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Eye Tracking for Early Anxiety Detection: Analysis of Fixation Duration, Dispersion, and Saccadic Patterns Among University Students

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ABSTRACT: Eye-tracking technology has emerged as a promising non-invasive tool for assessing cognitive processing and mental health conditions, including anxiety. This study aims to examine differences in ocular behavior between university students classified as **anxious** and **control**, based on expert psychological assessment. Thirty participants were involved, comprising 17 anxious and 13 control subjects. Four primary eye-movement metrics were analyzed during a 60-second visual task using a Tobii Eye Tracker: **fixation duration**, **fixation dispersion**, **percentage of time spent in saccades**, and **saccade rate**.

The results reveal distinct gaze behavior between the two groups. The anxious group exhibited **shorter fixation durations** (~0.18 s), **greater fixation dispersion** (≈480–520 px), **higher saccadic time proportion** (17–18.6%), and **faster saccade rates** (≈18 s^{-1}) compared to the control group. These patterns reflect the characteristics of *hypervigilance*, *attentional instability*, and elevated cognitive load commonly reported among individuals with anxiety. The findings align with the Attentional Control Theory and Threat Monitoring models, which posit that anxiety disrupts sustained attentional engagement and induces excessive environmental scanning. Overall, the study demonstrates that eye-movement biomarkers provide a reliable indicator for distinguishing anxiety levels among students. The results highlight the potential of eye-tracking–based systems for early mental-health detection and objective cognitive assessment in university settings.

KEYWORDS: Eye Tracking Modeling; Cognitive Load; Mental Health; Tobii Eye Tracking; Big Data

I. INTRODUCTION

The learning process is closely linked to the learner, particularly in the context of adaptive learning, where the learner's cognitive state plays a central role. Among the cognitive factors influencing learning, **cognitive control** is especially critical. Prior studies [1–4] define cognitive control as the learner's capacity to direct and regulate attention in order to achieve specific goals. However, research also indicates that anxiety substantially disrupts cognitive processes, including cognitive control, thereby impairing learning performance. More specifically, [3] found that anxiety triggers excessive processing of threat-related stimuli, which interferes with cognitive functions essential for effective learning.

Anxiety is commonly understood as an uncomfortable, disruptive, and undesirable emotional state. When it surpasses normal thresholds, it can manifest as a psychological disorder [5]. This condition is frequently experienced by university students, including those at the State Polytechnic of Jember. Supporting evidence is provided by [6], who reported significant differences in stress levels across academic departments. According to prior studies [7–10], such psychological conditions among students necessitate early detection mechanisms for cognitive load and anxiety. Furthermore, research in [10–11] demonstrates that Eye Gaze Modeling can serve as an effective tool for assessing both cognitive processes and anxiety levels.

This study aims to develop an Eye Gaze Modeling framework using a Tobii Eye Tracker integrated with Big Data technology for evaluating cognitive load and detecting anxiety (mental health) among students. The Tobii eye-tracking sensor data are stored within a Big Data infrastructure and subsequently extracted as input variables for analysis. The primary objective of this research is to infer students' cognitive load and anxiety levels through their eye-movement patterns during computer-based interactions [10]. Specifically, the application developed in this study identifies the participants' eye positions and converts them into corresponding screen coordinates (x, y). These gaze-coordinate data are then processed and modeled to estimate the cognitive load and anxiety conditions of the students.

This study aims to detect anxiety experienced by students by analyzing their eye-movement patterns during e-learning activities. The focus on e-learning is motivated by the growing trend within the polytechnic environment, where digital learning systems have become increasingly widespread, particularly as part of institutional efforts to enhance efficiency. The expected outcome of this research is the development of an early-warning mechanism capable of identifying elevated cognitive load and anxiety in students while they interact with e-learning platforms. Such a mechanism is intended to prompt students to engage in brief, positive, or relaxing activities to regulate their mental state. By enabling students to overcome these cognitive and emotional challenges, it is anticipated that their overall learning performance and academic achievement will improve.

II. RELATED WORK

A substantial body of research has examined cognitive load and anxiety using various methodological approaches. Early studies highlight a strong relationship between anxiety and cognitive functioning, demonstrating that anxiety disrupts cognitive control and reduces working memory capacity [2–4]. Large-scale population studies have similarly reported that higher levels of anxiety are associated with declines in cognitive performance.

