Participatory Design of Visual Analytics Tools for Different Target Groups

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***Abstract*—This paper reflects on the software engineering process behind the development of data visualization and analytics technologies tailored to the needs of diverse user groups. These considerations, introduced in our earlier work, are briefly revisited here. We focused on two use cases: one tailored to the needs and preferences of practitioners (data analysts), and the other directed towards meeting the requirements of non-professional, volunteer-based participants engaged in participatory citizen science. In both scenarios, we employed participatory methods, actively involving the target users in conceptualization and implementation phases. We observed diverse requirements and preferences concerning data visualization choices, additional functionalities, and analytical measures. To assess the effectiveness of these tools, in the current paper, we conducted a task-based evaluation with selected participants, asking them to perform specific tasks such as identifying faults in the data, patterns, or detecting outliers. This was supplemented with qualitative feedback gathered through interviews and surveys, providing insights into user satisfaction, perceived challenges, and suggestions for improvement. The evaluation process revealed several areas for improvement from non-practitioners, particularly in the visual clarity of visualizations and the explanations regarding their usage, while practitioners responded more positively, noting no critical issues in software design and function.**

***Index Terms*—Participatory design, Visualization design, Visual Analytics dashboard, Data quality.**

I. Introduction

In the field of technology development, and particularly related to the development of data visualization and analytics tools, a close collaboration with domain experts is a widely adopted approach. Such collaboration facilitates continuous evaluation of the tools' usability and the effectiveness of their core functionalities [1]. Quantitative user studies are frequently conducted to enable domain experts to reflect on, discuss, and gain insights into various data visualization and exploration techniques [2],[3]. However, at the core of these practices lies a common oversight where the design process prioritizes the needs and preferences of practitioners (e.g., data analysts), rather than the requirements of non-practitioners (e.g., the general public) [4]. Consequently, the resulting visualization tools may be too complex or may use a myriad of domain-specific technical terms that hinder comprehension and engagement among non-expert users.

This issue becomes particularly problematic in participatory citizen science initiatives, where these tools are utilized by non-professional, volunteer members of the general public [5]. Generally speaking, citizen science is a process that considers involvement of nonprofessionals in scientific research and knowledge production and is increasingly being recognized as a mainstream approach for collecting diverse types of environmental data [6]. It is thus not surprising that the number of ongoing citizen science projects is on the constant rise. A majority of these campaigns consider using some kind of supporting digital technology, e.g., for data collection or validation during environmental or biodiversity monitoring [7]. Although, digital tools are in principle meant to empower citizen scientists, their effectiveness hinges on factors such as usability and accessibility. As mentioned at the outset, this is due to the design process that only caters to rather narrow user demographics, which leads to such tools often being incomprehensible to a broader spectrum of the non-professionals [4].

In an effort to remedy these issues, this contribution focuses on the design, conceptualization, and evaluation of interactive data analytics dashboards tailored for diverse audiences. In all cases, the focus is on practitioners and non-practitioners. On one hand, we examined the specific needs, requirements, and comprehension of a diverse set of participants with limited or no prior analytical knowledge (i.e., non-practitioners). These participants are currently undergoing orientation and training to engage in environmental data collection campaigns. This section highlights the ongoing research efforts within the GREENGAGE project, funded under the Horizon Europe framework [8]. On the other hand, we focused on the preferences, needs, and usability of domain experts (i.e., practitioners), summarizing insights from continuous conceptualization and reflection sessions conducted at our research institution.

While our initial study [9] outlined two key processes related to the design and conceptualization of interactive data analytics dashboards, the current contribution expands the discussion by incorporating the outcomes of the related user evaluation process. To enhance clarity and better distinguish between our prior and current contributions, we provide a summary of the respective work as follows:

- To provide context for our current contribution, we reflect on our prior work [9] within Section II, specifically on the design and decision-making processes, along with the related considerations, involved in developing interactive

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data analytics dashboards for different target groups.
- We then detail the recently undertaken user evaluation process used to assess the effectiveness of these tools across different target groups (Section III).

This extended effort advances the research by incorporating a comprehensive evaluation step to assess the effectiveness and usability of the developed dashboards. By involving users in task-based evaluations and gathering qualitative feedback through interviews and surveys, we gained deeper insights into their experiences and challenges. Additionally, we took the first steps in implementing feedback-driven improvements, particularly for the non-practitioner dashboard, to enhance usability, functionality, and overall user satisfaction. This progression allows us to refine the tools further and provides a more holistic understanding of how participatory design can inform iterative development in visualization software engineering.

