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GazeViz: A Web-Based Approach for Visualizing Learner Gaze Patterns in Online Educational Environment

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Abstract: As online learning tools become more widespread, understanding student behaviors through learning analytics is increasingly important. Traditional methods relying on system log data fall short of capturing the full range of cognitive strategies students use. To address this, we developed an in-depth post-assignment reflection dashboard that visualizes gaze data to aid students in reflecting on their learning behaviors. This dashboard was made possible by ETProWeb, a system that integrates high-fidelity eye-tracking directly into the browser, enabling real-time analysis of gaze data aligned with user interactions. ETProWeb leverages the browser's Document Object Model (DOM) to track areas of interest (AOIs) dynamically, overcoming issues related to multiple timelines and manual alignment. In a pilot study with 38 sixth-grade students, the dashboard received positive feedback, with 90% of students expressing interest in the eye-tracking technology for its ability to help them observe and reflect on their reading behaviors. This interest highlights the potential of eye-tracking as a valuable tool for enhancing students' self-awareness and engagement in online learning environments.

Keywords: Eye-Tracking, Visualization, Dashboard, Browser, Scalable

1. Introduction and Motivation

With the increasing access to online educational tools and resources for students and teachers to utilize and track their progression, pedagogical instruction, and assignment work is shifting to take place in the browser. The shift to the web has expanded the scale of educational tools and brought about the age of massive open online classes (MOOC) and other EdTech such as LMS and other specialized learning environments. Through these computer-based learning environments and software, learning analytics has largely benefited from the insightful digital traces generated by students to understand student behavior (Rajendran et al., 2018). and predict learning outcomes (Arizmendi et al., 2022). However, many of these analyses only use system log data, which falls short of understanding students' holistic cognitive behaviors and strategies compared to a multimodal learning analytics approach (Di Mitri et al., 2018).

To dive deeper and understand how students are navigating through assignments, eye-tracking has been used to measure and understand gaze patterns and further contextualized log data (Sharma et al., 2020). Fixations, saccades, and scanpaths have all been used to study students' information gather patterns across various tasks, such as reading (Chen et al., 2023), video lectures (Srivastava et al., 2021), and graph construction (Rajendran et al., 2018). However, a major limitation of these studies and the broad use of eye-tracking hardware is that they are restrained within laboratory settings, significantly constraining the scalability of studies. Lastly, the collection of eye-tracking is largely performed independently of the browser session, resulting in 2 data timelines that require manual alignment to support log-gaze analysis. Because of the need for manual intervention by a researcher, real-time gaze analysis in online education applications is challenging and uncommon.

In many prior eye-tracking studies, the gaze data is collected and analyzed in post hoc, preventing immediate feedback or visualizations from being presented to the user. Therefore, it is uncommon for eye-tracking studies to include students' self-reflection on their gaze behaviors with data-driven visualizations. However, new real-time eye-tracking systems, such as those proposed in (Abeysinghe et al., 2023) and (Jayawardena et al., 2024), have pushed the research field toward leveraging end-to-end data pipelines to deliver gaze-based results during or right after data collection. These new systems have been used to present real-time eye-tracking data such as scanpaths for visual tasks – *Where is Waldo* – to validate the data flow from the eye-tracking device to the browser. However, these technologies are still being developed and have not been applied to real-world applications, such as educational and learning analytics technology.

Gaze analytics has been increasingly applied in education to understand student engagement (Miller et al., 2015), reading strategies (Chen et al., 2021), and learning outcomes (Rajendran et al., 2018). Eye-tracking studies have been used to analyze how students interact with learning materials, identify areas of difficulty, and provide insights into attention and comprehension. For example, eye-tracking has been used to measure students' focus on key content areas, track their reading patterns, and assess cognitive load during complex problem-solving tasks. While these methods have proven valuable for research, they are often limited to post-hoc analysis, where data is collected and analyzed long after the learning activity has concluded. Consequently, the insights gained from gaze analytics have rarely been presented back to students or teachers in real-time or immediately after assignment completion, missing opportunities for immediate reflection and feedback that could enhance learning outcomes.

