공학석사 학위논문

Determining Eye Blink Rate Level Utilizing Sitting Postural Behavior Data

- 착좌 자세와 관련된 행동 정보를 통한 눈 깜박임 빈도의 위험성 판별 -

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ABSTRACT

Dry eye syndrome (DES) affects many white-collars workers worldwide. Though it is known that low eye blink rate (EBR) is associated with the risk of DES, it is difficult to improve EBR through self-correction. One way to increase EBR is to warn the worker of low EBR using an external system. Existing EBR measurement devices have limitations, such as physical discomfort or invasiveness, which hinder their acceptance. For a solution that overcomes these limitations, this study aimed to develop a classification system that differentiates the levels of EBR using posture and postural variability data obtained from chair-embedded distance and pressure sensors. Additionally, this study attempted to investigate the relationship between EBR, posture, and postural variability. Participants completed three seated computer tasks, in which eye blink and postural sensor data were collected. The EBR classification system was developed by using a machine learning method; the accuracy of the EBR classification system was 93% across the three task types and study participants. The low EBR level was found to be associated with smaller postural variability and a tendency for the worker to hold a forward-leaning sitting posture. The EBR classification system developed in this study is expected to contribute to the prevention of DES.

Keywords: machine learning, dry eye syndrome, eye blink rate, smart chair, posture

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1. INTRODUCTION

Office workers make up 17% of the Korean working population (STATISTICSKOREA, 2013), and these workers are increasingly facing tasks involving VDTs (Visual Display Terminal) such as smartphones and tablet PCs; additionally, these tasks often require workers to sit for long periods of time. Such tasks may be harmful to the workers in terms of eye blink rate, as past studies reported an EBR (eye blink rate) drop to around 1 to 2 times (in 15 seconds) during tasks where VDTs are used, compared to the normal range of EBR, which is around 4-6 times (Freudenthaler, Neuf, Kadner, & Schlote, 2003; Patel, Henderson, Bradley, Galloway, & Hunter, 1991; Schlote, Kadner, & Freudenthaler, 2004; Tsubota & Nakamori, 1993).

On a related note, patients with dry eye syndrome have increased 77% in the last 10 years (Health Insurance Review and Assessment Service, 2015). Reduced EBR has been widely suggested as one of the main risk factors that cause dry eye syndrome in office workers. Previous studies suggested that low EBR may cause dry eyes in part due to the tear film failing to provide enough lubrication on the surface of the eyeball (Tsubota, 1998; Tsubota et al., 1996).

Blinking is an involuntary action, and thus it may be difficult for the worker to self-monitor and correct his or her own blinking frequency (Volkmann, Riggs, & Moore, 1980). Therefore, designing a system that monitors the worker's EBR risk in real time and warns the workers of their habits during the workday could help reduce dry eye syndrome. To conceive this Real-Time EBR Risk Evaluation and Warning System, a device for EBR measurement must be selected. Tools widely used for EBR measurement include the eye tracker, contact lenses, electrooculogram, and video camera

(Duchowski, 2007; Poole & Ball, 2006), but these tools have been found to be inappropriate for use in the office environment for various reasons (Noureddin, 2003). For example, the eye tracker, contact lens, and electrooculogram are too intrusive as they have to be worn or attached to the body, and have cons such as disturbing work, creating discomfort, and inducing fatigue (Cheung & Peng, 2015; Jacob & Karn, 2003; Morimoto & Mimica, 2005). Recent eye tracker technology includes that of attaching sensors to glasses in order to measure EBR (Dementyev & Holz, 2017; Kai Kunze et al., 2015), but such technology is only useful when the worker wears glasses, thus causing a similar case of discomfort and fatigue. In addition, the abovementioned technology requires the charging of external batteries, often viewed as an inconvenience.

In order to refine the inconveniences of contact lenses and electrooculograms, past studies have carried out projects in developing eye tracking systems that do not require wearing extra gear. Tsubota et al. (1996) attached a video camera to the computer monitor and analyzed the blinking patters of patients with dry eye syndrome, measuring EBR without physical contact. Haro et al. (2000) similarly attached a black-and-white camera with an infrared light on the top of the computer monitor to measure eye movement. However, the quality of images from the video camera may be affected by slight movement, in addition to the fact that users may feel repulsion to his or her face being recorded during the use of the equipment.

Therefore, it may be difficult to utilize existing EBR measurement tools in addressing the dry eye syndrome problem affecting workers. With regards to the abovementioned limitations, the newly developed real-time EBR risk evaluation and warning system should be designed so that it causes minimum

interference with a worker's main task, is non-invasive and non-contact, minimizes inconvenience, has little chance of personal data leakage, and minimizes resistance during use. In order to conceptualize an EBR analysis technology with such design requirements, it was deemed necessary to design a system which can measure EBR indirectly by utilizing variables that are related to blinking.

Various research in the field of brain science, applied physiology, and ergonomics have reported variables which, when analyzed further, may be suitable in the indirect estimation of EBR. Studies in the field of brain science have reported that the cerebral basal ganglia and cerebellum are both involved in eyeball movement and movement control (Gabrieli, Brewer, & Poldrack, 1998; Iwanaga, Saito, Shimomura, Harada, & Katsuura, 2000; Luna & Sweeney, 1999). Also, applied physiology research studies, such as Iwanaga et al. (2000) and Skotte (2007), have shown reductions in EBR associated with increased mental task demands. Ergonomics studies such as Qiu et al. (2012) reported that an increase of mental workload during a VDT task decreased posture variance in workers, as well as inducing an increase in a hunchback posture with the body leaning closer to the monitor. Such research supports the possibility of intermediary relationships between EBR and posture, and EBR and postural variability. On a related note, Waersted et al. (1994) and Iwanaga et al. (2000) found evidence of an increase of muscle contraction and muscle tension as mental task demands increased; this suggests the possibility of detecting changes in EBRthrough posture or movement patterns.

The findings of the abovementioned research studies were utilized in first developing the main hypothesis of this study: that there is a relationship

between EBR risk level (High risk EBR and low risk EBR) and a worker's posture and movement-related variables; in addition, that this relationship could be modelled as an individual-specific EBR risk levelprediction system. As it is known that one must blink an average of more than 4 times in 15 seconds in order to prevent dry eye syndrome (K. Kunze et al., 2015; Uchino et al., 2008; Yaginuma, Yamada, & Nagai, 1990), this paper defined High Risk EBR as blinking 3 times or less in 15 seconds, and Low Risk EBR as blinking more than 3 times in 15 seconds. As posture and movement-related variables, sitting posture and postural variability were selected, as in Qiu et al. (2012). As previous studies emphasized the importance of the measurement tool having the characteristics of being non-invasive and not causing resistance in the user, the authors decided that sensors attached to certain objects within the working environment would be beneficial as measurement tools for the abovementioned variables; in specific, the chair. Thus, posture and postural variability were measured with the use of the sensor-embedded chair designed in Jeong et al. (2016), which is one of many studies that have used a sensor-embedded chair to classify postures in real-time (Jeong et al., 2016; Schrempf, Schossleitner, Minarik, Haller, & Gross, 2011; Shirehjini, Yassine, & Shirmohammadi, 2014; Tan, Slivovsky, & Pentland, 2001; Zheng & Morrell, 2010). Additionally, this study designed a new system, theoretically based on findings from previous works, to predict EBR risk level from the posture and movement-related variables; also, the study explored, through experiment, the relationship between EBR risk level and posture/postural variability.

