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An Exploratory Study Investigating Users' Understanding of Noise Model Uncertainties Utilising Webcam Eye Tracking

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Abstract: We report on an exploratory study focusing on how people interpret uncertainties in noise models related to road traffic, as assessed using the Common Noise Assessment Methods in Europe (CNOSSOS-EU). Specifically, via an online eye movement study with 35 participants, we investigate how viewers' visual attention and behaviour can reveal uncertainties in studied uncertainty models. As a case study, we generated a preliminary noise model for Munich using the library and model builder by the NoiseModelling project. For simplicity, the examined model only accounts for road traffic noise and does not represent dynamic variations in noise levels throughout the day. Participants (n=35) engage in tasks using different noise maps and colour schemes, including those from the NoiseModelling documentation and ColorBrewer. The eye tracking data reveals significant patterns in user responses, including awareness of noise in major intersections, train stations, and residential areas. The study also assesses the performance of the participants while using RealEye.io's webcam-based eye tracking across devices: desktops, tablets, and smartphones. The participants using desktops exhibit the highest performance, while participants using smartphones show the lowest. Our exploratory study reveals the importance of device-specific considerations in eye tracking-based cartographic user studies and suggests future work to tailor stimuli for each device type.

Keywords: Uncertainties, noise model, online webcam eye tracking, user study, RealEye.io

1. Introduction

The European Union introduces the Common Noise Assessment Methods in Europe (CNOSSOS-EU), a method for assessing noise from roadways, railways, industries, and aircraft (Kephalopoulos et al., 2012). Its implementation in road traffic noise modelling assists in estimating population exposure in Ireland (Faulkner and Murphy, 2022). The spatial model includes uncertainties from various sources. The concept of uncertainties concerns spatial, temporal, and attribute-based information. These uncertainties are classified into nine categories: (1) accuracy/error, (2) precision, (3) completeness, (4) consistency, (5) lineage, (6) currency, (7) credibility, (8) subjectivity, and (9) interrelatedness MacEachren et al. (2005).

Uncertainty in geospatial data is a significant concern in GIScience, as it affects our understanding of the world and decision-making processes Goodchild (2020). Improved methods for modelling, visualising, and communicating spatial and spatiotemporal uncertainty are crucial for enhancing the reliability of geospatial analyses Delmelle et al. (2022), Doucette et al. (2012). Uncertainty visualisation in cartography has been a focus of research for decades, with studies exploring various techniques to represent and assess uncertainty in geospatial data Kinkeldey et al. (2014). This study focuses on the uncertainties in noise models or maps.

Recent research examines different facets of spatial noise modelling and mapping. A real-time construction site noise mapping system is developed using sensor networks and spatial interpolation, demonstrating high accuracy in estimating noise levels Lee et al. (2023). The spatial structure of urban RF noise in Boston is studied, leading to the proposal of a point source model that effectively describes the 25 MHz urban noise field Meyer et al. (2024). This preliminary study generates a noise model for Munich, Germany, using the library and model builder called NoiseModelling v4.0 Bocher et al. (2019). It only calculates road traffic emissions using the mathematical algorithm of CNOSSOS-EU. The uncertainties arise from different sources. Firstly, the noise level shown in the generated noise model is not representative, as the levels do not consider noise from stations, industrial areas, etc.

Furthermore, noise levels vary throughout the day, evening, and night. However, the noise model is a static visualisation showing the average noise level over 24 hours. Moreover, users may interpret noise sources differently, which could differ from the noise levels represented. Based on these examples of uncertainties, the main aim of this study is to visually reveal these uncertainties that arise from the noise models using online webcam eye tracking. We are eager to investigate how sensitive people are to the underlying uncertainties in the noise model.

The use of eye tracking in our study helps us learn about users' gaze behaviour towards the noise models or maps as stimuli. Eye tracking is a valuable methodology for studying map users' attentive behaviour and cognitive processes Ooms et al. (2014). One study demonstrates that eye tracking significantly aids in evaluating map design and exploring the cognitive processes of map users (Keskin and Kettunen, 2023). Moreover, eye tracking is widely used to measure cognitive processes and visual attention for various spatiotemporal tasks that involve maps and geovisualisations (Peter Kiefer and Duchowski, 2017).

