Dashboard Vision: Using Eye-Tracking to Understand and Predict Dashboard Viewing Behaviors

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***Abstract*—Dashboards serve as effective visualization tools for conveying complex information. However, there exists a knowledge gap regarding how dashboard designs impact user engagement, necessitating designers to rely on their design expertise. Saliency has been used to comprehend viewing behaviors and assess visualizations, yet existing saliency models are primarily designed for single-view visualizations. To address this, we conduct an eye-tracking study to quantify participants' viewing patterns on dashboards. We collect eye-movement data from 60 participants, each viewing 36 dashboards (16 representative dashboards shared across all and 20 unique to each participant), totaling 1,216 dashboards and 2,160 eye-movement data instances. Analysis of the data from 16 dashboards viewed by all participants provides insights into how dashboard objects and layout designs influence viewing behaviors. Our analysis confirms known viewing patterns and reveals new patterns related to dashboard layout design. Using the eye-movement data and identified patterns, we develop a saliency model to predict viewing behaviors with dashboards. Compared to state-of-the-art models for single-view visualizations, our model demonstrates overall improvement in prediction performance for dashboards. Finally, we propose potential dashboard design guidelines, illustrate an application case and discuss general scanning strategies along with limitations and future work.**

***Index Terms*—Eye-tracking, viewing behavior, saliency model, dashboard.**

I. Introduction

DASHBOARDS play a crucial role in presenting essential information across various fields [1], including business applications [2], healthcare systems [3], learning analysis [4], *etc*. To enable effective communication and foster user engagement, designing dashboards requires considering sophisticated design strategies [5]. First, a dashboard integrates various objects, including textual, visual, and hybrid objects [6]. Second, the layout of a dashboard is essential for establishing relationships and guiding viewing behaviors [7], [8]. In practice, designers often rely on intuition and experience to create dashboards that capture users' attention and achieve design goals [9], [10]. As reported by Burch and Schmid [11], there is an increasing need to analyze users' viewing patterns to better understand and improve dashboard designs.

Visual saliency is an important metric for analyzing viewing behaviors and providing essential insights on evaluating design effectiveness [12], [13]. However, designers often lack direct access to visual saliency data for their designs. Saliency prediction models provide a practical solution. Viewing behaviors are generally influenced by the visual context, which has driven saliency models tailored to specific visual content (*e.g.*, natural images [14], [15], user interfaces [16], [17], virtual reality [18], [19]). The data visualization community has contributed to the advancement of saliency models [20]–[23]. These models have also been integrated into design tools to create more effective visualizations [24], [25].

However, existing visualization saliency models are primarily tailored for single-view visualizations, but are not suitable for dashboards. Dashboard design involves more objects and layout considerations compared to single-view visualizations. For instance, dashboards often include a hierarchy of titles and subtitles, unique dashboard objects (*e.g.*, numbers, sliders, filter widgets), and layout patterns (*e.g.*, stratified, grouped) [6]. These additional factors complicate the prediction of viewing behaviors, thus using saliency models trained on eye-movement data for single-view visualizations [21], [27] to predict viewing behaviors on dashboards is inadequate. For example, some models tend to overemphasize visual elements such as titles and maps, while underestimating the influence of layout design.

To address this gap, we present a study analyzing user viewing patterns through eye-tracking and developing a saliency model customized for dashboards. Figure 1 illustrates the pipeline of our study. We start by constructing datasets containing dashboards with manual labels of dashboard objects and layout designs, with eye-movement data from 60 participants in a controlled laboratory setting (Sect. III). The dataset consists of two parts: First, the Dashboard Vision Elite Dataset (DVElite) includes 16 representative dashboards encompassing various dashboard objects and layout designs. These dashboards are viewed by all 60 participants for analyzing viewing behaviors, yielding 946 valid instances of eye-movement data. Second, the Dashboard Vision Crowd Dataset (DVCrowd) includes 1,200 dashboards, with each participant viewing 20 unique dashboards, resulting in 1,187 valid eye-movement instances after data cleaning.

Next, we conduct quantitative analyses on DVElite from two perspectives: dashboard objects and layout designs, based on three metrics: attention intensity, saliency coverage, and stationary gaze entropy (Sect. IV). The results indicate that both dashboard objects and layout designs significantly impact viewing behaviors. For dashboard objects, we validate known

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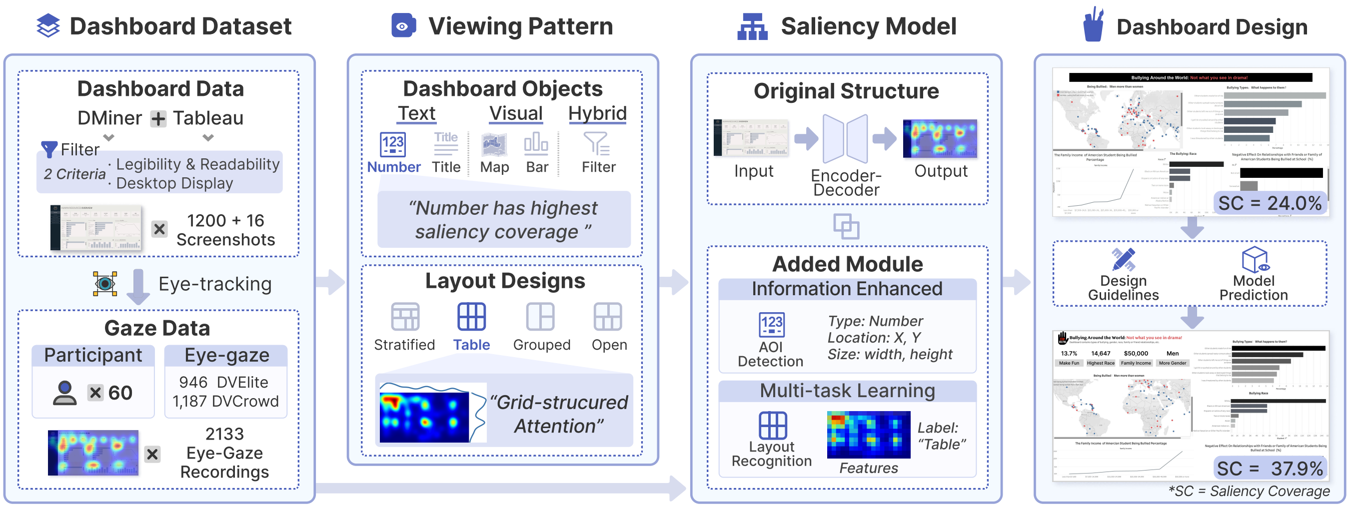

Fig. 1: Pipeline of the dashboard vision study. We assemble a dataset of 1,216 dashboards (from DMiner [26] and Tableau), including labels for dashboard objects and eye-movement data. This dataset supports the analysis of viewing behavior and the development of a saliency model to inform and guide dashboard design.

viewing patterns aligning with prior studies on single-view visualizations [28], [29] and reveal new patterns in unique dashboard objects. For layout designs, we analyze four types of layouts that Bach *et al.* [6] proposed (*e.g.*, the stratified layouts engage users more effectively than other layouts).

Incorporating the findings of viewing behaviors, we develop a saliency model for dashboards by extending an established encoder-decoder architecture used in predicting saliency maps for single-view visualization (Sect. V) trained on DVCrowd, named Dashboard Vision Saliency Model (DVSal). Quantitative and qualitative evaluations demonstrate that DVSal outperforms existing saliency models, with saliency predictions more aligned with ground truth. Finally, we discuss the potential dashboard design guidelines, application case, and the general scanning strategies with limitations and future work (Sect. VI).

In summary, our contributions are as follows:

- We construct DVElite and DVCrowd, an eye-tracking dataset for dashboards, comprising 1,216 dashboards with fine-grained labels and 2,133 valid instances of eye-movement data from 60 participants.
- We present viewing patterns on dashboards, covering different objects (text, visual, and hybrid) and layout designs (stratified, grouped, table, and open layouts).
- We introduce DVSal, a novel saliency prediction model tailored for dashboards, which incorporates objects and layout information of dashboards to improve saliency prediction performance.

II. Related Work

This work is related to prior studies on dashboard design, eye-tracking for visualization and visual saliency model.