The goals of this study were as follows:

- Develop an accurate, individually customized EBR risk level classification system utilizing the posture and postural variability

data from the sensor-embedded chair, with the use of machine learning methods, in order to design a real-time, EBR evaluation and alarm system in the future

- Experimentally explore the relationship between EBR and posture, and EBR and postural variability, which are the basis of this study

The following hypotheses will be examined in order to achieve the goals above.

- H1: It is possible to develop an individual-customized machine learning model (random forest algorithm) that accurately classifies the EBR risk level with the use of the posture and postural variability data from the sensor-embedded chair.
- H2: On average, a 15-second time interval with a high risk EBR exhibits a smaller level of postural variability than that with a low risk EBR.
- H3: On average, a 15-second time interval with a high risk EBR exhibits more pronounced forward bending in the sitting posture than that with a low risk EBR.H3: On average, a 15-second time interval with a high risk EBR exhibits more pronounced forward bending in the sitting posture than that with a low risk EBR.

This paper is organized as follows. The method section provides an overview of the development of the EBR Risk Level Classification System and process of its validation. In more detail, this section describes the sensor-embedded chair used in this study, along with the experimental process of

creating and preprocessing the data set used in the EBR Risk Level Classification System. Additionally, this section discusses the details of the development of the EBR Risk Level Classification System itself, in addition to the methods of statistical analysis used in observing the relationship between EBR and posture, and EBR and postural variability. The results section details the findings of the performance evaluation completed about the EBR Risk Level Classification System, along with the analysis results of the relationship between EBR and posture, and EBR and postural variability. Finally, the discussion section presents interpretations and implications of the study findings along with future study directions.

2. METHOD

This section addresses the development and validation process of the EBR Risk Level Classification System, as well as the statistical methods used in analyzing the relationship between EBR and posture, and EBR and postural variability.

2.1 Development and validation of the EBR Risk Level classification algorithm

2.1.1 Sensor-embedded Chair

This study utilized the sensor-embedded chair developed by Jeong et al. (2016) for the measurement of VDT worker's posture and movement data. The sensor-embedded chair was used for the posture and postural variability data collection, and was used as part of the EBR Risk Level Classification System.

As shown in Figure 1, 6 pressure sensors (Interlink, FSR406) embedded in the seat pan of the chair, and 6 distance sensors (Sharp, GP2Y0A41SK0F), in the seat back of the chair. As it is possible to not lean on the back of the chair at all, distance sensors were selected for the back of the chair over pressure sensors, which only operate when pressure is applied to the sensor.

The chair was anthropometrically designed in order to accommodate 99% of the Korean adult population, with regards to anthropometric measurements from SizeKorea (Figure 1). Distance sensors 1 and 4 (DS1, DS4) were set at the shoulder height of the 99th percentile Korean, and the distance between the right-hand and left-hand sensors were set as the chest width of the 99th percentile Korean. As the bottom part of the seat back meets the seat pan, the

bottom-most distance sensor was placed 0.05m above the bottom of the seat back, and the rest of the sensors were placed at equidistance. The pressure sensors on the seat pan were placed symmetrically with respect to the center line of the seat pan and their locations were determined considering the hip width of the 99th percentile Korean.

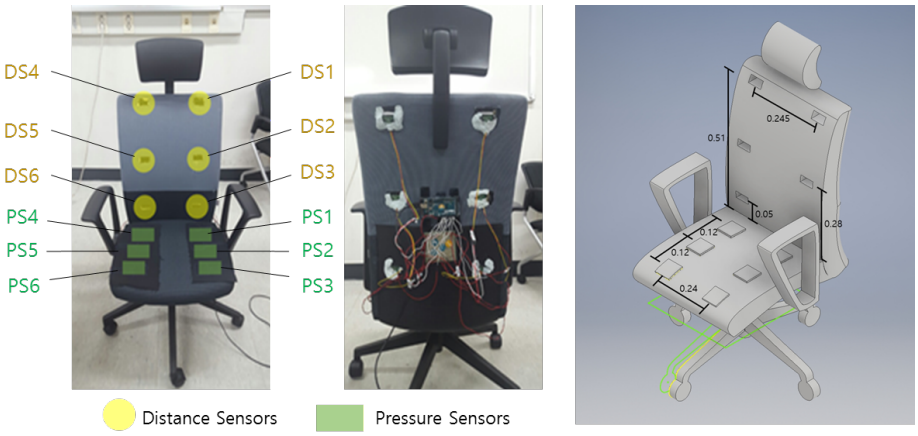

Figure 1 Sensor-embedded Chair

2.1.2 Posture and eye blink data collection and processing

An experiment was conducted to collect posture, postural variability and EBR risk level data for the EBR Risk Level Classification System development and evaluation. The collected dataset was also used to analyze the relationship between EBR and posture, and that between EBR and postural variability. 20 individuals participated in the data collection (9 male, 11 female; average age = 33.6 years, s.d. ± 11.3 years; avg height = 167.4 cm., s.d. ± 9.2 cm.; avg weight = 64.5 kg., s.d. ± 12.7 kg.). During the experiment, the participant sat in the sensor-embedded chair while wearing an eye tracker, and completed three representative work tasks – the watching, problem solving, and transcribing tasks.

The experiment was conducted in an office-like environment. The desk was 1.8 m. wide, 0.9 m. long, and 0.72 m. high, and the abovementioned sensor-embedded chair was used. The 12 pressure and distance sensors on the chair were set at a sampling frequency of 8Hz during the collection of posture and postural variability data. The chair was adjusted so that the center of the chair aligned with the center of the monitor, and the height of the chair was determined by the participant. The monitor used in the study was the DP2710LED display by Displayland©. The monitor was placed at a distance 0.6 m. from the eye of the participant, and the keyboard was placed 0.4 m. from the body of the participant.

The eye tracker used in the study was the Dikablis professional model from ERGONEERS. A 4-point calibration was completed for all participants. The EBR of each participant was collected through the eye tracker software program; the sampling frequency of 60 Hz. The eye tracker software program recorded the x and y coordinates of each pupil, and, it considered that a blink

had occurred when the x and y coordinates could not be identified on the screen. An EBR of 3 times or less was classified as High Risk EBR, and an EBR of 4 times or more was classified as Low Risk EBR (Uchino et al., 2008; Yaginuma et al., 1990). The data log was saved as a text file for easier analysis.

For the synchronization of measurement time between equipment, the UTCk program was used to synchronize the time on the PC for every trial. UTCk is provided by the Korea Research Institute of Standards and Science, and allows the synchronization to the Korean standard time, provided that the computer is connected to the internet.

