Eye-tracking support for adaptive document exploration: Design Space Model and Application Examples

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Abstract: Adaptive visualization systems often rely on user interaction data to personalize content presentation as well as improve user experience. We introduce a gaze-driven design space linking interface components (e.g., full text, word clouds, infographics), gaze metrics (fixations, dwell time, level of detail), and usage scenarios (history reconstruction, attention summarization, recommendation). We present two gaze-based visualizations as a part of our *Gaze-Adaptive Dashboard* as both data capture tools and as reflective interfaces: (1) a fixation timeline for the reconstruction of exploration histories, (2) a hierarchical bar chart illustrating attention across interface segments, and furthermore, we provide a recommender system, presenting adaptive recommendations based on gaze-based preferences. While our example is based on a Consumer Health Information System, the proposed approach is domain-independent and can aid any adaptive web application that benefits from visual analytics of user attention. We lay out the design trade-offs that emerge in visualizing noisy gaze data, handling incidental versus meaningful fixations, and integrating summarization approaches through Large Language Models (LLMs). Our paper highlights the potential of attention-aware visualizations to support more fine-grained user modeling and adaptive interface design, and reveals open challenges for future work at the intersection of interaction, visual analytics, and personalization.

1 INTRODUCTION

Adaptive visualization relies on handling user data gathered during visual exploration. Adapting presented content to individual needs can improve comprehension, reduce cognitive load, and aid in decision-making (Conati et al., 2015). True adaptability requires an informed perspective on how users engage with on-screen elements. For that, the system needs a more advanced understanding than simple click, scroll, or hover logs. Even though these discrete event logs are precise and well established, they cannot capture what users actually look at, where their attention shifts, or when they hesitate over complex material. Eye Tracking (ET), with increasing accuracy over the years, offers a new dimension for collecting interactions between users and systems (Oyekoya and Stentiford, 2006). By capturing real-time fixation and saccades (Carter and Luke, 2020), it reveals repeated readings, overlooked sections, exposes where users focus, for how long, and where they could hesitate, by that benefiting the overall visual exploration process of a user.

With this continuous gaze (what a person is looking at) information, the system has the ability to improve its visualizations based on user interest (Egner et al., 2018) and adjust its Level of Detail (LoD) (Tytarenko et al., 2025) with greater precision, giving more customized instructions according to where and for how long users direct their attention.

In this work, we integrate a screen-based eye tracker into a fully operational Consumer Health Information System (CHIS) – the Adaptive and interactive CHIS (A^+CHIS) (Lengauer et al., 2026), dedicated to conveying information on *Type-2 Diabetes Mellitus* through custom-built (text) visualizations and customized exploration tools. Similarly to Jianu et al. (2025), we organize the collected data and intended applications in a conceptual three dimensional model (Fig. 2), mapping component types (Close Reading,