A. Dashboard Design

The ubiquity of dashboards in various domains (*e.g.*, [1]–[4]) makes dashboard design an important topic in the visualization community. Dashboard authoring tools such as PowerBI [30] and Tableau [31] have democratized dashboard design, making it accessible to the general public. However, creating a dashboard that effectively communicates information and engages users is a non-trivial task [6], [32]. This process entails considerations of design goals, tools and technologies, labor, emerging crisis contexts, and public engagement [33]. Despite the proposals of design principles [34]–[36] and heuristics [37], dashboard design often relies primarily on designers' intuition and experience. Research on dashboard design patterns, as evidenced by the survey conducted for dashboards in the wild [5], highlights key aspects of the design space, including functional design, purpose, audience, and data semantics. Bach *et al.* [6] expanded the design space with eight groups of design patterns summarized from the perspectives of content and composition. Recently, Purich *et al.* [38] proposed a schematic representation of dashboard designs as node-link graphs to better understand dashboard spatial and interactive structures. This knowledge can be applied to inform and inspire the creation of future dashboards.

Another group of researchers uses a data-driven approach to provide recommendations or automatically generate dashboards [26], [39]–[42]. For example, DMiner [26] mines design rules of dashboard features to recommend dashboard design. However, the effectiveness of auto-designed dashboards lacks evaluation. There is a need to understand factors that affect information delivery and user engagement. This research leverages eye-tracking technology to provide an objective and precise analysis of viewing patterns on dashboards.

B. Eye-tracking for Visualization

Eye-tracking provides information about viewing behaviors, which can be used to understand how individuals view and explore visualizations [43], [44]. It has proven effective for various tasks in the visualization community, such as evaluating visualizations like tree diagrams [45] and parallel coordinates [46]. Some studies have also used eye-tracking to investigate cognitive processes, including viewing patterns across tasks and visual strategies for visualizations [11], [47], [48]. For instance, Gegenfurtner *et al.* [49] investigated expertise differences in understanding visualization between novices and experts. Borkin *et al.* [29] reported components of a visualization that attracted a viewer's attention and what information was encoded into memory. Recently, SalChartQA [23] employed eye-tracking to monitor user attention under a question-answering paradigm to understand the users' information needs.

However, existing studies primarily focused on single-view visualizations rather than dashboards, which typically featured multiple views and more information [5], [50]. As a result, it remains unclear how users allocate their cognitive effort and manage frustration tolerance [51] when interacting with dashboards. Majooni *et al.* [8] studied how layout influences comprehension and cognitive load in information graphics. Similarly, this study seeks to understand user viewing behaviors on dashboards by examining the effects of both object features and layout designs. This is achieved through the collection of eye-movement data and the development of a visual saliency model.

C. Visual Saliency Model

Visual saliency is used to depict human viewing behaviors, with the recognition that the visual context influences these behaviors. Building on this understanding, saliency models have been developed for various image types, *e.g.*, natural images [14], [15], user interfaces [16], [17], *etc*. These models are typically developed on either stimulus-driven heuristics, which employ bottom-up approaches highlighting the importance of visual elements (*e.g.*, [52]), or task-specific heuristics, which use top-down approaches based on semantic features in images (*e.g.*, [53]). With the advancement of deep learning, recent saliency models have primarily been based on these techniques [27], [54].

Visualizations are fundamentally different from natural images, presenting unique challenges for saliency prediction. Data visualization saliency (DVS) models [20] combine text saliency with user prior knowledge for saliency prediction in charts. Recent advances have leveraged deep learning techniques, with models like Scanner Deeply [21] and VisSalFormer [23]. However, these models are designed for single-view visualizations and do not account for the unique and complex design patterns of dashboards. This study aims to address this gap by introducing a new deep-learning model specifically tailored for dashboard saliency prediction, as described in the sections below.

III. Dataset Construction

In this section, we first detail the dataset construction, covering data sources, filtering criteria, and the process (Sect. III-A). Next, we describe the eye-tracking experimental setup and procedure for collecting eye-movement data (Sect. III-B). Finally, we outline data preprocessing steps for analysis and model training, including data reliability validation using Receiver Operating Characteristic (ROC) analysis (Sect. III-C) and discuss threats to validity with mitigation measures.

A. Dashboard Dataset

Our dataset comprises two parts: DVElite of eye-movement data on 16 dashboards for viewing behavior analysis, and DVCrowd of eye-movement data on 1,200 dashboards for training the saliency model. DVElite includes diverse visualization features and layouts viewed by all participants, enabling analysis of crowd-viewing behaviors. DVCrowd is a larger dataset that serves as training data for the saliency model and captures broader viewing behaviors.

Data Sources. Our data collection process consists of two main steps: First, we obtain 816 dashboards from the DMiner dataset [26]. Second, we use the Tableau Public platform to retain the top 800 dashboards using Tableau Public's *viz of the day* filtered by the keyword "dashboard" and sorting by the number of favorites. This yields 1,616 dashboards in total. The diverse data sources enhance quality and mitigate external validity threats, such as generalization to other dashboards [55].

Filtering Criteria. To ensure data quality and improve diversity, we apply two filter criteria to the dashboards.

- *Legibility & readability*. We prioritize the clarity of information on dashboards to ensure that participants can easily identify data content. To achieve this, we filter out dashboards containing overlapping dashboard content, low-quality images, and illegible text.
- *Desktop displaying*. We exclusively choose dashboards designed for desktop displays, aligning with the experimental setup conducted on a desktop screen. This criterion is applied to acknowledge the considerable impact that the type of display device can have on viewing behaviors [56].

Construction Process. We curate 16 representative dashboards to form DVElite for viewing behavior analysis, ensuring diverse objects and layouts while balancing diversity with participant's workload. Each dashboard in DVElite was viewed by all participants to identify consistent viewing patterns. DVCrowd comprises 1,200 dashboards, equally sourced from DMiner and *viz of the day*, based on two filtering criteria. In total, 1,216 dashboards are used to construct the dataset.

B. Eye-Movement Data Collection

Participant. We recruited 60 participants (26 males, 34 females) aged between 18 and 32 years, via social media, requiring normal or corrected-to-normal vision. The participants have diverse educational backgrounds, including computer science, finance, chemistry, media, art design, *etc*. This diversity ensures a broad range of perspectives in data visualization, reducing internal validity threats like prior knowledge and experience [57]. All participants passed the Ishihara Test, and their visualization literacy was assessed using Mini-VLAT [58], with an average score of 8.63 ($SD = 1.78$). Over 60% of the participants reported prior exposure to dashboards, and 13 participants had experience with eye-tracking experiments. The study was approved by the authors' institution's ethics board, with all participants providing informed consent.

Apparatus. The dashboard images were displayed on a 27-inch desktop monitor (LG 27UQ850) with a resolution of

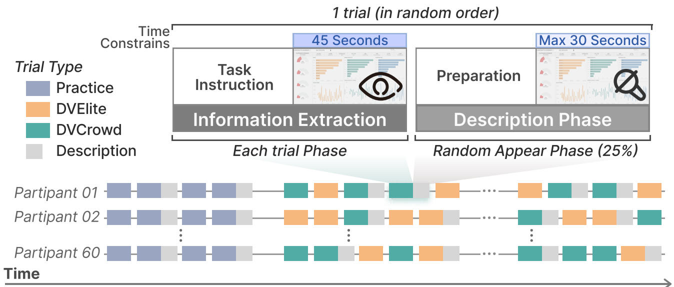

Fig. 2: Procedure for eye-movement data collection. Participants completed four informal practice trials to familiarize the experiment, followed by 36 formal trials. A repeated-measures design was employed, with randomized viewing sequences for each participant to mitigate order effects.

3840×2160 pixels. We used Pupil Labs' Pupil Core [1] eye tracker, featuring dual eye cameras (120 Hz) and a world camera (60 Hz) to record eye-movement data and visual stimuli. Apriltags (QR-like markers) mapped gaze to the defined surface [59]. A chin rest and an athletic strap stabilized the head of the participant and secured the tracker for accurate 2D eye-movement data. In other apparatus settings, we followed the best practices according to Pupil Labs' guidelines. [2] All experiments used artificial lighting to ensure consistent visual conditions and minimize confounding factors from lighting variability. The same monitor and eye-tracking apparatus were used for all participants, ensuring consistency in the data collection process. The viewing distance was set at approximately 65 cm, allowing participants to see the content while the world camera captured the full range of visual stimuli.

Procedure. Before the experiment, participants were shown an instructional video, including the experimental process, example trials, task descriptions, device introduction, precautions, *etc*. We used the Pupil Capture's 9-point calibration to calibrate each participant's parameters. During our experiments, we performed multiple calibrations, including after user-initiated rests and mandatory breaks every 10-15 minutes of viewing. Participants could also request additional breaks at the end of each trial. Each participant underwent calibration between 3 to 7 times (including recalibration because of head movement or eye-tracker slippage). Participants were also informed that they could withdraw from the study at any time.