Our contributions are summarized as follows, reflecting our cumulative effort across both prior and ongoing work:

- *Framework for Diverse Audience Design*: A structured approach to visualization software engineering that caters to expert practitioners (e.g., data analysts) and non-professional participants (e.g., citizen scientists), accounting for their varying requirements and expertise levels.
- *Participatory Design Process*: The implementation of participatory methods, involving target users throughout the conceptualization and development phases, ensuring the tools align with user-specific needs and goals.
- *Evaluation and Insights*: A task-based evaluation complemented by qualitative feedback (e.g., interviews and surveys), providing insights into user performance, satisfaction, and areas for improvement in the context of data visualization and analytics tools.

Our paper is structured as follows: Section II reviews related work and reflects on our initial study to provide context for our current study. Specifically, we reflect on two distinct approaches to participatory design of interactive data analytics dashboards, tailored for practitioners and non-practitioners. Section III outlines our evaluation methodology and presents the key findings from this process. Section IV concludes with a summary of our work and highlights initial improvements implemented for the non-practitioner dashboard based on user feedback.

II. Related Work and Prior Design Foundations

A. Value of Visualizations and Participatory Design

As technology becomes increasingly integrated across various fields, there is a growing need for computer sciences to recognize the importance of designing data analytics tools and respective data visualizations that cater to the diverse needs, skills, and goals of different users.

In 2005, van Wijk [10] examined the fundamental question of why visualization is valuable and how its impact can be assessed. He proposed a conceptual model in which the value of visualization emerges from the interaction between data, user knowledge, and visualization techniques. This model builds on the idea that effective visualizations should not only facilitate pattern recognition but also enhance decision-making and enable users to derive meaningful insights from complex data. These conceptual considerations were applied in the work of Fekete et al. [11] who explored the role of interactive visualizations in enhancing understanding, enabling pattern recognition, and supporting exploratory data analysis. They also examined key challenges in measuring the effectiveness of visualizations, such as defining objective evaluation metrics and balancing information density with usability. When considering different target groups, the work of Ridley and Birchall [12] emphasized that to fully understand how different target users engage with data visualizations, it is essential to consider user experience, contextual relevance, and socio-cultural influences. They further stressed the need to tailor visualization assessments to distinct user groups, ranging from casual users to domain experts, to ensure that visualizations are not only effective but also meaningful and relevant within their specific contexts.

In their work, Jänicke et al. [13] highlighted how this can be effectively achieved through participatory design, where different stakeholders actively contribute to the design process of data visualization tools. They demonstrated the advantages of this approach across several domains, including biodiversity research, digital humanities, sports analytics, and industrial applications. The findings of this study emphasize the importance of understanding how domain experts engage with state-of-the-art data visualization and analysis tools through ongoing mutual discussions. This ensures that a diverse range of visualization techniques can be developed and tailored to meet the varying needs of different users. Additionally, the study emphasizes the value of early prototyping to bring concepts to life and the necessity of fostering transparency in how data is processed and represented within visualizations. This aligns with the findings of Martínez-Fernández et al. [2] who emphasized the significance of incorporating user feedback loops in modern software development. Their study demonstrated how engaging practitioners and assessing their perceptions of a tool's usability, by focusing on attributes like understandability, reliability, usefulness, and relevance, can significantly improve the tool's adoption and effectiveness.

Despite these advancements, current participatory and user-centric design methodologies often remain constrained by catering primarily to a limited group of domain experts. Even in contexts that depend on digital tools for citizen participation, these tools are frequently offered as fully developed, ready-to-use solutions by developers, limiting opportunities for deeper engagement with citizens (e.g., non-experts) and the consideration of their specific needs and requirements [14]. Considering that only around 28% of people in Europe possess above basic digital skills [15], it is reasonable to anticipate a low level of comfort when engaging with such out-of-the-box digital solutions. Additionally, Herodotou et al. [16] highlighted the value of continuous citizen participation during development, demonstrating that it not only enhances usability but also cultivates a sense of ownership among participants. Thus, expanding participatory frameworks to include diverse user profiles is critical to fostering greater adaptability and inclusivity in the design and application of data analytics tools.