In the educational context, several investigations have shown that students with elevated anxiety levels tend to exhibit lower academic achievement and greater difficulty maintaining sustained attention during learning activities [6][8]. These findings underscore the importance of developing early detection methods for cognitive load and anxiety, particularly among university students, who are increasingly exposed to complex learning environments and heightened academic demands.

Eye-tracking–based approaches have increasingly been explored to address these challenges. Michalska et al. (2017) found that children with anxiety symptoms exhibit distinct gaze patterns during fear-learning tasks, suggesting altered attentional mechanisms in anxious individuals [12]. Similarly, Schulze et al. (2013) demonstrated that individuals with social anxiety disorder display characteristic gaze-perception patterns, particularly in response to socially relevant stimuli [11]. Complementary findings from meta-analyses by Bar-Haim et al. (2007) and Armstrong and Olatunji (2012) further confirm that attentional bias in anxiety can be objectively quantified through gaze behavior [15–16]. These studies collectively establish eye tracking as a promising tool for identifying cognitive-emotional processes associated with anxiety.

Beyond clinical psychology, the application of eye-tracking has expanded into domains such as social interaction and communication. Tiselius and Sneed (2020) employed eye-tracking to examine gaze behavior in dialogue interpreting, demonstrating its usefulness for understanding real-time cognitive processing in multilingual communication. Similarly, Hausfeld et al. (2021) identified strategic gaze patterns within interactive economic experiments, highlighting how visual attention shapes decision-making in social contexts. These findings illustrate the methodological flexibility of eye-tracking and its applicability across a wide range of research fields [10][14].

In the context of higher education applications, Agustianto et al. (2022) developed an eye-gaze–based model for detecting anxiety among engineering students [17]. Their findings further reinforce the notion that Eye Gaze Modeling using the Tobii Eye Tracker holds considerable potential as a mental-health detection tool. This potential becomes even more significant when combined with Big Data analytical approaches, which can enhance the reliability, robustness, and validity of the detection system.

Building upon these prior findings, the present study integrates eye-gaze modeling with Big Data analytics to develop a more accurate, adaptive, and practical system for detecting cognitive load and anxiety in higher education settings. This integration is expected to enhance the precision of mental-state assessment and support the development of technology-driven interventions that can be readily implemented within university learning environments.

III. METODOLOGY

The research methodology is illustrated in Figure 1, which outlines the sequential stages designed to ensure that the study proceeds systematically and yields outcomes of high quality. Each stage in the framework serves to validate the research process, strengthen the reliability of the findings, and support the development of a final product that is ready to be integrated into the TEFA JTI Innovation program at the State Polytechnic of Jember.

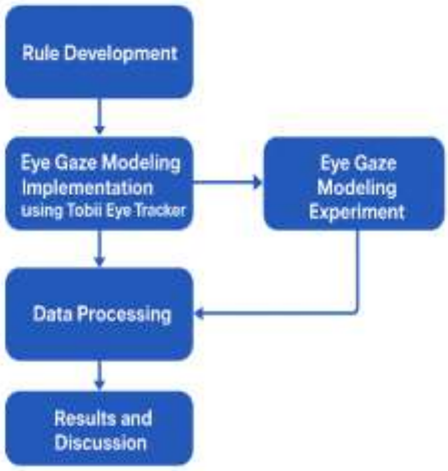

Figure 1. Research Methodology Framework

A. Rule Development

Rule development serves as a critical stage in this study, as the research relies on eye-tracking sensors to capture users' eye movements during their interaction with the application. These gaze behaviors are subsequently interpreted and classified into specific UX categories. Establishing well-defined rules is therefore essential to ensure that the system can accurately distinguish user experiences based on measurable eye-movement parameters.

B. Implementation of Eye Gaze Modeling Using the Tobii Eye Tracker and Big Data for Cognitive Load and Anxiety Detection

The rules established in the previous stage are subsequently implemented within the Eye Gaze Modeling framework using the Tobii Eye Tracker integrated with Big Data analytics for cognitive load assessment and anxiety detection. These rules operate in conjunction with the classification results produced by the Naïve Bayes model, enabling the system to generate tailored recommendations for students based on their detected anxiety levels. This integration ensures that the application not only identifies cognitive and emotional states but also provides adaptive support aligned with each user's mental-health profile.

