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Pupil Dilation as an Indicator of Debugging Strategy in a Location-Based AR Learning Environment

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Abstract

Debugging process plays a crucial role in helping students pinpoint their specific learning weaknesses, allowing them to modify their strategies for enhanced academic performance. Notably, changes in pupil dilation serve as an indicator of arousal associated with confronting learning challenges. This physiological response acts as a "physiological footprint" that reflects cognitive engagement, facilitating internally focused cognitive processes such as insight generation and mind-wandering. In this study, we proposed that pupil dilation could be a valuable predictor of students' metacognitive awareness throughout the debugging process, specifically within an augmented reality (AR) learning environment. The findings revealed significant differences in pupil dilation among students categorized by their varying levels of debugging, which represents a specific dimension of the Metacognitive Awareness Inventory.

Keywords

augmented reality, debugging strategy, pupil dilation

Introduction

Virtual learning environments, particularly AR–based platforms, encourage knowledge construction and innovation development by fostering creative thinking and enabling learners to explore and interact with concepts in real-time (Chiu et al., 2024). This aligns with multimedia learning theory, which suggests that well-structured AR applications can enhance learners' innovation capacities (Çeken & Taşkın, 2022). Beyond conceptual learning, AR could also play a crucial role in metacognition, which refers to "thinking about one's thinking"—a cognitive process where individuals monitor, regulate, and reflect on their learning strategies. Metacognition consists of two primary dimensions: metacognitive knowledge and metacognitive regulation. Metacognitive knowledge involves awareness of one's cognitive abilities, the complexity of tasks, and appropriate learning strategies, such as chunking information to aid memory (Flavell, 1979). Metacognitive regulation, on the other hand, involves actively monitoring and directing cognitive processes, such as recognizing an ineffective learning strategy and adjusting it accordingly (Nelson, 1990). Magno (2010) asserts that metacognitive engagement requires awareness of all cognitive processes, including declarative, procedural, and conditional knowledge, as well as executive functions like information management and strategic adjustment. For instance, when using AR for argument preparation in a debate, students monitor their comprehension, organize information, plan their argument, test different presentation strategies, and evaluate their reasoning. This dynamic interaction between cognition and metacognition reflects how higher-order thinking tasks encourage the strategic application of learning techniques. Building on the role of metacognition in AR-based learning, debugging strategies play a crucial role in identifying and correcting errors in both understanding and performance. The concept of debugging—is a process, where learners reassess and modify their understanding or strategy upon realizing a discrepancy between expected and actual outcomes (Schraw & Graham, 1997). Given novices lack of established schemas and relevant debugging experience (Van Gog et al., 2010), they must handle multiple types of information in their working memory while debugging. In the debugging process, students must explore various potential strategies, select the most effective approach, and implement it to move toward their goal. If students lack adequate support and rely on trial-and-error, which

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consumes considerable cognitive resources, they may face elevated extraneous cognitive load (Van Merrienboer & Sweller, 2005). Put differently, students with a higher level of expertise deal with fewer interacting elements (linked to the task's complexity) and consequently experience a reduced intrinsic cognitive load (Seufert, 2018). In many educational contexts, instructional content has largely emphasized two types of knowledge: declarative and procedural. Declarative knowledge refers to "know-what"—such as facts, concepts, and definitions—while procedural knowledge involves "know-how," encompassing skills like driving, swimming, or problem-solving (Anderson, 1982). Improving outcomes for both types of knowledge requires examining how students' learning behaviors connect to their metacognitive debugging strategies—the deliberate processes of identifying and addressing comprehension breakdowns (Chi et al., 1989). When engaging with declarative knowledge, these strategies often trigger error detection and activate working memory and conflict-monitoring systems (Metcalfe, 2009). In contrast, when applied to procedural knowledge, debugging supports error correction through rule-based reasoning and mental simulation (VanLehn, 1999). Given the cognitive demands associated with both the detection and correction of errors, it is feasible that these cognitive processes could be analyzed through pupil dilation (PD) measurements. Research indicates that pupil size scales with the attentional load (Robison & Brewer, 2022), workload (Kim & Yang, 2020; Yang & Kim, 2019), and even the value of information (Ariel & Castel, 2014). In addition, evidence suggests that the cognitive effort during encoding can be reliably indexed by the mean pupil size (Kahneman & Beatty, 1966; Mohanty et al., 2024). Notably, a larger pupil size during encoding is correlated with higher accuracy in recalling information (Papesh et al., 2012). Metacognitive monitoring, through physiological responses, reveals self-regulation patterns (Järvelä et al., 2019). PD changes indicate arousal levels linked to learning challenges (D'Mello et al., 2014) and serve as a "physiological footprint" of cognitive engagement (Pijeira-Díaz et al., 2018). Pupil size, influenced by locus coeruleus-norepinephrine (LC-NA) activity, reflects attention shifts (Bouret & Sara, 2005), while PD changes support internally focused thought like insight and mind-wandering (Franklin et al., 2013). Although many studies have explored the relationship between pupil size and memory, fewer have examined how pupil size relates to metacognitive debugging during learning in AR. Thus, in this study, PD has been utilized as an index of debugging strategy applied by a student based on different knowledge types within the learning contents.