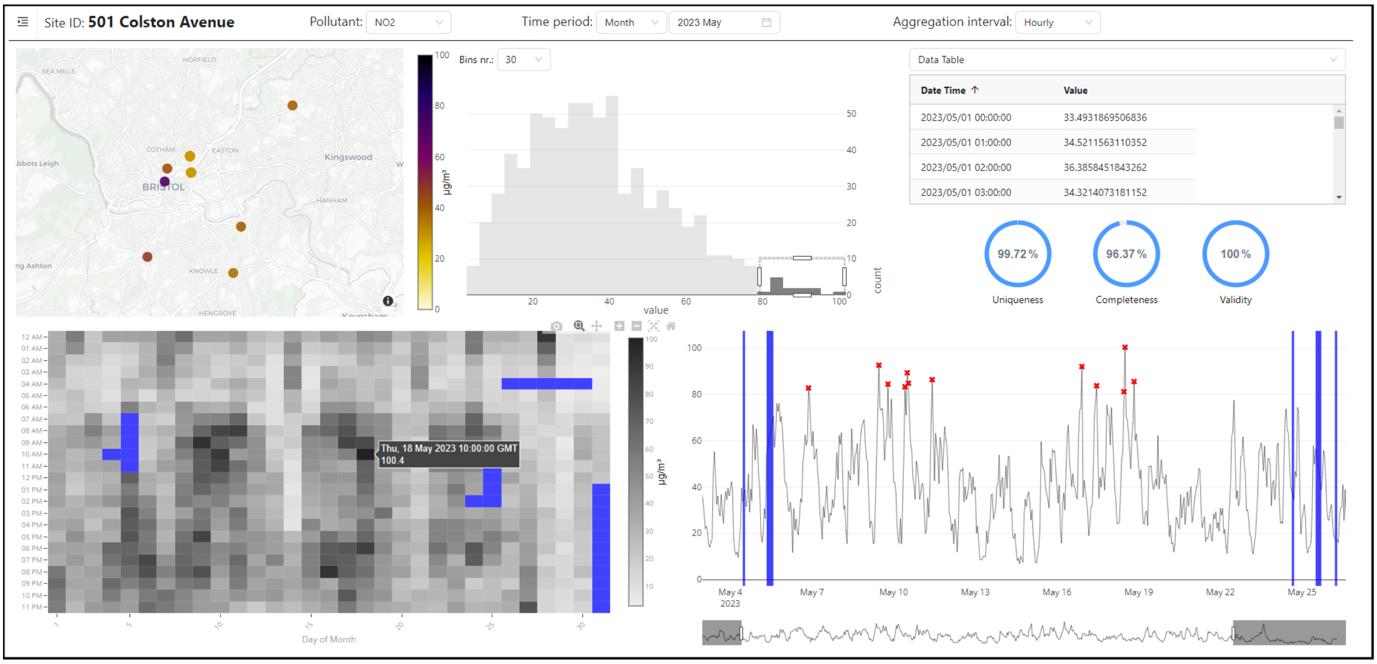

Fig. 1. Web-based data analytics dashboard developed for the non-practitioners used to analyse and monitor data quality through visual cues, quality metrics, and descriptive statistics, allowing users to quickly identify potential issues.

To the best of our knowledge, this is the first study to directly compare the participatory design process and guiding principles of visualization software engineering tailored to the development of data visualization and analytics technologies for diverse target audiences.

B. Authors' Prior Design Foundations

In our prior related work [9], we presented two distinct design and decision-making approaches for developing interactive data analytics dashboards for data quality assessment, each tailored to meet the unique needs of practitioners and non-practitioners. A brief reflection on the respective insights is provided below.

1) Non-practitioners: Our earlier work leveraged insights from the EU-funded GREENGAGE project [8], which focuses on using digital tools, such as mobile apps and web platforms, to actively engage the general public (non-practitioners) in observing, sensing, and monitoring their urban environments. These activities are implemented across five pilot sites in distinct European cities and regions: *Copenhagen, Turano, Gerace, Bristol, and North Brabant*, where the choice of tools was guided by the unique information needs of each pilot, aimed at understanding and tackling diverse environmental challenges specific to their local contexts.

Looking at the respective technology design process, this use case was shaped by a set of user requirements developed through multiple collaborative intra-consortia sessions. These sessions were instrumental in defining the most effective graphical representations for the understanding and analysis of citizen-collected data and for gaining valuable insights into the diverse needs and preferences of end-users across various pilot locations. Key considerations such as varying levels of digital literacy and user-specific requirements emerged, all of which influenced the design direction. Consequently, we developed a prototype (Figure 1) featuring a user-friendly interface with simplified functionalities, a single-page dashboard layout, while placing a strong emphasis on accessible color schemes designed to support users with visual impairments, such as color blindness.

In terms of supporting visual elements, we recognized the importance of using simple data representations to make complex information more accessible and understandable (Figure 1). An interactive map was chosen as the most effective way to display geospatial data, particularly for visualizing individual data collection locations. To provide an overview of the acquired data, we selected a simple line chart, offering a clear view of the temporal evolution of the explored parameter. A histogram was also included to visualize the distribution of continuous data, helping users identify tendencies in specific values or ranges. An additional key requirement was the incorporation of a heatmap to visualize time-based patterns in the acquired data. To enhance the interpretability of the data quality, we included clear data quality metrics such as temporal uniqueness, completeness, and validity. Alongside these visualizations, a data table was provided, offering a tabular representation of individual data points, enabling users to explore specific data points and their corresponding values for a more detailed analysis.