Every participant was provided with and agreed to a participation consent form, and the experimental protocol of the study was approved by the Seoul National University IRB. Participants were notified in advance about the reason for the experiment along with other details, such as the process of the experiment and possible side effects. After the experiment explanation and eye tracker calibration, the three tasks (watching, problem solving, transcribing) were given for 15 minutes each, for a total of 45 minutes. The order of the tasks was randomized, and the participants were instructed to move on to the next task after 15 minutes, and 30 minutes had passed since the start of the experiment.

The watching task consisted of watching a video clip on the computer, and the video clip titled “satisfying video” was used in this task. These video clips are known to be aesthetically pleasing to most viewers, and participants were shown the video clip for 15 minutes (Figure 2).

The problem solving task consisted of reading a passage and answering a multiple-choice question based on the passage for 15 minutes (Figure 3). The

questions in this task were selected from those of the national competency examinations, which are often used by companies when hiring workers. National competency standards systematically organize the necessary knowledge and skills required to complete a worker's duty, and thus this exam evaluates a worker's skill in understanding a document and critical thinking among other skills. Participants were instructed to skip a question if it was too difficult to understand, and plenty of questions were provided, considering the different speeds at which participants solve the questions.

The transcribing task consisted of providing participants with data as in Figure 4, and instructing them to transcribe the excel sheet exactly as seen for 15 minutes. Participants were instructed to transcribe the given excel sheet as accurately as possible, with detailed instructions about the letters, numbers, and design of the figure. Also, participants were instructed to move on to the next figure after transcribing as much as they could, if the current figure was deemed too difficult to transcribe. A sufficiently large number of figures were provided, with consideration to the different speeds at which participants may transcribe the given data.

Figure 2 Example of the satisfying video in the watching task

II. 다음 글의 제목으로 가장 적절한 것은?

1. ( )

사회 방언은 지역 방언과 함께 2대 방언의 하나를 이룬다. 그러나 사회 방언은 지역 방언만큼 일찍부터 방언 학자의 주목을 받지 못하였다. 어느 사회에나 사회 방언이 없지는 않았으나, 일반적으로 사회 방언 간의 차이는 지역 방언들 사이의 그것만큼 그렇게 뚜렷하지 않기 때문이었다. 가령 20대와 60대 사이에는 분명히 방언차가 있지만 그 차이가 전라도 방언과 경상도 방언 사이의 그것만큼 현저하지는 않은 것이 일반적이며, 남자와 여자 사이의 방언차 역시 마찬가지다. 사회 계층 간의 방언차는 사회에 따라서는 상당히 현격한 차이를 보여 일직부터 논의의 대상이 되어왔었다. 인도에서의 카스트에 의해 분화된 방언, 미국에서의 흑인 영어의 특이성, 우리나라 일부 지역에서 발견되는 양반 계층과 일반 계층 사이의 방언차 등이 그 대표적인 예들이다. 이러한 사회 계층 간의 방언 분화는 최근 사회 언어학의 대두에 따라 점차 큰 관심의 대상이 되어 가고 있다.

A. 2대 방언-지역 방언과 사회 방언

B. 최근 두드러진 사회 방언에 대한 관심

C. 부각되는 계층 간의 방언 분화

D. 사회 언어학의 대두와 사회 방언

E. 사회 방언의 특징

Figure 3 Example of the problem solving task

장난감 제품관리 현황

제품코드	분류	제품명	제조사	판매가격	출시일	월납품수량
CA1-01	승용완구	헬로붕붕카	영토이스	69000	42348	200개
RP2-01	역할놀이	운전놀이	하나통상	55000	42224	150개
ED1-01	교육완구	도미노월드	미래완구	63000	42379	80개
RP1-02	역할놀이	공구가방	영토이스	43000	41988	100개
CA2-02	승용완구	우리씽씽이	미래완구	51000	42259	170개
CA1-03	승용완구	파란흔들말	하나통상	48000	42410	120개
RP1-03	역할놀이	왕소꿉놀이	미래완구	52000	42318	250개
ED2-02	교육완구	지능구슬	영토이스	33000	42384	180개

Figure 4 Example of the transcribing task

In order to construct the machine learning classification model for the EBR risk level classification (H1), the posture and postural variability data was collected in addition to the EBR risk level data. Data was collected from the pressure sensors, distance sensors, and eye tracker, from the beginning of the first task to the end of the last task. The sampling frequency of all collected data was synchronized at 1Hz for analysis.

The posture data was preprocessed by selecting one representative value, ($P^i(t)$, $D^i(t)$), from the 8 data points collected within 1 second for each of the 6 pressure sensors and 6 distance sensors.

$P^i(t) =$ for time interval [t-1, t], mode of the pressure values (Pa) from pressure sensor i (1)

$D^i(t) =$ for time interval [t-1, t], mode of the distance values (cm) from distance sensor i (2)

where

t = time within the experiment

i = 1, 2, …, 6

Postural variability data was collected by calculating the standard deviation of each sensor measurements from time t-14 to time t seconds.

$$S_P^i(t) : \sqrt{\frac{1}{15-1}\sum_{\alpha=0}^{14}\{P^i(t-\alpha) - \frac{1}{15}\sum_{\beta=0}^{14} P^i(t-\beta)\}^2} \quad (3)$$

$$S_D^i(t) : \sqrt{\frac{1}{15-1}\sum_{\alpha=0}^{14}\{D^i(t-\alpha) - \frac{1}{15}\sum_{\beta=0}^{14} D^i(t-\beta)\}^2} \quad (4)$$

The sensor data and standard deviation value of the sensor data were recorded in different units: Pa for the pressure sensors and centimeters for distance sensors. In order to overcome the problems related to units, the collected data was preprocessed by min-max normalizing the distance sensor and pressure sensor measurements so that their values were between 0 and 1. The normalization process for the posture and postural variation data is as follows.

$$P_N^i(t) = \frac{P^i(t) - P_{min}}{P_{max} - P_{min}} \quad (5)$$

where

P_{min} = the minimum value for variable P

P_{max} = the maximum value for variable P

$$D_N^i(t) = \frac{D^i(t) - D_{min}}{D_{max} - D_{min}} \quad (6)$$

where

D_{min} = the minimum value for variable D

D_{max}= the maximum value for variable D

$$S^{i}_{P,N}(t)= \frac{S^{i}_{P}(t)-S_{P,min}}{S_{P,max}-S_{P,min}} \quad (7)$$

where

$S_{P,min}$= the minimum value for variable S_P

$S_{P,max}$= the maximum value for variable S_P

$$S^{i}_{D,N}(t)= \frac{S^{i}_{D}(t)-S_{D,min}}{S_{D,max}-S_{D,min}} \quad (8)$$

where

$S_{D,min}$= the minimum value for variable S_D

$S_{D,max}$= the maximum value for variable S_D

The preprocessed posture and postural variability data, as well as the EBR risk level data was processed to fit a 15 second time window.