Methodology

Experiment Set Up

This research used an innovative location-based AR learning platform (Guo & Kim, 2021; Yu et al., 2023). This dynamic system harnesses the power of the Dikablis Glass 3, an advanced eye-tracking device, in combination with the cutting-edge Microsoft HoloLens 2 (see Figure 1). Throughout the educational activities, this technology captures changes in PD, providing valuable insights into students' engagement as they immerse themselves in an interactive learning experience.

A total of twelve industrial engineering students engaged in this intriguing research study. The AR learning modules comprised two lectures (see Figure 2). Lecture 1 introduced core biomechanics principles, focusing on how forces interact with the human body. Lecture 2 emphasized calculating those forces and moments to help students analyze human motion scientifically (see Table 1).

To measure metacognitive awareness, students completed the Metacognitive Awareness Inventory (MAI) (Schraw & Dennison, 1994) at the start and end of the experiment, capturing changes in their self-regulation and reflective thinking.

The learning content in each module was categorized by knowledge type: declarative when defining concepts, and procedural when demonstrating step-by-step calculations. This classification helped students better understand and engage with the material.

Data Preparation

In our study, we focused on Lecture 2 because the Metacognitive Awareness Inventory (MAI) was given at the start of Lecture 1 and again at the end of Lecture 2. The score after Lecture 2 reflects students' updated metacognitive awareness after going through the full learning experience. Students were divided into high and low-debugging groups based on their MAI scores. A cutoff score of 92, representing the average, was established to differentiate between the two groups: those scoring above 92 were classified as high debuggers. In contrast, students with scores below 92 were classified as low debuggers.

Utilizing footage captured by the Dikablis Glass 3 scene view camera (see Figure 3), we accurately segmented the eye-tracking dataset into two distinct phases marked by the timestamps recorded through the HoloLens device. These phases were defined as the learning phase (L) and the solving phase (S). For each AR module presented, we identified specific timestamps to indicate when students were fully engaged in absorbing the lecture content (Learning phase), and when they shifted their focus to tackling questions (Solving phase) following the completion of each module.

This careful segmentation enables a deeper understanding of student engagement and strategies employed during the learning process. To better understand the dilation effect induced by various debugging strategies, we measure the pupils of the participants at the beginning of their learning—prior to any exposure to virtual stimuli (3 s). This initial measurement, known as the baseline (B), serves as a crucial reference point, capturing the natural state of their pupil size (P_i) and setting the stage for comparison as they engage with the AR environment. In addition, pupil area data was

Figure 1. Dikablis eye tracking with the HoloLens 2 device.

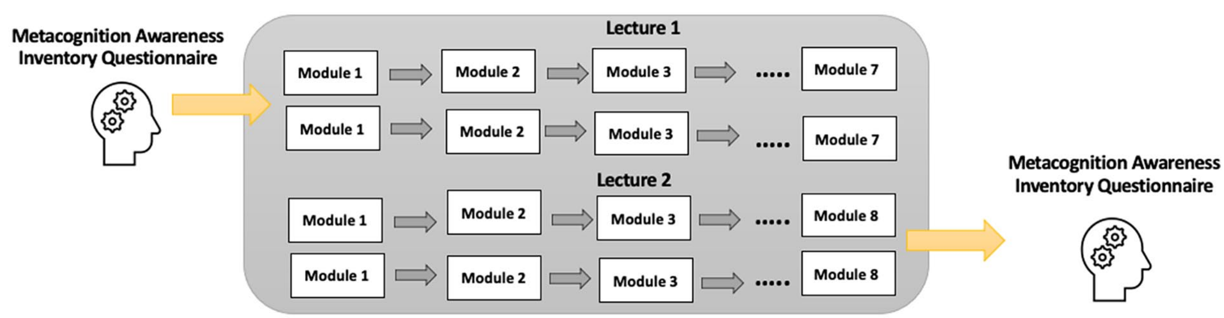

Figure 2. Overview of the experiment setup for lectures and modules in the AR environment.

normalized using Equation (1). $Pnorm_i$ is the normalized pupil data for P_i ($i = 1, \ldots, n$).

$$Pnorm_i = \frac{P_i - \min(P)}{\max(P) - \min(P)} \quad (1)$$

Then the left eye pupil area points during Learning in each module were subtracted from the averaged left eye pupil area during baseline (Kim et al., 2024). These values represent the normalized difference in pupil size when participants were engaged in different knowledge types of the learning content, compared to their initial pupil size.