In this paper, we present the first steps toward bringing eye-tracking to the browser, performing real-time gaze analysis, and presenting the process data in an immediate visualization for students and teachers to reflect on their reading assignments after completion.

2. System Architecture

A main contributor to a deficiency in eye-tracking technology for the browser is that eye-tracking manufacturers and companies provide solutions that mandate specialized hardware and software that are technologically incompatible with the browser. For example, EyeLink eye-trackers can only be integrated with 3rd party applications via system programming languages such as Python, C++, and Java – while other eye-tracking devices simply do not provide software integration solutions. Moreover, compiling these programs to WASM or any other web runtime is not feasible without the entire codebase. Existing web-friendly eye-tracking solutions such as WebGazer (Papoutsaki et al., 2016) or GazeCloudAPI do not achieve reliable gaze data and can cause performance issues within the browser session.

For our first step in bringing high-fidelity eye-tracking to the browser, we have developed ETProWeb (as shown in Figure 1) as a means to stream gaze data from Tobii's line of Pro eye-trackers (Spark, Fusion, and Spectrum). Through this solution, the system is composed of two components: (1) a Python Eye-Tracking Server, tasked with identifying Tobii Pro SDK compatible eye-trackers, reading incoming gaze data, and streaming gaze data to the browser; (2) a client JS library that receives this gaze. The relaying of the gaze data from Python to JS, the gaze data is obtained within the browser's runtime, a single timeline is used to save logs and gaze, and the time alignment problem is resolved.

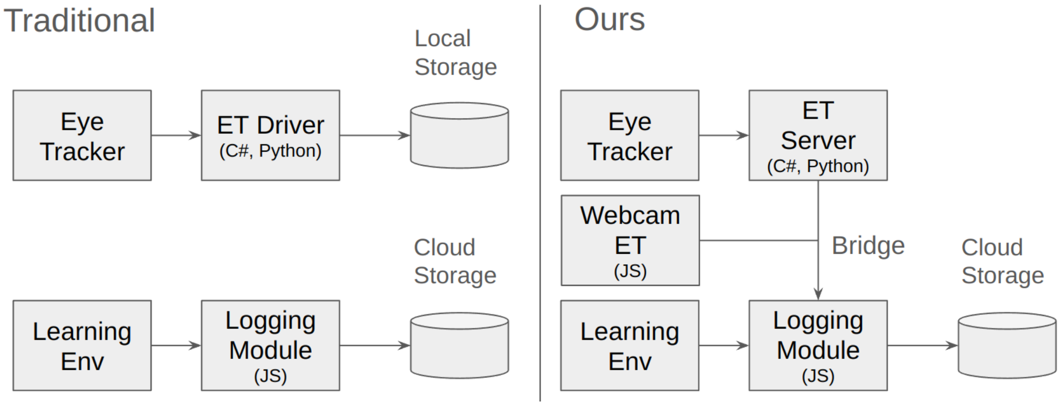

Figure 1. ETProWeb Subsystem

2.1 Instantaneous AOI Preprocessing

A major challenge in eye-tracking research in computer-based learning environments, largely as a byproduct of separate gaze & log timelines and separate runtimes, is the tracking areas-of-interests (AOIs) and linking gaze to these critical visual elements (Davalos et al., 2023). This is especially important when considering that most modern websites and applications have dynamic content, scrolling, and zooming functionalities, which further complicate the aspect of tracking AOIs. Prior approaches use screen recordings and computer vision methods, such as optical character recognition (OCR), to detect and track dynamic AOIs. Performing this approach adds substantial computational load and lowers AOI tracking reliability. By utilizing ETProWeb and having a single JS runtime, we can perform instantaneous AOI preprocessing since the JS runtime has direct access to the rendered document object model (DOM). AOIs are presented as elements with the DOM whose geometrical bounding rectangle with respect to the screen and viewport can be queried. With the AOIs' geometrical information readily available, all incoming gaze points can be determined to fall within or outside an array of AOIs.

In our learning environment (shown in Figure 2), 3 main AOIs are present: (1) the Document panel on the left, (2) the PDF Viewer in the center, and (3) the Task Panel on the right. Through this approach, we were able to project gaze stream data into PDF pages in a reading learning environment. Performing the AOI encoding concurrently with the user session supports our ability to perform mixed gaze-log analysis without needing screen recordings and provide immediate results and visualizations.