2) Practitioners: In contrast, the needs and requirements of the practitioners were drawn from our daily practices, where the continuous refinement of our data visualization and analytics tools is done in close collaboration with industry partners. As a research center, we prioritize an open exchange of ideas with our partners through ongoing dialogue and feedback loops, ensuring that our solutions are both technically robust and practically applicable. This dynamic approach enables us

Fig. 2. Web-based data analytics dashboard developed for the practitioners with advanced and responsive visualization and customization options.

Fig. 3. An example of repositioning the core visualization panels within the data analytics dashboard to align with a user-centred workflow needs.

to adapt our tools to the evolving needs and expectations of our users and stakeholders, ensuring their long-term relevance and value.

The respective technology design process focused on continuous conceptualization and refinement sessions, involving both domain experts (data analysts and engineers) and dashboard designers. These sessions began with a collaborative analysis of common data analytics workflows, tasks, and daily practices, forming the foundation for the technology's development. Based on these insights, a prototype was developed tailored to address the identified needs, specifically being able to handle and display complex multivariable datasets and enable simultaneous visualization of multiple time-series for comparative assessment across a dataset (see Figure 2). These are simultaneously depicted across a number of tailored visualization panels, including a line chart with a range slider, a histogram, a boxplot, a duration curves plot, and a calendar heatmap. Additionally, a data table and a descriptive statistics table allow for a detailed inspection of raw data values and further support hierarchical sorting of variables to facilitate ordering based on a desired criteria.

C. Summary of Insights from Different Target Groups

The above-mentioned processes provided several valuable insights. The non-practitioners typically required simplified functionalities and intuitive data visualization solutions to ensure ease of use, particularly to accommodate the generally lower levels of digital and data literacy. Their needs emphasized the importance of clear, straightforward interfaces and easy-to-interpret visual elements that would enable effective engagement with presented information without overwhelming the users. The design also restricted the display to a single time-series at a time, reducing visual clutter and ensuring a clean, focused data visualization.

Practitioners, on the other hand, demanded a more advanced and sophisticated design. They stressed that the solution should prioritize key aspects such as responsiveness, flexibility, and customization to accommodate the complex and varied workflows of domain experts. This adaptability would ensure that the tool seamlessly integrates into their daily practices, enabling efficient data exploration and analysis without compromising on functionality. This entailed a wide range of advanced data visualization options, guided by established principles for effective visualization [17], to ensure clarity and insight. This also included the ability to examine multiple time-series simultaneously, enabling comparative analysis across various parameters and scales. Furthermore, interactive filtering and drill-down functionalities allowed users to explore data at multiple levels of detail, while advanced data manipulation and transformation features provided the options for adjusting and changing the data. All these capabilities were integrated into a flexible multi-panel dashboard structure. The dashboard's flexibility was further enhanced by enabling users to freely reposition individual visualization panels (see Figure 3), allowing them to tailor the layout to their specific workflow requirements and align it with their analytical sensemaking process [18].

III. Evaluation

Building on the insights mentioned above, our current contribution extends the discussion by integrating the results of the corresponding user evaluation process. For both use cases, our evaluation methodology was based on task-oriented, think-aloud techniques [19]. This encouraged users to verbalize their thoughts while performing specific tasks on our interactive analytics dashboards. This further allowed us to identify potential usability issues, and better understand how users interacted with the tools in real time.

A. Evaluation with Non-practitioners

1) The Process: For non-practitioners, we adopted a guided evaluation process involving six participants, whereby each session was conducted individually. The guided evaluation process involved instructing participants on how to use specific data visualization modules for each task or question, while we assessed how easy or difficult the process was for them. The selected participants are members of the GREENGAGE consortium with no background in data science or computer science. Specifically, they included three municipality representatives and three social science professionals specializing in participatory citizen science, who do not typically engage in data analytics as part of their daily work.

We based our evaluation on a synthetically generated time-series dataset representing ambient air temperature, spanning a range of several months, where we intentionally introduced quality issues like missing values and outliers. The reasoning behind the focus on temperature data was that this is a more familiar and understandable measure for laypeople, making outliers easier to identify and interpret.