Results

The differences in pupil size between the baseline phase (B) and the learning phase (L), is denoted as "B-L-1" to "B-L-8,". For example, "B-L-1" denotes the pupil area difference between AR module 1's phases B and L. The findings (see Table 2) indicated that the PD difference between baseline and learning in Lecture 2 was significantly associated with debugging strategy, showing a positive relationship in Module #4 and a negative relationship in Module #5.

Additionally, *t*-tests were employed to analyze the differences in PD between 2the High and Low-debugging groups across various knowledge types.

Comparison Between High and Low-Debugging Level in Module #4

In Module 4, the virtual instructor clarified the complex problem statement and provided essential supplementary information needed for problem-solving. During this process, students categorized as Low-debugging level showed noticeable PD, a

Table 1. Learning Content from Lectures 1 and 2—Biomechanics.

Module (lecture 1)	Learning content summary
1. What does biomechanics mean?	Definition of biomechanics
2. Example of force and moment	Mechanical effects of applied forces and moments on objects
3. Explanation of static equilibrium	How forces/moments lead to static equilibrium
4. Example for Static Equilibrium	Example problems for static equilibrium
5. Acting forces and moments on the body	Human avatar lifting object; forces/moments explained
6. Calculation of force and moment	Summing forces/moments for static equilibrium
7. Important table and figures	Use of the center of mass table and figure for calculations
Module (Lecture 2)	**Learning content summary**
1. Review of lecture 1	Overview of previously covered topics
2. 2D external single segment example	Posture-based biomechanical forces
3. Answer to the previous question	Solution explanation and reasoning
4. Multilink problem explanation	Forces/moments for multiple segments
5. Forces and Moments acting on the lower arm and corresponding calculations	Explaining forces acting on the lower arm and calculating associated forces and moments
6. Upper arm calculations	Computing upper arm forces/moments
7. Back and L5/S1 calculations	Force/moment calculations on the back
8. Testing student's knowledge	Asking students to solve a question

