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Catching the Wanderer: Temporal and Visual Analysis of Mind Wandering in Digital Learning

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Abstract. As a rapidly rising trend, digital learning redefines educational boundaries with its accessibility and adaptability. However, this transformation reduced availability of non-verbal cues like facial expressions and body language. While platforms like Teams allow for the possibility of viewing student expressions when cameras are on, this is often not the case. The limited visual interaction hinders teachers' ability to gauge student engagement and detect mind wandering of students —a significant barrier to effective learning. Current research on mind wandering focuses on attention control and visual processing, but it fails to capture the dynamic nature of mind wandering in digital contexts and the potential of eye movement correlations for real-time interventions. This study addresses this challenge by examining the temporal patterns and dynamics of eye movement features over 26 lessons in a controlled online setting. Our findings reveal a periodic attention drift every 15 minutes, yet the focus notably intensifies during the final 15 minutes of class. Through significance and correlation matrix analyses, we identify three critical gaze metrics from 34 indicators—fixation dispersion, fixation quality, and blink frequency—as precise markers for distinguishing between focused and wandering minds. This research contributes to transdisciplinary engineering by integrating insights from educational technology and cognitive psychology to reveal the underlying attention mechanism behind mind wandering through a reduced set of reliable gaze metrics. It also provides a scientific basis for course designers to enhance learning engagement, such as timely interactive prompts or attention-capturing cues, fostering a healthier and sustainable digital learning environment.

Keywords. Mind wandering, Eye-tracking, Digital learning, Attention mechanism, Transdisciplinary engineering

Introduction

In the modern education landscape, digital technology plays a crucial role, fostering the need for digital literacy as part of essential 21st-century skills [1]. This shift towards online learning platforms offers benefits like flexibility and personalized learning, but also challenges student engagement due to mind wandering—a significant issue in digital environments [2]. Mind wandering, which can consume up to 50% of our waking time, notably affects learning efficiency [3]. The virtual nature of digital learning reduces instructors' ability to use non-verbal cues for engagement and to monitor student

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attention, posing the challenges on learners to stay focused [4]. This highlights the critical need for effective strategies to comprehend and alleviate mind wandering to enhance learning outcomes in digital education.

To address the challenge, previous literature on mind wandering has transitioned from initial behavioral observations to sophisticated analyses incorporating physiological metrics. Early investigations, such as an exploration of digital game-based learning's impact on preschoolers, laid the groundwork by highlighting the dual nature of mind wandering's effects on learning outcomes [1]. Subsequent studies introduced physiological measures—ranging from skin conductance and temperature [5] to advanced eye-tracking and electroencephalogram technologies [3, 6, 7]—to objectively distinguish mind wandering states. This shift towards physiological markers has not only validated the feasibility of detecting mind wandering but also underscored the complexity of its underlying mechanisms and its impact on learning efficiency [8, 9]. For example, Faber et al. [10] verified that mind-wandering is closely related to fewer but longer fixations. Robison et al. [11] and Unsworth et al. [12] examined the relationship between mind-wandering, individual differences and memory performance decline when dealing with complex visual information.

Nevertheless, despite significant progress has been made in mind wandering research, existing studies primarily focus on factors affecting attention control and gaze behaviors in lab settings. They lack insights into the dynamic nature of mind wandering in actual digital learning environments where information density and visual targets continuously change. In dynamic scenarios, fixation duration alone may not be a reliable indicator of mind wandering, as it is highly influenced by the visual target. Therefore, there is a critical need to explore how mind wandering manifests in dynamic digital learning contexts. Meanwhile, the correlation analysis among eye movement features remains unexplored, yet it holds promise for identifying more reliable and representative eye movement characteristics that can differentiate between mind wandering and focused attention in scenarios with varying information densities and dynamic changes.

Therefore, this study aims to address these gaps by conducting a comprehensive analysis of the temporal distribution of mind wandering and eye movement analyses with a focus on significance and correlational dynamics. The patterns of attentional lapses and essential eye movement indicators are pinpointed. The analyses not only inform digital course designs based on attention patterns but also guide the initial gaze feature selection in future research aimed at developing mind-wandering detection models. Hence, this research provides empirical evidence on the temporal and visual dynamics of student mind wandering, laying the groundwork for developing more effective interventions to foster engagement and optimize learning outcomes in online environments.

