Development of Eye Blink Rate Level Classification System Utilizing Sitting Postural Behavior Data

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ABSTRACT The prevalence of dry eye syndrome (DES) has rapidly increased in recent years, negatively affecting the eye health of many office workers worldwide. Although low eye blink rate (EBR) has been pointed out as one of the main risk factors for DES, it is difficult for office workers to continuously monitor and increase their own involuntary blinking, especially when they are focused on the primary work task. Thus, as an effort to help office workers correct their low EBR, the current study developed a real-time EBR level classification system utilizing sitting postural behavior data. A total of twenty participants performed typical computer tasks on a sensor-embedded chair. The participants’ eye blinking and postural behavior data were collected to develop the EBR level classification system with a random forest algorithm. After evaluating the system performance, the relationships between EBR and postural behaviors were empirically examined to help understand how the system worked for EBR level classification. As a result, the developed system showed high classification performance overall; and compared with high EBR condition, low EBR condition was related to less overall postural variability and greater extent of forward bending posture. The real-time EBR level classification system is expected to contribute to preventing/relieving DES and thereby enhancing the eye health of office workers.

INDEX TERMS Dry eye syndrome (DES), eye blink rate (EBR), machine learning, postural behavior, sensor-embedded chair

I. INTRODUCTION

Many workers worldwide use computers, as one of the most common/necessary office tools, in performing their work tasks [1], [2] – it is estimated that more than 55% of jobs in the states involve computer use [3]. An increasing number of computer workers are performing their tasks using visual display terminals (VDTs), such as computer monitors and tablet devices. Prolonged computer work using VDTs requires continuously gazing at the screens, which could lead to dry eye syndrome (DES). DES is characterized by symptoms or complications of ocular discomfort/irritation, blurred vision, permanent corneal scarring, and visual loss [4]-[8]. The prevalence of DES has rapidly increased in recent years – tens of millions of people in the United States and up to one-third of the world’s population are suffering from DES, becoming a population health problem with significant worldwide economic costs [8]-[10]. Thus, it would be crucial to pay careful attention to the prevention of DES – prevention is cheaper, more practical and beneficial than treatment [11].

DES occurs when human tear film cannot sufficiently lubricate the ocular surface [12]-[14], the cause of which is often low eye blink rate (EBR) – note that although DES could occur or become worse also due to other reasons, such as diabetes, aging, and adenoviruses, the current study was focused on low EBR, which has been pointed out as a main risk factor for DES of office workers using VDTs. Thus, increasing the EBR is considered as a basic step to prevent/relieve DES by increasing the tear supply to the ocular
surface and reducing ocular surface exposure [7], [15]-[16]. Some previous studies reported that the normal range of EBR is around 4 to 6 times within 15 seconds, the EBR during VDT tasks tended to drop to around once or twice within 15 seconds [17]-[20]. Thus, office workers performing VDT tasks would need to be careful so as not to get their EBR lowered for the eye health. However, as blinking is an involuntary action, it is difficult for the workers to continuously monitor and correct their own EBR [21], especially when they are focused on their primary work tasks. Therefore, developing a real-time system that can monitor EBR and provide relevant feedback when necessary would be beneficial to preventing/relieving DES of office workers.

In developing such a real-time EBR monitoring system, some typical eye gaze tracking devices including contact lenses and head-mounted systems could be utilized. However, these devices are too invasive/intrusive to be employed in the office environments in that they have to be worn or attached to the body, possibly disturbing the primary task or inducing some physical discomfort or even fatigue [22]-[24]. As an effort to monitor EBR in a less or non-invasive/intrusive way, some previous studies have developed sensor-based glasses. For example, Kunze et al. [25] developed smart glasses equipped with three electrooculography (EOG) electrodes around the nose, which could monitor the workers’ EBR, and provide negative feedback for insufficient blinking. Dementyev and Holz [7] also developed similar glasses that could measure EBR using an infrared reflectance sensor and, upon infrequent blinks, induce blinks by emitting light flashes or small puffs of air near the eyes. But still, these sensor-based glasses are limited in that they always need to be worn or directly attached to the body/skin, which could be inconvenience to most workers, regardless of whether or not they originally wear ordinary glasses – thus, such body-worn/attached devices could be a less appropriate EBR monitoring approach for everyday use [23], [24].