Webcam-based eye tracking has become a promising and cost-effective alternative to traditional laboratory systems Hutt et al. (2024), Wang et al. (2024). One study also shows that webcam-based eye tracking is a viable, low-cost alternative to remote eye tracking for user studies Wisiecka et al. (2022). It offers convenience and scalability for remote user studies and online behaviour research. Recent advancements improve gaze estimation accuracy and stability by 79%, making it suitable for applications in education, such as investigating student engagement and personalised learning Jain et al. (2024), Dostálová and Plch (2023).

In our context regarding maps, online studies provide opportunities for assessing web maps in real-world contexts. While they are limited by factors such as uncontrolled equipment specifications and participant behaviour, which can compromise the reliability of findings (Roth et al., 2017), online user studies also offer other benefits, e.g., allowing researchers to gain more participants.

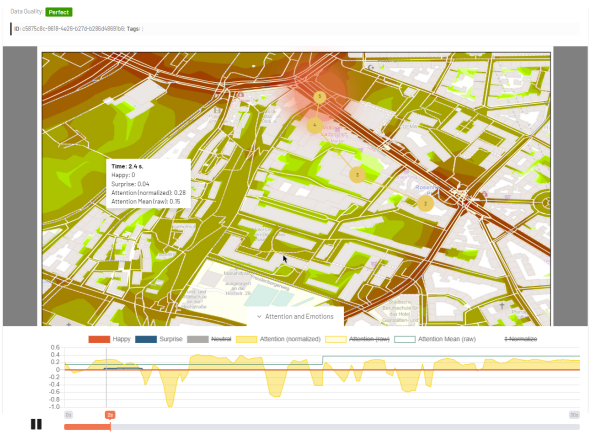

Figure 1. An example result from the online webcam eyetracker for one participant in our study, showing the eye tracking metrics and the user's emotions on the graphic below the map.

Therefore, this study uses an online webcam eye tracker from RealEye.io to achieve its aims. The same system has been previously shown to be viable, e.g., colour-related research Bruno et al. (2023), which we also touch upon; and eye tracking has various benefits from a scientific point of view for this study, such as revealing users' cognitive processes as they examine the uncertainties Çöltekin et al. (2009, 2010). Eye tracking metrics, such as fixation count and duration, can be used to analyse users' visual behaviour and cognitive load when interpreting maps Çöltekin et al. (2009), Keskin et al. (2019). This online webcam eye tracking shows gaze, fixation sequence, mouse clicks, attention, and user emotions, as illustrated in figure 1.

We also endeavour to investigate user performance with different colour schemes for the stimuli. Colour schemes on maps are vital for data visualisation and interpretation. Established cartographic principles suggest using varying colour values for quantitative data Golebiowska (2019). Therefore, we adopt the colour schemes offered in the NoiseModelling documentation, which was proposed by (Weninger, 2015), and the colour scheme from the cartography community using ColorBrewer. The default classification in the NoiseModelling consists of 11 noise level classes, which is unreasonable according to studies from the psychology community that suggest seven plus minus two, i.e., maximum nine classes (Miller, 1994).

In summary, this paper presents findings from a user experiment inspired by previous work. This method enhances the experiment using webcam eye tracking to examine users' understanding of noise model uncertainties.

2. Methods

2.1 Noise model creation

This initial research produces a noise model for Munich, Germany, utilising the library and model builder from NoiseModelling v4.0Bocher et al. (2019). This tool functions as an effective framework for creating noise maps. It offers a web-based Graphical User Interface (GUI) for accessibility, command-line functionality for custom scripts, and Docker support for easy deployment. Its architecture incorporates four libraries for noise emission, pathfinding, propagation, and database connection tasks. The tool integrates seamlessly with databases such as H2GIS and PostGIS, making it adaptable to various user needs while ensuring efficient data management [1].