1. Methodology

1.1. Participants

Twenty-six students from the Hong Kong Polytechnic University were recruited for this experiment. All of them have normal or corrected-to-normal vision and hearing. The ages of the 26 participants had a mean of 24.65 with a standard deviation of 2.72. They are required to take one lesson of the online course in a lab with their eye movements being recorded. Besides, to reduce the effects of supervision, they will stay in the lab alone. Informed consent was obtained from all participants prior to scanning. The study protocol was approved in accordance with the institutional ethics guidelines.

1.2. Apparatus

In this study, eye movement metrics were collected using a desktop setup featuring a 27-inch monitor (1920x1080 pixels) and a Gazepoint 3 eye tracker. The eye tracker, which records various eye movement metrics at 60 Hz, was operated from a separate laptop connected via HDMI and is designed to target the subject's eyes from below, positioned ideally 30 cm beneath eye level and 65 cm away.

1.3. Experimental procedures

The experiment procedures can be divided into the preparation phase and formal experiment phase. During the preparation period, participants arrived at the laboratory half an hour before the start of the class, familiarized themselves with the experimental procedure, signed informed consent form, and calibrated the eye tracker.

In the structured 50-minute formal experiment, participants engage in an online lecture derived from a required course within their major field of study, employing digital learning modalities. As shown in the experiment procedure in Figure 1, participants were required to maintain focused engagement with the online lecture, consistently self-monitoring their attentional focus by pressing 'Y' for self-detected mind wandering [13]. Meanwhile, participants face periodic questioning through an automated prompt, requiring them to evaluate their attention state and respond within 5 seconds: press 'N' for focused or 'Y' for wandering. The experimental design incorporates the collection of both eye movement data and participant responses, enabling a comprehensive analysis of attentional dynamics within a digital learning environment.

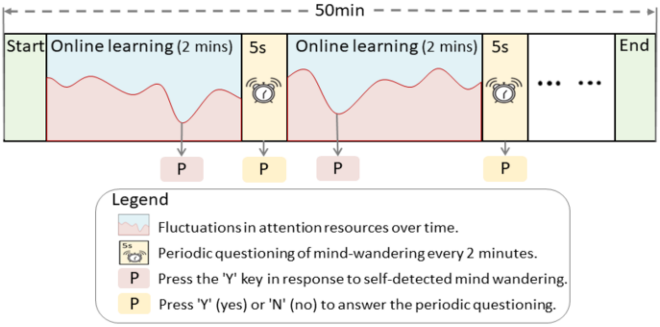

Figure 1. Experiment procedures.

1.4. Gaze data collection and feature extraction

In our study, we define a sample as the gaze data collected within the two-minute interval prior to each participant's self-detected mind wandering and periodic questioning of mind wandering. Thirty-four eye movement features are extracted from the 2-minute gaze data, as shown in the Table 1. The 34 features are classified into four categories: fixation, saccade, scanpath, and blink and pupil, to understand visual attention and cognitive processing.

As shown in Table 1, in the analysis of fixation characteristics, basic metrics like fixation count, duration, and dispersion provide insight into the frequency and focus of visual attention, indicating how often and for how long viewers engage with specific points [14, 15]. Advanced metrics, including the fixation-saccade ratio and the number of fixation clusters, further study the dynamics between gaze stability and movement, as well as the spatial organization of attention across the visual field. Additionally, fixation frequency and fixation quality (or gaze stability [12]) offer a detailed look at the attentiveness and steadiness of the gaze, enriching our understanding of cognitive processing strategies during visual interaction [16]. Saccade metrics, including count, amplitude, and velocity, examine the rapid movements between fixations, indicative of information-seeking behavior and cognitive transitions. Blink and pupil metrics reveal cognitive and emotional states by tracking changes in blink rate and pupil size. To address individual differences, we use baseline normalization, comparing stimulus-induced pupil diameters to initial minute baselines to define task-evoked pupillary responses [17]. Scanpath features, capturing the trajectory and duration of gaze across visual scenes, shed light on the strategies of visual exploration and information processing [18]. Together, these features provide a multidimensional view of eye movement behavior, essential for understanding visual attention dynamics in cognitive tasks.

Table 1. Eye-tracking features collected by feature extraction.