Also, as an approach free from the invasiveness and inconvenience of the body-worn/attached devices, camera-based systems have been developed to allow EBR measurement without physical contacts [6], [26]. However, these camera-based approaches are also limited in that EBR measurement could be inaccurate due to pupil detection error when the workers move/rotate their eyes or head outside the specific range accurately detectable by the camera [23], [24] – for example, pupil being undetected by slight movements without blinks could be regarded as blinking. Also, the accuracy of the data obtained from camera-based systems could be adversely affected by noise from the eyelid, eye makeup, and/or illumination variations [27]. Additionally, the users may feel uncomfortable with their faces being monitored [28].

In order to address the above limitations, a new real-time EBR monitoring system would need to have the characteristics of being 1) non-invasive and convenient without requiring to be worn or directly attached to the body/skin for office workers’ daily use; 2) accurate in terms of pupil detection regardless of the eye and head movements/positions; and 3) less burdensome without directly monitoring individual face. Considering these design characteristics, conceptually, a new system would need to be able to indirectly measure EBR, rather than directly measuring oculomotor activities or detecting pupil.

One feasible approach for this new system would be to estimate EBR with factors indirectly related to eye blinking. Relatedly, some previous studies have found that 1) reduced EBR was associated with increased mental task demands [29]-[31]; and 2) increased mental workloads during a VDT task led to an increase in the extent of hunchback posture with the body leaning forward and a decrease in the postural variance [32]-[34]. These study findings implied the existence of indirect relationships between EBR and postural behaviors (sitting posture and postural variability), which hinted at the possibility of indirectly measuring EBR with postural behaviors. Therefore, as an effort to develop an indirect real-time EBR monitoring system leveraging such plausible indirect relationships, the current study aimed at addressing the following two research questions:

1) Is it possible to develop an accurate real-time EBR monitoring system utilizing the variables for postural behaviors?

2) If it is possible, what are the relationships between EBR and postural behaviors?

In order to address the first research question, the current study developed a classification system that can monitor the workers’ EBR level with their sitting postural behaviors in real time. As an indirect EBR measurement device, a sensor-embedded chair was chosen – it has been widely used to classify real-time sitting postures [35], [36]. Participants’ eye blink and postural sensor data were collected while they were performing typical computer tasks sitting on the sensor-embedded chair; and the collected data were used to develop an EBR level classification algorithm utilizing machine learning method. After the development and validation, the relationships between EBR and postural behaviors were empirically examined to address the second research question.

Note that the real-time EBR monitoring system developed in the current study was mainly targeted at sedentary office workers performing VDT tasks who need to carefully monitor/correct their own EBR to prevent/relieve DES. Thus, some other cases, such as non-sedentary (e.g., standing) workers or those doing non-VDT/work tasks (e.g., reading a book or daydreaming relaxedly/comfortably) would need to be considered out of the scope of this study.

II. METHOD

A. DEVELOPMENT AND VALIDATION OF EBR LEVEL CLASSIFICATION SYSTEM
The EBR level classification system developed in the current study consisted of a sensor-embedded chair and an EBR level classification algorithm.

1) DATA COLLECTION

A sensor-embedded chair was implemented as follows: six pressure sensors (Interlink, FSR406) and six distance sensors (Sharp, GP2Y0A41SK0F) were symmetrically/equidistantly embedded in the seat pan and seat back, respectively (Fig. 1). From the twelve sensors, the pressure (Pa) applied to the seat pan and the distance (cm) between the seat back and upper-body were collected as integer values, which were subsequently processed to derive the participants’ sitting postural behaviors (posture and postural variability). The sampling frequency was 8 Hz, and the collected sensor data was managed using Arduino microcontroller (Arduino Uno Rev3) and MATLAB (MathWorks Inc.). Besides the participants’ postural behaviors, their eye blinking data was collected using Dikablis head-mounted eye tracking system (Ergoneers). A blink was defined as eyelid closures (identified by the pupil not being detected in the eye-tracking system) lasting for more than 100 ms based on some previous study findings – human’s average blink duration is known to be about 100 ms, sometimes even up to 400 ms [37]-[41].