As mentioned in the previous section, the calculations are based solely on road traffic emissions, employing the mathematical algorithm known as CNOSSOS-EU. Thus, it does not represent all noise sources, as noise emissions are only calculated for road traffic. The OpenStreetMap (OSM) data utilised in this research is obtained from BBBike Extract OSM. In order to generate road emissions from the traffic noise model, we calculate building geometry, road networks, and land use with absorption coefficients from OSM.

2.2 User study

The methodological framework comprises three core components: participants, materials, and procedure APA (2025), Roth et al. (2017). This arrangement ensures a systematic and thorough examination of the research topic, providing clarity and coherence throughout the study design. The subsequent sections elaborate on these components, outlining how each contributes to achieving the study's objectives.

[1]Read here for more information: NoiseModelling Architecture Documentation

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2.2.1 Participants

At the EuroCarto2024, we participated in a workshop on online experiments in cartography using webcam-based eye tracking, where we conducted part of the study as a hands-on activity. This workshop represents a collaborative effort of the ICA Commissions on Geovisualization and User Experience (UX), which advance methods for studying map user behaviour remotely [2].

The user study involves 35 participants, including workshop attendees and additional ones recruited outside the workshop. The study was a part of the workshop itself and was designed to be a hands-on activity. Thus, we collected some of the data at this workshop. However, since we couldn't gather enough participants at the workshop, we extended the study to include voluntary participants after the workshop ended. These additional participants were recruited by word-of-mouth and mainly included university students and colleagues from the authors' universities. Since the workshop was at a cartography conference, we consider the workshop attendees to be experts in cartography. Among the participants, 19 are male, 13 are female, and the gender of 3 participants is unspecified. Participants' ages range from 22 to 66, with an average age of 33.

The participants used three types of devices during the study: desktops (n=4), smartphones (n=28), and tablets (n=3). To keep the ecological validity as high as possible, i.e., simulate a real-life situation, and as we were set to explore webcam eye tracking, participants were not instructed to select a specific device. Instead, they have chosen their devices based on personal preference. It could be better to restrict the variation in devices for experimental control. Still, since our study is exploratory, we kept ecological validity as a more important goal and analysed the effect of device types post-hoc. Studies on users' device preferences in online user studies report mixed findings. While offering device choice may increase response rates, it can also lead to lower data quality in some cases Metzler (2020).

2.2.2 Materials

The materials comprise sections of a noise model or map used as stimuli and presented at a scale of 1:10,000 for the Munich, Germany area. The generated noise model follows the default settings from the model builder, resulting in 11 distinct noise level classes. These multiple classes are expected to overwhelm users. Therefore, the stimuli only include a simplified legend showing the colour values corresponding to the noise levels to minimise confusion and prevent unnecessary complexity. At first, each stimulus is designed on ArcGIS only for desktop and tablet use with landscape orientation. We do not expect that the participants prefer to use their smartphones for the study. However, RealEye.io only allows vertical orientation for smartphones.

The stimuli are designed based on the tasks and feature different colour schemes. The study includes four task types in total. We provide the participants with OSM as stimuli for the first task type. For the second task type, participants compare areas of interest in noise maps, which consist of three squares labelled with numbers. Next, we present them with a noise map of distinguishable neighbourhoods in Munich for the third task type, such as the central train station, which indicates low noise levels. For the last task type, we offer a noise map of a randomly selected neighbourhood in Munich.

In terms of the colour scheme, we adopt those recommended in the NoiseModelling documentation, which was proposed by (Weninger, 2015) as the first one. Then, another colour scheme is the one from ColorBrewer.

2.2.3 Procedure

The study flow in RealEye.io presents the instructions first for each stimulus before participants can view it. Afterwards, participants must click on their answers for each stimulus before proceeding to the next one. The display time for visual stimuli in online user studies should be adapted to participants' cognitive abilities and the complexity of the stimuli Kuric et al. (2024). Beforehand, we conducted a small pilot test between authors to decide on a more effective display time. Therefore, we set up a display time of 30 seconds for every stimulus.