Feature groups	Features	Descriptions	Total	Mean	Max	Std.
Fixation	Fixation count	The number of fixations within a time window of 2 minutes preceding the participants' responses (2-minute period).	√			
	Fixation duration	The duration of all fixations during the 2-minute period.	√	√	√	√
	Fixation dispersion	Root mean square of the distances from each fixation to the average fixation position during the 2-minute period.	√			
	Fixation-saccade ratio	The proportion of fixations to saccades observed during the 2-minute period.	√			
	Number of fixation clusters	This measures the frequency of closely grouped fixation points, indicating the organization of visual attention during the 2-minute period.	√			
	Fixation frequency	The number of fixations per second during the 2-minute period.	√			
	Fixation quality	The standard deviation of positions in pixels of gaze points belonging to each fixation during the 2-minute period.		√	√	√
Saccade	Saccade count	The number of saccades during the 2-minute period.	√			
	Saccade amplitude	The mean, maximum and standard deviation of the distance in pixels between two subsequent fixations during the 2-minute period.		√	√	√

	Saccade velocity	The gaze point velocity belonging to the saccades during the 2-minute period.		√	√	√
	Saccade frequency	The velocity of the gaze points belonging to the saccades during the 2-minute period.	√			
Blink & Pupil	Blink frequency	The number of blinks in the previous 60 second period during 2-minute period.		√	√	√
	Left pupil diameter change	The mean, maximum and standard deviation of left pupil diameter during the 2-minute period compared to the baseline.		√	√	√
	Right pupil diameter change	The mean, maximum and standard deviation of right pupil diameter during the 2-minute period compared to the baseline.		√	√	√
Scanpath	Scanpath length	The length of distances between a sequence of fixations during the 2-minute period.	√	√	√	√
	Scanpath duration	Scanpath duration during the 2-minute period.	√			
Total			10	8	8	8 34

1.5. Data analysis

The data analysis encompasses temporal examination of mind wandering and comparative eye movement study between wandering and focused states. For temporal analysis, we statistically assess the distribution of mind wandering episodes across class time, mapping out the timeline of attention shifts. For the eye movement study, we emphasize analyzing data on an individual basis rather than by sample. By calculating mean values for each participant, we ensure our analysis reflects personal behavioral patterns, thus avoiding inflated statistical significance from large sample sizes and identifying authentic behavioral trends. Subsequently, we differentiate visual characteristics of wandering and focused states, primarily using the t-test for normally distributed data and the Mann-Whitney U test for non-normal distributions to discern between distracted and focused visual patterns. Further, we analyze a correlation matrix of features that significantly differ between focused and wandering attention states. Utilizing Python 3.10, the Pearson correlation coefficients are calculated to pinpoint features exhibiting strong and weak correlations. This approach offers a refined insight into the relationships among eye movement parameters, thereby uncovering key indicators of mind wandering.

2. Results and discussions

2.1. Temporal Analysis of Mind Wandering

The fluctuations in mind wandering events over a 50-minute online learning session were demonstrated in Figure 2. Each data point in Figure 2 represents the total number of mind wandering events observed among 26 participants within a 2-minute window starting from the corresponding timestamp. Two prominent peaks in mind wandering occur at approximately 960 seconds (15 minutes) and 1920 seconds (32 minutes), indicating critical periods of decreased attention. This suggests that learners are most susceptible to distraction during these timeframes, highlighting the need for targeted interventions to maintain engagement and optimize learning outcomes.

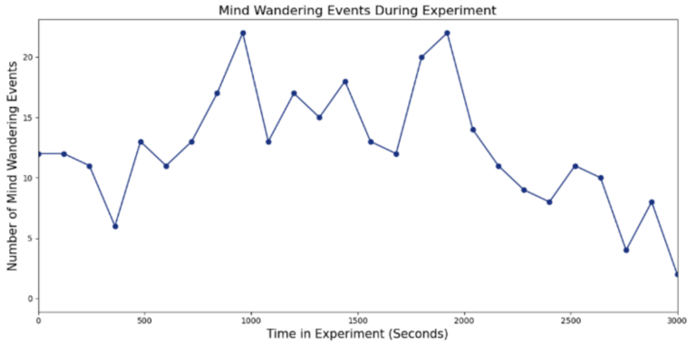

Figure 2. The occurrence of mind wandering events among 26 participants throughout a 50-minute online course.