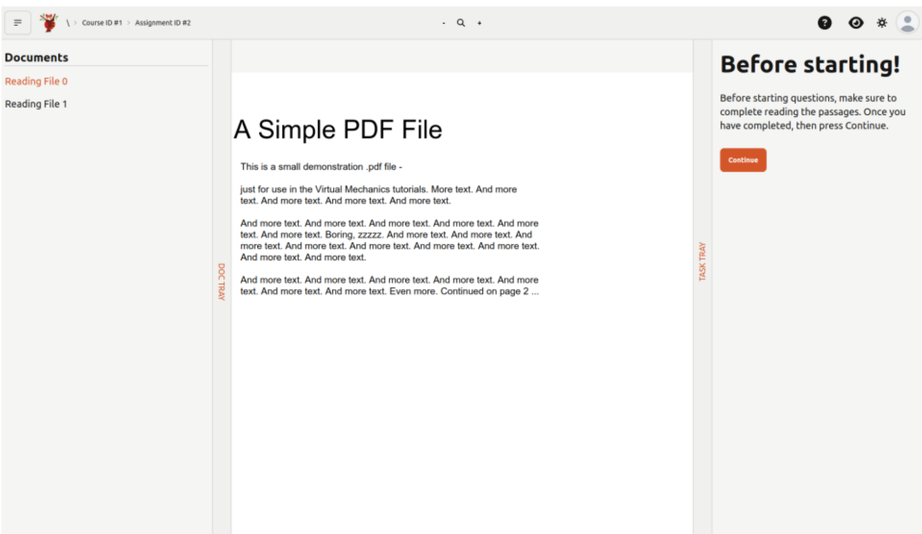

Figure 2. Learning Environment Design

2.2 Post-Assignment Data Visualization

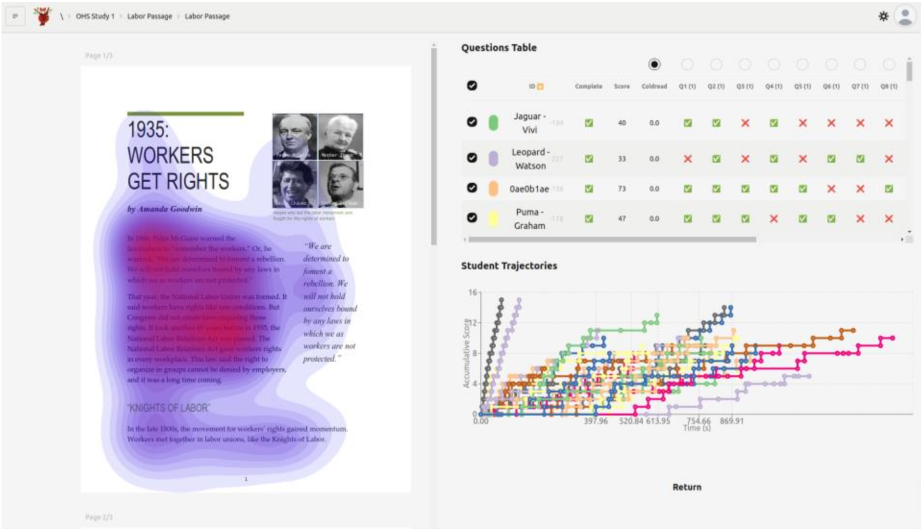

Figure 3. High-Fidelity Prototype

With the completion of students' assignments, their session data (logs & gaze) is stored in the cloud. Students and teachers are then able to open an in-depth assignment report, as shown in Figure 3. The session data is fetched and loaded into the browser to support the creation of gaze and learning outcome scores. On the left side, a gaze heatmap visualization is overlaid on top of the entire PDF using the D3 library. This component of the dashboard aims to help students reflect on what areas of the PDF they spend the most time focusing on. On the top right, a table of their responses to questions is shown, with the feature to support isolating gaze based on the entire assignment and per-question. Lastly, on the bottom right, the temporal trajectory of the students' scores is shown. For the teacher dashboard, the entire class' process and outcome data is available for investigation, while the student is only able to explore their own assignment data.