The procedures begin with a pretest comprising five stimuli to familiarise participants with the task types. The stimuli include one OSM stimulus and two areas of interest comparisons. The first comparison features the NoiseModelling colour scheme, while the second uses the ColorBrewer colour scheme, with three squares as areas of interest. Two more stimuli are included: one styled with the NoiseModelling colour scheme and another with the ColorBrewer colour scheme.

Afterwards, it is followed by eight stimuli representing four tasks. We also ask them for a qualitative measure as a post-question for every stimulus. It is essential to confirm their answers qualitatively.

Task types

The first task is a visual search task showing the plain OSM map without noise levels. Participants are tasked with identifying the noisiest area on the map, using either their interpretation of the visual stimuli (perception) or prior knowledge about the environment (expectation). This approach explores the relationship between perceptual cues and cognitive biases in spatial decision-making regarding noise levels. We asked why they chose the area afterwards so they could answer freely with a maximum of 50 letters.

The second task type is a comparison task. We draw three squares as areas of interest with different noise level classes and ask the participants to choose which areas of interest have the highest noise level. We then show each participant different colour schemes in a random order to avoid bias. We ask them how they choose the area afterwards using a multiple-choice question. The options are "Comparing the legend to the map" and "Based on the area condition (street types, etc.)".

[2] For further details: EuroCarto2024 workshop.

The third task type is another visual search/comparison task in which participants must identify an area with low noise levels despite their expectations. For instance, the central train station is depicted as having low noise levels, even though one might anticipate it to be considerably louder. We are eager to see whether the participants detect this uncertainty in the stimulus, so we provide a distinguishable neighbourhood. We then asked them again why they chose the area using a multiple-choice question. The options are "The area should be noisier because of the street types" and "The area should be noisier because of noise propagation".

The fourth and last task type is a decision-making task in which participants must choose which area they desire to buy a house based solely on noise information. For this task type, we provide random neighbourhoods in Munich as stimuli. Next, we asked them why they chose the area so they could answer freely with a maximum of 50 letters. This approach confirms their answers and is valuable for the analysis. The participants might choose or click accidentally, so we ensure their answers by giving them a post-question.

3. Results and Discussion

3.1 User performance on tasks

We have designed the tasks such that there are right and wrong answers; thus, there is a measure of performance in task success. Furthermore, eye tracking captures detailed behavioural metrics, facilitating the analysis of visual attention, interaction patterns, and decision-making processes. This approach explores how users perceive, interpret, and interact with noise models or maps across different design contexts. We are specifically interested in analysing how individuals respond to the noise model with underlying uncertainties, as reflected in the various task types. We also provide post-questions for every stimulus, so we attempt to analyse those answers.

The study comprises four tasks to investigate participants' interactions with noise maps. Outcomes are assessed based on answer accuracy/pattern and the heat maps generated from all participants using RealEye.io. Global heat maps are visual representations that simultaneously illustrate the collective visual attention of all participants, combining results from all tests [3].

3.1.1 Task type 1: Visual search

In this task type, participants are instructed to identify a location expected to have low or high noise levels. Overall, the results reveal clusters of responses around major road intersections for high noise levels. Meanwhile, the responses are concentrated around large rivers with small islands, parks, and sports fields for low noise levels. Based on the post-questions, the participants' answers align with this observation.

However, some answers are incorrect at low and high noise levels. We presume some participants are confused about the instructions for these two stimuli. This confusion is likely due to the stimuli's random order, which requires participants to focus closely on the instructions before selecting their answers. Heat maps clearly illustrate the areas of interest mentioned; we can see the clusters based on the fixation intensities.

As for the number of clicks, the points are also grouped in the specific areas where participants pay the most attention. This finding demonstrates that participants tend to direct their attention toward environments they perceive as potential noise sources, such as densely populated urban areas with significant traffic or large open spaces hosting recreational activities. This behaviour underscores the influence of visual stimuli on participants' cognitive associations and their ability to identify noise-generating sources based on visual characteristics.