2.1.3 Algorithm development and validation

An individual-customized EBR Risk Level Classification System was developed with the use of the posture and postural variability data from the sensor-embedded chair, the EBR risk level data from the eye tracker, and a machine learning algorithm (the random forest algorithm). The abovementioned classification system uses posture and postural variability as inputs to classify EBR risk level (Figure 5).

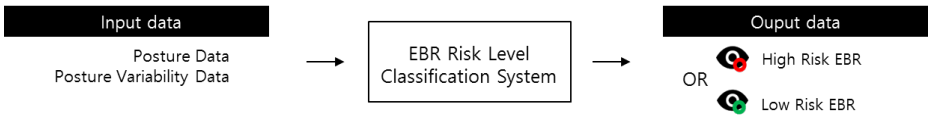

Figure 5 EBR Risk Level Classification System

Python and scikit-learn's random forest library was used when developing the EBR Risk Level Classification System. Random forest is an ensemble learning method for classification, which constructs decision trees during training and uses them to create a final prediction model (Breiman, 2001). A fundamental characteristic of random forest is that the constructed trees have different characteristics at random, which reduces the effect of noise from the input variables on performance of the model (Breiman, 2001). Pre-analysis of the data determined that general statistic models such as discriminant analysis or decision tree were not adequate in classifying the EBR risk level; therefore, the random forest model was selected for use.

For validation of the EBR Risk Level Classification system, an EBR Risk

Level Classification System was developed and evaluated for each participant. 70% of the data was randomly chosen for training, and the remaining data was used for validation of the model.

To measure the performance of the EBR Risk Level Classification System, accuracy, sensitivity, and specificity metrics were defined as shown in Table 1 (Menéndez, de Cos Juez, Lasheras, & Riesgo, 2010). High Risk EBR was considered positive, and Low Risk EBR was considered negative. The accuracy (Equation 9) ratio was calculated to assess the overall effectiveness. Sensitivity (Equation 10) measures the proportion of actual positives that are correctly identified, and specificity (Equation 11) measures the proportion of negatives that are correctly identified(Sánchez, Iglesias-Rodríguez, Fernández, & de Cos Juez, 2016).

$$\text{Accuracy} = \frac{tp + fn}{tp + fp + fn + tn} \tag{9}$$

$$\text{Sensitivity} = \frac{tp}{tp + fn} \tag{10}$$

$$\text{Specificity} = \frac{tp + fn}{fp + tn} \tag{11}$$

Table 1 The confusion matrix of EBR Risk Level Classification System

Class	Recognized	
	As positive	As negative
Positive	true positive (tp)	false negative (fn)
Negative	false positive (fp)	true negative (tn)

As it is necessary to provide live feedback of the EBR risk level to the workers, the speed of the system as well as its accuracy was considered in selecting the final model. The resulting specifications of the model were 20 trees with the basic values of the random forest library for the other hyper parameters, and additional information can be found at the random forest classifier ensemble explanation page (http://scikit-learn.org/).

2.2 Data analysis for observing the association between EBR risk level and posture/postural variability

The collected data was preprocessed to aid the observation of the relationship between EBR and posture, and, that between EBR and postural variability.

The difference in postural variability in regards to EBR risk level was examined in order to test H2. All calculations made in testing H2 was done by preprocessing the postural variability data to create new data points from data collected during 15-second time frames (t-15 to t). Each data point was calculated by taking the average of the standard deviation (Equation 7, 8) of all 12 sensor data within the 15-second time frame (Equation 12).

$$\bar{S}_N(t) = \frac{1}{12}\left(\sum_{i=1}^{6} S^i_{P,N}(t) + \sum_{i=1}^{6} S^i_{D,N}(t)\right) \quad (12)$$

Lastly, H3 was tested by observing the difference in forward bending occurrence according to EBR risk level. All calculations made in testing H3 was also done by preprocessing the distance sensor data to create new data points from data collected during the 15-second time frames (t-15 to t). Each data point was calculated to represent the amount of forward bending during a time frame. Forward bending is distinguishable by analyzing a forward shift in weight and upper body tilting and can be calculated by front-end pressure sensors and the top and middle distance sensors. The amount of forward bending was quantified by collecting the pressure applied to the front-end pressure, and taking the sum of the front end sensors (PS3, PS6) in order to define the pressure applied to the front-end sensors (Equation 13).

$$P_{seat\ \ front}(t) = P^3(t) + P^5(t) \tag{13}$$

The upper body tilt was also calculated to test hypothesis 3. This upper body tilt can be expressed as the difference between the top and middle distance sensors (Equation 14).

$$trunk\ \ inclination(t) = \frac{1}{2}\{(D^1(t) - D^2(t)) + (D^4(t) - D^5(t))\} \tag{14}$$

The t-test was used to statistically analyze the significance of the difference in postural variability, the seat's front-end pressure, and upper body tilt. Due to the possibility of the large amount of data positively affecting the significance of the data, the results were analyzed by utilizing the mean of the low risk level EBR as a baseline to compare the difference between the mean of the low and high risk level EBR, in addition to tests of statistical significance.

3. RESULTS

3.1 EBR Risk Level Classification System validation

The performance evaluation results of the EBR Risk Level Classification System were organized into confusion matrices for the 20 participants. An example confusion matrix is shown as examples in Table 2 (Participant 10). The distributions of accuracy, sensitivity, and specificity of the EBR risk level classification are graphically summarized in Figure 6.

The EBR Risk Level Classification System had high accuracy, sensitivity, and specificity – the averages were 93.30%, 93.58%, and 93.08%, respectively.

Table 2 Example of the confusion matrix of the EBR Risk Level Classification System (Participant 10)

Class	Recognized	
	As positive	As negative
Positive	652 (98.34%)	11 (1.66%)
Negative	22 (15.38%)	121 (84.62%)