C. Testing the Eye Gaze Modeling System Using the Tobii Eye Tracker and Big Data for Anxiety (Mental Health) Detection

In this stage, the Eye Gaze Modeling system undergoes experimental testing to verify the accuracy and reliability of the sensor readings. The objective of this phase is to ensure that the eye-tracking measurements align with expected behavioral patterns and that the system operates as intended. A licensed psychologist is involved to validate the detection results by comparing the system's classification outcomes with expert psychological assessments. This validation process is essential for confirming the system's capability to accurately identify anxiety levels and for establishing the credibility of the proposed detection model.

D. Data Processing

The data obtained from the experimental phase are subsequently processed to evaluate the performance of the Naïve Bayes Classification algorithm implemented on the user gaze-log data. This stage involves cleaning, structuring, and transforming the raw eye-tracking outputs into analyzable features, followed by the application of the classification model to determine its accuracy in detecting anxiety levels. The results of this data processing phase provide essential insights into the effectiveness of the Naïve Bayes approach and its suitability for modeling cognitive load and anxiety based on eye-movement behavior.

E. Results and Discussion

The results obtained from data processing in the form of the instrument's accuracy were subsequently compared with manual calculations to assess the accuracy based on ground truth measurements. The outcomes of this stage are discussed in relation to the factors that influence the accuracy values obtained.

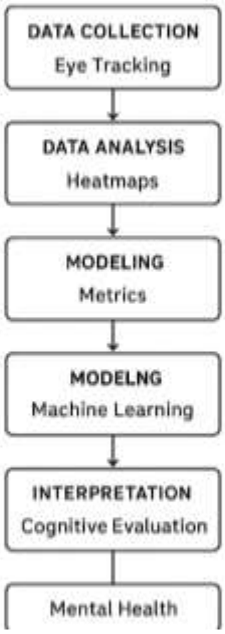

Figure 2. Block Diagram of the System

IV. RESULT AND DISCUSSION

This study aims to evaluate students' eye movement patterns as indicators of cognitive state and mental health, particularly to distinguish between individuals with anxiety (anxious group) and those without anxiety (control group) through the analysis of eye movement parameters. The results of the modeling based on summarized metrics—including mean fixation duration, median fixation duration, fixation dispersion, saccade rate, and percentage of time in saccade—demonstrate consistent and distinguishable pattern differences between the two groups.

The resulting dataset consists of two respondent groups, each comprising 30 participants. The observed parameters include fixation duration, saccade rate per second, fixation dispersion, and percentage of time in saccade. These parameters are used to characterize visual scanning patterns and attentional stability as indicators for reading behavior and for distinguishing cognitive conditions between the anxious and control groups [18].

A. *Interpretation of Fixation Duration*

The interpretation of fixation duration is observed from the mean and median values, as shown in Figure 3, while the comparison between the anxious and control groups is presented in Table 1. The shorter fixation duration observed in the anxious group indicates a higher level of attentional shifting and difficulty in maintaining focus on a stimulus. This finding is consistent with the hypervigilance model, which suggests that anxious individuals tend to engage in rapid environmental scanning to detect potential threats [15]. Such a pattern reflects attentional instability, which, in the context of learning activities, may interfere with deep information processing. Other meta-analytic studies have also reported that individuals with anxiety exhibit increased attentional bias toward emotionally salient stimuli, thereby reducing their short-term attentional capacity [16].

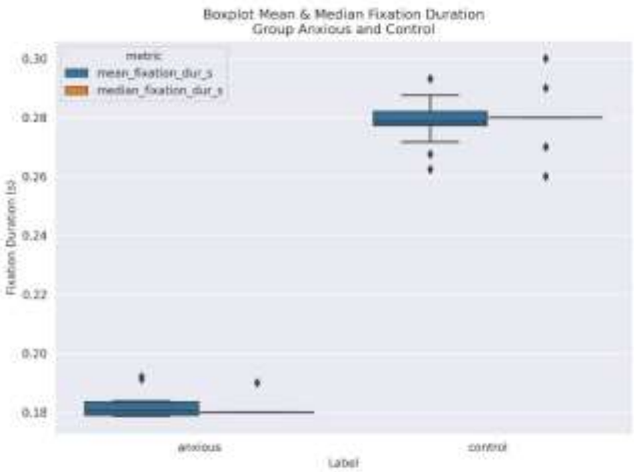

Figure 3. Mean and Median Fixation Duration

The eye movement analysis conducted on $N = 30$participants (two groups: anxious vs. control, with expert-based labeling) reveals systematic differences in fixation duration. The anxious group exhibits a mean fixation duration of approximately 0.18 s, whereas the control group shows a higher mean of approximately 0.28–0.29 s. An independent Welch's t-test yields $t = -39.84$, $p < 1 \times 10^{-16}$for mean fixation duration, and $t = -4.03$, $p = 0.0016$for median fixation duration. The boxplot visualization in Figure 3 further supports these statistical findings, showing that the distribution of mean and median fixation durations in the anxious group is concentrated well below that of the control group, with minimal overlap.