Our evaluation process was carried out through online video calls, which were recorded with participants' prior consent. Our evaluation process consisted of three consecutive steps:

- *Onboarding*: We started with a short onboarding session during which we walked each of the participants through every data visualization module, explaining its purpose, the specific information it was designed to display, and how to interpret it to extract insights. We then shared with them a structured, standardized questionnaire with specific tasks they are expected to do and questions they need to answer. We also included a Likert scale, a numerical rating scales from 1 to 5 for a very negative to a very positive feedback, to assess how difficult or easy a specific task was for them. However, following the first user study, we recognized the need to revise the onboarding process, particularly regarding the interaction modalities of each data visualization module. To address this, we included short videos demonstrating how to interact with each individual visualization module. This was prompted by the first participant's uncertainty about how and in what way they could interact with the visualization modules, as these actions did not align with their intuitive way of thinking.
- *Task-based assessment*: Our tasked-based questionnaire was structured around four core topics: *location analysis, general data quality assessment, pattern recognition, and outlier detection*. For location analysis, participants were asked to use a geospatial map to explore the number of data collection points and their respective positions. The general data quality assessment involved using data quality metrics to identify potential issues with the data, alongside a line chart to detect missing values over time. Pattern recognition relied on a heatmap to identify any temporal patterns related to missing data. Outlier detection involved using a histogram to spot outliers and then investigating these problematic data points in the line chart once selected from the histogram. Additionally, participants were asked to look for outlier patterns in the heatmap after identifying them in the line chart.
- *Qualitative feedback*: We encouraged participants to provide verbal feedback as they completed the predefined tasks, sharing their thoughts, challenges, and observations in real-time to help us better understand their experiences and improve our interactive analytics dashboard.

2) The Feedback: Overall, the feedback on the user interface was mixed among participants, with municipality representatives experiencing more difficulty navigating the data visualization modules. At times, they encountered confusion and frustration. However, it is important to note that these participants belong to a group with little to no digital literacy and hardly ever engage with data analytics in their daily work. In contrast, the social science professionals generally found the data visualization modules intuitive and easy to navigate.

One common remark from both groups was that they were sometimes confused by the lack of clear visual distinction between the data visualization modules and the labels associated with each module. They suggested that clearer visual separation, such as bounding boxes, and more intuitive labeling could help improve user understanding and navigation, particularly for non-practitioners who may not be familiar with data visualization conventions. Furthermore, participants highlighted the need for introducing titles and brief descriptions for each module, clarifying both its purpose and how to use its interactive features. They noted that this would help users better understand the purpose of each module and guide them in navigating its functionalities more effectively.

Another issue arose with the selected color scheme. The system's default color gradient used black to represent the highest value, but this color was unintentionally associated with the presence of gaps in the data, creating confusion with the existing blue representation of missing values. This problem was especially evident in the heatmap visualization. Apparently, the tool's default color scheme is not well-suited for scenarios with a wide amplitude between high-value and low-value data points, a situation amplified by the inclusion of synthetically generated outliers. Although our tool provides the flexibility to customize the color scheme, we decided to stick with the default gradient for this user study to ensure consistency.

Figure 4 provides a summary of participants' satisfaction with each visualization module evaluated based on its ease of use and its ability to answer our questions, broken down by each topic and the corresponding visualization module. These ratings were derived from numerical ratings on a scale from 1 to 5 for a very negative to a very positive feedback, which are then averaged across the sample, with 95% confidence intervals calculated to ensure statistical reliability and provide insights into the variability of the responses. It was observed that participants encountered the greatest difficulty when interacting with the histogram module and the concept of data distribution in general. This challenge may arise from participants' limited familiarity with histogram-based data visualization techniques, which are not as widely represented or utilized in mainstream contexts. Similarly, the concepts behind the data quality metrics were seen as confusing and needed a more thorough explanation to clarify their meaning.

B. Evaluation with Practitioners

1) The Process: For practitioners, we adopted the heuristic-based ICE-T methodology [20] to systematically assess the effectiveness and value of the proposed data analytics solution.

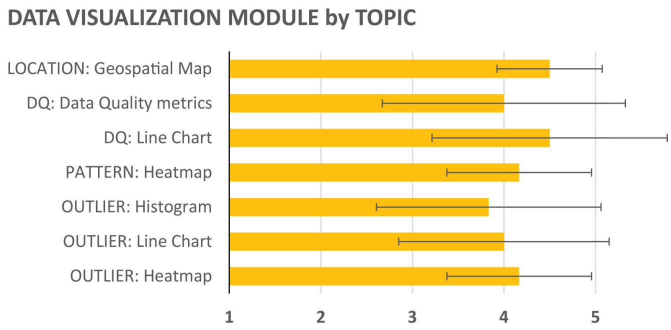

Fig. 4. Participants' responses regarding the ease of use of each visualization module and its features divided per considered topics (location analysis (LOCATION), general data quality assessment (DQ), pattern recognition (PATTERN), and outlier detection (OUTLIER)), derived from numerical ratings (1 to 5), and averaged over the sample with 95% confidence intervals.