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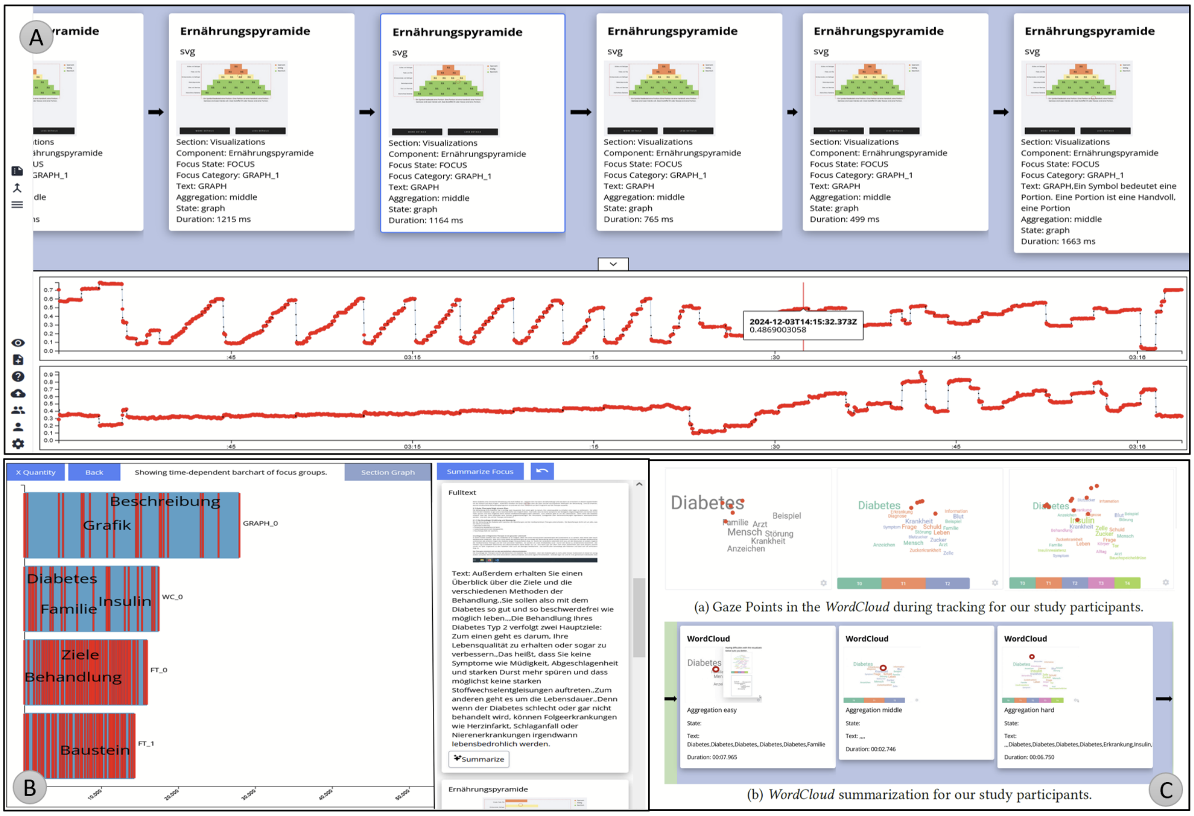

(a) Gaze Points in the *WordCloud* during tracking for our study participants.

(b) *WordCloud* summarization for our study participants.

Figure 1: Overview of the gaze-adaptive dashboard for exploring interaction histories in a document exploration application. The dashboard provides coordinated views: Ⓐ **Timeline Analysis** for the *Infographic* component, showing fixation cards and x-/y-gaze traces (line plots). Ⓑ **Summative Analysis** with a time-dependent bar chart of total dwell time (ms) per focus component (*Fulltext* blocks, *Word Clouds*, aggregated across all study participants; red ticks indicate individual fixation events. The right panel displays the LLM-generated summary for the selected text component. Ⓒ **Word Cloud results** from the user study, comparing (a) recorded gaze points and (b) the corresponding summary.

Distant Reading, Infographic), over the tracked items (Time, Word, LoD, etc.) to usages. In this model, we distinguish between three usages our gaze adaptive system should support:

Timeline Analysis (Fig. 1 Ⓐ, Sec. 4.1) reconstructing exploration histories with grouped fixations – controlling non-linear reading behavior and regressions – and adding optional LLM summaries to support rapid comprehension and provenance;

Summative Analysis (Fig. 1 Ⓑ, Sec. 4.2) – aggregating attention into hierarchical bar charts that show where users placed sustained or repeated attention;

Recommendations (Sec. 4.3) – combining fixation-weighted structural similarity to identify relevant unseen content in a component- and content-based manner.

We validate the usefulness of these components through an expert walkthrough and a controlled user study. Our findings illustrate how attention-aware visualizations can aid in session reconstruction, pinpoint areas of interest, and offer practical insights for adaptive guidance.