Table 1. Comparison Between Anxious and Control Groups Based on Fixation Duration

Group	Mean Fixation	Median Fixation	Pattern
Anxious	~0.18 s	~0.17–0.18 s	Short, rapid attentional shifting
Control	~0.28–0.29 s	~0.28 s	Longer, more stable processing

The analysis of mean and median fixation durations demonstrates a highly pronounced difference between the anxious and control groups. This difference is consistent with the hypervigilance model, which posits that individuals with anxiety tend to exhibit faster and less stable visual scanning behavior [15–16]. In contrast, the longer fixation durations observed in the control group indicate greater attentional stability and deeper visual processing [18]. Therefore, mean and median fixation durations can serve as valid biomarkers for distinguishing anxiety conditions in the context of cognitive evaluation among students.

The cognitive and emotional interpretation of the shorter fixation durations observed in the anxious group can be associated with reduced visual attentional stability and increased attentional shifting or hypervigilance. Two complementary cognitive mechanisms may explain this pattern:

1. **Attentional bias toward threat / hypervigilance.**
   Individuals with anxiety tend to scan their environment more rapidly to detect potential threats, resulting in shorter fixation durations due to more frequent gaze shifts [15–16].
2. **Increased cognitive load and reduced executive control.**
   Anxiety consumes cognitive resources (e.g., working memory), thereby reducing the processing capacity available to sustain deep visual attention on a single target. As a compensatory mechanism, the visual system shifts toward a more superficial scanning pattern [2–3].

In contrast, the longer fixation durations observed in the control group indicate more stable attentional patterns and more efficient visual processing [18]. These findings are consistent with previous studies that identify fixation-related metrics as sensitive biomarkers for assessing cognitive load and affective states [17–18].

B. Fixation Dispersion

Visual inspection of fixation dispersion across participants reveals distinct group-level patterns. Participants in the anxious group generally exhibit moderately to highly dispersed fixation patterns, predominantly within the upper-mid pixel range, indicating broader spatial scanning behavior. In contrast, the control group shows greater between-subject variability: some individuals display highly concentrated fixation distributions, while others exhibit very high dispersion values, appearing as notable outliers. These descriptive findings motivate further inferential statistical testing of group differences as well as correlation analyses with fixation duration and anxiety-related measures.

The higher fixation dispersion observed in the anxious group is consistent with theoretical accounts of anxiety-related hypervigilance and fragmented attentional deployment [15–16]. When combined with the earlier finding of shorter fixation durations in anxious participants, the dispersion profile suggests a visual scanning strategy that prioritizes rapid environmental monitoring at the expense of sustained visual processing. This pattern has clear implications for learning tasks that require focused and stable attention. Future work should further quantify the predictive utility of fixation dispersion for early anxiety detection, ideally through the integration of multimodal biomarkers (e.g., pupilometry and heart rate variability) and cross-validated classification pipelines [17,19].