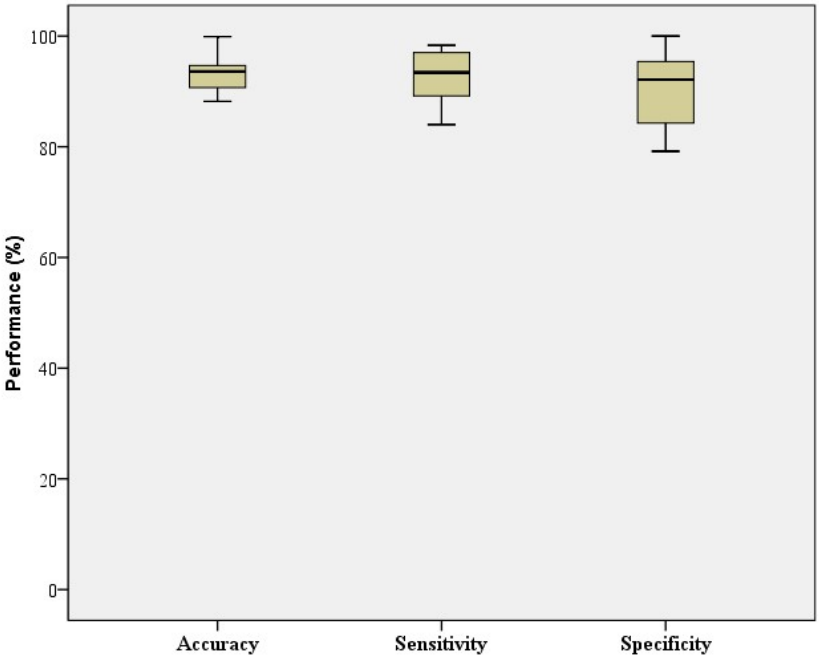

Figure 6 EBR Risk Level Classification performance distribution

3.2 EBR and posture, EBR and postural variability

The relationship between EBR risk level and posture and that between EBR risk level and postural variability were analyzed as these relationships were the grounds of development of the EBR Risk Level Classification System. On average, there was a smaller postural variability (Equation 9) during time periods when EBR was of high risk, than of low risk (Figure 7). Across all tasks, the postural variability when EBR was of high risk (M = 0.0299, SD = 0.0665) was 24.30% lower than that of when EBR was low risk (M = 0.0395, SD = 0.0827), and is shown in Figure 7 (p-value < 0.01).

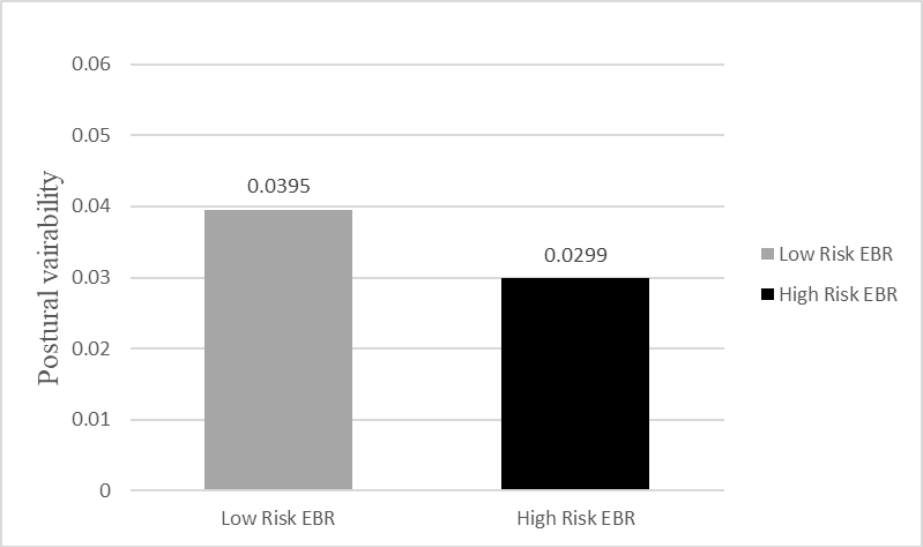

Figure 5 Postural variability according to EBR Risk Level

A similar trend across all tasks and for each individual task was observed for postural variability (Figure 8). When performing the watching task, the postural variability when EBR was of high risk (M = 0.0201, SD = 0.0549)

was 39.27% lower than that of when EBR was of low risk (M = 0.0331, SD = 0.0809). When performing the problem solving task, the postural variability when EBR was of high risk (M = 0.0329, SD = 0.0672) was 19.36% lower than that of when EBR was of low risk (M = 0.0408, SD = 0.0802). When performing the transcribing task, the postural variability when EBR was of high risk (M=0.0329, SD = 0.0708) was 32.16% lower than that of when EBR was of low risk (M = 0.0485, SD = 0.0884). The results of the t-tests showed statistical significance (p-value<0.01).

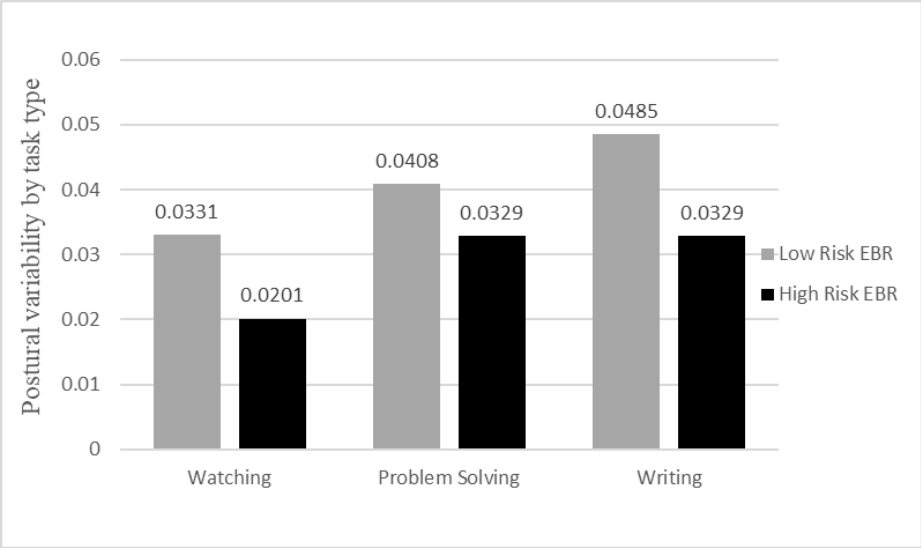

Figure 6 Postural variability for EBR risk level by task type

On average, the pressure level measured by the front-end seat pan sensors was higher (Equation 10) during time periods when EBR was of high risk, rather than of low risk (Figure 9). Across all tasks, the seat pan front pressure

when EBR was of high risk (M = 16.6031, SD = 11.8829) was 26.61% higher than that of when EBR was of low risk (M = 13.1137, SD = 12.0609), and is shown in Figure 9 (p-value < 0.01)