The experiment included 40 trials per participant: 4 practice trials and 36 formal trials. The formal trials covered 16 dashboards from DVElite and 20 from DVCrowd, with each DVCrowd dashboard viewed by only one participant. To mitigate order effects in repeated measures designs [60], the order of dashboards viewed by each participant was randomized.

As illustrated in Figure 2 setting, the Information Extraction Phase was fixed in each trial and the Description Phase appeared with 25% frequency in all trials.

- *Information Extraction Phase.* This phase contains no time-limited task instruction and a fixed 45-second viewing duration. The duration was determined through a pilot study with 6 participants and was gradually adjusted from 30 seconds to 2 minutes. Most participants recognized 45 seconds as sufficient to view the entire dashboard while a longer duration may cause a loss of focus and result in invalid gaze data [61], [62].
- *Description Phase.* To simulate natural viewing behaviors while collecting data without influencing analysis, an occasional description task after the participant views a dashboard to elicit broader and contextualized observations [63]. After a preparation phase, the dashboard was shown again for 30 seconds, and participants were asked to describe the contents that they had observed in a dashboard.

The total experiment duration is under 1.5 hours. After the experiment, each participant was compensated with \$15 for their time and effort.

C. Data Preprocessing

We collected a total of 36 (trials) $\times$ 60 (participants) = 2,160 eye-movement data: 960 from 16 DVElite dashboards viewed by all participants and 1,200 from 1,200 DVCrowd dashboards viewed once each.

Eye-Movement Data Processing. Recordings that showed sudden, dramatic shifts, caused by actions such as sneezing, adjusting the eye-tracker, or participants touching the headset (*e.g.*, scratching their heads), resulted in significant errors and were excluded. These excluded data were recorded by the study operator who monitored the participants' real-time fixation points on the screen during the experiment using Pupil Labs' Pupil Capture v3.5.1 software and marked the invalid data. The valid raw data was processed using Pupil Labs' Pupil Player v3.5.1 software to extract the fixation points. We filtered the exported data using the confidence threshold of eye detection (0.8, higher than the recommended 0.6) to ensure the accuracy of the fixation points. In total, 946 (98.54%) valid eye-movement data from DVElite were used to analyze user viewing behavior, and 1,187 (98.91%) valid recordings from DVCrowd were used to train the saliency model.

Heatmap Generation. We blurred fixation points using Gaussian smoothing [43] (Chapter 7), with the kernel size corresponding to a 1-degree viewing angle in our experimental conditions [64]. This process transformed the fixation points into a heatmap. To ensure that the heatmaps are comparable and can be analyzed using statistical methods, we normalized the heatmap scalar values to one unit. This approach allows for additional analyses, including the use of information-theoretic measures such as entropy, and accounts for variations in the number of participants or the amount of fixation data.

Area of Interest (AOI) Annotation. To analyze the correlation between participants' viewing patterns and engagement with dashboard objects, three co-authors of this paper manually annotated Area of Interests (AOI) for dashboards in DVElite. Initially, they annotated independently and then discussed to reach a consensus on AOIs and their types. For dashboard objects of text, the regions were divided according to semantics (*e.g.*, a complete sentence or paragraph as one AOI). Each AOI was defined as a non-overlapping rectangular

[1]https://docs.pupil-labs.com/core/
[2]https://docs.pupil-labs.com/core/best-practices

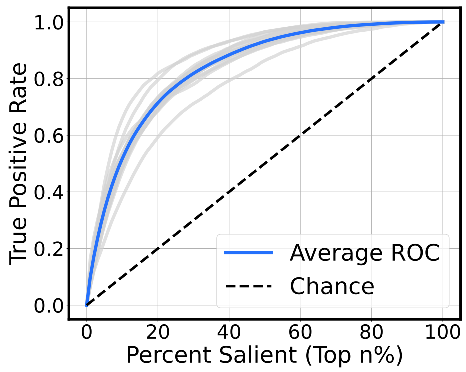

Fig. 3: ROC curve measured for the 16 DVElite dashboards viewed by 60 participants. Gray lines depict individual dashboards, while the blue line represents the average ROC curve.

area corresponding to different types of dashboard objects. In total, we collected 401 AOI labels for dashboards in DVElite, with one dashboard having a mean AOI count of 25.06 (max: 62, min: 10).

Validate Data Reliability. To validate the reliability of the collected eye-movement data, we estimate whether the viewing behaviors of different participants are similar for the same dashboard. We use receiver operating characteristic (ROC) analysis which is an used approach to evaluate the degree of similarity between two heatmaps [65].

ROC analysis treats user i's heatmap as a predictive outcome and the average heatmap of other users as ground truth. It calculates how many of the top n most salient regions in user i's heatmap overlap with the ground truth, with n varying from 0% to 100%, incrementing by 1% at each step. This approach frames the comparison as a binary classification problem, determining whether a point in a user i's heatmap matches a significant region in the ground truth. Figure 3 shows the ROC curves for the 16 DVElite dashboards viewed by 60 participants. The curves rapidly approach 1 as n increases, indicating strong similarity in viewing behaviors. Seventy percent of fixations within the top 20% most salient regions reflect consistent patterns, aligning with previous studies [18], [65]. These results confirm the reliability of the collected eye-movement data for analyzing viewing behaviors.

IV. Dashboard Viewing Behaviors

In this section, we explore the influence of dashboard designs on viewing behaviors. Types of dashboard objects and layout designs are treated as independent variables, as they are key components of dashboard design [66] (Chapter 15), while analysis metrics serve as dependent variables. Potential confounding variables, such as participants' prior knowledge, display characteristics, and environmental brightness, were controlled as described in Sect. III-B. We first introduce the dashboard objects and analysis metrics used in the study (Sect. IV-A). Then, we investigate the participants' viewing behaviors on dashboard objects (Sect. IV-B) and layout designs (Sect. IV-C), and present a summary of these behaviors (Sect. IV-D).

A. Dashboard Objects and Analysis Metrics

We first present the definition of the dashboard objects and analysis metrics, then present the statistical analyses of the relationships between objects and viewing behaviors.

Dashboard Objects. Consistent with Ware's definition (p. 277) [67], we interpret *"dashboard objects"* as "any identifiable, separate, or distinct parts" within the visualization, underscoring the element of identifiability in the objects present in dashboards [68]. We categorize dashboard objects into three groups as below:

- *Text Objects (TOs)*, including title, subtitle, number, legend, axis, and other-text (*e.g.*, additional description). As the dashboard design patterns define [6], number, as a special text type, use larger fonts and occupy prominent positions.
- *Visual Objects (VOs)*, encompassing various visualization types. Based on Purich *et al.*'s study [38], we analyze five visualization types: *bar chart, line chart, map, table,* and *area chart*, with others grouped as *other-vis*.
- *Hybrid Objects (HOs)*, combining textual, visual, and interactive features. These include filters (dropdowns, sliders, or icons like) and multimedia (images, embedded web pages, logos, *etc.*) [38].

In DVElite, each dashboard contains a mean number of 17.25 (max: 45, min: 6) text objects, a mean number of 6.06 (max: 15, min: 1) visual objects and a mean number of 1.75 (max: 3, min: 0) hybrid objects.

Analysis Metrics. We employ three metrics to quantify user viewing behavior on different AOIs [10], [23]: attention intensity, saliency coverage, and stationary entropy.

- *Attention Intensity*, the magnitude of attentional effort on specific dashboard objects, is quantified using Gaussian-Smoothed heatmap values [43] (Chapter 7). Smoothed data are preferred over fixation counts to reduce inaccuracies from device precision limitations.
- *Saliency Coverage*, the percentage of the stimulus covered by gaze, is calculated as the activated pixel percentage in the binary map [69]. We use Otsu's [70] thresholding algorithm to calculate the threshold for converting binary maps. Higher coverage indicates a larger area explored.
- *Stationary Entropy*, derived from the distribution of fixation points using Shannon's entropy formula [71], [72], reflects gaze dispersion during the viewing interval. Lower values indicate uniform distribution, while higher values suggest concentrated distribution.

To determine whether objects influence viewing behaviors, we conducted a significance test. The Shapiro-Wilk normality test was performed before selecting the appropriate statistical method to assess whether the data followed a normal distribution. The results indicated that all metrics significantly deviated from normality, with all p-values are $< .05$ (fixation intensity, $W(400) = 0.52, p < .001$; saliency coverage, $W(400) = 0.85, p < .001$; stationary entropy, $W(400) = 0.94, p < .001$). Given this result, we employed the Kruskal-Wallis test, a nonparametric method, to assess significant differences in these metrics across different objects.