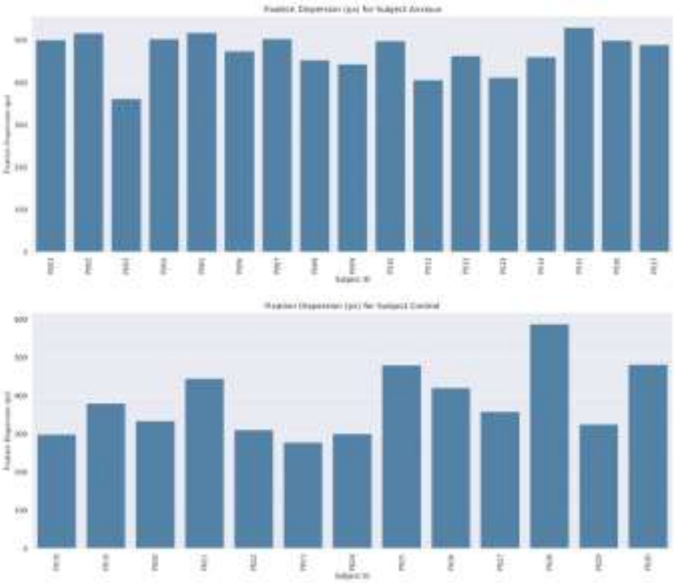

Figure 4. Fixation Dispersion Data for the Anxious and Control Groups

In contrast, the control group (participants P018–P030) exhibits greater variability, with some individuals showing narrow and stable focus, while others appear as outliers with more dispersed patterns. The higher dispersion observed in the anxious group can be interpreted as a compensatory response to perceived uncertainty, which drives the visual system to broaden its observational coverage [12]. This pattern also reflects a higher cognitive load, under which the cognitive system is less able to sustain focused attention over extended periods [2]. A comparison between the anxious and control groups across several dispersion aspects is presented in Table 2, while a comparison of the corresponding group-level metrics is provided in Table 3.

Table 2. Comparison Between Anxious and Control Groups Based on Dispersion Level

Aspect	Anxious Group	Control Group
Dispersion Level	Consistently high (450–520 px)	Variable, lower on average
Between-Participant Variability	Low (homogeneous)	High (heterogeneous)
Outliers	Nearly absent	Present (e.g., P028 ≈ 590 px)
Interpretation	Broad scanning pattern, reduced focus	Mixture of narrow focus and exploratory scanning

Table 3. Comparison of Metrics Between Anxious and Control Groups

Metric	Anxious Group	Control Group
Fixation Duration	Short	Long
Fixation Dispersion	High	Lower / more variable

The analysis of fixation dispersion reveals a pronounced difference between the anxious and control groups. As shown in Table 2, anxious participants exhibit consistently high dispersion across all subjects (approximately 450–520 px), indicating a broad and unfocused visual scanning pattern. In contrast, the control group demonstrates greater variability, with some participants showing low to moderate dispersion, while others exhibit higher values. This pattern is consistent with the hypervigilance theory, which suggests that individuals with anxiety tend to engage in distributed visual scanning in response to uncertainty or perceived threat [15–16]. The elevated dispersion observed in the anxious group may also reflect increased cognitive load and attentional instability, as described by Cognitive Load Theory [20]. Overall, fixation dispersion is confirmed as an important metric for differentiating the stability of visual attention between anxious and non-anxious individuals, as summarized in Table 3.

C. Saccade Activity as an Indicator of Cognitive Dynamics

Although the difference in saccade rate between the two groups is not always statistically significant, the direction of the effect remains consistent with theories suggesting that anxiety increases ocular motor activity due to more intensive visual scanning. Elevated saccade activity indicates an imbalance between exploratory phases and information-processing phases, as demonstrated in several neuroscience and clinical psychology studies [21]. In the context of university students, this pattern may reflect difficulties in maintaining focus during reading tasks or when engaging with digital learning materials.

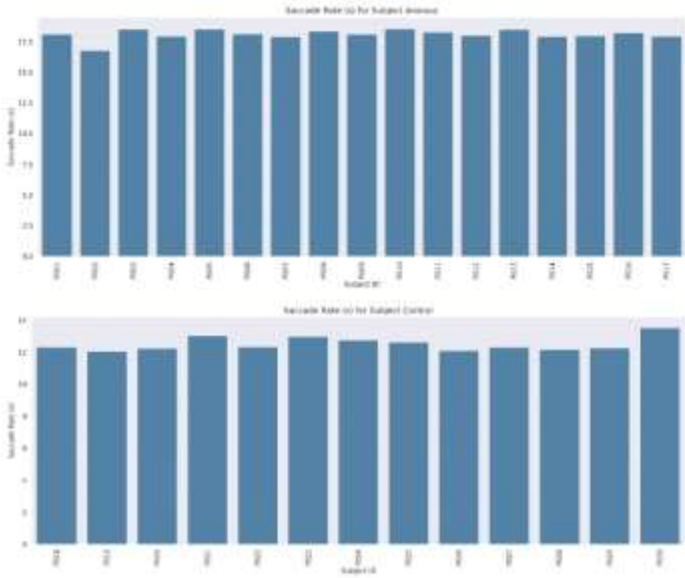

Figure 5. Saccade Rate for the Anxious and Control Groups

The most prominent difference between the two groups is observed in the saccade rate. The anxious group exhibits an average saccade rate of approximately 18 saccades per second, which is substantially higher than that of the control group, ranging from 12 to 13.5 saccades per second. The consistently elevated values in the anxious group indicate hyperactive and repetitive visual responses, which are associated with continuous efforts to rapidly scan the surrounding environment.