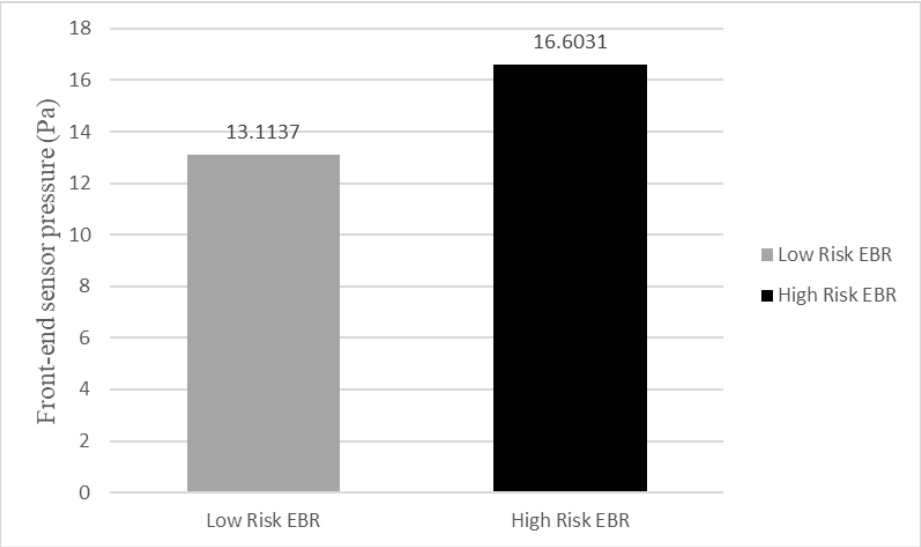

Figure 7 Front-end sensor pressure by EBR Risk Level

A trend similar to that found from the postural variability analyses was observed in both the front-end seat pan pressure analysis across all tasks and for each individual task (Figure 10). When performing the watching task, the seat front pressure when EBR was of high risk (M = 16.8316, SD = 10.7510) was 27.33% greater than that of when EBR was of low risk (M = 13.2184, SD = 11.5662). When performing the problem solving task, the seat front pressure when EBR was high risk (M = 16.6075, SD = 12.0901) was 22.60% lower than that of when EBR was low risk (M = 13.5462, SD = 12.8981). When performing the transcribing task, the seat front pressure when

EBR was of high risk (M=16.6029, SD = 11.5638) was 26.89% lower than that of when EBR was of low risk (M = 13.0846, SD = 11.1212). The results of the t-test showed statistical significance (p-value<0.01).

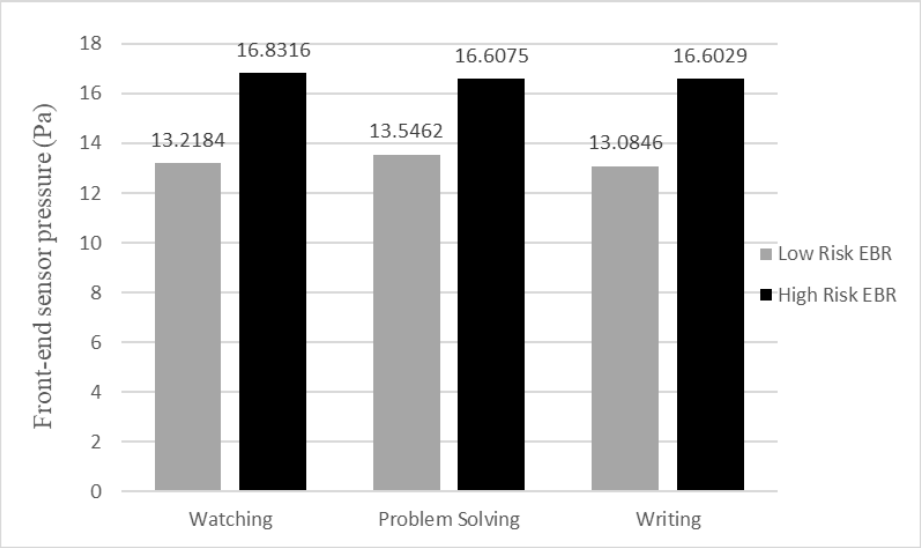

Figure 8 Front-end sensor pressure for EBR risk level by task type

On average, there was a larger trunk forward inclination (Equation 11) during time periods when EBR was of high risk, rather than of low risk (Figure 11). Across all tasks, the trunk inclination when EBR was of high risk (M = 9.4149, SD = 4.6431) was 6.50% higher than that of when EBR was of low risk (M = 8.8403, SD = 4.4995), and is shown in Figure 11 (p-value < 0.01).

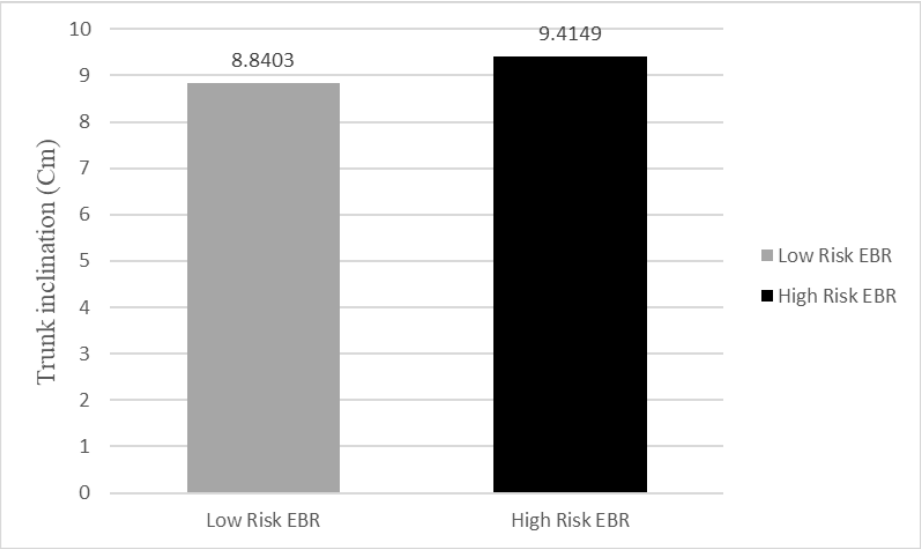

Figure 9 Trunk inclination by EBR Risk Level

In terms of trunk inclination, there was a similar trend across all tasks and for each individual task (Figure 12). When performing the watching task, the trunk inclination when EBR was of high risk (M = 9.4948, SD = 5.0184) was 6.88% greater than that of when EBR was of low risk (M = 8.8835, SD = 4.7162). When performing the problem solving task, the trunk inclination when EBR was of high risk (M = 9.1287, SD = 4.3073) was 3.63% lower than that of when EBR was of low risk (M = 8.8089, SD = 4.2589). When performing the transcribing task, the trunk inclination when EBR was of high risk (M=9.2970, SD = 4.3581) was 6.12% lower than that of when EBR was of low risk (M = 8.7609, SD = 3.9350). The results of the t-test showed statistical significance (p-value<0.01).