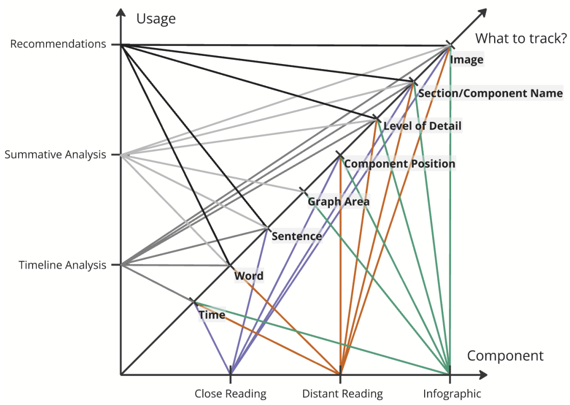

Figure 2: Our conceptual model links the tracked components (Close Reading, Distant Reading, Infographic) to the different usages (**Timeline/Summative Analysis** and **Recommendation**) over a third axis pertaining to the various tracked aspects (Time, Word, Sentence, Graph Area, etc.).

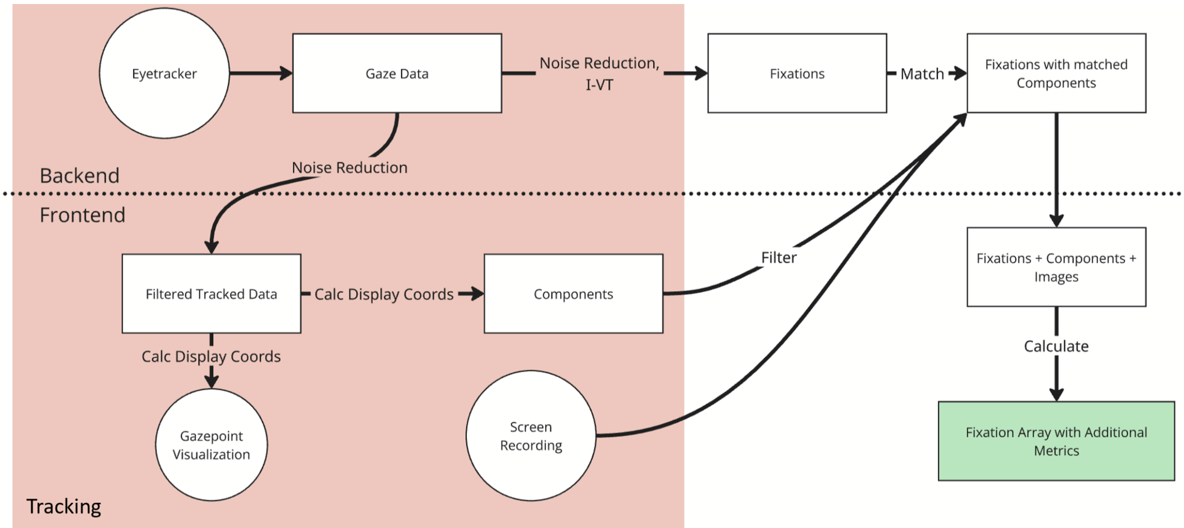

Figure 3: Illustration of our ET input data processing pipeline: raw gaze samples are streamed to the backend, then forwarded to the frontend for noise reduction and real-time DOM-component tagging alongside screen recording. After the end of a session, tagged data and video frames are returned from the frontend to the backend, which computes fixations, matches them to components, and extracts the corresponding frames for visualization.

2 RELATED WORK

Eye Tracking for Visualization ET is a powerful tool for understanding how users focus on and interpret visual information by tracking their gaze in visual interfaces (Holmqvist, Kenneth and Nyström, Marcus and Andersson, Richard and Dewhurst, Richard and Halszka, Jarodzka and van de Weijer, Joost, 2011; Blascheck et al., 2014). In work by Raschke et al. (2014), ET has also been employed to uncover cognitive mechanisms underlying visual analysis, for example, how viewing strategies are developed or attention is shifted across different tasks and visual forms. Gegenfurtner et al. (2011) examined differences in gaze patterns between novices and experts. More recently, ET has been used in interactive chart question answering to observe attention and infer information needs (Wang et al., 2024).