These findings support the theory of **attentional bias toward threat**, which posits that individuals with anxiety tend to continuously monitor their environment to anticipate potential risks, even in the absence of explicit threatening stimuli [15]. In contrast, the control group exhibits a lower saccade rate, indicating a greater ability to sustain stable attention without being driven toward excessive visual exploration.

Table 4. Comparison Between Anxious and Control Groups Based on Saccade Rate

Aspect	Anxious Group	Control Group
Saccade Rate Range	17.0–18.7	12.0–13.6
Higher Mean Value	✔ Yes	✖ No
Between-Subject Variability	Low	Moderate
Psychological Interpretation	Hypervigilance, heightened visual scanning	Focused attention, calm processing
Association with Anxiety	Strong (consistent with literature)	Not significant

D. Presentage of time saccade

The data indicate that the anxious group exhibits an average percentage of time in saccade of approximately 18%, which is substantially higher than that of the control group, which ranges from 12% to 13%. This difference is highly consistent across subjects and indicates that individuals with anxiety engage more frequently in rapid gaze shifts. This pattern aligns with the hypervigilance theory, whereby anxiety drives increased visual scanning behavior to monitor potential threats [15]. Furthermore, the elevated saccade activity observed in the anxious group reflects instability in attentional control and increased cognitive load, which hinder deep visual information processing [2,16]. In contrast, the control group shows a lower and more stable distribution of saccades, indicating more directed visual focus and more efficient information processing. Therefore, the percentage of time in saccade can be regarded as a strong biomarker for distinguishing anxiety conditions among students in the context of eye-tracking–based cognitive evaluation.

Table 5. Comparison of Percentage of Time in Saccade Between Anxious and Control Groups

Aspect	Anxious Group	Control Group
Mean Saccade Time (%)	~18%	~12–13%
Between-Participant Variability	Very low	Low
Pattern Consistency	Highly consistent at a high level	Consistently low
Primary Interpretation	Rapid and unstable eye movements	Better focus and sustained attention

Based on Table 5, the percentage of time spent in the saccade state differs significantly between the anxious and control groups. The anxious group exhibits relatively homogeneous values in the range of 17–18.6%, whereas the control group remains within a lower range of 12–13.6%.

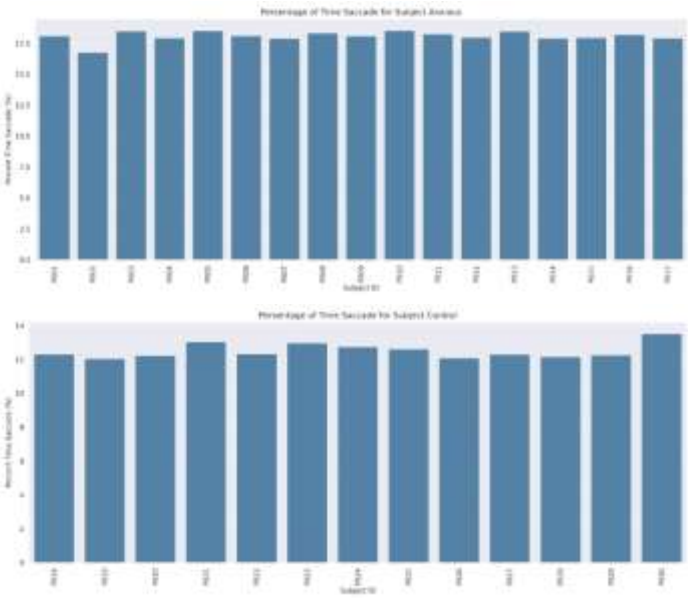

Figure 6. Percentage of Time in Saccade

A higher proportion of time spent in the saccade state indicates more frequent shifts in visual focus, which is a common characteristic of individuals with higher levels of anxiety [22]. This also implies that the anxious group spends less time in the fixation phase, which is critical for visual encoding processes. This finding is consistent with the previously discussed pattern of shorter fixation durations observed in the anxious group.