For data collection, a total of twenty participants (9 males and 11 females) participated and their demographic information (age, height, and weight) is summarized in Table 1. All participants were general office workers without expertise in this research topic and they had no eye diseases nor history of eye surgery. The sample size of 20 was determined in consideration of some previous relevant studies that successfully developed a real-time posture classification system with a sensor-embedded chair using datasets collected from about twenty participants [42]-[44] – relatedly, Cohen et al. [45] also stated that at least 15 participants were required for experimental methodologies. The specific dimensions of the testing chair and table were: 46 cm in width and 53 cm in height for the seat back of the chair; 48 cm in width and 44 cm in depth for the seat pan of the chair; and 190 cm in width and 100 cm in depth for the table – the heights of the chair and table were adjustable. This research complied with the tenets of the Declaration of Helsinki and was approved by the Institutional Review Board at Seoul National University. Informed consent was obtained from each participant.

| TABLE 1. Participant demographic information |
|---------------------------------------------|
| Mean | Standard deviation |
| Age (year) | 33.6 | 11.3 |
| Height (cm) | 167.4 | 9.2 |
| Weight (kg) | 64.5 | 12.7 |

During the data collection, the participants conducted three typical computer/VDT tasks – watching, transcribing, and problem-solving. For the watching task, the participants watched some video clips known as ‘oddly satisfying videos’ portraying repetitive events/actions that most viewers watched some video clips known as ‘oddly satisfying videos’ portraying repetitive events/actions that most viewers find satisfying [46]. In the transcribing task, the participants were
instructed to transcribe a given datasheet containing some words (written in their native language, Korean) and numbers onto a new blank datasheet in Microsoft Excel. As for the problem-solving task, the participants solved a series of questions that have been widely used for evaluating office workers’ basic/key job skills on the basis of national competency standards (NCS) – the task (provided in their native language, Korean) was performed by reading a passage and then answering a multiple-choice question in Microsoft Word. Each of the three tasks was conducted for 15 minutes and the order of the three tasks was randomized for each participant. While the participants were performing the three tasks for 45 minutes on the sensor-embedded chair with the head-mounted eye tracker (the head unit of the eye-tracking system), their sitting postural behavior and eye blinking data were collected (Fig. 2). All the participants could participate in the experiment without any discomfort/inconvenience in that they could 1) wear the eye tracker (only weighing 160 grams) like regular eye glasses, even together with all types of glasses; 2) freely adjust several adjustable parts (e.g., the nosepiece and elastic strap at the back of the head) to get the most comfortable fit; and 3) immediately cease the participation whenever feeling any discomfort/inconvenience during the tasks.

2) DATA PREPROCESSING

Prior to the development of EBR level classification algorithm, the collected eye blinking and postural behavior data were preprocessed to derive the variables required to address the first research question – they were EBR level, and posture and postural variability.

First, from the eye blinking data, EBR level was defined/classified as low EBR in the case of blinking three times or less within 15 seconds; otherwise, high EBR – this was based on the fact that blinking more than three times within 15 seconds has been recommended for preventing DES [25], [47]-[49]. Hence, as shown in (1), EBR level was obtained every second based on the eye blinking data of the preceding 15 seconds, with the first EBR level classification occurring 15 seconds after the onset of the experimental task.

\[
EBR\ level(t) = \text{Low, when blinking three times or less for time interval } [t-15, t]; \text{ else, High,}
\]

where \( t = 15, 16, \ldots, 2700 \) (45 min)  

A preinvestigation using this equation revealed that the percentage of low EBR (number of low EBR instances \( \times 100 \) \( / \) total (low EBR and high EBR) instances) computed with the entire datasets collected from the twenty participants was 43.6% - and thereby that of high EBR was 56.4%. Thus, it can be said that the datasets collected from the current study would not involve some performance issues concerning data imbalance.”

