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Evaluating the Usability and Decision Support Effectiveness of Public Health Dashboards Using Eye Tracking

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ABSTRACT

Public health professionals increasingly rely on complex data related to social determinants of health (SDOH), food insecurity, and healthcare access to support evidence-based decision-making. Interactive dashboards can facilitate the interpretation of these data. However, their effectiveness depends on how clearly and efficiently information is visually communicated to users. This study evaluates the usability and decision-support effectiveness of three interactive public health dashboards using task-based performance, user feedback, and eye tracking analysis. Six graduate-level participants completed a within-subjects experiment involving three randomized dashboard conditions, with two decision-making tasks performed for each dashboard. Eye-tracking data was collected using a Tobii Pro Spectrum and Tobii Pro Lab to examine visual attention and interaction patterns across dashboard elements. Areas of Interest (AOIs) were used to capture measures including fixation behavior, gaze patterns, and mouse interactions. Participants achieved an overall task accuracy of 88.89%, although performance varied across dashboard tasks, suggesting potential differences in the clarity and usability of specific visualizations. Findings from this study can inform the development of more intuitive public health dashboards by identifying visual design features that effectively attract attention, communicate information, and support accurate decision making.

Keywords: Eye tracking, Usability, Visual analytics, Evidence based decision making

INTRODUCTION

Public health decision-making increasingly depends on understanding complex data related to social determinants of health (SDOH), including factors such as income, food access, and healthcare availability. These determinants are well established as key drivers of health outcomes and disparities across populations (Centers for Disease Control and Prevention (CDC), 2024; Marmot et al., 2008). However, decision-makers often face challenges in synthesizing large, fragmented datasets and translating them into actionable insights (Al-Hajj et al., 2013). Traditional reporting approaches, such as static tables and summary reports, can limit the ability to identify geographic disparities, monitor trends, and allocate resources effectively. This creates a need for tools that integrate diverse data sources

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and support more intuitive, evidence-based decision making (Al-Hajj et al., 2013; Wu et al., 2026).

Interactive dashboards have emerged as a promising solution by enabling users to explore complex datasets through visual interfaces (Ansari, Martin, 2022; Wu et al., 2026). Dashboards allow decision-makers to monitor trends, compare regions, and analyze relationships between variables more efficiently than traditional formats (Schulze et al., 2023). Prior research has shown that dashboards play an important role in communicating public health information and supporting decision-making, particularly when timely and accurate insights are required (Wu et al., 2026). However, existing literature also highlights that many dashboards are deployed without rigorous evaluation of usability or effectiveness, leaving uncertainty about whether they truly support user needs (Ansari, Martin, 2022; Schulze et al., 2023; Yanovitzky, Stahlman & Kim, 2025).

In addition, research in human–computer interaction and information visualization demonstrates that the way data is visually presented significantly affects how users interpret and act on information (Ansari, Martin, 2022). Studies using eye tracking methods have shown that user attention and comprehension are strongly influenced by visual design, and that poorly designed dashboards can lead to misinterpretation or overlooked insights (Huang, Yang & Jeng, 2022). More broadly, visual analytics have been shown to enhance cognitive processing by reducing complexity and enabling users to identify patterns and relationships more effectively (Thomas, Cook, 2005; Al-Hajj et al., 2013). These findings underscore the importance of evaluating both the usability and decision-support value of dashboard tools (Thomas, Cook, 2005; Yanovitzky, Stahlman & Kim, 2025).

Given these challenges and gaps in the literature, this study is needed to evaluate the usability, clarity, and effectiveness of interactive dashboards designed to monitor SDOH, food insecurity, and healthcare access. By assessing how users interact with these tools and complete realistic decision-making tasks, the study aims to ensure that dashboards effectively support identifying disparities, understanding trends, and guiding equitable resource allocation in public health contexts. In this pilot study, a usability study was conducted on three public health dashboards using eye tracking.