While these studies have been very informative, most of them have been focused on single-view visualizations rather than complex dashboards that integrated multiple coordinated views and richer visual information (Chen et al., 2021). In contrast, our work investigates gaze behavior within the web-based CHIS system that integrates heterogeneous health and knowledge data, and delves into how ET can elevate expert-level dashboards that capture user interaction histories and visual behavior patterns.

Gaze-Enabled and Adaptive Visualizations ET is being used as an increasingly important aid in the area of user adaptive visual research (Silva et al., 2019). Its capacity to provide close-up views of the user behavior and the advances in analytical techniques put ET as a foundation base on which more effective and customized visual analytics systems can be constructed (Andrienko et al., 2012). Jianu et al. (2025) propose a set of design considerations regarding the implementation of ET into an adaptive visual exploration system. They present modalities for the data source, adaptation and usage, as well as possible limitation factors for them. Early research demonstrated how quantitative analyses of gaze (e.g., fixation duration, saccade patterns, and scan-paths) can be used to inform adaptive interface design by revealing where individuals are having difficulty or were doing fine (Kurzhals et al., 2016; Conati et al., 2015). Follow-up studies by Pouw et al. (2016) have explored how gaze metrics connect to our cognitive states, like working memory load – and applied statistical and classification techniques to detect user states (Koch et al., 2023).

We find that integrating gaze-driven adaptation is crucial for creating smart visualization systems. These systems should not only react to where users are looking but also adapt and grow based on their interaction patterns and expertise over time.

Visual Analytics Dashboards for Gaze Interpretation Visual analytics dashboards can be valuable to make ET data clear and comprehensible, and allow users to reflect on their interaction. Technologies such as VisME (Munz et al., 2019) and early dashboards from Kurzhals and Weiskopf (2013) visualize measures such as fixation counts and gaze paths, allowing for rapid pattern detection and easier interpretation of users' behavior. Moreover, dashboards can visualize ET data through heatmaps, providing intuitive representations of user focus areas, thus making it easier for users to interpret the data (Merčun et al., 2024). Work by Göbel et al. (2018) showed how content update in real time according to where the reader looks on the map, illustrating how dashboard elements can be "diminished" or made more prominent based on fixation. Another relevant work was conducted by Takahashi et al. (2022). The authors monitored the spatiotemporal distribution of viewers' gaze to identify which items attract attention, then reposition or replace products in real time to support proactive exploration. Similarly, Borkin et al. (2016) were able to identify which visual components draw the most attention, and which elements are most likely to be remembered. The study by Yang et al. (2025) delves into how different types of objects and layout designs affect gaze patterns on dashboards, providing valuable insights into how user attention can be effectively predicted and leveraged for adaptive visualizations.

In our work, we introduce an expert dashboard with two visualizations: a timeline that integrates non-linear interaction and reading behavior into stable fixation clusters and augments them with short LLM-generated summaries for rapid provenance and comprehension; and summative analysis that aggregates attention into hierarchical summaries to highlight sustained or repeated focus. Together, they enable experts to audit behavior, reconstruct exploration paths, and inform adaptive guidance.

3 System Overview and Conceptual Framework

The foundation of this work is to offer a framework for the A$^+$CHIS. The basic architecture for ET implementations vary strongly and is usually defined by the used ET device, which is, in our case, a *Tobii Pro Spark*[1] to capture real-time gaze data. The data pipeline is sketched and explained in Fig 3. The raw gaze data from the eye tracker is first checked for missing values before calculating the center of the left and right eye coordinates.

