Changing the Awareness Level of Learning Space Dynamically Based on Learner Concentration

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Abstract. Advances in information technology have diversified learning environments. Some learners prefer settings that involve the presence of others, possibly due to psychological effects such as synchronization or competition. However, learners ' concentration can still be disrupted by external factors, even in socially shared environments. In this study, we developed a system that adjusts the brightness of the learning environment based on concentration levels estimated from blink frequency to promote focus. The system aims to sustain and enhance concentration by dynamically adapting the environment according to learners ' attention levels. Nonetheless, potential issues remain, including the possibility that its use may not directly improve learning outcomes and that prolonged use may be hindered by the weight and heat of the head-mounted display. Future work will address these factors to further evaluate the system ' s effectiveness.

Keywords: Awareness Control System · Concentration · Blink · Immersive Learning Environment

1 Introduction

Advancements in information technology have enabled the development of learning environments that allow individuals to study at their own pace, regardless of time and location [1]. Moreover, the coronavirus disease 2019 pandemic has promoted the acceptance of flexible learning environment choices [2]. Therefore, learners can choose flexible learning environments. In this context, some learners can concentrate in shared spaces such as libraries, whereas others find it difficult to maintain focus when studying alone in private spaces such as their rooms [3]. This may be a psychological effect of phenomena such as synchronization or competition triggered by the presence of others in a library, which in turn facilitates concentration on learning [4]. However, learning environments involving others may be either too visually quiet or overly distracting and therefore may not meet learners ' preferred conditions. These differences in preferred environmental conditions necessitate the development of methods that adjust external factors to promote concentration. Approaches that engage learners through audiovisual stimuli have been employed to support concentration [5]. However, some participants in these studies showed better learning outcomes under nonintervention conditions than when these methods were applied. This issue reflects a presentation problem and an analytical problem. First, the presentation of information to learners remains constant, disregarding differences in their concentration levels. Second, analysis is performed uniformly, without accounting for learners' preferences for learning environments. Therefore, learning environments should be dynamically adjusted based on concentration levels, and analyses should reflect individual preferences.

This study proposes a method to enhance learner concentration by dynamically adjusting the learning environment according to attention level. Specifically, we developed a system that promotes concentration by changing environmental brightness based on learner attention, which is estimated from blinking. We intend to compare the proposed system with a conventional condition (without brightness adjustment) to examine whether considering learners' environmental preferences influences learning outcomes and concentration.

2 Related Works

2.1 Learning in Socially Shared Environments

Many individuals prefer studying in environments involving other people, such as libraries and cafés. Such environments can positively affect learners. In pair learning, prior awareness of a partner enhances motivation [6]. In other words, the presence of other learners can increase motivation to study. Additionally, environments shared with others promote immersion and engagement [7] and can improve learning outcomes.

However, negative effects have also been reported. In group learning, a larger group size increases perceived cognitive load [8]. In other words, the presence of multiple people imposes an additional burden and impairs performance. Furthermore, being observed by third parties reduces attention and cognitive functioning [9]. Therefore, social gaze diverts cognitive resources and disrupts concentration.

Studying in the presence of others has both positive and negative effects. The negative effects stem from mismatches between the external learning environment and a learner's internal state. Adapting the external environment to a learner ' s state is inherently difficult, but adjusting visual input may selectively enhance the beneficial effects of studying in shared environments.

2.2 Estimation of Learner State

Concentration is a common indicator of learner state, and multiple estimation methods have been proposed. For example, blink frequency is inversely correlated with attention level [10], while increases in heart rate are associated with arousal, attention, and active learning [11].

Various methods exist to estimate learner state, each with its own value. However, the use of physiological indicators raises privacy concerns. Therefore, in this study, we employ blinking, which can be measured using the same device that delivers information.

2.3 Techniques for Promoting Learner Concentration

Concentration is essential for effective learning. However, sustaining or restoring concentration without external support is often difficult. Numerous studies have explored system-based interventions to enhance concentration. These interventions include introducing changes through information presentation and eliminating factors that hinder focus. For instance, blurring or grayscaling the peripheral visual field has been shown to enhance task performance [5]. Moreover, eye closure, which blocks visual input, has been associated with improved memory [12]. Thus, regulating peripheral visual information can benefit learning. However, in these studies, the performance of some learners decreased rather than improved after the interventions [5].

These studies present three main limitations. First, they address only unidirectional information change (increase or decrease). Brightness adjustment, which enables bidirectional modulation, offers a more versatile approach. Second, they apply static changes without considering learner states, highlighting the need for dynamic adaptation. Third, they overlook individual preferences in learning environments, underscoring the importance of detailed analyses that account for such preferences.