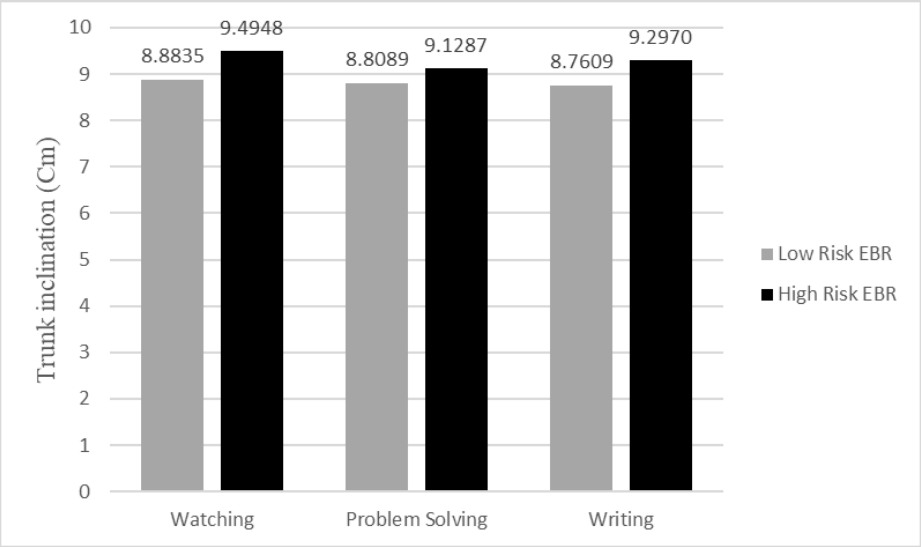

Figure 10 Trunk inclination for EBR risk level by task type

4. DISCUSSION

This study developed an accurate EBR Risk Level Classification System by using a sensor-embedded chair, along with posture and postural variability data; in addition, the relationship between EBR and posture, and that between EBR and postural variability was explored experimentally. In regards to the hypotheses set at the beginning of this paper, the results supported all three hypotheses. H1 was confirmed as the study developed an individual-customized machine learning model, along with a classification system that used posture and postural variability data to indirectly and accurately determine EBR. H2 and H3 were also confirmed, as the relationships between EBR, and posture and postural variability were confirmed as previously stated.

20 participants were asked to complete three VDT tasks in an office-like environment. Posture and postural variability data was collected from the sensor-embedded chair throughout the experiment, and the EBR risk level was collected from the eye tracker to generate the data set.

This study developed a system which uses pressure and distance sensors to classify the EBR risk level indirectly. In creating the machine learning algorithm to classify the EBR risk level, posture and postural variability were entered as inputs and EBR risk was entered as the output to train the machine learning model; 70% of the data was used for training, and the remaining data was used for validation of the random forest model used in the classification system. Additionally, the practical significance and statistical significance of the data were evaluated for the difference in posture and postural variability between high risk EBR and low risk EBR. The accuracy of the system was around 90%, justifying use of the system in practical situations (Figure 6).

The developed system does not require the user to wear any measurement tools; this may allow the system to be utilized in an office environment. Thus, the EBR Risk Level Classification System may contribute to the reduction of dry eye syndrome, as this syndrome often occurs due to long-time use of VDTs in the office. As the system was constructed by simply attaching sensors to a regular chair, other researchers may be able to develop a new sensor-chair based system with different types of chairs or sensor types. The EBR Risk Level Classification System performed consistently high for all 20 participants (Figure 6). Thus, the classification system developed in this study may be able to be applied to other office workers through data collection.

The data for a few participants showed low specificity, and these cases occurred in participants who had a high EBR throughout the entire experiment trials. This phenomenon can be explained by the fact that most of the training data was of Low Risk EBR, which may have resulted in a less accurate classification of High Risk EBR. An unusual case was that of a participant who had very few High Risk EBR training data that the machine learning model was not able to correctly predict the High Risk EBR; however, because there was a small number of High Risk EBR cases to predict, the overall accuracy of the system was still high. Therefore, this does not seem hinder the utility of the EBR Risk Level Classification System.

The EBR Risk Classification System performed consistently well with the random forest model, but general statistical analysis methods such as discriminant analysis and decision tree did not perform as well in classifying the EBR Risk Level. This hints at the complexity of the relationship between EBR risk level, and posture and postural variability, but the analysis results for H2 and H3 (Figures 7-12) demonstrate the systematic relationship between

EBR Risk Level, and posture and postural variability. This systematic tendency is consistent with results from the previous ergonomics and physiological research studies, and may be the main reason for the high accuracy of the EBR Risk Level Classification system. However, there is a possibility of variables other than posture and postural variability that may have contributed to the high accuracy of the classification system.

The difference in postures among the individual participants may be another possible rationale for the poor accuracy of classification with general statistical analysis methods. Existing studies have suggested that posture is affected by culture, nutritional state, and apparel (Hewes, 1955; Kleinsmith, De Silva, & Bianchi-Berthouze, 2006); thus, posture and postural variability may have enough of a relationship to classify EBR Risk Level with high accuracy, but this relationship may be different and complex for each individual. Additionally, the high-performance of the classification system for the 20 participants implies the possibility that the developed system may have categorized individual characteristics of the participants through combinations of the sensor data, and then determining the EBR Risk Level. Such an observation may hint at the possibility of future studies exploring the concept of using a chair to not only classify EBR Risk Level, but to classify what kind of services or needs the person in the chair has in order to provide individual-customized service.

For all three task types (Figures 7, 9, and 11), postural variability decreased and forward bending increased in size as high risk EBR was more often detected (Figures 8, 10, 12). This relationship between EBR, and posture and postural variability is compatible with results from previous studies (Iwanaga et al., 2000; Skotte, Nojgaard, Jorgensen, Christensen, & Sjogaard, 2007).

Skotte et al. (2007) and Iwanaga et al. (2000) reported that there was a reduction in EBR as mental demand increased. Also, the increase of mental workload and forward bending has been linked in previous studies (Qiu & Helbig, 2012). That is, an increase in mental process is related to the reduction in EBR, decrease in postural variability, and increase in forward bending. The abovementioned research hints at the possibility of a relationship of EBR, and posture and postural variability with mental process as an intermediary. The inter-relationship between these four variables are consistent with the findings of existing works (Gabrieli et al., 1998; Iwanaga et al., 2000; Luna & Sweeney, 1999). Luna et al. (1999), Gabrieli et al. (1998), and Iwanaga et al. (2000) stated that the cerebral basal ganglia and cerebellum were related to eyeball movement and motor control (Figure 13). The existence of a shared brain area stated in various works insinuates the interrelationship between mental process, eye blinking, posture, and postural variability.

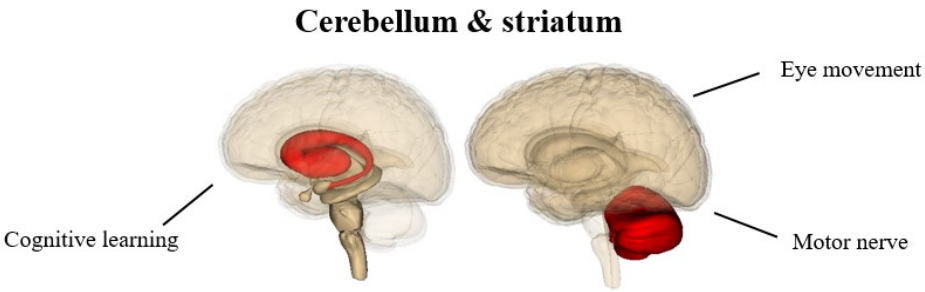

Figure 11 Brain areas related to cognitive learning, eyeball movement, and motor control

Future research may look into integrating the EBR Classification System with an alarm display in order to analyze the significance of EBR improvement when the system is used, thus demonstrating the effect of the current system in reducing dry eye syndrome. In addition to estimating the EBR risk level of an office worker, further studies may explore the possibility of attaching sensors on automobile seats, in order to determine the EBR of a driver. Such a detection in EBR may aid in the detection of drowsy driving (Caffier, Erdmann, & Ullsperger, 2003), and how focused the driver is while driving (Stern, Beideman, & Chen, 1976).