Real-time gaze samples are captured via a screen-mounted ET and streamed into our Python/Django backend. We feed raw screen-space coordinates through a basic low-pass filter to smooth, then split fixations and saccades Carter and Luke (2020) using the Velocity Threshold Identification (I-VT) algorithm by Salvucci and Goldberg (2000). Fixations are timestamped and bundled with their centroid location for downstream processing. The data pipeline is sketched and explained in Fig. 3

On the client side, every interactive object is tagged with a four-tier Document Object Model (DOM) tag identifying its hierarchical position (section), component type, LoD, and atomic unit (sentence, keyword, or chart area). We distinguish between navigation elements controls such as buttons, menus, and tabs, and focus components, where content is consumed. The A$^+$CHIS consists of three primary component types: Close Reading (e.g., full-text views), Distant Reading (e.g., Word Clouds for keyword-level abstraction), and Infographics (e.g., the Nutrition Pyramid for structured visual content). These focus components are aligned with three generic classes as introduced on the Component axis in Fig. 2. After each interaction period, fixations are mapped to the closest tagged element using timestamps and client bounding boxes. Screenshots are taken per fixation for later provenance visualization. Each fixation record includes: time range, DOM path, component type, aggregation level, and (for text) the sentence(s) covered. This standard format is the input to all subsequent visualizations and recommendation algorithms.

4 Implementation

Building on our fixation records and the dimensionality model (Fig. 2), we employ three interconnected modules (as discussed in the following) that both expose and accumulate attention information.

4.1 Timeline Analysis

Explainability is an important instrument for systems to offer the user information about the computation model, regardless of whether it is used for recommendations, adaptations, or summaries (Weber et al., 2021; Ali et al., 2023). As pointed out by Blascheck et al. (2017), due to the temporal nature of gaze data, a timeline visualization is appropriate.

The timeline that we introduce (Fig. 1 Ⓐ) is a horizontally scrollable interface with 3 main features: Fixation Grouping, Interactive Gaze Graph, and LLM-based text summarization. The utilized tracked values are shown in our dimensionality model. Additionally, we compute the duration for each fixation and determine whether it serves navigational purposes. Besides a time-dependent interactive lineplot for the gazepoints in x- and y-direction, this work introduces a card-based

[1] https://www.tobii.com/products/eye-trackers/screen-based/tobii-pro-spark

fixation visualization, where viewed components and information about them can be retraced. We support a visualization of the fixations in their "raw" form (Fig. 5, bottom). However, since they can exhibit high fluctuation frequencies (e.g., when reading a text, a user's focus on specific sentences changes within fractions of a second), it makes sense to cluster them to get an idea of the high-level exploration process (Fig. 5, top). For textual representations (in our case, the *Fulltext*-component), it takes all fixations from an Area of Interest (AoI) (for us, a component in focus), and creates a set of read sentences and phrases. Infographical representations, such as an illustration of Nutrition Pyramid (as we call it in our system), that is shown in Fig. 4, or distant reading approaches, such as a Word Cloud, are grouped by aggregation form. This grouping function does not only offer a better understanding of the timeline, but also allows to compute further metrics.

A set of tracked texts for text-based grouping does not necessarily follow the linear structure of the read text, as typical reading behavior also incorporates regressions. It is also possible that the user does not comprehend the read text passage during exploration. For this matter, the option of summarization by a LLM has been implemented, which is taking the set of sentences, together with a predefined message as a prompt and returns the summary as an answer.

4.2 Summative Analysis

Also known as the Hierarchical Knowledge Collection graph, Summative Analysis offers a multi-level bar chart summarizing either the number of fixations or total time across three levels – Section, Component, and Atomic Unit (Fig. 1 Ⓑ). The graph is then created using *d3.js* with the user-selected hierarchy (focus/section), counter (# of fixations or time), and level. Interactivity is added by sorting, hover/click events, and smooth transitions. The right-hand side of the chart lists all fixations included in the selected hierarchy level and uses the same summarization function as the timeline visualization. At the top level, the length of each Section bar captures cumulative attention; drilling down captures Component-level summaries, and an additional drill-down shows individual sentences or chart areas. Thin vertical ticks inside each bar indicate individual fixations, showing fragmentation over time. Inline *Word Cloud* previews offer immediate semantic summaries of any underlying keywords or text. Interactive controls allow analysts to switch the x-axis between count and time, sort bars by magnitude, and click on any bar to both zoom and filter an adjacent list of fixation details.