The post-assignment dashboard enables both students and teachers to explore the detailed gaze data collected during the assignment. By linking gaze data with learning outcomes, the visualizations offer insights into the reading behaviors that contributed to students' responses and scores. For teachers, the dashboard reveals the class's collective attention and shows whether students overlooked critical sections of the text. It also allows for analysis at different levels—individual, group, or entire classroom—to support various levels of data inquiry. When examining an individual student's data, the dashboard can help identify why a student with strong reading skills may have answered incorrectly, such as by missing key answer-containing sections. On the other hand, it can reveal if struggling students read the relevant parts but still responded incorrectly, pointing to issues with comprehension or retention.

When focusing on a subgroup, such as struggling students, the dashboard helps identify broader patterns and behaviors within different groups, allowing teachers to tailor curriculum and instruction to better support these subgroups. At the whole-class level, the dashboard provides a macro view of the class's reading abilities, helping teachers understand fluctuations in performance between assignments. This can offer insights into pacing and the difficulty of the content. Across all levels, the dashboard delivers evidence-based measurements and strategies to address the needs of individual students, subgroups, and the entire class effectively.

For students, the interactive dashboard allows them to view their gaze patterns alongside their outcomes, serving as a tool for self-regulated learning. It encourages reflection on their reading strategies and their understanding of the text. The gaze heatmap highlights which parts of the text they overlooked, helping them adjust and improve their reading approach. By showing the time spent on different areas, the heatmap informs students about their reading habits, allowing them to monitor their focus, coverage, and overall engagement with the text.

3. Pilot Study

We conducted a pilot study with 38 sixth-grade students from a private school in the southeastern region of the United States. The demographic data provided by the teacher indicated that the cohort consisted of 22 male and 16 female students. The racial composition was predominately White (N=35), with 2 Black and 1 Asian student. Among the White students, 2 identified as Hispanic or Latino. Additionally, 8 students were identified as having special education needs: 1 student with legal blindness/limited vision, 4 students with dyslexia, 2 students with ADHD, and 1 student with a combination of ADHD, dyslexia, and slow processing speed. We lost 1 student data due to a technical error.

In the study, as shown in Figure 4, the students were asked to read a PDF passage and answer a set of questions through our custom web application. The text had about 500 words and according to the Common Core Standards, was at the 6th grade level with a Lexile level between 810-1000 according to lexile.com. Before starting the session, students performed a 9-point calibration routine, provided by the Tobii Pro Eye-tracker Manager. The eye-tracker used was the Tobii Pro Spark eye-tracker at 60 Hz. During each session, students were required to read a passage and subsequently answer a series of questions. The initial reading of the passage termed the "cold read," was conducted without access to the questions. Upon completing the passage, students then commenced the question portion of the session. During this phase, students could reference the passage but were required to answer the questions in sequence and were not permitted to revisit previous questions. At the completion of their assignment, students were presented with their in-depth assignment report, similar to the one shown in Figure 3.

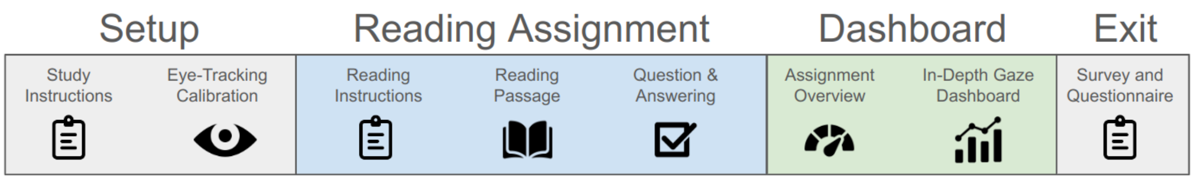

Figure 4. Study Flow Diagram

Following the reading experiment, the students were asked to provide feedback on the dashboard by responding to two questions designed to evaluate their experience:

- **Challenges**: Did you notice any challenges with the protocol or the interface? What was confusing?
- **Likes**: What did you like about the interface?

These questions aimed to gather insights into the usability and effectiveness of the dashboard from the students' perspectives.