2.4 Research Question

Studying in environments with other people offers positive and negative effects. Adjusting a learner ' s peripheral visual field according to their state has considerable value, as it may selectively enhance the beneficial aspects of shared environments. Accordingly, this study aims to promote learner concentration by adapting the peripheral visual field based on the learner ' s state. Specifically, the research question is : How does the proposed system affect concentration? In addition, we intend to investigate the relationship between learners' usual preferences for learning environments and their concentration levels under the proposed system.

3 The Proposed System

The proposed system uses the Meta Quest Pro head-mounted display (HMD). Blink frequency is captured using the Meta Quest Pro's face-tracking feature for gaze measurement. The system is developed in Unity 2022.3.23f1 and runs entirely within the Meta Quest Pro application.

3.1 System Overview

The system is illustrated in Figure 1. The background of the learning environment is a spherical panoramic image of an empty library. E-learning video content is displayed on a frontal plane. A red object changes color depending on the condition (with or without brightness adjustment), and a gray object is displayed when the eyes are closed. These objects are hidden while the e-learning video content is playing. The system also enables operations such as video playback and condition changes via the Meta Quest Pro controller.

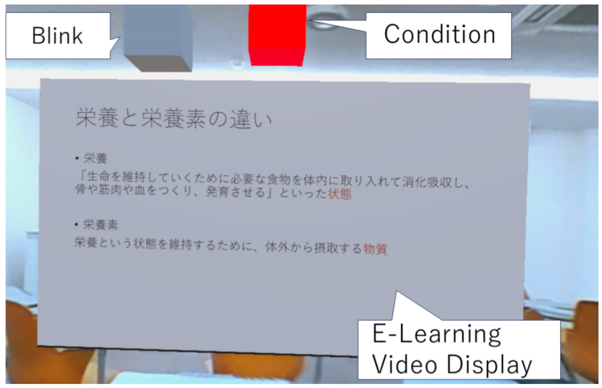

Fig. 1. Overview of the Proposed System

3.2 Measurement of Blinking and Drowsiness

Blinking is measured using the Meta Quest Pro's face-tracking feature. Specifically, the face-tracking application programming interface (API) provides facial expression data. Within this API, the degree of closure of both eyes is acquired as a real value between 0 and 1. If both eye values are 0.9 or higher, the eyes are considered closed. This assessment is performed every frame within the update function. A frame with open eyes following a frame with closed eyes is counted as a blink. Drowsiness is also measured using the same face-tracking feature. A frame with open eyes following more than 5 s of continuous eye closure indicates drowsiness.

3.3 Assessment of Concentration State

In this experiment, blink frequency is defined as the number of blinks per minute. Because blink frequency varies greatly among learners, a personalized is required for concentration assessment. In this study, exploratory concentration assessment and classification (concentrated versus nonconcentrated states) are conducted as follows.

Preliminary blink frequency measurement is performed under each condition during the first 5 min of learning. The 5 min average serves as the learner's concentration threshold. Concentration assessment is then conducted every minute using the 5 min preliminary data. The number of concentration and non-concentration classifications differs by e-learning video content: Video 1 yields 24 classifications, Video 2 yields 27, and Video 3 yields 25. If the learner's blink frequency is below the threshold and no drowsiness classifications occur, the learner is considered to be in a concentrated state; if the blink frequency is above the threshold or at least one drowsiness classification occurs, the learner is classified as nonconcentrated; If the blink frequency equals the threshold and the number of drowsiness classifications is zero, concentration is considered unchanged, and the classification from 1 min earlier is retained.

3.4 Modification of Learning Space Brightness

Brightness is changed according to the concentration state derived from blink frequency. Specifically, the brightness of the learning environment is adjusted when the state changes from nonconcentrated to concentrated or from concentrated to nonconcentrated.

Brightness adjustment occurs during the first 30 s of the 1 min interval between concentration assessments. The brightness of the cube object with the background attached is represented as a real value between 0 and 1. For darkening, the value (1 - elapsed time)/30 is calculated per frame over 30 s and applied as the brightness value. For brightening, the value (elapsed time)/30 is calculated per frame over 30 s and applied similarly. After the adjustment, the modified brightness is maintained for 30 s until the next concentration classification is received.

3.5 Experimental Approach

The experiment comprises three conditions. Condition A approximates conventional learning for participants here: brightness is consistently high, and the proposed system is not applied. Conditions B and C employ the proposed system. In condition B, brightness is reduced during concentrated states and increased during nonconcentrated states. In condition C, brightness is increased during concentrated states and reduced during nonconcentrated states. The experiment includes three learning sessions per condition, with each video session lasting 30 min. Evaluation is conducted based on test results, questionnaires, and blink data.

4 Conclusion

In this study, we developed a system that adjusts the brightness of the learning environment based on learners' concentration levels to promote focus. The system was designed to sustain and enhance concentration by dynamically adapting the environment according to learners ' attention states. However, several potential issues remain. First, learning with this system may not directly improve learning outcomes. Second, prolonged use may be hindered by the weight and heat generated by the HMD. Future work will address these limitations to further evaluate the system ' s effectiveness.

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