METHODOLOGY

Participants

Six graduate-level students participated in this study, consisting of three male and three female students. Three participants were aged between 18-24 years old, two participants were aged between 25-34 years old, and one participant was aged between 35-44 years old. Five participants stated they were either not familiar or slightly familiar with SDOH, and one participant stated they were moderately familiar with SDOH. Three participants and one participant were moderately familiar with food insecurity issues and healthcare access issues, respectively. Two participants and three participants

were very familiar with food insecurity issues and healthcare access issues, respectively. One participant and two participants were extremely familiar with food insecurity issues and healthcare access issues, respectively. Five participants also reported they were extremely comfortable in interpreting charts, maps, and graphs, while one participant stated they were somewhat comfortable.

Stimuli

The stimuli consisted of three interactive public health dashboards in Tableau, a visual analytics platform to help people see and comprehend data through interactive and graphical dashboards without the need for programming (Tableau, 2026). The State-Wide Healthcare Divide dashboard consisted of county-level information in North Carolina related to food insecurity, healthy food access, median household income, and the primary care provider rate. This dashboard then can be filtered based on the year (2020–2025), the defined region, and county. The SDOH Driver Correlation Matrix provided data related to correlations on three charts between food insecurity versus average median household income, healthy food access, and primary provider care rate. This dashboard can be filtered by the year (2020-2025), the defined region in North Carolina, and rurality (Urban, Mixed, or Rural). The Regional Food Insecurity & Healthcare Program Screening Dashboard shown in Figure 1 includes a data related to the percentage of food insecurity per county in North Carolina, the average percentage of food insecurity by the defined region per year, and the percentage of food insecure population screened per region for statistics such as child health, primary care, immunizations, tuberculosis, family planning, etc. Visualizations included choropleth maps, bar charts, correlation matrices, and line graphs meant to explore geographic patterns and differences across all dashboards. Interactive features allowed participants to examine county data and variables to complete the study tasks. The dashboards were designed to support data exploration and decision-making by presenting multiple public health indicators within a single interface.

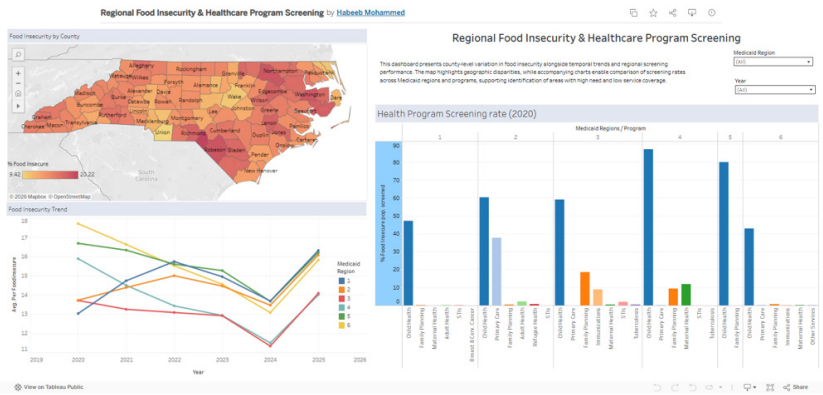


Figure 1: Regional Food Insecurity & Healthcare Program Screening Dashboard.

Equipment

In this study, a Dell computer connected to the Tobii Pro Spectrum was used to collect eye tracking data.

Experimental Design

The experiment utilized a within-subjects design consisting of three rounds. Each round was designated for each dashboard. Each dashboard had its own set of tasks to be completed, with each dashboard having two tasks.

To ensure and minimize order effects, the dashboards were randomized within the design across all participants. As a result, the dashboards the participants experienced first varied across each recording. This random assignment was used to create equal comparison groups, eliminate selection bias, and "averaging out" the effects of extraneous factors (Montgomery, 2013; Cherry, Swaim, 2025).

Tasks and Procedures

On the day of experimentation, participants provided written consent and completed a pre-survey gathering demographic and baseline information. Before beginning the main task, participants completed an eye tracking calibration to confirm accurate and precise gaze mapping. After the eye tracking calibration, participants then looked at an example dashboard to be familiar with Tableau's interface and platform.

The experiment contained three randomized rounds, each linked to one of the three dashboards. Each round began with participants gaining familiarity and an exploration of the dashboard so participants could get a feel of the different charts. Once the participants were done exploring the dashboard, they then would be presented with their first task. They would then be sent back to the dashboard to find the answer to the task. Once the participant identified the answer, a text slide appeared and the participant selected the appropriate answer. This would repeat for a total of two times per dashboard. Table 1 shows the dashboard and its related tasks.