E. Overall Comparison of Parameters Between the Anxious and Control Groups

The results of the eye movement analysis reveal consistent and significant differences between the anxious and control groups across several primary metrics obtained from the Tobii eye-tracking recordings. The most prominent difference is observed in fixation duration, where the anxious group exhibits a substantially shorter mean fixation duration (±0.18 s) compared to the control group (±0.29 s). This pattern indicates that students with higher anxiety levels experience greater difficulty in maintaining visual focus on specific stimuli, leading to faster and more frequent gaze shifts. These findings are consistent with the studies of Bar-Haim et al. (2007) and Armstrong & Olatunji (2012), which report that individuals with anxiety demonstrate attentional hypervigilance and increased attentional shifting toward environmental stimuli [15–16].

For the other metrics, such as saccade rate and fixation dispersion, although the differences do not always reach statistical significance, psychologically meaningful trends are still observed. The anxious group exhibits a tendency toward higher saccade rates, indicating more intensive and less stable visual search processes. This pattern suggests the presence of internal conflict in attentional regulation, wherein the cognitive system attempts to compensate for anxiety-driven impulses by increasing visual scanning activity to anticipate potential threats or uncertainty.

The differences observed in fixation and saccade patterns further reinforce the potential of eye movement metrics as early biomarkers of anxiety, particularly in the context of digital learning environments. When students interact with e-learning materials, cognitive load and anxiety levels are directly reflected in the stability of their visual attention. Studies by Michalska et al. (2017) and Schulze et al. (2013) also demonstrate that gaze patterns serve as strong indicators of emotional states, including anxiety, and can be detected even within relatively short observation durations [11–12].

Accordingly, an early anxiety detection model based on Tobii Eye Tracking integrated with the Naïve Bayes algorithm becomes highly relevant. Naïve Bayes leverages the distribution of features such as fixation duration, saccade rate, and gaze dispersion to efficiently classify students into anxious or control categories. This probabilistic model is well suited for real-time applications due to its relatively low computational complexity and its robustness to noise, which is inherently present in eye movement data.

The implementation of this system has significant potential as an early warning mechanism within e-learning environments. When students exhibit gaze patterns that indicate increased cognitive load or heightened anxiety, the system can provide adaptive recommendations such as learning breaks, relaxation exercises, or content adjustment. This approach aligns with the principles of affective computing and adaptive learning systems, which leverage students' emotional and cognitive states as the basis for personalized learning.

Overall, the findings of this study confirm that the integration of Eye Gaze Modeling, Tobii Eye Tracking, and Naïve Bayes Classification constitutes an effective approach for the early detection of anxiety among students. This approach not only contributes to the growing body of literature on anxiety biomarkers, but also opens up significant opportunities for practical applications in the development of more intelligent, empathetic, and responsive e-learning systems that are adaptive to users' mental states.

CONCLUSIONS

This study provides empirical evidence that eye-movement metrics can effectively differentiate students with anxiety from those in a non-anxious control group. Four key conclusions can be drawn:

1. **Shorter Fixation Durations in Anxious Participants**
   The anxious group demonstrated significantly shorter fixation durations (~0.18 s) compared to the control group (~0.28 s), indicating reduced ability to maintain stable visual attention.
2. **Greater Fixation Dispersion**
   The anxious group showed wider spatial distribution of fixations (≈480–520 px), reflecting less focused visual exploration and higher attentional variability. In contrast, the control group exhibited more centralized fixation patterns.
3. **Higher Percentage of Saccadic Time**
   Anxious individuals spent more time in saccadic movements (17–18.6%), suggesting increased scanning behavior consistent with *hypervigilance*.
4. **Increased Saccade Rate**
   The anxious group produced more frequent saccades (≈18 s^{-1}) compared to the control group (≈12–13.5 s^{-1}), indicating heightened internal arousal and instability of visual attention.

Collectively, these results reflect core anxiety-related attentional characteristics: **excessive vigilance, impaired attentional control, and increased cognitive effort**. The findings reinforce the viability of eye movement metrics as objective biomarkers for detecting anxiety in student populations.

The study contributes to the growing body of research on eye-tracking for mental-health assessment and underscores its potential for integration into early-screening systems, adaptive learning platforms, and cognitive monitoring tools. Future work should incorporate larger and more diverse samples, multimodal physiological signals, and machine-learning classification models to enhance diagnostic accuracy and generalizability.

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