3.1.2 Task type 2: Comparison

For this task type, participants are tasked with selecting the area displaying the highest noise level from three areas of interest options. With the first colour scheme (from NoiseModelling documentation), 94.29% of participants identify the correct areas of interest, while a different colour scheme (from ColorBrewer) reaches an accuracy of 91.43%. We ask them how they chose the area by comparing the legend to the map (option A) or based on the area condition (street types, etc.), as option B. For both stimuli, 80% of participants choose option A.

Based on the heat maps (as shown in figure 2), we can see that they make the comparison. However, those heat maps indicate that participants do not spend much time comparing the areas with the legend or other areas of interest. It is evident from clustering clicks in the regions with the highest fixation intensities. Consequently, we conclude that participants can quickly and accurately identify the correct areas of interest. This implies that the choice of colour scheme has a minimal impact on their decision-making process.

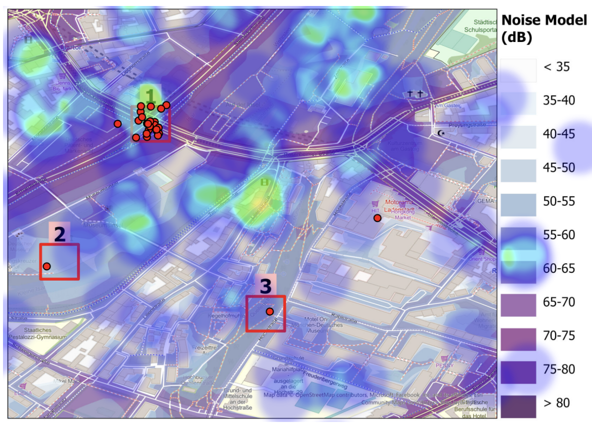

Figure 2. The areas of interest comparison task heat map styled with colour scheme from ColorBrewer (red dots are the answers from participants)

3.1.3 Task type 3: Visual search and comparison

In this task, participants are asked to point to areas where they expect high noise levels but instead find low levels.

[3] Based on the explanation on this blog: "How to analyse heatmaps"

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There are two stimuli for this task type. For the first stimulus, thirteen participants choose the area around Hauptbahnhof, Munich's central train station. Meanwhile, the remaining participants select areas near major roads, reflecting perceived uncertainties in expected noise levels. As for the post-questions, 57% of the participants answered that the area should be noisier because of the street types.

Next, for another stimulus, their answers cluster around major roads and prominent intersections. Even though the clicks are distributed throughout the whole stimulus, we can see the pattern of the answers. Then, in the post-questions, 57% of them answered that the area should be noisier because of noise propagation.

Heat maps display the distribution of high attention intensity in those areas. We conclude that participants carefully inspect their anticipated noise sources before clicking on their answers. This result shows that participants are influenced by their expectations of noise sources, and the uncertainties lead to more prudent consideration and selection of areas.

3.1.4 Task type 4: Decision making

As for the final task, participants have to indicate their preferred locations for purchasing a house. The click distribution shows a clear preference for quiet residential areas. The analysis of post-survey responses reveals that the majority of participants prioritise noise levels when choosing a location. Moreover, considerations such as the availability of facilities, including schools and green spaces, also influence their decisions. Then, heat maps illustrate that none of the high-noise areas attract potential buyers' interest. This finding suggests that noise levels are crucial in decision-making, with prospective houseowners valuing quieter environments highly.

To sum up, the results of this study demonstrate the use of eye tracking in capturing detailed behavioural metrics. It reveals visual attention, interaction patterns, and decision-making processes when users engage with noise maps. Specifically, the study's main aim is to visually uncover uncertainties arising from noise models using online webcam eye tracking, and we successfully investigate how sensitive individuals with underlying uncertainties are to the noise model. This sensitivity is reflected in the task results. Moreover, the four tasks effectively highlight participants' interactions with the maps and their ability to interpret noise levels in various contexts.