After both tasks were completed for each dashboard, the participants were then presented with a post-survey to gather what they liked about each dashboard and if there could be any improvements to the usability.

All tasks were recorded using Tobii Pro Lab software. The stimuli such as the graphs, filters, and charts of each dashboard and the correct answers on the text slide with the answers were defined as Area of Interests (AOIs) to capture metrics such as mouse clicks, fixation time, gaze pattern, task accuracy, etc. The entire session lasted approximately 30 minutes per participant.

Table 1: Tasks for each dashboard.

Dashboard	Tasks
Regional Food Insecurity & Healthcare Program Screening	Identify the Highest Food Insecurity County in region 4 in the year 2023
	Identify the region with the lowest Child Health Screening in 2021.
SDOH Driver Correlation Matrix	Identify the county in region 2 that has rural geography, the highest average median household income, and the lowest percentage of food insecurity in the year 2024.
	Identify the county in the year 2025 that has the lowest primary care provider rate and the lowest percentage of food insecurity between mixed and urban geography rurality across all regions.
State-Wide Healthcare Divide	Identify the "double burden" county (high food insecurity and low food access) in Medicaid region 5 in the year 2023.
	Identify the primary care provider rate in Wake County in the year 2024.

Data Collection

Pre-surveys and post-surveys were collected using Qualtrics. Eye tracking data was collected using the Tobii Pro Lab.

RESULTS AND DISCUSSION

Performance Data

Accuracy data was collected from the participants using the three dashboards and can be seen in Table 2. The average percentage of correct responses was 88.89% with a Standard Deviation of 24.85%. Task 2 on the SDOH Driver Correlation Matrix dashboard received the lowest percentage signifying trouble reading the metrics and charts with underlying design issues.

Table 2: Participant accuracy data.

Dashboard	Accuracy
Regional Food Insecurity & Healthcare Program Screening	Task 1: 100.00%
	Task 2: 100.00%
SDOH Driver Correlation Matrix	Task 1: 100.00%
	Task 2: 100.00%
State-Wide Healthcare Divide	Task 1: 100.00%
	Task 2: 33.33%
Mean	88.89%
Standard Deviation	24.85%

Eye Tracking Data

From the dashboards, saccades and heat maps were created from the Eye tracking data collected by each participant related to the participants browsing through the dashboards. An example is shown in Figure 2 and Figure 3.



Figure 2: All participants heat map for SDOH Driver Correlation Matrix Dashboard.

The heat map visualization revealed for this participant that they glanced at the filters and continued to spend most of their attention towards the actual charts. Notice that for the chart in the bottom left corner that the participant did not glance at the x-axis. For Task 2 on the SDOH Driver Correlation Matrix Dashboard, this matrix was needed to do the task correctly, and 4 out of 6 participants did this task incorrectly. Similar patterns were seen for the saccade visualization as well for this dashboard as all participants concentrated most of their focus onto the center of the dashboard and not across charts equally.

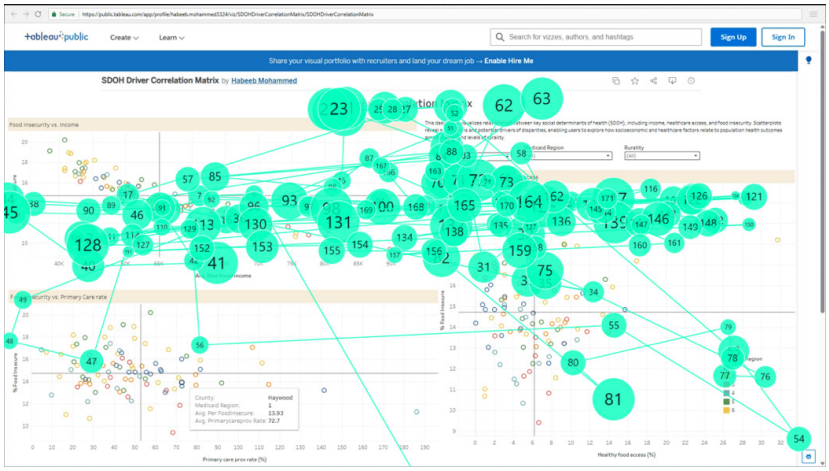


Figure 3: Participant 4's saccade data for the SDOH Driver Correlation Matrix Dashboard.