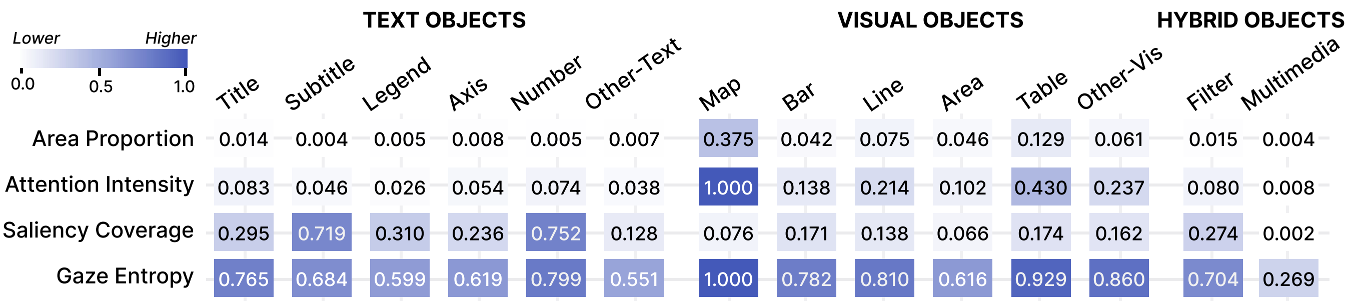

Fig. 4: The heatmap illustrates mean values of area proportion and saliency coverage, alongside normalized average attention intensity and gaze entropy for different dashboard objects. It is evident that on area proportion and attention intensity, the visual objects have the highest values, while text objects have the highest saliency coverage.

The Kruskal-Wallis tests revealed significant differences among AOI types across the three metrics: attention intensity, $H(13) = 117.25$, $p < .001$; saliency coverage, $H(13) = 176.97, p < .001$; and gaze entropy, $H(13) = 104.29, p < .001$. This indicates statistical differences across the three metrics among different dashboard objects. Furthermore, Pearson correlation coefficients (r) were calculated to explore the relationships between area size and various metrics. The results indicated a significant positive correlation between area size and attention intensity, $r(399) = 0.75, p < .001$, as well as between area size and stationary entropy, $r(399) = 0.63, p < .001$. However, a significant negative correlation was found between area size and saliency coverage, $r(399) = -0.14, p = .006$.

B. Viewing Patterns on Objects

This subsection reports the analysis results of viewing behaviors associated with dashboard objects, including the overall patterns of Text Objects (TOs), Visual Objects (VOs), Hybrid Objects (HOs), and detailed viewing patterns on specific objects, as shown in Figure 4.

1) Overall Pattern: **Text objects have more attentive viewing behaviors than others.** TOs account for 42.96% of the overall attention intensity whereas VOs constitute 52.02% and HOs 5.02%. The average saliency coverage for TOs is 47.21% much higher than 14.37% for VOs and 21.57% for HOs. This disparity in saliency coverage underscores more attention on TOs than VOs and HOs. This aligns with prior studies [28], [73], showing texts are perceived as information-rich and directly understandable, unlike visual encodings that require interpretation.

Conversely, our result diverges from some previous studies. The Data Visualization Saliency (DVS) model [20] suggests most text objects are salient, while Scanner Deeply [21] shows attention to text can be equal to or even less than that to visual objects. This difference may originate from the task-specific nature of data collection in Scanner Deeply, where the 7-second time constraint for identifying visualization types promotes reliance on visual features rather than textual information. Our findings suggest that users' attention is neither overly concentrated nor excessively dispersed, indicating a middle ground compared with DVS and Scanner Deeply.

2) Text Objects: The schematic diagrams in Figure 5 a to c illustrate the viewing patterns of text objects.

a **Number indicates the highest attention in all objects.** Number gains the highest saliency coverage, serving as the primary focal point of user visual attention. These familiar dashboard elements are often used to present vital or overall information. Numbers typically appear in groups and are placed in a prominent position on a dashboard, such as below the title or in the leftmost column. It is the most salient not only because it has more prominent visual features like bigger and bolder font size, but also because its position follows the title or the front of the viewing sequence, and the information presented is more concise from an overall perspective, thus attracting more attention.

b **Subtitle requires more viewing effort than titles.** Title and subtitle are both TOs with structured information. The title refers to the main title of the dashboard, while subtitles serve as individual visualization titles or as immediate text following the dashboard's main title, as in Figure 5 b. One dashboard could contain multiple subtitles, but only one title. Title is the most important visual object among all TOs [29] and helps viewers frame content structure [68]. Subtitles show significantly higher saliency coverage than titles, shown as post-hoc Dunn's Test with a Bonferroni correction ($p < .001$). A post-hoc test is used after the Kruskal-Wallis test to determine which specific groups differ significantly. Titles usually have a larger font size, while subtitles contain more text. Both are essential for understanding dashboards.

c **Legend needs more attention than axis.** The legend is characterized by a broader spectrum of colors and labels, while axes mainly include labels, values, and units. Existing research suggests that viewing a legend requires a higher cognitive load, because viewers need to discern the diverse colors and labels [74]. Our results support this, with axis entropy exceeding legend entropy, reflecting the more dispersed spatial arrangement of axes information compared to the concentrated information in legends (Figure 5 c). Viewing a legend requires careful consideration to understand the visualization's full context, whereas axes often require targeted inspection of specific parts. In summary, a legend requires more attention due to its complexity and information density.

3) Visual Objects: The schematic diagrams in Figure 5 d to f illustrate the viewing patterns of visual objects.

This article has been accepted for publication in IEEE Transactions on Visualization and Computer Graphics. This is the author's version which has not been fully edited and content may change prior to final publication. Citation information: DOI 10.1109/TVCG.2025.3532497

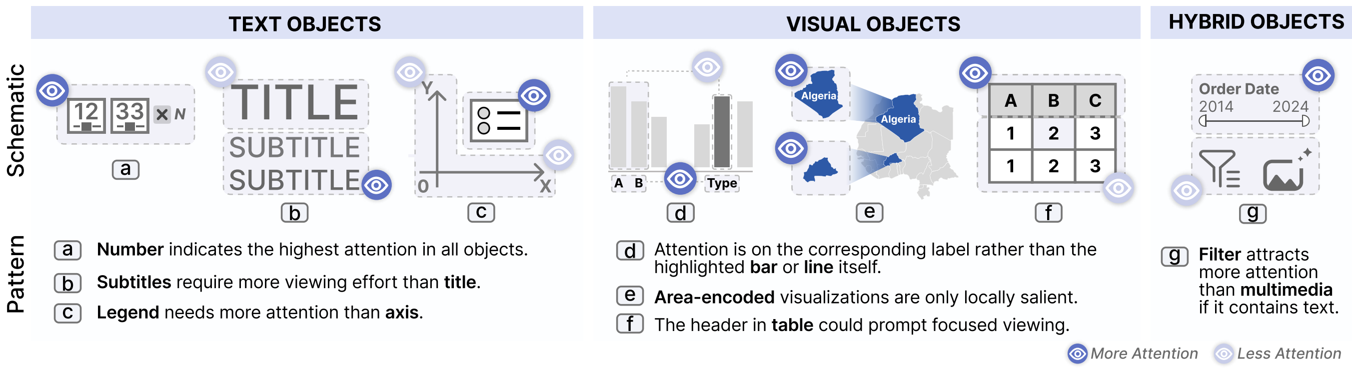

Fig. 5: The schematic diagrams illustrate the viewing patterns of text objects (a-c), visual objects (d-f), and hybrid objects (g). The darker eye area indicates higher attention, and the lighter eye area indicates lower attention. The corresponding text explains the viewing patterns of objects.

d **Attention is on the corresponding label rather than the highlighted bar or line itself.** Viewing patterns of the bar chart and line chart are similar with no significant differences in the three evaluation metrics. Users tend to focus on specific axis labels rather than the entire axis. In a bar chart, labels near the subtitle of visualizations or on the left side are more noticeable. When a certain bar is highlighted, users tend to focus on the text label on the axis corresponding to the highlighted bar, rather than the bar itself, as in Figure 5 d. Similarly, extreme points in a line chart and points with graphical overlay such as an annotation attract the user's attention [75]. In other words, highlighting a visual object directs attention to the corresponding text rather than the highlighted elements themselves.

e **Area-encoded visualizations are only locally salient.** Map and area chart both use area to represent data. Map displays geographic locations and has the highest area proportion among all visual objects, *i.e.*, it covers a larger percentage of the dashboard area than others. Consistent with the overall correlation results, the map has the highest attention intensity and gaze entropy among all visual objects because of its larger area. However, the map's saliency coverage (7.61%) is similar to that of area charts (6.64%) and both are lower than most other visual objects. Maps' high entropy and low saliency coverage suggest localized attention (Figure 5 e), with color-coded regions drawing focus regardless of labels or numerical annotations. Area charts show lower saliency coverage and entropy, indicating less concentrated focus than maps. In summary, maps and area charts attract attention to larger areas but with localized focus.

f **The header in tables could prompt focused viewing.** The table organizes textual and numerical information in a grid structure. Unlike maps and other visualizations containing axes and legends, a table's visual features are primarily the arrangement of numbers and text. A table exhibits a high entropy value, second only to map, suggesting a concentrated focus on the table's contents. The header gains more attention than the data itself because of its textual composition, facilitating immediate understanding and influencing data interpretation, as in Figure 5 f.