3.2 Statistics on eye movement data quality for all users on RealEye dashboard

When we examined the data quality metrics (i.e., "quality statistics" as RealEye names them), we discovered that participant performance varies while using RealEye.io across three device types: desktops (n=4), smartphones (n=28), and tablets (n=3). This variety of device usage during the study leads to differences in data quality, revealing interesting exploratory insights. RealEye.io posts a blog about the "Webcam eye tracking Hardware and Software Requirements", which explains what kind of hardware the participants should use for the study.

However, we cannot control the devices' availability and specifications for all participants. Thus, the display resolutions and physical requirements also exhibit considerable variability. For tablets, logical resolutions range from 1080x740 px to 2880x1800 px. Desktops are tested with configurations spanning 1494x934 px to 3840x2160 px. Smartphones present the broadest range of physical resolutions, varying between 720x1290 px and 1440x2430 px. These device variations lead to differences in quality statistics across devices.

First, we evaluate each device type's key quality and accuracy metrics. It is important to note that the data do not reflect a balanced distribution of the devices used by participants. In this study, the number of smartphones significantly exceeds that of tablets and desktops, resulting in an insufficient representation of each device category. eye tracking data integrity reaches 100.00% on desktops, 99.33% on tablets, and 96.39% on smartphones.

For gaze-on-screen detection, participants perform at 97.25%, 93.33%, and 92.93% of the time for desktops, tablets, and smartphones, respectively. These findings indicate that participants show reduced attentional engagement when using smartphones. However, the uneven distribution of devices may suggest that smartphone users contribute more significantly to the variability in the results. Furthermore, it is essential to note that we receive considerable negative feedback from participants. They report difficulty viewing the stimuli properly due to the landscape orientation on vertical smartphone screens.

The eye tracking sampling rates vary significantly across devices, with smartphones achieving the highest rate at 46.61 Hz, tablets at 31.67 Hz, and desktops at 30.50 Hz. The maximum achievable sampling rate for participants is 60 Hz [4]. This variation can be attributed to device specifications, as some devices might not be capable of recording at 60 frames per second. Thus, achieving the maximum sampling rate is not possible. Regarding the gaze versus click accuracy, desktops demonstrate the highest performance at 86.50%. At the same time, tablets achieve 81.00%, and smartphones merely reach 63.25%. These numbers show the accuracy/quality of the tests by participants. The study of this accuracy has only been done for desktops or computers [5].

These findings highlight the diversity in device capabilities and their implications for RealEye.io's performance across platforms. These variations affect the patterns in the heat maps generated from certain stimuli. For example, the patterns and accuracy of gaze fixations across different devices are illustrated in Figure 3. The heatmaps reveal that, for all devices, attention is not consistently concentrated in specific areas of interest. In the heatmaps for smartphones and desktops, there is minimal intensity of attention in the correct areas of interest. In contrast, the heatmap for tablets shows a relatively more vigorous attention intensity within the areas of interest, although it is not perfectly centred in each area.

[4] For the details, click here: "Webcam eye-tracking at 60 Hz".

[5] For more information, read here: "RealEye Accuracy on Computers".