4. Evaluation of the Dashboard

4.1 Challenges encountered by students:

In response to the question regarding challenges with the protocol or interface, the majority of the students reported no significant difficulties.

- **No Challenges**: 23 out of 37 students (62%) explicitly stated that they encountered no challenges or found nothing confusing about the interface.

- **Minor challenges**: 14 out of 37 students (38%) reported specific difficulties, such as:
  - Difficulty navigating back to find information (N=2) *[P13: Some challenges were that it was hard going back to find information]*
  - Confusion locating elements on the interface (N=2) *[P35: Sometimes I couldn't understand where things were, but that's really it]*
  - Eye strain (N=1) *[P31: The computer hurt my eyes]*
  - Page formatting issues (N=1) *[P1: It was a weirdly formatted page]*

4.2 Positive aspects of the interface:

In response to the question about what students liked about the interface, the feedback was overwhelmingly positive (90%), with students expressing particular interest in the eye-tracking technology:

- **Appreciation for eye-tracking technology**: The majority of students (76%) specifically mentioned the eye-tracking feature as a highlight. They found it fascinating that the technology could track their eye movements, with comments such as:
  - *[P13: I liked how it tracked my eyes]*
  - *[P17: Cool that it tracks eyes]*
  - *[P2: I liked how it track exactly where you were reading]*
  - *[P26: I liked it, I thought it was a cool experience and how it tracked where you read the most]*

- **Unique features:** Some students appreciated specific features of the dashboard, with comments such as:
  - *[P44: I liked that it showed me the pink and blue at the end of what I was looking at]*
  - *[P28: I like the name of the website and the icon]*
  - *[P18: I liked how you could go back in the text]*

Overall, the eye-tracking technology was the most frequently praised feature, with students expressing a strong interest in how the system monitored and visualized their reading patterns.

5. Conclusion & Future Work

First-class integration of eye-tracking into online learning environments demonstrates significant potential for enhancing student engagement and self-awareness through real-time gaze analysis. Our pilot study with sixth-grade students showed that 90% of participants responded positively to the system, particularly appreciating the ability to observe their reading behaviors through eye-tracking technology. This feedback highlights the value of incorporating multimodal learning analytics into educational tools, as it provides deeper insights into student behavior and fosters a more interactive and reflective learning experience.

While this study demonstrates the potential of using gaze data to enhance learning analytics, it also highlights the need for better integration with existing industry standards, such as xAPI, to ensure compatibility within the broader EdTech ecosystem. Although xAPI is commonly used for storing event-based logs, it is not specifically designed to handle high-frequency time-series data, such as eye-tracking metrics. Given that our approach involves collecting time-series multimodal data that needs to remain synchronized, there is a challenge in storing this data effectively within xAPI's current framework. Future research should focus on developing methods and extensions for xAPI or exploring alternative standards that can accommodate the storage of synchronized, time-series multimodal data. This will be crucial for advancing the interoperability of gaze-based learning analytics tools with existing educational technologies.

Our future work will focus on two main areas. First, while ETProWeb is suitable for research-focused studies, it lacks scalability compared to webcam-based eye-tracking. We aim to explore more scalable eye-tracking solutions for broader applications. Second, we plan to refine the dashboard through a co-design process with key stakeholders, including students and teachers, to better align with their needs.

In this co-design process, we will use established measurement tools like the Technology Acceptance Model (TAM), System Usability Scale (SUS), and NASA Task Load Index (NASA-TLX) to iteratively improve the dashboard. A webcam-based system will allow us to scale up studies and gather more user feedback, helping us make the dashboard more user-friendly. We recognize the challenge of presenting data that is both digestible for users and detailed enough to highlight critical information. Our goal is to find a balance between simplicity and depth.

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References

Rajendran, R., Munshi, A., Emara, M., & Biswas, G. (2018, November). A temporal model of learner behaviors in OELEs using process mining. In *Proceedings of ICCE* (pp. 276-285).