4) Hybrid Objects: The filter and multimedia objects are compared to each other in terms of viewing patterns. The schematic diagram in Figure 5 g shows the differences.

g **Filters with text attract more attention than multimedia.** Multimedia ranks lowest across all metrics, indicating a limited impact on capturing user visual attention. This result is surprising because prior research suggests multimedia could enhance data comprehension by acting as redundant information [29], [76], [77]. We find that most multimedia objects in our data are logos or icons, rather than images or illustrations with semantic information. In our static dashboard images, where users lack interactivity, filters attract more attention than expected. There are two types of filters: a funnel-shaped icon and a slider with text indicating filter conditions or objects (*e.g.*, "order data from 2014-2024"). Filters with text inform users about the information being compared and filtered, leading to higher attention even without interaction. In summary, text in filters attracts attention, while the lack of semantic content in multimedia diminishes their appeal.

C. Viewing Pattern on Layout

Previous research showed that the layout can affect the user's visual behavior [7], [8]. In this work, we analyze the impact of different layouts on user viewing behavior, classifying each dashboard into one of four patterns: *stratified, table, grouped*, and *open* (see Figure 6 and Figure 7 for examples of these layouts). These layouts follow previous research, the classification of dashboards by Bach *et al.* [6], which identifies common layout designs in dashboards. While previous research suggests that these layouts can be combined, we classified each dashboard based on the most prominent layout feature. This allows us to focus on the primary layout type that characterizes each dashboard. Through manual labeling, the dashboards in both DVElite and DVCrowd are categorized into stratified (15.95%), table (11.35%), grouped (16.94%) and open (55.75%). We compared the saliency coverage and gaze entropy of the four layouts, and the Kruskal-Wallis test revealed significant differences. The H-values for saliency coverage and gaze entropy were $H(3) = 42.80, p < .001$ and $H(3) = 36.26, p < .001$, respectively.

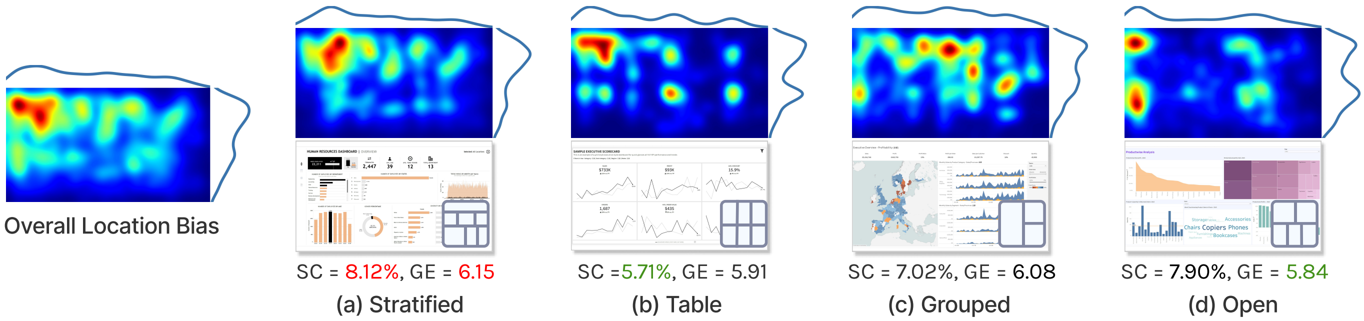

Fig. 6: Overall location bias and the attention distribution of the four layout designs: stratified (a), table (b), grouped (c), and open (d). The blue lines on the top and right are the attention density distribution curves in the horizontal and vertical directions, respectively. An example dashboard with mean saliency coverage (SC) and gaze entropy (GE) are presented below.

1) Overall Location Bias: Our finding indicates a significant location bias when users view dashboards. Similar patterns have been observed in other contexts, such as central attention bias in natural images [78], a tendency for the upper left quadrant of user interfaces to attract more attention [17]. We first analyze the distribution of visual attention as a whole, as shown in Figure 6, by drawing a heatmap aggregating all valid eye-movement data of all users for DVElite. The heatmap shows that the user's attention is concentrated in the upper left corner, consistent with prior research [17], followed by the lower left corner and the upper right corner, and finally the lower right corner.

2) Layout Designs: We analyze each layout's design-specific as in Figure 6 (a) - (d).

Stratified layout exhibits hierarchical attention and encourages users to view more regions. The stratified layout emphasizes a top-down hierarchical design, with more important information presented in Figure 6 (a) and Figure 7. Numbers often appear in this layout to present vital overall information. Participants' attention shows a gradual decline with the hierarchical structure of the information. The stratified layout shows significantly higher saliency coverage among the four layouts, as indicated by post-hoc Dunn's Test with a Bonferroni correction ($p < .001$). Users tend to explore the entire dashboard by following the logical order of the information display. When the information to be displayed is complex, using a stratified layout with inherent logic can help users navigate the information space.

Table layout decreases attention from left to right, and from top to bottom. The table layout employs a grid-based structure to align visual objects into meaningful columns and rows, similar to small multiples in coordinated multiple-view systems. It typically presents the same visualization types across rows, columns, or all grids. Viewers tend to focus on the first view and pay less attention to subsequent ones, with visual attention primarily concentrated in the upper left corner and diminishing towards the lower right corner, following a left-to-right reading habit. The table layout has the lowest saliency coverage among the four layouts. This behavior is consistent in all table layouts, regardless of the number of views, as shown in Figure 6 (b) and cases shown in Figure 7.

Grouped layouts draw more attention to the grouped views than the main view. A grouped layout typically includes a main view, along with grouped views of similar visual objects organized by proximity or closure. Despite having a larger area, the main view attracts less attention than the grouped views. For example, in the grouped layout cases shown in Figure 6 (c) and cases in Figure 7, both dashboards feature a map as the main view, but the objects within the grouped views garner more attention. This layout may be particularly useful in scenarios where a large primary view is complemented by related grouped views. When additional visualizations of the same type or complementary information are needed, the grouped layout can provide users with a broader range of insights.

Open layout attracts more attention from left to right, but not from top to bottom. The open layout offers flexibility with no restrictions on view size or arrangement, allowing users to customize their display. Without a clear viewing pattern as in the other layouts, the open layout has the lowest gaze entropy among the four layouts, resulting in a more evenly distributed focus. Attention decreases from left to right, but no significant difference is observed from top to bottom. This may be due to the wide aspect ratio of desktop displays, allowing multiple views to be arranged horizontally but only a few vertically. Viewers are more inclined to complete reading the leftmost views but may be less motivated to finish additional views on the right. This suggests placing more important views on the left side for optimal attention in the open layout.

D. Summary

The results of the analysis suggest how dashboard objects and layout designs affect user viewing behavior. Text objects are most effective in capturing attention, consistent with prior studies [28], [29] of single-view visualizations, showing titles and legends attract significant focus. New patterns for dashboard visualizations include subtitles requiring more effort than titles and numbers displaying critical values being the most salient objects. Filters with text attract attention, while multimedia components are less effective.

For visual objects, while previous studies show that highlights can draw more attention, we find that the labels in bar and line charts attract more attention than the highlighted bars or lines. Area-encoded visualizations, including maps and area charts, exhibit localized saliency, with color-coded regions

Fig. 7: Viewing patterns for different dashboard objects and layouts. The colored areas in the middle columns represent AOIs for dashboard objects. Dashboards were selected to illustrate representative viewing patterns across diverse objects and layouts.

effectively drawing attention. Tables, especially their headers, prompt focused viewing behavior.