Namely, the ICE-T methodology is a qualitative framework used in visualization research to assess the effectiveness and value of visual representations. This approach relies on a series of detailed, task-specific questions during the execution of predefined evaluation activities and it focuses on how users perceive, interpret, and interact with visualizations, which are largely shaped by cognitive processes rather than statistical variability.

The ICE-T methodology comprises four key components: *Insight, Confidence, Essence, and Time*. Insight evaluates how effectively a visualization enables users to uncover patterns, relationships, or unexpected findings. Confidence assesses whether the visualization reduces uncertainty and enhances trust in decision-making. Essence measures how quickly users grasp the dataset's most important aspects. Time examines the efficiency of data interpretation and analysis. The ICE-T survey form includes structured questions based on these components, gathering qualitative feedback on how well a visualization supports pattern recognition, interpretation confidence, data comprehension, and analytical efficiency.

Given that the methodology requires only a small number of participants, a practice that was equally deemed acceptable and effective in previous studies [20], we selected five test users based on their extensive prior knowledge and experience with information visualization and data analytics. Specifically, the authors of the ICE-T methodology [20] state that the ICE-T is designed to capture rich qualitative insights rather than rely on large-scale statistical validation. It focuses on how well users gain insights, build confidence, grasp the essence of data, and complete tasks efficiently. These aspects do not necessarily require a large sample, as deep qualitative feedback from a few participants can already reveal meaningful trends.

We based our evaluation on a complex, multi-parameter generic time-series dataset designed to effectively emulate a real-world scenario. Specifically, the dataset represents a set of multiple time-series of photovoltaic (PV) operational data alongside environmental parameters, such as air temperature, relative humidity, and wind, which are known to influence PV energy production.

The evaluation sessions were conducted in person, with each participant individually, at our research institution's premises. The participants represented a diverse group of experts, including three data visualization specialists (P1, P2, and P5) and two immersive visualization professionals (P3 and P4). This combination of expertise was considered sufficient to offer a well-rounded perspective on the system's functionality, usability, and effectiveness. Our evaluation process consisted of three consecutive steps:

- *Onboarding*: Similar to the process conducted for non-practitioners, we began with a short onboarding session to explain the evaluation procedure, outline the purpose of the tool, and present the key components of the proposed data analytics solution. Participants also provided their consent regarding data processing for the evaluation.
- *Free exploration*: The process continued with a free exploration phase, allowing participants to familiarize themselves with the system and its features. This phase allowed them to explore its features at their own pace, experiment with various functionalities, and develop a deeper understanding of how the system operates in a real-world context.
- *Task-based assessment*: We then proceeded with the predefined task-based performance phase, which focused on three core topics: general data quality assessment, pattern recognition, and outlier detection. In contrast to the evaluation with non-practitioners, we excluded location analysis because the data typically handled by our target domain experts is more abstract and not necessarily tied to specific geographical locations. The general data quality assessment focused on identifying data gaps and assessing the significance of their occurrences within each time-series, as well as examining the length of the time-series to assess their overall application value. Pattern recognition focused on identifying prominent regularities within the observed data gaps, hypothesizing their potential origins, and evaluating their implications for subsequent analyses. Outlier detection focused on identifying data points that significantly deviated from the particular time-series.
- *Heuristic evaluation*: After completing these tasks, participants were invited to complete the heuristic value-based ICE-T survey by Wall et al. [18]. In this evaluation framework, participants assess four key aspects of the provided visualization solutions: insight, time, essence, and confidence. These aspects include the visualization's ability to reveal patterns and relationships (insight), its efficiency in helping users understand the data (time), how well it conveys the data's meaning (essence), and how much it builds confidence in users' understanding (confidence). These four key aspects are evaluated using 21 statements that are evaluated based on a 7-point Likert scale (1 = strongly disagree, 7 = strongly agree).

2) The Feedback: Overall, the feedback on the user interface and functionality was highly positive. Both user groups (i.e., data visualization specialists and immersive visualization professionals) expressed appreciation for the tool's flexibility, particularly the ability to customize their digital workspace

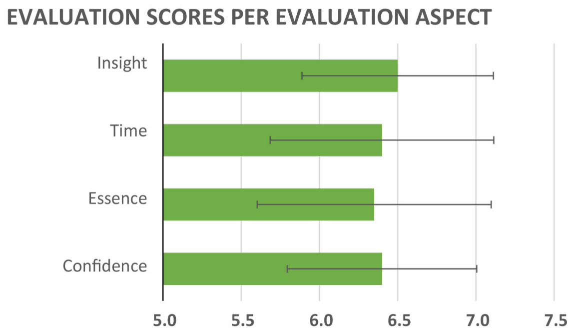

Fig. 5. Participants' responses regarding the evaluation aspects Insight, Time, Essence, and Confidence, derived from numerical ratings (1 to 7), and averaged over the sample with 95% confidence intervals.