To synchronize with the EBR level, sitting posture and postural variability were also derived every second from the postural behavior data that had been collected from the 12 sensors with a sampling frequency of 8 Hz. As shown in (2), posture was defined as a set of 12 representative values from the 12 sensors – each representative value was computed as the mode (the actual value that was most frequently observed and less affected by irregular data) of 8 data points collected from each sensor every second.

\[
Posture(t) = \{P_i(t), D_i(t)\},
\]

where \( t = 15, 16, \ldots, 2700 \) (45 min)
Also, as shown in (3), postural variability was defined as a set of 12 variability values for the 12 sensors, each of which was computed as the standard deviation of 15 above-computed $P^i(t)$ or $D^i(t)$ obtained over the past 15 seconds for each sensor.

$$\text{Postural variability}(t) = \{S_p^i(t), S_p^i(t)\}$$  \hspace{1cm} (3)

where

$$S_p^i(t) = \text{standard deviation of} \quad P^i(t-14), P^i(t-13), \ldots, P^i(t-1), P^i(t)$$

$$S_p^i(t) = \text{standard deviation of} \quad D^i(t-14), D^i(t-13), \ldots, D^i(t-1), D^i(t)$$

$i = 1, 2, 3, 4, 5, 6$

$t = 15, 16, \ldots, 2700 \text{ (45 min)}$

As illustrated in Fig. 3, through the above data preprocessing based on a 15-second time window, a total of 2686 instances (one instance per second) were obtained throughout the 45-minute-long experiment for each participant. Each instance consisted of posture (with 12 representative values from the 12 sensors), postural variability (with 12 variability values for the 12 sensors), and EBR level.

Before developing EBR level classification algorithm with the datasets, min-max normalization (i.e., $x' = \frac{x - \text{min}(x)}{\text{max}(x) - \text{min}(x)}$) was conducted for each of $P^i(t)$, $D^i(t)$, $S_p^i(t)$, and $S_p^i(t)$ to standardize the two different units (Pa and cm) – thus, each of the four postural values ranged between 0 and 1.

3) ALGORITHM DEVELOPMENT AND VALIDATION

With the preprocessed data of the posture, postural variability and EBR level, the EBR level classification algorithm was developed utilizing a machine learning method as shown in Fig. 4.

In developing a classification algorithm, it is crucial to select an appropriate model based on the domain knowledge and expected relationship of the variables [50]. The current study considered the following two functional requirements: first, considering that some previous studies suggested complex/indirect relationships between EBR and postural behaviors [29]-[30], [32], [51], the model needed to be able to deal with such relationships. Second, although the current study focused on postural behaviors as input features, there could be other features which could help classify EBR level - thus the model needed to be able to perform well robustly only with some parts of the entire possible/candidate features. Accordingly, the current study adopted Random Forest (RF) as an EBR level classification algorithm, as RF is 1) applicable to different types of variables even with complex/high-order interaction effects [52] and 2) robust in the performance with a reduced/small number of input features [53]. Additionally, by randomly generating multiple decision trees, RF is known to have advantages of reduced noise effects from the input variables and less biased/overfitting results with lower generalization error than other classification algorithms [54]. Indeed, a preinvestigation revealed that in classifying EBR level, the RF algorithm performed better than some classification techniques such as linear discriminant analysis and decision tree.

An EBR level classification algorithm was developed with the datasets collected from the twenty participants. In addition, in an attempt to investigate whether an accurate EBR level classification algorithm could be developed with individual data collected from each participant, the algorithm development was also conducted for each of the twenty...
participants—thus, a total of twenty-one algorithms were developed. In developing each algorithm, 70% of the datasets were randomly chosen for training, and the other 30% were used for validation of the algorithm. As shown in Fig. 4, output feature (EBR level) had two classes—high (the negative class) and low (the positive class). Table 2 presents a confusion matrix for EBR level classification.

![Input features diagram](image1)

**FIGURE 4. EBR level classification algorithm**

After the development and validation of EBR level classification system, the relationship between EBR and posture, and that between EBR and postural variability were investigated to address the second research question. As mentioned in the introduction section, increased mental demands are associated with reduced EBR [29], [30]; and also associated with an increase in the extent of hunchback posture with the body leaning forward and a decrease in the postural variance [32]. From these study findings, it could be inferred that EBR is indirectly related to posture and postural variability with the mental workload as an intermediary factor. In an effort to empirically demonstrate the conjectural relationships, the current study examined how the overall variability of sitting posture and the extent of forward bending posture varied with the EBR level. As shown in (4), overall postural variability was calculated every second by taking the average of the above-normalized 12 variability values shown in (3) for the 12 sensors.