Regarding layout designs, our work is the first to analyze how different layouts influence user attention patterns. We identify patterns such as an upper-left-location bias [17] and distinct attention trends across layouts. In stratified layouts, users are drawn to engage with multiple regions, which helps hierarchically guide their attention. Table layouts display a pattern similar to grid structures, with a decreasing trend in attention from left to right. In grouped layouts, although the main view dominates the area, related grouped views, especially those with textual content, attract significant attention. Open layouts distribute attention uniformly, suitable for dashboards without emphasis on specific information. These insights highlight the impact of layout design on user engagement and the importance of strategically organizing dashboard elements to enhance attention distribution.

V. Dashboard Saliency Model

This section introduces the saliency model we build for dashboards, which we refer to as the Dashboard Vision Saliency Model (DVSal). We first list several existing baselines for predicting saliency maps to compare them with DVSal (Sect. V-A). Then we describe the framework of DVSal (Sect. V-B). Finally, through quantitative and qualitative evaluation with ablation experiments, we demonstrate that DVSal improves accuracy over existing saliency models for predicting dashboard viewing behaviors (Sect. V-C).

A. Baseline Methods

To fairly evaluate the ability of different models to predict viewing behaviors, we select six existing saliency models as baselines in our evaluation experiment: VisImportance [79], DVS [20], UMSI [80], TranSalNet [81], Scanner Deeply [21], and SimpleNet [27]. These models predict saliency maps in various scenarios, with some capturing bottom-up attention, others focusing on top-down information, and some considering both. From these, we choose SimpleNet [27] for training on the constructed dataset to confirm the dataset's effectiveness in predicting visual cognitive behaviors. We further enhance the traditional framework by incorporating dashboard visual object and layout information, as demonstrated in Section IV, which significantly correlated with viewing behaviors. This information is integrated into the training process of SimpleNet [27] with PNASNet-5 and DenseNet-161 backbones, improving the model's ability to predict visual saliency. PNASNet-5 is known for its adaptive design that balances performance and efficiency [82], while DenseNet-161 excels at capturing detailed visual features [83]. They are both popular benchmarks for visual recognition tasks.

B. DVSal Framework

Encoder-Decoder Architecture. Figure 8 illustrates the overall structure of the DVSal network. This framework represents an advancement over the traditional encoder-decoder architecture by incorporating both AOI Detection and Layout Recognition through a Multi-task Learning mechanism. Consequently, the Encoder and Decoder components within this framework can be replaced with any pre-existing model conforming to the Encoder-Decoder Architecture. In subsequent experiments, we replace the Encoder-Decoder module in SimpleNet [27] with various backbone architectures to assess the effectiveness of the framework. We present the experimental results using the DenseNet-161 backbone in Table I. The complete quantitative evaluation results are provided in the supplementary material.

AOI Detection. Based on our earlier finding that users' viewing behaviors correlate with visual object types (Sect. IV-B), we introduce the AOI Detection module (as shown in Figure 8) within the encoder-decoder architecture to simulate users' viewing behavior with visual objects during dashboard exploration. Here, the AOIs correspond to the visual objects

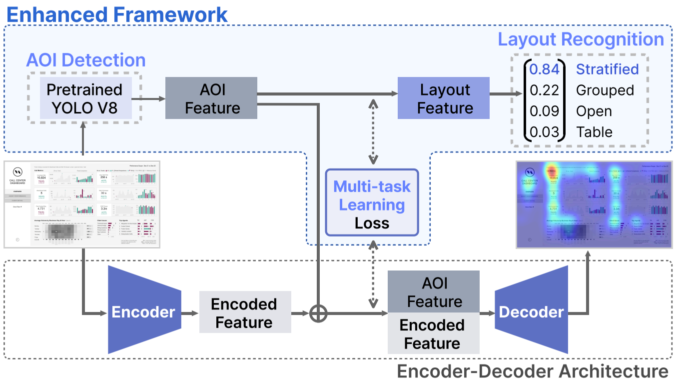

Fig. 8: Overview of DVSal network. An AOI detection module and a layout recognition module are integrated into the encoder-decoder architecture. A multi-task learning mechanism is further adapted to collectively train the entire network.

defined in Sect. IV-A. Considering that diverse visual objects can influence the distribution of salient regions, we use a convolutional layer within the AOI Detection module to align the high-dimensional information with the size of the Encoded Features. Within this context, we leverage a pre-trained YOLOv8 [84] model as our detector, which has been tuned specifically for the task of detecting visual objects pertinent to dashboards. YOLOv8 is an advanced object detection model, known for its robustness and adaptability across diverse tasks, making it well-suited for detecting a variety of dashboard elements. To maintain training stability throughout the entire training process, we lock the parameters of the AOI Detection module, solely updating parameters within the other modules.

Layout Recognition. Building upon the conclusion that behaviors are notably influenced by dashboard layout (Sect. IV-C), we introduce the Layout Recognition module (illustrated in Figure 8) into the enhanced framework. This module constrains the AOI Feature to concurrently capture more precise layout pattern information. Following the global average pooling of the Layout Feature, a classifier is integrated to discern various layout types. Due to the lightweight nature of the classifier, the parameters within the recognition module are also updated during the training of the entire framework.

Multi-task Learning Mechanism. The entire framework is jointly trained through multi-task learning, where the tasks of saliency map prediction and layout type recognition are simultaneously optimized by sharing the AOI Feature, thereby enhancing the model's generalization capability. The AOI Feature from the AOI Detection module aids in guiding the Encoded Feature to accomplish saliency map prediction and assists the model in better comprehending the data. The integrated loss in the training process is given as follows:

$$\mathcal{D}_{kl}(p \parallel q) = \int_{-\infty}^{\infty} p(x) \log \frac{p(x)}{q(x)} dx, \tag{1}$$

$$\mathcal{L}_{cls} = -\sum_{i=1}^{N} y_i \log(\hat{y}_i), \tag{2}$$

$$\mathcal{L}_{total} = \lambda_1 * \mathcal{D}_{kl}(p \parallel q) + \lambda_2 * \mathcal{L}_{cls}, \tag{3}$$

where $p(x)$ represents the ground truth, while $q(x)$ denotes the saliency map predicted by the model. y_i denotes the ground truth of class labels, $\hat{y}_i$ signifies the class probability predicted by the model, and N represents the total number of categories. λ_1 is a parameter to adjust the weight of saliency map prediction loss and λ_2 balances the weight of the layouts classification loss. We empirically set $\lambda_1 = 1$ and $\lambda_2 = 0.5$. Although combining additional saliency map losses, such as Normalized Scanpath Saliency (NSS) and Pearson's Correlation Coefficient (CC) loss, have been demonstrated to be effective in existing saliency models [85], [86], we found that optimizing the model using only KL divergence and classification loss resulted in better performance across several experiments with different loss combinations in our settings (more comparison results can be found in Table I, row 11 *vs.* row 12 *vs.* row 13).

C. *Quantitative and Qualitative Evaluations*

We conducted quantitative and qualitative evaluations to compare the performance of DVSal with state-of-the-art saliency models. Different ablated versions were also tested to assess the importance of each component in DVSal.

1) Quantitative Evaluations: Following Jiang *et al.* [17] and Matzen *et al.* [20], we selected seven commonly used metrics to assess the performance of saliency model in predicting saliency maps: *Normalized Scanpath Saliency* (NSS), *Pearson's Correlation Coeffcient* (CC), *Similarity* (SIM), *Kullback-Leibler divergence* (KL), *AUC-Judd* (AUC-J), *AUC-Borji* (AUC-B), and *shuffled AUC* (sAUC). These seven metrics cover dimensions based on value (NSS), distribution (CC, SIM, KL), and location (AUC-J, AUC-B, sAUC).

Results. We compared the performance of DVSal with six baselines (VisImportance [79], DVS [20], UMSI [80], TranSalNet [81], Scanner Deeply [21], and SimpleNet [27]), as shown in Table I. The results indicate that DVSal outperforms other baseline methods in all metrics, demonstrating better performance in predicting user visual behavior on dashboards. For the three models trained on DVCrowd, DVSal exhibits the best performance results, followed by fine-tuned SimpleNet (SimpleNet-DVCrowd), and finally fine-tuned TranSalNet (TranSalNet-DVCrowd). The performance of SimpleNet-DVCrowd trained from scratch using DVCrowd shows significant improvement over SimpleNet [27] trained on the open-source dataset SALICON [87], with an average improvement of 13% in NSS, 29% in CC, 13% in SIM, 82% in KL, 10% in AUC-J, 4% in AUC-B, and 10% in sAUC. The performance improvement indicates the significance of the collected dataset in enhancing the model's predictive ability. DVSal, with Layout Recognition and AOI Detection components, achieves the best performance among all models, with the improvement of 5% in NSS, 8% in CC, 4% in SIM, 15% in KL, 4% in AUC-J, 2% in AUC-B, and 4% in sAUC, compared to the best baseline SimpleNet-DVCrowd.