Srivastava, N., Nawaz, S., Newn, J., Lodge, J., Velloso, E., M. Erfani, S., ... & Bailey, J. (2021, April). Are you with me? Measurement of learners' video-watching attention with eye tracking. In *LAK21: 11th international learning analytics and knowledge conference* (pp. 88-98). https://doi.org/10.1145/3448139.3448148

Arizmendi, C. J., Bernacki, M. L., Raković, M., Plumley, R. D., Urban, C. J., Panter, A. T., ... & Gates, K. M. (2023). Predicting student outcomes using digital logs of learning behaviors: Review, current standards, and suggestions for future work. *Behavior research methods*, *55*(6), 3026-3054. https://doi.org/10.3758/s13428-022-01939-9

Di Mitri, D., Schneider, J., Specht, M., & Drachsler, H. (2018). From signals to knowledge: A conceptual model for multimodal learning analytics. *Journal of Computer Assisted Learning*, *34*(4), 338-349. https://doi.org/10.1111/jcal.12288

Sharma, K., Giannakos, M., & Dillenbourg, P. (2020). Eye-tracking and artificial intelligence to enhance motivation and learning. *Smart Learning Environments*, *7*, 1-19. https://doi.org/10.1186/s40561-020-00122-x

Xiuge Chen, Namrata Srivastava, Rajiv Jain, Jennifer Healey, and Tilman Dingler. 2023. Characteristics of Deep and Skim Reading on Smartphones vs. Desktop: A Comparative Study. In *Proceedings of the 2023 CHI Conference on Human Factors in Computing Systems* (CHI '23). Article 516, 1–14. https://doi.org/10.1145/3544548.3581174

Rajendran, R., Kumar, A., Carter, K. E., Levin, D. T., & Biswas, G. (2018). Predicting learning by analyzing eye-gaze data of reading behavior. *Proceedings of the 11th International Conference on Educational Data Mining, EDM 2018*, 30–32.

Papoutsaki, A., Daskalova, N., Sangkloy, P., Huang, J., Laskey, J., & Hays, J. (n.d.). *WebGazer: Scalable Webcam Eye Tracking Using User Interactions*. https://webgazer.cs.brown.edu

Eduardo Davalos, Caleb Vatral, Clayton Cohn, Joyce Horn Fonteles, Gautam Biswas, Naveeduddin Mohammed, Madison Lee, and Daniel Levin. 2023. Identifying Gaze Behavior Evolution via Temporal Fully-Weighted Scanpath Graphs. In *LAK23: 13th International Learning Analytics and Knowledge Conference (LAK2023)*. Association for Computing Machinery, New York, NY, USA, 476–487. https://doi.org/10.1145/3576050.3576117

Špakov, O., Siirtola, H., Istance, H., & Kari-Jouko, R. (2017). Visualizing the Reading Activity of People Learning to Read. *Journal of eye movement research*, 10(5), 10.16910/jemr.10.5.5. https://doi.org/10.16910/jemr.10.5.5

Knoop-van Campen, C. A. N., Kok, E., van Doornik, R., de Vries, P., Immink, M., Jarodzka, H., & van Gog, T. (2021). How teachers interpret displays of students' gaze in reading comprehension assignments. *Frontline Learning Research*, 9(4), 116–140. https://doi.org/10.14786/flr.v9i4.881

Abeysinghe, Y., Mahanama, B., Jayawardena, G., Sunkara, M., Ashok, V., & Jayarathna, S. (2023, August). Gaze Analytics Dashboard for Distributed Eye Tracking. In *2023 IEEE 24th International Conference on Information Reuse and Integration for Data Science (IRI)* (pp. 140-145). IEEE. https://doi.org/10.1109/IRI58017.2023.00031

Jayawardena, G., Ashok, V., & Jayarathna, S. (2024). Advanced Gaze Analytics Dashboard. *arXiv preprint arXiv:2409.06628*.

Miller, B. W. (2015). Using Reading Times and Eye-Movements to Measure Cognitive Engagement. *Educational Psychologist*, *50*(1), 31–42. https://doi.org/10.1080/00461520.2015.1004068

Chen, X., Srivastava, N., Jain, R., Healey, J., & Dingler, T. (2023, April 19). Characteristics of Deep and Skim Reading on Smartphones vs. Desktop: A Comparative Study. *Conference on Human Factors in Computing Systems - Proceedings*. https://doi.org/10.1145/3544548.3581174