\[
\text{Overall postural variability}(t) = \text{mean of the normalized } S_1^6(t), S_2^6(t), \ldots, S_6^6(t) \tag{4}
\]

Also, in the current study, the extent of forward bending posture was represented as a combination of a forward weight shift, upper-body curvature, and lower-body curvature. Forward weight shift was calculated as the sum of the values from the two frontmost pressure sensors (PS3 and PS6 in Fig. 2) as shown in (5); upper-body curvature as the mean difference between the topmost distance sensors (DS1 and DS4 in Fig. 2) and middle distance sensors (DS2 and DS5 in Fig. 2) as shown in (6); and lower-body curvature as the mean difference between the bottommost distance sensors (DS3 and DS6 in Fig. 2) and middle distance sensors (DS2 and DS5 in Fig. 2) as shown in (7).

\[
\text{Forward weight shift}(t) = P^3(t) + P^6(t) \tag{5}
\]

\[
\text{Upper-body curvature}(t) = \frac{[D^1(t) - D^2(t)] + [D^4(t) - D^5(t)]}{2} \tag{6}
\]

\[
\text{Lower-body curvature}(t) = \frac{[D^3(t) - D^2(t)] + [D^6(t) - D^5(t)]}{2} \tag{7}
\]

where \(t = 15, 16, \ldots, 2700 \text{ (45 min)}\)

As some performance measures for each of the twenty-one classification algorithms, accuracy (i.e., the proportion of actual positives and negatives that are correctly identified), sensitivity (i.e., the proportion of actual positives that are correctly identified), and specificity (i.e., the proportion of actual negatives that are correctly identified) were calculated respectively.

In developing a real-time EBR monitoring system for DES prevention/alleviation, the system performance in terms of the classification speed, as well as accuracy needs to be considered. When it comes to developing RF classification algorithm, there is a trade-off between speed and accuracy—fewer decision trees could speed up the classification but, at the same time, compromise accuracy. Since one instance consisting of the posture, postural variability and EBR level was used every second to develop the algorithm (Fig. 3), the classification also needs to be done within one second. The optimal number of decision trees (i.e., maximal number of trees allowing classification within one second) with a desktop computer used was found to be twenty—the RF algorithm with twenty decision trees could conduct the classification within 0.95s, and was eventually adopted in this study. For other hyper parameters in the RF algorithm, the default values provided by scikit-learn’s library were used—for example, the quality of a split was measured by the Gini impurity and the maximum depth of the decision tree was set to be unlimited.

### B. EXPLORATION OF THE RELATIONSHIPS BETWEEN EBR AND POSTURAL BEHAVIORS

| Class         | Recognized            |
|---------------|-----------------------|
| Positive      | As positive (As low EBR) | As negative (As high EBR) |
| Positive (Low EBR) | true positive (\(t_p\)) | false negative (\(t'_n\)) |
| Negative (High EBR) | false positive (\(t_p\)) | true negative (\(t'_n\)) |

| Table 2. Confusion matrix for EBR level classification |

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the mean difference between high EBR and low EBR conditions in overall postural variability, forward weight shift, upper-body curvature, and lower-body curvature. All statistical tests were conducted at an alpha level of 0.05 using SPSS 25.0 (SPSS Inc., Chicago, USA).

III. RESULTS

A. PERFORMANCE OF EBR LEVEL CLASSIFICATION SYSTEM

Table 3 shows a confusion matrix for the EBR level classification system developed with the entire datasets from the twenty participants – accuracy, sensitivity, and specificity were 93.3%, 93.6%, and 93.1%, respectively.

| Class (EBR) | Recognized
|-------------|-------------------|
|             | As positive (As low EBR) | As negative (As high EBR) |
| Positive    | 6648               | 456               |
| Negative    | 624                | 8392              |

Table 3: Confusion matrix results for the EBR level classification system developed with the entire datasets from the twenty participants

Fig. 5 shows a box plot for the performance (accuracy, sensitivity, and specificity) of the twenty EBR level classification systems individually developed with the datasets from each of the twenty participants – the medians of accuracy, sensitivity, and specificity of the twenty classification systems were 93.6%, 93.2%, and 92.1%, respectively.