TABLE I
SUMMARY OF DATA VISUALIZATION SOLUTIONS EMPLOYED BY EACH PARTICIPANT FOR EACH TASK.

Participant	*Data Quality*	*Pattern Recognition*	*Outlier Detection*
P1	heatmap	linechart	boxplot
P2	descriptive statistics & linechart	heatmap & linechart	boxplot
P3	heatmap	heatmap & histogram	boxplot
P4	heatmap	heatmap	heatmap
P5	heatmap	heatmap	boxplot

to better align with their individual data analytics workflows. During the free exploration phase, users actively experimented with different layout configurations, refining their workspace to better support their unique daily practices and to effectively prepare for the subsequent tasks.

During the task-based assessment, data visualization specialists demonstrated better ease in utilizing the information from the multi-panel data visualization modules, while the two immersive visualization professionals faced slightly more challenges. Specifically, they expressed some uncertainty with tasks related to pattern recognition and outlier detection, resulting in slightly longer response times when addressing these questions.

An interesting observation was that all users, regardless of their background, used different visualization solutions to answer the same questions. Particularly, we noted that while the majority of users were more inclined to visually identify issues, some domain experts still preferred to rely on numeric indicators and supporting metrics as their primary approach.

TABLE II
SUMMARY OF EVALUATION SCORES ACCORDING TO THE EVALUATION ASPECTS INSIGHT, TIME, ESSENCE, AND CONFIDENCE AS DEFINED BY WALL ET AL. [17].

Participant	*Insight*	*Time*	*Essence*	*Confidence*	*Avg.*
P1	7	7	6.8	6.8	*6.9*
P2	6.5	6.3	6.5	6.3	*6.4*
P3	6.9	6.8	7	7	*6.9*
P4	5.8	5.5	5.5	5.8	*5.6*
P5	6.4	6.5	6	6.3	*6.3*