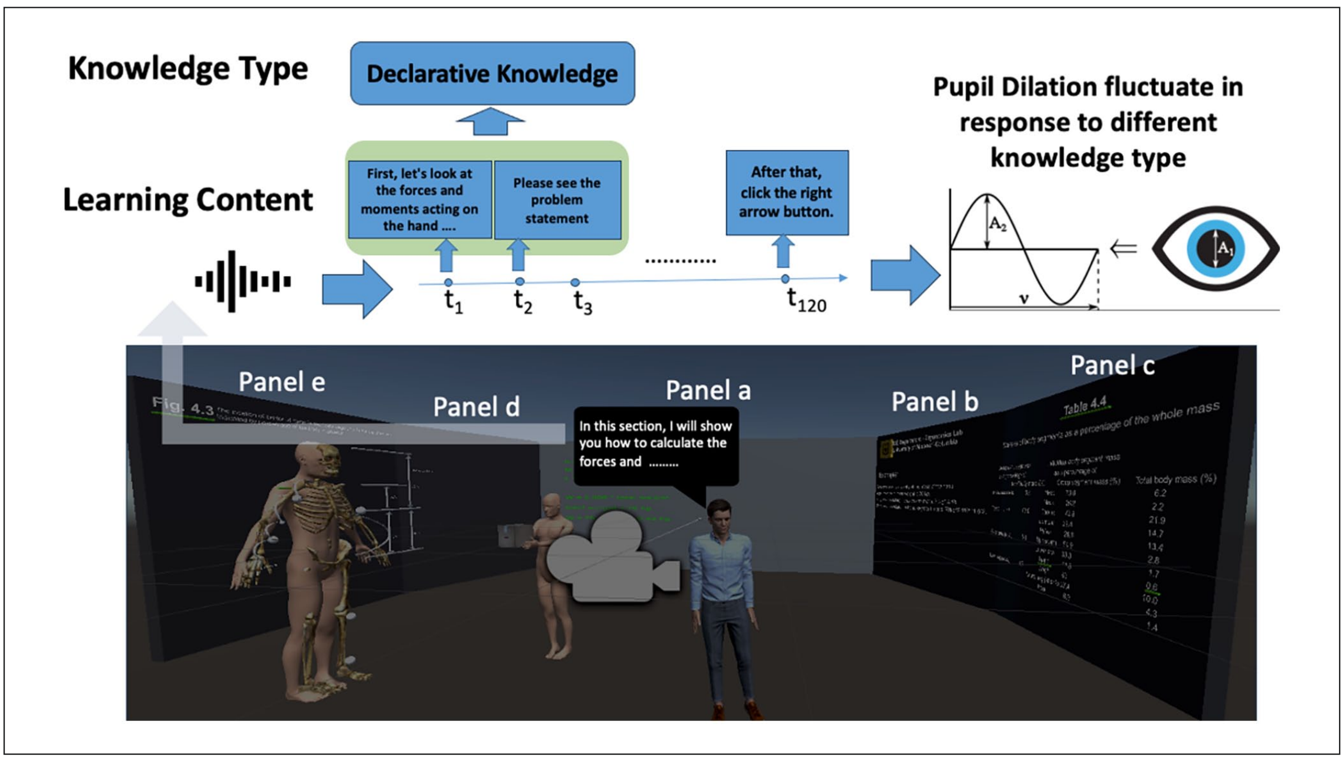

Figure 3. Overview of the data processing steps.

clear indicator of their heightened cognitive effort as they grappled with memorization and engaged deeply with the problem at hand (see Table 3). This physiological response could reflect their superior ability to allocate resources effectively and manage cognitive load with ease (Sweller, 1988).

Table 2. The Results of the Regression Model in Lecture 2.

Term	Estimate	Std error	*t* Ratio	Prob>|*t*|
Intercept	108.318	8.942	12.11	<**.0001****
B-L-2	−69.555	30.642	−2.27	0.063
B-L-4	−126.036	39.973	3.15	**0.019***
B-L-5	123.764	46.554	−2.66	**0.037***
B-L-6	−81.191	36.620	−2.22	0.068

$^{*}p < .05$, $^{**}p < .01$.

Table 3. The Comparison Between High and Low-debugging Level in Module #4.

Knowledge type	Level	*N*	Mean	Std error	*p*-value
Declarative 1	**L**	2,880	0.221	0.002	<**.0001****
	H	5,640	0.146	0.001	
Declarative 2	**L**	9,840	0.228	0.001	<**.0001****
	H	1,927	0.195	0.001	
Procedural 1	**L**	720	0.230	0.004	<**.0001****
	H	1,410	0.157	0.002	
Procedural 2	**L**	2,880	0.207	0.002	<**.0001****
	H	5,640	0.184	0.001	

Note. N denotes the quantity of data points captured by the eye tracking device at each time-window corresponding to different knowledge types. $^{*}p < .05$, $^{**}p < .01$.

Comparison Between High and Low-Debugging Level in Module #5

Module #5 includes complex calculations and dynamics of the forces and moments acting on various body segments. The results indicate significant PD patterns among students classified as high debugging. These learners showed a significant increase in PD when they engaged with certain pieces of declarative knowledge, clearly indicating their strong memory encoding and allocation of cognitive resources. This not only demonstrates their ability to retain information but also highlights their capacity to navigate their learning environment with intention and focus (see Table 4). Conversely, students who demonstrated a higher debugging level exhibited higher PD in procedural knowledge when required to engage in deep concentration. On the other hand, students with a low debugging level exhibited a different pattern; their PD peaks were predominantly associated with specific elements of procedural content, particularly in Procedural 6, 7, and 9. This observation could suggest that these students exert greater cognitive effort as they navigate the challenges presented during the learning process.

Discussion

This study uncovers the new role of pupil dilation (PD) as a potential window into the debugging strategies employed by students in augmented reality (AR) learning environments.

Table 4. The Comparison Between the High Debugging Score Group and the Low Debugging Score Group in Module #5.