B. RELATIONSHIPS BETWEEN EBR AND POSTURAL BEHAVIORS

Fig. 6 and Fig. 7 show the mean and the standard deviation of each EBR level condition for overall postural variability and the extent of forward bending posture (forward weight shift, upper-body curvature, and lower-body curvature) – note that for all of these measures, the mean differences between high EBR and low EBR conditions were statistically significant with p values less than 0.001, as indicated by asterisks (***)

The t-test results for overall postural variability (Fig. 6) showed that low EBR condition had a smaller mean than high EBR condition.

As for the extent of forward bending posture (Fig. 7), compared to high EBR condition, low EBR condition showed consistently larger mean values across forward weight shift, upper-body curvature, and lower-body curvature.

IV. DISCUSSION

As an effort to contribute to preventing/relieving the DES of office workers, the current study aimed at addressing the two research questions: 1) Is it possible to develop an accurate real-time EBR monitoring system utilizing the variables for postural behaviors? and 2) If it is possible, what are the relationships between EBR and postural behaviors?

In order to address the first research question, the current study developed an accurate EBR level classification system consisting of a sensor-embedded chair and an EBR level classification algorithm. Posture and postural variability data were collected using the sensor-embedded chair from twenty participants while they performed three types of typical computer tasks. The participants’ EBR level data were collected from a head-mounted eye tracker. The collected data were first preprocessed, and then utilized to develop an EBR level classification system with RF algorithm and the performance of the developed classification was evaluated.
relationship between EBR and posture, and that between EBR and postural variability were empirically investigated by comparatively examining the overall variability of sitting posture and the extent of forward bending posture between high EBR and low EBR conditions.

Related to the first research question, the EBR level classification system developed with the entire datasets from the twenty participants showed high performance overall with accuracy, sensitivity, and specificity greater than 93%, which could be considered as having excellent classification performance [55]. The twenty EBR level classification systems individually developed with the datasets from each participant also showed high performance with the median values of accuracy, sensitivity, and specificity of the twenty classification systems at around 93%. The study results that the EBR level classification system performed well regardless of whether the data had been collected from each individual or from a group of individuals demonstrate the possibility of developing an accurate real-time EBR monitoring system with postural behavior data.

![Bar graph for overall postural variability with mean (standard deviation) values and asterisks indicating significance in the t-test](image1)

![Bar graph for the extent of forward bending posture with mean (standard deviation) values and asterisks indicating significance in the t-test](image2)
The study finding that the EBR level classification system could be successfully developed for each of the most participants as shown in Fig.5 suggests that the system could be individually customized for different individuals with different characteristics (e.g., gender and age). Moreover, if the more individuals become to utilize EBR level classification system, the larger database of human postural behavior and EBR level data would be established in the future. Then, such database could be utilized to develop a universal EBR level classification system that can be used by the majority of population without individual experimental sessions (data collection).

It may be worth noting that among the twenty classification systems individually developed for each participant, only three systems showed relatively low sensitivity values, such as 0%, 33.3%, and 54.1% (Fig. 5). These cases can be explained by the fact that the EBR level data from the corresponding participants mostly pertained to high EBR level (the negative class) – in other words, the frequency of their blinking was high enough to result in the lack of datasets for low EBR level (the positive class). Such lack of the positive class caused the scarcity of true positives (tp), and thus, even only a few false negatives (fn) led to a substantial reduction in the sensitivity. Despite the low sensitivity values in these three cases, however, the EBR level classification system developed in the current study still could be considered effective in that the system mainly targeted those who need to monitor/correct their low EBR to prevent/relieve DES.

Regarding the second research question, the current study revealed the following relationships between EBR and postural behaviors. As for the relationship between EBR and postural variability, compared with the high EBR condition, low EBR condition showed a 24.5% reduction in the mean overall postural variability (Fig. 6). This relationship, as aforementioned, may have been mediated by mental task demands – again, according to some previous studies, higher mental task demands were associated with lower EBR [29]-[32], [60]-[61], and also with smaller postural variability [32], [34]. For the relationship between EBR and posture, compared with the high EBR condition, low EBR condition was associated with significantly greater extent of forward bending posture (Fig. 7), with 26.6%, 6.5%, and 550% increases in the mean forward weight shift, upper-body curvature, and lower-body curvature, respectively. Mental task demands may have also mediated such relationship, in accordance with some previous study results that high mental task demands were associated with low EBR and also with greater tendency of upper-body leaning forward [32], [33].