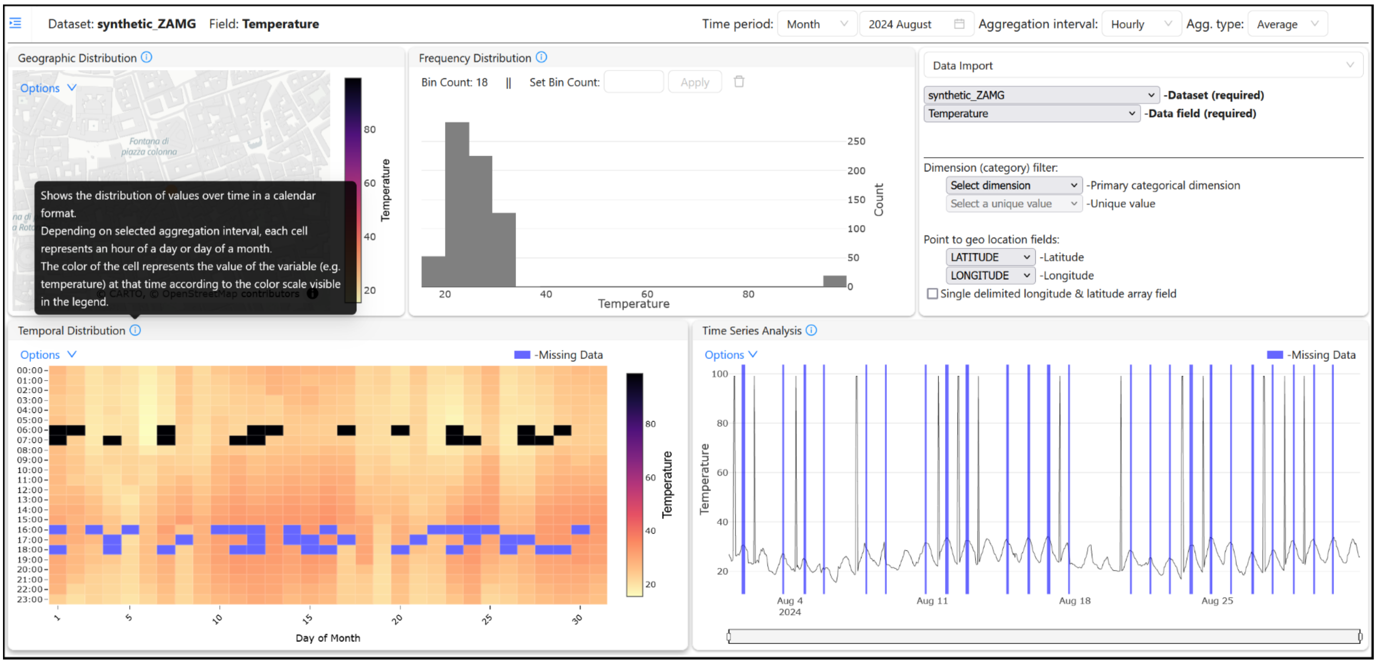

Fig. 6. First implementation of changes to the dashboard for non-practitioners including the visual separation of data visualization modules, the addition of clear titles, and the incorporation of concise descriptions of functionalities for each respective data visualization module.

This distinction was most evident when answering questions related to data quality and potential faults in the data where the majority employed the heatmap visualization, and one participant (P2) instinctively used the descriptive statistics table first, which provided the information on the amount of missing data in each time-series (see Table I). We also observed a strong preference for using the heatmap visualization to identify patterns, while the boxplot was commonly chosen for outlier detection.

The average ratings for each evaluation question from the ICE-T methodology, organized by evaluation aspects and averaged across the sample, are presented in Table II and Figure 5. A rating above six is considered indicative of success. Overall, the majority of participants rated the data analytics solution highly across the categories of Insight, Time, Essence, and Confidence. However, the lowest scores was given by the P4, a domain expert accustomed to using highly specialized data visualizations in immersive environments. This departure may be attributed to the inherent distinctions in both the visualization and interaction paradigms between desktop and immersive systems, which likely affected comfort levels when working with desktop-based interfaces.

IV. Limitations

While our study offers valuable insights into the participatory design process and the guiding principles of visualization software engineering for diverse target audiences, it is equally important to acknowledge certain limitations.

Firstly, although the sample size is acceptable for qualitative usability studies (6 non-practitioners, 5 practitioners), it may limit the generalizability of our findings, as it does not fully capture the diversity of user experiences across broader audiences. Particularly given the composition of our non-practitioner participant pool, comprising municipal representatives and social scientists rather than members of the general public such as local community members from the involved pilot areas, our findings should be interpreted with this limitation in mind when considering their broader applicability. A similar consideration applies to the practitioner use case, where the focus was primarily on data visualization specialists working with different media formats, such as 2D screens and immersive environments, rather than a broader range of professional users.

Secondly, our evaluation primarily relies on subjective user feedback, without incorporating objective performance metrics such as task completion time, error rates, or success rates. While this approach provides rich insights into user perceptions, expectations, and contextual needs, specially valuable in early-stage prototype design process, integrating quantitative measures would offer a more comprehensive assessment of interaction and efficiency.

In future work, we aim to expand the participant pool and incorporate quantitative performance metrics to further validate and strengthen our findings.

V. Conclusion and Future Work

We documented the process of designing digital analytical tools tailored to individuals with varying levels of technical proficiency and familiarity with analytical concepts. This included exploring the preferences and expectations of both non-practitioners and domain experts to guide the development of interactive data analytics technologies.

Our findings revealed distinct needs and preferences in terms of data visualization options, supporting features, and analytical metrics, closely reflecting the tool's purpose and the users' knowledge levels. For non-practitioners, the design specifications focused on creating an intuitive and accessible interface. Key features included a single-page dashboard layout, clear labeling, inclusive color schemes, simplified functionalities, and minimal visual clutter. In contrast, practitioners required a more advanced and customizable design, emphasizing responsiveness and flexibility. Their preferences included multi-panel dashboards with advanced data visualization options, interactive filtering, drill-down capabilities, and robust data manipulation features.

The evaluation process provided valuable context for assessing the application potential of the designed solutions, offering valuable insights for the refinement of the interfaces to more effectively align with users' needs and preferences. While practitioners provided generally positive feedback with no critical issues identified, non-practitioners highlighted several areas for improvement. Their feedback emphasized the need for greater visual clarity and more detailed explanations of each visualization module's purpose. Specifically, these concerns related to the clarity of individual modules, their presentation, and the labeling within the dashboard.

To address these concerns and make our tool more accessible and user-friendly for individuals without domain expertise, we have prioritized these changes in our initial improvements. Figure 6 illustrates the solution we implemented to improve the visual separation of the modules. Additionally, we assigned clear titles to each module and included descriptions that explain their functionality in more details. Future iterations will continue to build on this foundation, incorporating user feedback to further refine the interface and enhance its accessibility.

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