Remarkably, sustained attention is observed during the initial and final 15-minute intervals (0-900s and 2100-3000s), contrary to expectations of declining attention towards the session's conclusion. One mechanistic explanation for this finding comes from the Hawthorne effect [19], where participants change their behavior because they know they are being observed, might also explain this increased attention. However, Worthy et al. [20] found that eye-tracking typically does not induce Hawthorne effects in most common psychological tasks, except in scenarios involving risky decisions with known outcome probabilities. Since this study does not involve such scenarios, it is likely that the Hawthorne effect does not significantly impact the increased attention in final 15-minute intervals. Potential explanations for this phenomenon include anticipation of upcoming content, the desire to consolidate learning, or the expectation of impending closure stimulating heightened engagement. Understanding these attentional nuances informs instructional strategies, emphasizing the importance of dynamic and engaging materials throughout the session, including transitional phases, to strategically manage attention and enhance learning efficacy.

2.2. Eye Movement Analysis of Mind Wandering vs. Focused Attention

2.2.1 Significance Analysis of Eye Movement Features

In this section, we meticulously analyze eye movement features during digital learning to uncover significant differences among 34 distinct characteristics. From this rigorous analysis, five features have emerged as statistically significant indicators. These findings are visually represented in Figure 3, providing a comprehensive overview of the observed distinctions.

As shown in Figure 3, blink frequencies (mean and maximum) were notably higher in mind wandering (p = 0.023 and p = 0.031, respectively), underscoring a potential correlation between increased blinking and diminished engagement or elevated cognitive load. This pattern suggests that in mind wandering, the brain might be seeking brief reprieves from the task at hand, indicative of a struggle to maintain continuous focus. This observation aligns with the research findings of Ranti et al. [21] and Krasich et al. [22], which observed that blink rate patterns can serve as a reliable indicator of viewer engagement. Therefore, the elevated blink frequencies observed in our study further support the notion that increased blinking is associated with reduced engagement. Consequently, the higher blink rate is a physiological marker of reduced attentiveness, revealing the need for strategies to minimize cognitive overload and sustain learner focus.

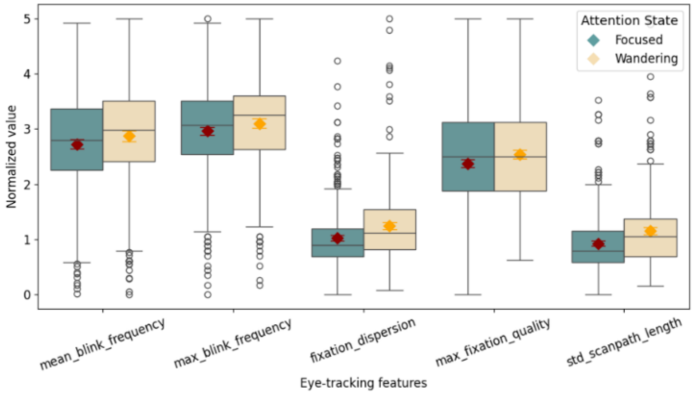

Figure 3. Eye-tracking features with significant differences between mind wandering and focused attention states. (Please note that the red and orange dots represent the mean values for the respective groups)

Fixation dispersion was also significantly greater during mind wandering ($p = 0.041$), indicating a broader spread of visual attention across the learning material. This dispersion indicates a lack of concentrated focus, potentially leading to shallower information processing [22]. Faber et al. [10] also noted that scattered visual attention in tasks demanding spatial allocation is linked to reduced concentration on content, which can impair comprehension and retention. This insight highlights the importance of designing digital learning materials that capture and maintain learner focus to ensure effective information processing.

Furthermore, the analysis revealed a significant difference between mind wandering and focused attention in maximum fixation quality ($p = 0.047$), pointing to less stable and more dispersed fixations when mind wandering. This instability in gaze suggests a lack of deep engagement with the material, as attention drifts rather than being anchored to relevant content. This supports the research conclusions of Grandchamp et al. [23], which found evidence of poorer fixation stability during mind-wandering compared to on-task periods. The resulting poorer gaze stability underscore the challenges in maintaining consistent cognitive engagement, emphasizing the need for interactive and captivating learning environments that can foster sustained attention and deeper learning.

Lastly, the standard deviation of scanpath length was higher during mind wandering ($p = 0.048$), reflecting more erratic and less directed visual paths. This finding aligns with research of Zhang et al. [24], which observed that scanpaths during unintentional mind wandering were more repetitive, characterized by higher refixation rates and more stereotypical fixation sequences. Such non-linear and inefficient exploration of the learning material likely hinders effective information processing and retention. These movement patterns reveal the cognitive disarray associated with mind wandering, pointing to the potential benefits of structured learning paths that guide attention effectively through the material.

