foster stakeholder collaboration, insight, and consensus. Moreover, this future work could apply the workshops proposed in Section 5.2 to real-life urban planning situations.

Additionally, in the evolving landscape of participatory urban planning, flexibility and accessibility are essential. Therefore, future work could focus on developing interactive platforms that accommodate a variety of data layers and provide users with greater freedom to explore and interact with urban data. This includes the creation of user-friendly interfaces that allow stakeholders to customize their visualizations, add additional layers of information, and actively engage with the data. Such platforms will enable more dynamic and user-driven urban planning processes.

6 Conclusions

This study aimed to identify optimal cartographic visualization strategies that combine objective data and citizen knowledge, serving as decision-making tools within the framework of participatory urban planning. To achieve this goal, this study has developed a methodology to create visualizations that merge the two data types. These visualizations included varying complexity, granularity, and generalization levels. The Lichtental Superblock project in Vienna served as a case study, and the evaluation process involved technical experts and residents.

This study showed that the complexity of the visualization influences the pattern interpretation and map preferences among the two groups of stakeholders. Low complexity maps showed that fine-granularity representation was more effective for supporting decision-making due to its balance between accuracy maximization and minimal effort. On the other hand, medium complexity maps delivered more complex results. Stakeholders with expertise showcased a higher ability to identify connections in complex maps. However, those without expertise achieved comparable results when provided with hints. This emphasizes the importance of considering users' needs to provide adaptable solutions to improve their understanding of visualizations. In terms of preferences, the fine-granularity map was favored by both groups regarding accuracy, but the generalized map was chosen regarding ease of interpretation.

This research opens possible directions for future research, including the possibility to test a broader range of case studies to increase the reliability and applicability of the results, the practical implementation of the visualizations as effective dialogue tools in participatory planning processes, and the implementation of interactivity in the visualizations to accommodate a variety of data layers and provide users with greater freedom to explore and interact with urban data.

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8 Appendixes

All the appendixes can be accessed at this link: https://kartoweb.itc.nl/msc-carto-thesis/materials/camila_narbaitz_sarsur/

List of appendixes:

Appendix A: Catalog of visualization strategies.

Appendix B: Survey questions - Google Forms.

Appendix C: Survey responses.

Appendix D: Analyzed results.