The idea of mental task demands mediating the observed relationships seems partly understandable in the following aspects. First, the relationship between high mental task demands and low EBR could be explained by the facts that blinking serves as a kind of mental punctuation, associated with an increase in alpha waves which are characteristic of the brain in the most relaxed moments [56]-[59]. Especially during demanding mental tasks, blinking could be inhibited until enough information has been collected – for example, drivers blink less often when overtaking or driving on busy roads; and aviators blink half as often when manning the pilot's position as when sitting in the copilot's seat [56]. Second, the relationships between mental task demands and postural behaviors could be explained by some physiological phenomena occurring when humans are stressed due to demanding mental tasks. In these situations, the body releases certain hormones (e.g., adrenaline and cortisol) associated with the ‘fight or flight’ responses that are known to heighten the blood pressure and change the breathing patterns. Such responses may cause strain/tension on the shoulder and back/spine muscles, eventually resulting in slumped posture (with the head dropped forward and shoulders hunched up) and reduced postural flexibility/variability [29], [51], [60]-[61]. In order to empirically examine the above line of reasoning, future studies would need to directly measure the mental workloads during the experiment with some evaluation methods such as NASA-Task Load Index (NASA-TLX) and electroencephalography (EEG). Also, future research studies might empirically investigate the interrelationships among EBR, postural behaviors, and mental task demands, by directly controlling the degree of mental task demands, with the use of experimental tasks that can vary in the level of difficulty – for example, some executive function tasks or working memory maintenance/ manipulation tasks with different levels of difficulty, such as digit span forward/backward tasks with different lengths of number sequence could be employed as experimental tasks [62], [63].

It may be worth noting that the two postural behaviors significantly associated with low EBR condition are known to be high-risk sitting postures/behaviors that can lead to musculoskeletal disorders [64] – forward-bending posture can cause musculoskeletal diseases such as disc degeneration and back pain [65]; and reduced postural variability can give rise to musculoskeletal complaints/discomforts and spinal disorders [66], [67]. Thus, the current study results hint at the possibility that correcting low EBR may help contribute to preventing/relieving DES and also even musculoskeletal disorders, both of which are the most typical work-related diseases of office workers – this possibility would need to be investigated in future research efforts.

One noteworthy observation is that the RF algorithm performed well in classifying EBR level with the accuracy higher than 93%, whereas some classification techniques such as linear discriminant analysis and decision tree did not (their accuracy was found to be less than 60%). Such performance gap seems to be partly due to the following two distinctive characteristics of RF. One pertains to its capability of dealing with complex interactions/structures among a variety of variables [52], [68] – in this context, the performance gap implies a complex relationship between EBR and postural behaviors. The other is regarding its learnability of irregular patterns by building a random forest with multiple decision
trees of different attributes [54], [69]. In general, postural behaviors are affected by many different human factors, such as muscular strength, general health, age, or state of mind [70]. Such factors may have caused the individual differences across the participants, and perhaps the degradation in the classification performance. Nonetheless, RF might have classified EBR level well with the characteristic of being robust to the high inter-individual variability, widening the performance gap with other classification techniques. Admittedly, the idea of the postural behaviors having a complex relationship with EBR and high inter-individual variability is a conjecture and needs to be investigated in future research efforts.

Overall, the current study found that 1) it was possible to develop a real-time EBR monitoring system with overall high classification performance (accuracy, sensitivity, and specificity) utilizing the variables for posture and postural variability; and 2) compared with high EBR condition, low EBR condition was related to less overall postural variability and greater extent of forward bending posture. Consequently, the second research finding seems to be able to explain the first research finding (i.e., the possibility of developing an accurate real-time EBR monitoring system with postural behavior data). The developed real-time EBR monitoring system, with the advantages of being convenient/non-invasive, accurate and less burdensome (without monitoring face), is expected to contribute to preventing/relieving office worker's DES and thereby enhancing the eye health.