These findings illustrate the complex interplay between eye movement patterns and cognitive states, offering profound insights into the mechanisms of attention during digital learning. By understanding the visual cues associated with mind wandering and focused attention, educators and technologists can tailor digital learning experiences to enhance cognitive engagement, facilitate deeper information processing, and improve learning outcomes.

2.2.2 Correlational Dynamics of Significant Eye Movement Features

In this section, the correlations between significant features will be analyzed, and the examination of their interactions can reveal more complex relational dynamics. When multiple features show high correlations, it may indicate that they provide similar information in measuring cognitive states. This helps in identifying which features are unique and which may be redundant, thus streamlining models and measurement methods. Such integrated analysis aids in understanding how features jointly affect cognitive states, thereby enabling more accurate monitoring and more effective intervention measures.

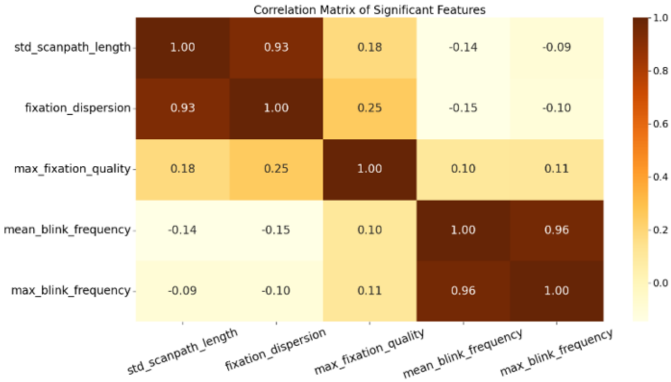

Figure 4. Correlation matrix of eye movement features with significant differences between mind wandering and focused attention states.

As shown in Figure 4, a notable insight from the correlation matrix is the strong positive correlation (0.93) between the standard deviation of scanpath length and fixation dispersion, highlighting that a less focused attention span exhibits both longer and more scattered scanpaths. This suggests that these two metrics could serve as reliable indicators of attentional shifts, particularly useful in identifying when users are likely to be mind-wandering. But these two metrics demonstrate weak negative correlations with fixation quality and blink frequency (e.g. correlation coefficient of -0.10 between fixation dispersion and max blink frequency), underscoring a minimal linkage between these specific eye movements and physiological blink responses. Another significant finding is the almost identical correlation (0.96) between mean and max blink frequencies, emphasizing their role as interchangeable markers of cognitive distraction. This uniformity points to a robust relationship between blink frequency and attentional state, irrespective of how it is measured, reinforcing its utility in attention-focused studies. Notably, max fixation quality's weak correlations (not exceeding 0.25) with the other four metrics underscore its distinctiveness in identifying attentional shifts, reinforcing its value in discerning focus from mind wandering.

Conclusively, max fixation quality stands out as a unique metric for distinguishing attentional states, owing to its distinct correlation pattern. These findings extend the research results of Unsworth et al. [12], which indicated that gaze stability is linked to superior attention control as a cognitive indicator. Conversely, fixation dispersion and total scanpath length are interchangeable due to their similar functionality in mapping attention landscapes. Similarly, mean and max blink frequency are effectively substitutable for each other. Hence, by focusing on blink frequency, fixation dispersion, and fixation quality, we can streamline the identification model and measurement methods for mind wandering, achieving a more concise and targeted approach to monitoring attentional states. This refined focus on key eye movement features simplifies the complexity of cognitive state detection, offering a clear pathway for designing interventions and adaptive systems that enhance engagement and learning efficiency.

3. Conclusion

This research investigates the dynamics of mind wandering in digital learning through temporal analysis and 34 eye-tracking feature analysis. Key findings outline not only the temporal patterns and specific timeframes prone to mind wandering, but also reveal distinct eye movement characteristics differentiating mind wandering from focused attention. The correlation matrix of significant features highlights that a reduced set of metrics—fixation dispersion, fixation quality, and blink frequency—can effectively distinguish between focused and wandering attention states. This research highlights the intricate relationship between visual attention mechanisms and cognitive states, providing a foundation for developing precise mind wandering detection methods. The results pave the way for future research focused on refining detection techniques and exploring varied interventions to establish a healthier and sustainable digital learning environment.

Future research should address several limitations such as potential bias from self-reported mind wandering. Expanding the dataset with diverse participants and contexts could enhance the generalizability of the findings. Incorporating additional indicators and physiological features like electroencephalogram could improve accuracy, leading to better detection techniques and interventions for sustainable digital learning.

Acknowledgment

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