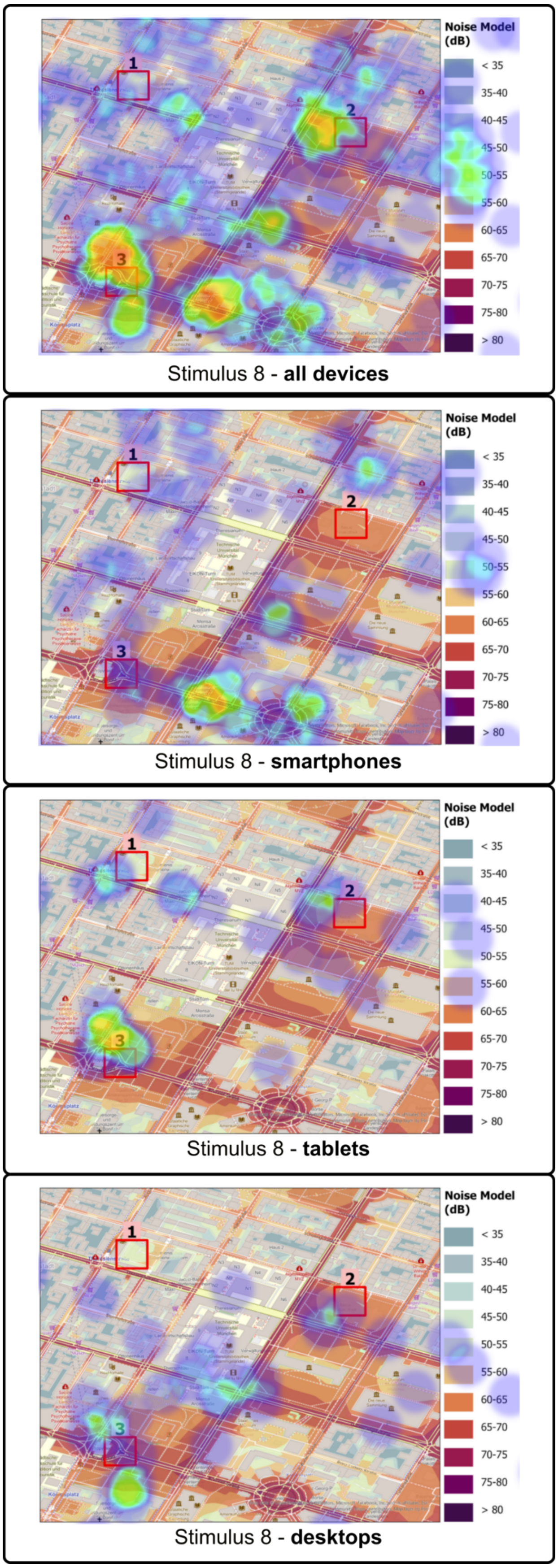

Figure 3. The comparison of heat maps for all devices, smartphones, tablets, and desktops. This stimulus is for the areas of interest comparison task type.

This study is an experimental effort highlighting challenges and opportunities for improvement. For example, we do not specify the types of devices participants should use, resulting in an imbalanced distribution across device categories. This imbalance affects the representativeness of our sample and limits our confidence in analysing device-specific results. Each stimulus is designed for desktop and tablet use in landscape orientation. We are unaware that participants would prefer using their smartphones. RealEye.io only supports vertical orientation for smartphones, which led to some negative feedback during the workshop regarding this limitation. These shortcomings occur because the study is initially designed as part of a workshop hands-on contribution rather than a rigorously controlled experiment. While this leads to certain logistical constraints, the experiment also uncovers interesting findings with significant implications for the community.

4. Conclusions

This exploratory study shows the potential of online user experiments to generate valuable insights efficiently utilising webcam eye tracking. We explored visual attention, interaction patterns, and decision-making in noise map interpretation. We examined task types, visual stimuli, and device capabilities. From this, we identified the following early insights and hypotheses:

- Visual Attention: Participants focus on perceived noise sources, suggesting visual stimuli strongly influence cognitive associations.
- Decision Accuracy: Accurate identification of high noise levels persists across colour schemes, indicating enhanced visual cues can improve precision without affecting accuracy.
- Expectations and Uncertainty: Participants' evaluations are shaped by expectations, with greater caution under uncertainty, highlighting the need for precise visual representations.
- Noise Levels and Preferences: Noise levels strongly influence residential choices, favouring quieter areas.

Our findings emphasise the importance of considering device variability in webcam-based exploratory studies for cartographic purposes. Future work will examine stimulus requirements tailored to specific devices or restrict certain stimuli to particular categories. We hypothesise that adapting experimental stimuli based on device type can improve data consistency and participant experience.

To conclude, this exploratory study offers early insights and lays the groundwork for further investigations, contributing to understanding behavioural patterns in noise map interpretation and the broader potential of online experimental platforms.

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