Ablation Study. To assess the significance of each component in our model, we conducted two ablation experiments to investigate the individual importance of AOI Detection and Layout Recognition, as outlined in Table I (rows 9, 10, and 13). The first experiment involved testing the model without AOI Detection. By eliminating the AOI Detection component and comparing its performance to DVSal, we aimed to discern the

TABLE I: Evaluation of saliency models on the DVCrowd dataset (the best results are highlighted in **bold**). Compared to the prior state-of-the-art saliency models customized for single-view visualization, our model DVSal achieves better performance in all value, distribution, and location metrics. Results of ablation experiments also necessitate the AOI Detection and Layout Recognition modules in DVSal.

Model	DVCrowd Training	Value Metric	Distribution Metrics			Location Metrics		
		NSS↑	CC↑	SIM↑	KL↓	AUC-J↑	AUC-B↑	sAUC↑
VisImportance [79]	×	0.4412	0.3683	0.4224	1.3059	0.7494	0.6243	0.7480
DVS [20]	×	0.3917	0.4207	0.4459	1.0690	0.7517	0.6015	0.7486
UMSI [80]	×	0.2557	0.1240	0.3444	2.0024	0.6492	0.5692	0.6467
Scanner Deeply [21]	×	0.3184	0.2174	0.3762	1.4416	0.7098	0.5905	0.7071
TranSalNet [81]	×	0.3634	0.2050	0.3718	1.8576	0.7047	0.5979	0.7017
	✓	0.4752	0.4183	0.4035	1.1434	0.7615	0.6359	0.7612
SimpleNet [27]	×	0.3468	0.1913	0.3616	1.7636	0.7032	0.5896	0.6979
	✓	0.4801	0.4878	0.4866	0.9383	0.8031	0.6250	0.8005
Ablation w/o AOI Detection	✓	0.4847	0.5110	0.4945	0.9043	0.8064	0.6226	0.8032
Ablation w/o Layout Recognition	✓	0.4998	0.5198	0.4980	0.8884	0.8126	0.6269	0.8087
DVSal (ours) w/ $\mathcal{L}_{NSS} + \mathcal{L}_{CC}$	✓	0.4288	0.5109	0.5073	0.8757	0.8241	0.5784	0.8078
DVSal (ours) w/ $\mathcal{L}_{CC}$	✓	0.4566	0.5204	0.5095	0.8856	0.8250	0.5954	0.8115
DVSal (ours)	✓	**0.5283**	**0.5656**	**0.5225**	**0.7904**	**0.8395**	**0.6429**	**0.8379**

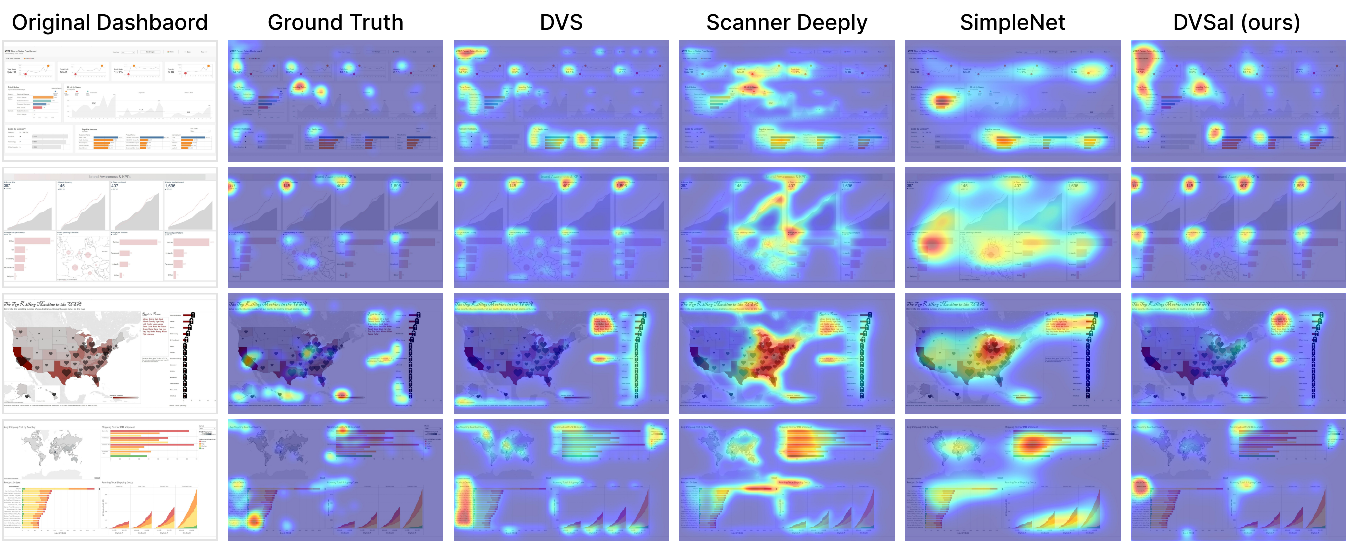

Fig. 9: The qualitative comparison of DVSal with other methods. DVSal predicts saliency maps more accurately compared to DVS [20], Scanner Deeply [21], and SimpleNet [27], effectively distributing visual attention across all visual objects.

impact of this feature on the overall performance. A substantial decrease in performance (row 9 *vs.* row 13) for the model without AOI Detection suggests that this component plays a crucial role in enhancing the model's accuracy and effectiveness. Similarly, the second experiment focused on testing the model without Layout Recognition. When excluding the Layout Recognition component, we find a notable performance decline in performance (row 10 *vs.* row 13), indicating that this component plays a pivotal factor in the model's performance.

2) Qualitative Evaluations: We qualitatively compared DVSal with other saliency models for predicting user visual behavior on several dashboards covering different visual objects and layout designs, as shown in Figure 9 (more examples are provided in the supplementary material). Given the absence of saliency models specifically tailored for dashboards, we compared with state-of-the-art saliency models customized for visualizations [20], [21]. We also included SimpleNet [27], which was trained on natural images, as a comparative reference.

Figure 9 shows DVSal saliency maps align more closely with ground truth, indicating a better understanding of viewing behaviors for dashboards. Compared to DVS [20], DVSal predicts salient regions more robustly, selectively identifying text objects rather than labeling all as salient. While Scanner Deeply [21] and SimpleNet [27] focus more on chart areas, their predictions deviate significantly from the ground truth.

For visual objects, DVSal accurately captures the importance of subtitles, numbers, and selective viewing of axis labels (row 1, Figure 9). For layouts, DVSal reflects reading order (left-to-right, top-to-bottom) and visual attention distribution across dashboards (row 2, Figure 9). Additional qualitative evaluation results are provided as supplementary material.

DVSal still has areas for improvement. First, DVSal struggles to fully capture viewing behaviors, as users' attention to text is consistent, but their focus on details within views varies. The limitations of the training data itself may also lead to such results. Secondly, while the accuracy of the salient regions has improved, there is still a gap compared to the ground truth. For instance, although the location of the salient region may match the ground truth, its predicted area tends to be larger than that indicated by the ground truth. Finally, dashboards with fewer views can result in unstable attention distribution predictions due to limited training samples.

VI. Discussion

In this section, we present potential design guidelines (Sect. VI-A), followed by a practical application of our findings (Sect. VI-B). Then we report the results of a study on scanning strategies (Sect. VI-C). Finally, we discuss the limitations of our work and future research directions (Sect. VI-D).

A. Design Guidelines

Based on the analysis of viewing behaviors, we summarize potential design guidelines related to dashboard objects (O1-O4) and layout design (L1-L3). These guidelines are intended to help designers improve dashboard effectiveness and enhance user engagement.

O1. Use *subtitles* to summarize conclusions or takeaways. *Subtitles* are more salient than *titles*, making them effective for summarizing key insights and guiding users.

O2. Use *numbers* to present key data or quantitative information. *Numbers* receive high attention, making them ideal for conveying quantitative information. Placing them beneath *titles* or *subtitles* in the top-left allows users to grasp key data quickly.

O3. Highlight the role of *filters* in exploration. *Filters* like *menus* or *sliders* aid exploration by providing context, even without direct data. For instance, a *slider* showing a year range helps users understand temporal scope.

O4. Combine *visual objects* with text to emphasize key information. Highlighting alone may not capture attention; overlaying text on visual elements, such as value labels on bars, effectively emphasizes data.

When designing a dashboard layout, it is essential to consider both the dashboard objects to be included and the tasks that need to be accomplished.