Knowledge type	Level	*N*	Mean	Std error	*p*-value
Procedural 1	L	1,440	0.198	0.005	<**.0001****
	H	2,820	0.266	0.003	
Procedural 2	L	3,120	0.223	0.003	**.0204***
	H	6,110	0.232	0.002	
Procedural 3	L	4,560	0.220	0.002	<**.0001****
	H	8,930	0.249	0.002	
Procedural 4	L	1,440	0.221	0.005	<**.0001****
	H	2,820	0.261	0.003	
Procedural 5	L	4,560	0.227	0.002	<**.0001****
	H	8,930	0.256	0.002	
Procedural 6	**L**	5,040	0.254	0.002	<**.0001****
	H	9,870	0.234	0.001	
Procedural 7	**L**	1,440	0.298	0.005	<**.0001****
	H	2,820	0.231	0.003	
Procedural 8	L	9,120	0.220	0.002	<**.0001****
	H	1,786	0.269	0.001	
Procedural 9	**L**	5,760	0.226	0.002	**.0008****
	H	1,128	0.216	0.001	
Procedural 10	L	3,840	0.223	0.003	<**.0001****
	H	7,520	0.254	0.002	
Declarative 1	L	2,400	0.188	0.003	<**.0001****
	H	4,700	0.228	0.002	
Declarative 2	L	1,008	0.209	0.001	<**.0001****
	H	1,974	0.256	0.001	
Declarative 3	L	1,680	0.200	0.004	<**.0001****
	H	3,290	0.254	0.003	
Declarative 4	L	1,440	0.218	0.004	<**.0001****
	H	2,820	0.255	0.003	
Declarative 7	L	1,920	0.202	0.004	<**.0001****
	H	3,760	0.257	0.003	
Declarative 9	L	720	0.191	0.007	<**.0001****
	H	1,410	0.285	0.005	

$^{*}p < .05$, $^{**}p < .01$.

The responses of PD vary intriguingly based on the nature of the learning content. Among the eight modules explored in Lecture 2, Module #4 emerged as a standout, demonstrating a negative correlation between PD and debugging strategy. The learning contents related to declarative knowledge and procedural knowledge in this module primarily consist of text-based animated sentences. Interestingly, students with lower debugging skills showed higher PD, indicating significant challenges in understanding this text-only material. Their struggles were further compounded by difficulties in accessing additional information suggested by their virtual instructor. Encoding sensory input into mental representations requires efficient cognitive resource allocation (Baddeley, 2010; Chen et al., 2016). Those with weaker debugging skills often struggle to encode both declarative and procedural knowledge effectively. Consequently, pupil size may serve as an indicator, not just reflecting the intensity of cognitive effort but also shedding light on task engagement and the role of norepinephrine in regulating attention (Ariel & Castel, 2014; Robison & Brewer, 2022). In Module #5, students faced increased challenges as they were required to integrate a variety of information. This added complexity called for strategic thinking, resulting in significant differences in PD responses. High-debugging students showed more substantial PD when engaging with both declarative and procedural content, indicating greater focus, accurate memory recall, and a deeper level of engagement with the task. In contrast, students with lower debugging levels exhibited notable pupil dilation, particularly when wrestling with procedural content (6, 7, and 9). This reaction might suggest their mental struggle to filter through the overwhelming confusion in search of relevant information. An expansion of the pupils usually indicates a surge in cognitive effort and memory retention. For other modules—such as #1 ~ #3 and #6 ~ #8—PD seemed to play a minimal role, which can likely be traced back to the nature of the content. Module #1, for example, served as a refresher of Lecture 1, presenting familiar material that required less cognitive engagement. Similarly, Module #8 was predominantly focused on assessing students' existing knowledge rather than introducing new concepts, leaving little room for profound cognitive effort. Module #7, on the other hand, may have sparked more instinctive, automatic responses from learners. Moreover, it's essential to recognize that pupil dilation is not solely a response to cognitive load; it can also be caused by emotional arousal, levels of fatigue, and even the interplay of lighting in the environment.

Conclusion

This study sheds light on PD as a potential indicator of debugging strategies within the immersive realm of AR learning. The variation in PD responses is significant, influenced by the intricacies of the learning content, which reveals the nuanced interplay between attention and cognitive processing. By harnessing physiological markers like PD to explore the depths of metacognitive processes, we launch intriguing research toward designing adaptive educational systems. This innovative approach not only deepens our understanding of human experience but also drives remarkable advancements in the realm of educational technology.

Limitations

This study has several limitations that should be noted. The small sample size of only twelve participants is a major drawback, significantly affecting the generalizability of our findings. This issue is particularly important, given the complex nature of collecting physiological data in immersive environments. With such a limited dataset, we also run the risk of overfitting our models. However, this research marks a pioneering effort, offering vital pilot evidence for the feasibility of using physiological signals to monitor metacognitive processes in AR settings. Moving forward, future studies will employ advanced techniques, such as bootstrapping and cross-validation, to further enhance the reliability of our findings. We also recognize that individual differences in familiarity with AR technology, as well as varying levels of technical skill, might have influenced participants' responses. Consequently, our upcoming research will aim to incorporate these factors as covariates, thereby enriching the depth and precision of our analyses.

Declaration of Conflicting Interests

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