Post-Survey Data

Participants were asked to complete a post-survey for each dashboard and to rate on a scale of 1 to 5 (with 1 representing strongly disagree and 5 representing strongly agree) the following statements listed in Table 3.

Table 3: Post-survey data.

Statement	Average Score (Standard Deviation)		
	SDOH	Regional Food Insecurity	State-Wide Healthcare Divide
The dashboard was easy to use.	4.50 (0.50)	4.83 (0.37)	4.83 (0.37)
The layout of the dashboard was clear and well organized.	4.50 (0.50)	4.50 (1.12)	4.83 (0.37)
It was easy to find the information needed.	4.50 (0.50)	4.83 (0.37)	4.83 (0.37)
I felt comfortable navigating the dashboard without assistance.	4 (1.41)	5 (0)	5 (0)
The information presented in the dashboard was clear.	4.50 (0.50)	4.50 (1.12)	4.83 (0.37)
The charts and visuals were easy to understand.	4.17 (1.07)	4.67 (0.75)	5 (0)
I was able to interpret the data correctly.	4.33 (0.47)	4.83 (0.37)	5 (0)
The dashboard helped me identify important patterns or trends.	4 (1)	4.83 (0.37)	5 (0)

For the SDOH Driver Correlation Matrix Dashboard, one of the participants strongly disagreed on the fourth, sixth, and last statements, and the rest either somewhat or strongly agreed with the rest of the statements.

For the Regional Food Insecurity & Healthcare Screening Dashboard, one participant either one of the participants either somewhat disagreed, neither agreed nor disagreed, or somewhat agreed on all statements except the fourth statement. All participants strongly agreed with the fourth statement.

For the State-Wide Healthcare Divide Dashboard, all participants either somewhat agreed or strongly agreed with all the statements.

Extracting standardized quantitative eye-tracking metrics from dynamic, interactive dashboards presents significant methodological limitations. Traditional metrics, such as Total Fixation Duration within predefined AOIs, are predicated on spatial stability. However, the ecological validity of this study required participants to actively manipulate the dashboards using filters, zoom functions, and interactive tools. These interactions continuously shifted the spatial coordinates of visual elements, creating unique visual states for each participant and breaking the stimulus uniformity required for standard cross-participant aggregation. Furthermore, while dynamic gaze mapping onto static reference images is possible, transient visual elements, such as temporary hover tools, cannot be reliably mapped without introducing a high margin of error. Consequently, evaluating interactive visualizations

requires balancing the necessity for precise quantitative gaze metrics with the fluid, non-linear reality of user interaction.

Recommendation

This pilot study discovered that there are some usability concerns in the dashboards. Participants had concerns linked to filters, texts, and color scheme.

For all dashboards, we recommend making the filters larger so that users do not have to take long to find the data that they desire. If the size of the filters becomes larger, users can locate them rapidly to segment the data that they need.

For the SDOH Driver Correlation Matrix Dashboard, we recommend the colors used for the data were not distinguishable. Using colors that are noticeable can help with faster data searches.

For the Regional Food Insecurity & Healthcare Dashboard, we recommend making the text bigger for the titles of charts, filters, and data so participants are not dissuading from reading each chart and graph.

For the State-Wide Healthcare Divide Dashboard, we recommend moving the double burden legend key somewhere from the bottom so participants do not have to search deeply for something that should be more noticeable.

CONCLUSION

A pilot study was carried out using eye tracking on three public health dashboards. Eye tracking data gathered from the study revealed vital knowledge on how participants used the dashboards. Findings from this study can help public health officials create more effective dashboards for the general public.

To overcome the methodological challenges of extracting static eye-tracking metrics from interactive dashboards, future research will incorporate spatial-independent quantitative measures. Because active user filtering and dynamic tools disrupt traditional AOI stability, subsequent studies will utilize Task-Evoked Pupillary Response (TEPR) to objectively quantify fluctuations in cognitive workload during interactive tasks. Additionally, incorporating global metrics such as gaze entropy will allow for the evaluation of visual search efficiency and dashboard usability regardless of coordinate instability, ensuring robust quantitative analysis in dynamic environments.

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