L1. Prioritize *stratified layouts* for hierarchical information. Stratified layouts follow a narrative sequence, guiding users through sections effectively. Designers should organize the information in a narrative sequence to fully use this highly narrative layout type.

L2. Ensure consistency in *table layouts* to reduce cognitive load. In *table layouts*, it is crucial to aim for consistency in visualization types, color schemes, and element sizes, to minimize cognitive load and enhance focus and comprehension of data dimensions.

L3. Minimize text in grouped views to emphasize the main view in *grouped layouts*. To direct attention to the main view in *grouped layouts*, reduce text in grouped views while maintaining readability. As with *table layouts*, ensure consistency in grouped views to further reduce cognitive load.

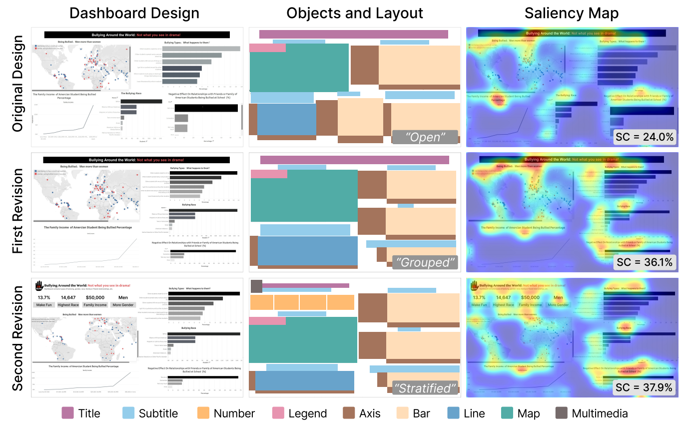

Fig. 10: The original dashboard design (top) and two revisions (middle and bottom). The saliency coverage of the improved designs increased by 12.1% and 1.8%, respectively.

B. Application

To illustrate the practical use of our findings, we present a case scenario in Figure 10. Visualization designer Amy aims to highlight campus bullying issues, presenting data on demographics, methods, and relationships, and seeks to engage viewers by emphasizing key statistics.

Amy's initial dashboard featured three bar charts, a line chart, and a map in an open layout (Figure 10, top), resulting in a low saliency coverage (SC) score of 24.0%. To improve, she adopts a grouped layout (**L3**), using the map as the main view and grouping the bar charts with consistent colors and widths (Figure 10, middle). This redesign results in a 12.1% increase in the SC score.

For further enhancement, Amy adds subtitles (**O1**) and numbers (**O2**) to emphasize critical data and reorganizes the dashboard into a stratified layout for better data exploration (Figure 10, bottom). She further organizes these objects into a stratified layout to guide users through the data exploration process. This second revision raises the SC score by 1.8%, demonstrating the effectiveness of these adjustments in highlighting bullying issues.

C. Scanning Strategies

This paper aims to explore viewing behaviors in dashboards, focusing on visual saliency as an indicator of viewer attention. The eye-movement data we collected can be leveraged for further analyses, including an examination of scanning behaviors. We have conducted preliminary studies on how participants' scanning strategies relate to different dashboard objects by using the DVElite data. Figure 11 presents the Element Fixation

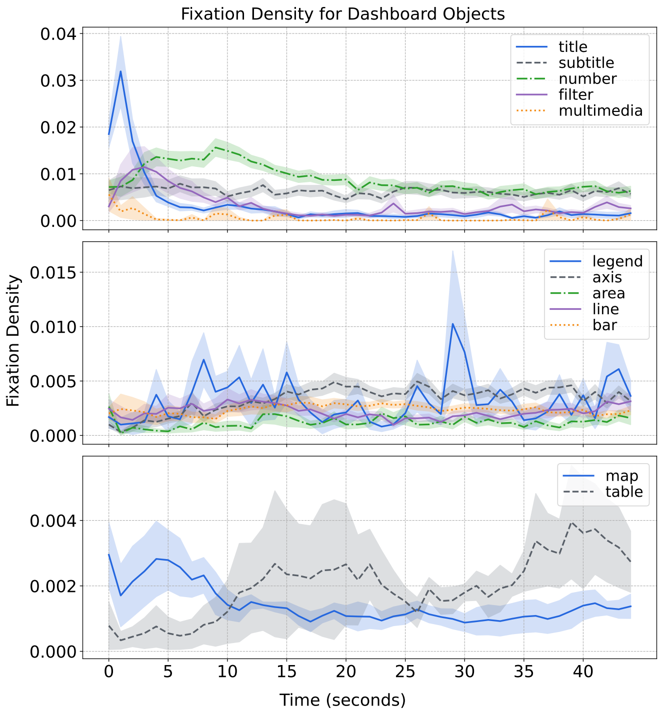

Fig. 11: The Element Fixation Density (EFD) curves depict attention distribution over 45 seconds for different dashboard objects. Shaded regions represent the standard error of the mean, illustrating both the central tendency and variability in attention distribution.

Density (EFD) [22] curves over the 45 seconds for text and hybrid objects (top), visual objects (middle), and map *vs.* table (bottom). The EFD metric quantifies the accumulated number of fixations divided by the area of objects [88], reflecting how attention shifts across dashboard objects.

Figure 11 (top) shows that user attention initially focuses on *title* and *filter* at the start of the viewing process, aiding users in grasping an overview of the dashboard. As the exploration progresses, user attention gradually shifts towards *subtitle* and *number*. *Multimedia* consistently receives less attention, with minor fluctuations observed at specific times. Figure 11 (middle) illustrates that *legend* periodically attracts attention, indicating that users' gaze alternates between *legend* and *visual objects* for comprehension. *Area chart*, *line chart*, and *bar chart* do not significantly capture attention throughout the entire period, aligning with the observation d (Sect. IV-B3) that users' focus is drawn more towards the axes rather than these specific visual objects. Figure 11 (bottoms) compares *map* and *table*, both visual objects have no axis. *Map* attracts attention at the beginning of the viewing process, while attention on *table* peaks twice and varies significantly among different participants. The analyses shed light on diverse scanning strategies for different dashboard objects. Future studies will investigate how these scanning behaviors correlate with layout designs and analysis tasks.

D. Limitation and Future Work

Dashboard Dataset Diversity. We have curated a new dashboard dataset sourced from DMiner [26] and Tableau Public's *viz of the day*. Various criteria were used to ensure the quality of the dashboards, *e.g.*filtering out low-legible designs and selecting highly favored ones. However, this approach may inadvertently impact the diversity of collected dashboards. First, dashboards in both DMiner and *viz of the day* are created using Tableau, excluding other tools like PowerBI. Incorporating dashboards from diverse tools and designers would enhance dataset diversity. Second, our dataset focuses on dashboards designed for desktop displays, excluding platforms like tablets and mobile phones. Given the growing use of mobile devices, future work could explore the applicability of these models to mobile-friendly dashboards.

Participant Viewing Behavior Diversity. Participant viewing behavior diversity also influences the analysis results. The study identifies a top-left location bias and a decrease in attention from left to right in table and open layouts. While we included participants with varied backgrounds and visualization literacy, it remains unclear if these patterns stem from left-to-right reading behavior or reflect general tendencies. Future research should collect eye-movement data from more diverse participants in real-world settings to better understand user interactions with dashboards.

Task-based Analysis. This study examines overall viewing patterns without considering specific tasks, similar to prior work on single-view visualizations [21]. However, dashboards support more complex tasks. SalChartQA [23] recently introduced a task-based model for single-view visualizations, which could be adapted for dashboards. Future research should develop tasks reflecting real-world scenarios and analyze viewing behaviors under various conditions. Carefully selecting values to compare, trends to uncover, and insights to extract is crucial for meaningful analysis.

VII. Conclusion

In this paper, we construct DVElite and DVCrowd containing 1,216 dashboards and 2,133 instances of eye-movement data collected from 60 participants. First, we analyze viewing patterns on dashboard objects and layout designs, expanding our understanding from single-view visualizations to dashboards. Second, we develop a saliency model for predicting viewing behaviors on dashboards. Additionally, we propose dashboard design guidelines, explore scanning strategies for dashboard objects, and demonstrate the model's application by a case study. The dataset and saliency model are available at https://manlingyang123.github.io/Dashboard-Vision/, to facilitate broader research.

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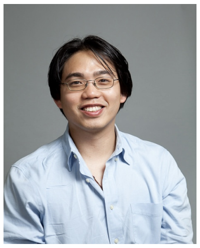

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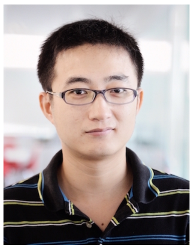

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