Some practical implications of the current research findings are provided here: first, the real-time EBR monitoring system developed in the current study could be utilized to develop a warning system that can provide a real-time EBR feedback to help office workers correct their low EBR. In developing such EBR warning system, future studies would need to consider that EBR monitoring and correction become the secondary tasks to office workers who perform the primary work task. Thus, the feedback display for the system would need to be designed to provide the feedback in an unobtrusive way so as not to disturb the primary task – in general, divided attention negatively affects the task performance [71]. One desirable design solution for EBR warning system could be an ambient display as it is effective for providing secondary task feedback in a variety of multitasking situations [36]; and also, reflex blinks are produced involuntarily in response to peripheral stimulation [21].

Second, considering that EBR significantly increased under the conditions of sleep deprivation and fatigue [56], [72]-[73], the real-time EBR monitoring system could be also utilized as a human fatigue/drowsiness detection system. For example, the real-time EBR monitoring system could be applied to driving contexts by attaching some distance and pressure sensors to automotive driver seats, which could contribute to identifying drivers' fatigue/drowsiness, and thereby, preventing/reducing car accidents – it is known that drivers showing physical signs of fatigue/drowsiness are two times more likely to have an accident [74]. In addition, taking into account that less EBR indicates an individual’s higher level of engagement/attention [75], [76], the real-time EBR monitoring system could be also applied to develop an attention monitoring/warning system, which can be useful for enhancing human performance of many different mental/cognitive tasks.

Third, the sensor-embedded chair developed in the current study could be utilized to indirectly determine/classify not only the EBR level but also other human behavioral characteristics that are directly or indirectly related to one's sitting posture. For example, considering that one's posture could express/reveal the affective states [77], future research may develop a real-time feeling/emotion monitoring system with postural behavior data. Also, based on the fact that one's posture could reflect the level of interest [78], future studies may investigate the possibility of developing a real-time interest level monitoring system using the sensor-embedded chair.

Finally, some limitations of the current study are acknowledged here, along with future research ideas: first, for a better understanding of the relationships between EBR and postural behaviors, future studies are needed to consider different postures besides the forward bending posture, and also, even a baseline condition of not performing a task nor sitting on a chair (i.e., the condition of doing nothing in the neutral position). Having such an understanding can help explain the black box in the RF algorithm, which could contribute to selecting more appropriate/relevant input features and algorithm, such as convolutional neural network and/or multi-modal deep learning [79] and therefore, enhancing the system performance in terms of the accuracy and/or speed. Second, given the possibility of developing an accurate real-time EBR monitoring system with postural behavior data, further efforts may be warranted to enhance the system performance by implementing a more accurate/elaborate posture sensing system. For example, 1) the total number of the embedded sensors could be increased; 2) pressure sensors could be embedded also in the seat back besides the seat pan; 3) some pressure and distance sensors could be also attached to different parts of the chair including the headrest/armrest; 4) different posture monitoring systems, such as optical motion capture systems [80] or inertial measurement unit (IMU)-based systems [81] could be employed in combination; or 5) multi-view input features could be integrated/utilized by using multi-view learning method, which considers learning with information from different views [82], [83]. Lastly, future studies would need to investigate if it is possible to indirectly monitor EBR also with different views [21].
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**TABLE 1. Participant demographic information**

|             | Mean | Standard deviation |
|-------------|------|--------------------|
| Age (year)  | 33.6 | 11.3               |
| Height (cm) | 167.4| 9.2                |
| Weight (kg) | 64.5 | 12.7               |
| Class              | Recognized             | As positive (As low EBR) | As negative (As high EBR) |
|--------------------|------------------------|--------------------------|---------------------------|
| Positive (Low EBR) | true positive (tp)     | false negative (fn)     |
| Negative (High EBR)| false positive (fp)    | true negative (tn)      |
**TABLE 3. Confusion matrix results for the EBR level classification system developed with the entire datasets from the twenty participants**

| Class          | Recognized               |
|----------------|--------------------------|
|                | As positive (As low EBR) | As negative (As high EBR) |
| Positive (Low EBR) | 6648                     | 456                        |
| Negative (High EBR) | 624                      | 8392                       |
Figures:

![Sensor-embedded chair](image)

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