4.3 Recommendations

Recommendations are computed based on a user's fixations, excluding all fixations identified as belonging to navigational processes. We first reduce each component to a 4-dimensional feature vector $\langle text, graph, aggregation, state \rangle$ and weight these vectors by the user's total fixation time to generate a 'user profile'. A nearest-neighbor search among unused components then yields the top three structurally similar elements. Simultaneously, for the Content-based Recommendation, we use TF-IDF (Sparck Jones, 1972) to represent all the fixed sentences and compare this 'text profile' with unseen passages' TF-IDF vectors using cosine similarity. To make future suggestions more relevant, users can give feedback by marking items as helpful or dismissing them. With a combination of both approaches – structural similarity in the interface and semantic proximity in the text – we propose an approach on how gaze information can trigger recommendations.

5 Use Case Example and Evaluation

To illustrate our gaze-driven input visualizations, we conducted both an expert walkthrough and a controlled user study, focusing on how well **Timeline Analysis**, **Summative Analysis**, and **Recommendations** perform. Two visualization experts and eight medical students participated, exploring three components: *Fulltext*, *WordCloud*, and *Infographic*. The study focused on assessing usefulness, identifying design flaws, and collecting honest feedback.

5.1 Timeline Analysis

We conducted two small-scale qualitative studies to gather early-stage feedback about the interpretability and perceived usefulness of our dashboard components. First, we conducted an informal cognitive walkthrough with two experts through the main features of the timeline analysis component. The second was a controlled user study with eight participants that engaged in free exploration and answered tasks on a pre-recorded session in which they completed a fixed sets of exploration tasks, such as identifying viewed components, summarizing key passages, and interpreting gaze-based indicators. This setup allowed us to test the informativeness and usability of the Timeline Analysis, Summative View, and Recommendation features without requiring live tracking sessions.

In the expert walkthrough, two visualization experts spent approximately 60-90 minutes each, explor-

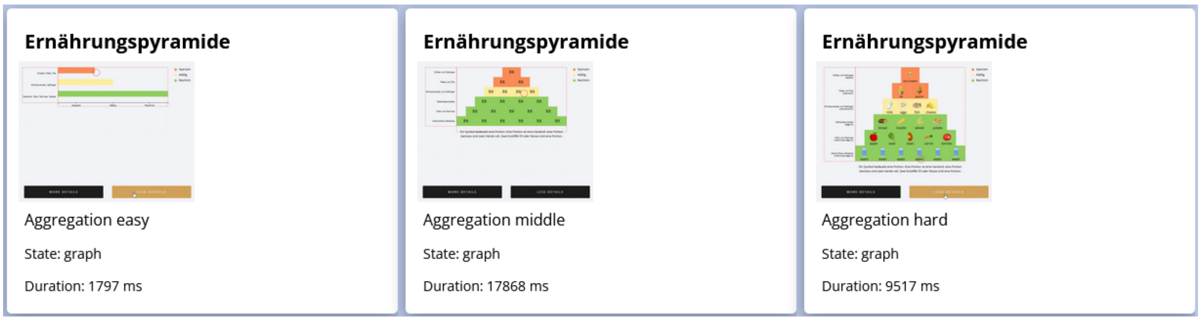

Figure 4: Example of the *Nutrition Pyramid* ("Ernährungspyramide") infographic recreated from the AOK educational brochure "Den Diabetes im Griff" (Baumgart et al., 2021) and used as part of the gaze-based exploration interface. The pyramid illustrates dietary recommendations across six nutritional levels, from beverages at the base to occasional sweets at the top. In our dashboard, this visualization serves as an infographic component used to study attention distribution and comprehension at different LoD.

Figure 5: In the **Timeline Analysis**, fixations are visualized with a card-like analogy, with the card showing a preview of the used component and additional meta information such as dwelling time. We support both a raw form (one card per fixation) and a clustered form (adjacent fixations clustered by common component). Although the fixation cards may appear similar, each one captures a slightly different text segment and duration. These subtle variations reveal regression and reading progression within a sentence, allowing users to reconstruct the reading behavior more precisely than with traditional interaction logs.

ing all three modules guided by a predefined task script. They were first asked to retrace a predetermined reading sequence using the **Timeline Analysis**. Fig. 5 shows excerpts of the grouped (top) and non-grouped timeline (bottom). Given the grouped view as an initial input, both commented: *"it was far better to read through one such summary than to read a number of short-length fixations"*. The ungrouped raw fixation stream was made "visually overwhelming" and concealed major navigation steps. Fig. 1 Ⓒ shows both (a) the actual gaze points from the tracking and (b) the summarization in the **Timeline Analysis**.

In the controlled study, 8 medical students performed a Path Reconstruction task: sorting four target sentences via the Timeline interface. They were correct 92% of the time, with a mean of 45±10 seconds to finish and a mean trust rating of 4.4 out of 5. Some participants reported: *"The grouped cards made it easy to concentrate on large reading chunks instead of every small gaze point."* (Fig. 5). Two users requested a search box so they could jump right to certain sentences within long timelines. All study participants found the grouping function to be one of the most useful features in the implementation. Two of them suggested first showing the grouped view and provide details on demand.

5.2 Summative Analysis

Fig. 1Ⓑ shows results from the **Summative Analysis**. The left part shows the time spent in each component, corresponding to the second level of our focus hierarchy (Focus State → **Focus Group** → Text/Position). The user in this visualization spent the most time in the first visit of the *Nutrition Pyramid*. The study participants (who took part in the controlled study described earlier) had difficulties finding this information, because the *Fulltext* component was viewed longer in total. Infographic areas with an intermediate LoD received most attention, followed by sentence-level text passages and lastly *Word Cloud* abstractions.

In debrief interviews, users confirmed that the highest bars related to the sections ranked most highly by them as being most important, explaining that this concise bar-chart summary provided an easy way to identify high-interest content without having to review individual fixations.

6 Conclusion & Future Work

As demonstrated, our proposed dashboard visualizations provide experts with valuable functionalities for the fundamental analysis of users' exploration processes. However, during our initial evaluation with a small group of participants, we uncovered some clear limitations: while the current tools allow for a detailed look at individual users, they fall short when it comes to analyzing groups. Consequently, one of our next steps would be to create an overview that showcases the variety and differences in tracked behaviors, complemented by clustering to group users into manageable similarity clusters.

Beyond this proof of concept, our approach can be seamlessly integrated into any web-based CHIS. The main challenge we face is the need for customized tags on DOM elements; we implemented this manually, but since the tagging strategy is fairly straightforward, we believe that generative Artificial Intelligence (AI) could automate this process to enhance scalability. Such created tags can then be added to a CHIS's HTML templates or even be injected via a man-in-the-middle proxy.

Looking ahead, we see several ways to extend this work: (i) complex dashboards call for richer visual modalities (tables, maps, interactive graphs), (ii) enhance recommendations through predictive models and tighter feedback loops, and (iii) deepen the integration of gaze context with LLMs by utilizing attention trails to create personalized summaries, clarify any confusing sections, and ask targeted questions. Ultimately, we aim to expand this approach to accommodate multi-component, multi-user, and cross-platform environments, as well as to extend the design space to include dynamic stimuli (e.g., videos, interactive maps, or collaborative reading), allowing us to further test its generality.

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