Additional research may take into account that the inter-relation between EBR, posture, and postural variability presumably exists not only while someone is sitting, but also standing up. Future studies may look at ways to indirectly measure the EBR Risk Level of a standing worker by using measurement tools such as the force plate or piezoelectric sensors to collect posture and postural variability data. Also, as posture plays a large role in expressing one's emotions (Kleinsmith & Bianchi-Berthouze, 2013), future research may choose to develop the smart chair system from this study into a system that correctly evaluates one's feelings or emotions. On a related note, previous research correctly predicted the interest level of children with the use of pressure sensors on a chair (Mota & Picard, 2003); future research may similarly investigate how to indirectly measure the interest level or focus level of workers through their chairs.

The inter-relationship between EBR, and posture and postural variation can be confirmed by the results of this research (Figures 7-12), as well as previous works. However, as this study did not measure mental workload or attention, future works may choose to utilize tools such as NASA-TLX in order to

measure these variables, and explore the inter-relationship between mental workload or attention, and EBR, and posture and postural variability. In addition, the differences in the abovementioned relationships may be explored through experiment. A larger forward bending occurred when the user was at high risk EBR, and such a forward posture may cause musculoskeletal diseases such as disc degeneration and back pain in office workers (ISO, 1998). Thus, it may be possible to predict the probability of musculoskeletal diseases in workers, or on the contrary, assess the change in EBR after a reduction of unsafe postures.

As EBR and learning ability have also been linked in the past, future research may choose to investigate the difference in posture between groups of students with higher and lower learning ability.

5. CONCLUSION

This study utilized posture and postural variability data in order to develop an accurate EBR Risk Level Classification System. Also, this study observed the relationship between EBR and posture, and EBR and postural variability through experiment, as this was the grounds of the development of the system. The results yielded an EBR Risk Level Classification System that consistently showed a high accuracy for all participants in the study. Additionally, this system may be able to overcome the limitation of existing EBR measurement tools deemed inappropriate for use in the workplace, as EBR risk level is indirectly measured. Such a system may contribute to the enhancement of worker health by preventing and reducing dry eye syndrome. An additional finding of this study was that postural variability decreased and forward bending increased when EBR was at high risk. Future studies may consider an alarm display that utilizes the EBR Risk Level Classification System to provide real-time information about eye blinking to the user, and further investigate the improvement of eye blinking habits in regards to the feedback from such a system.

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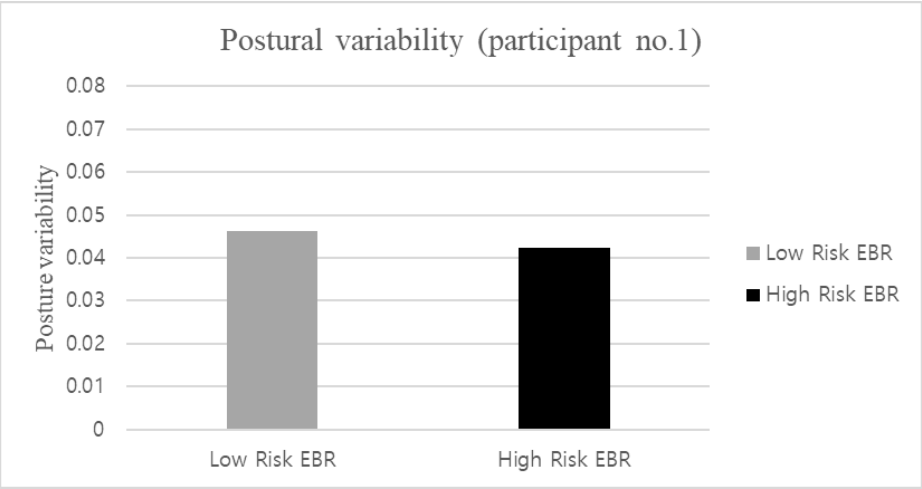
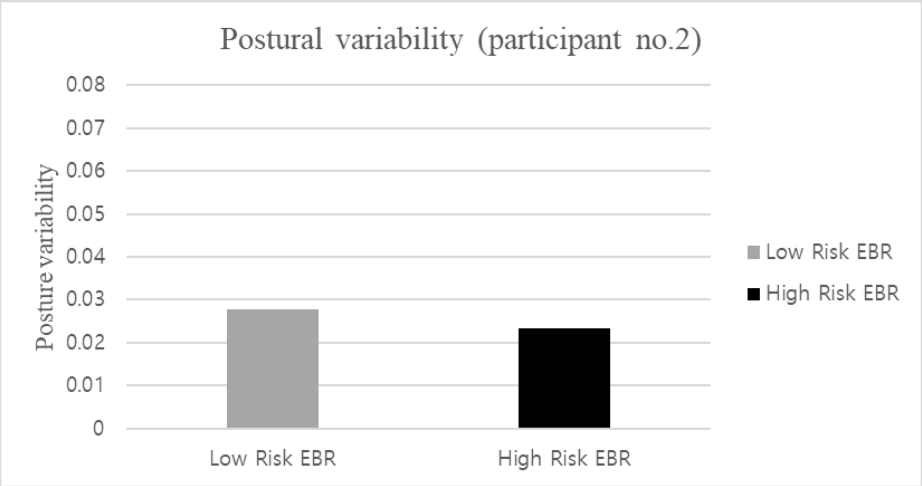
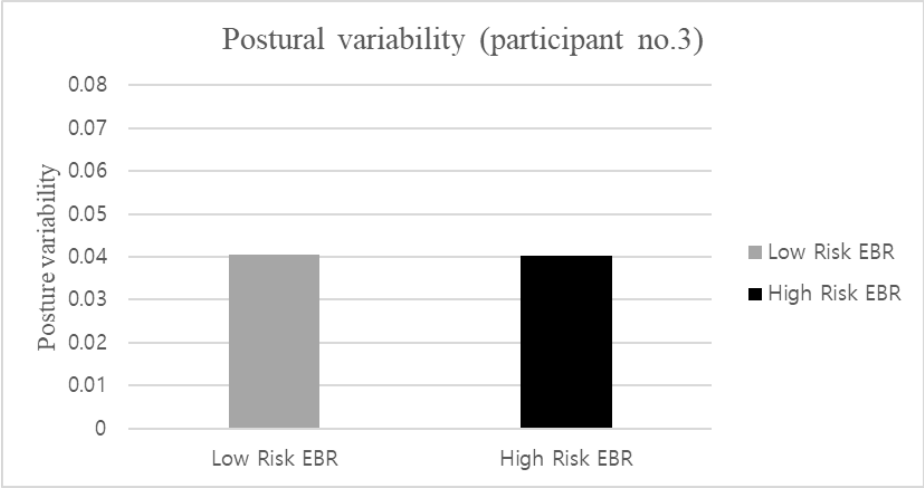
Appendix A: Postural variability by participants



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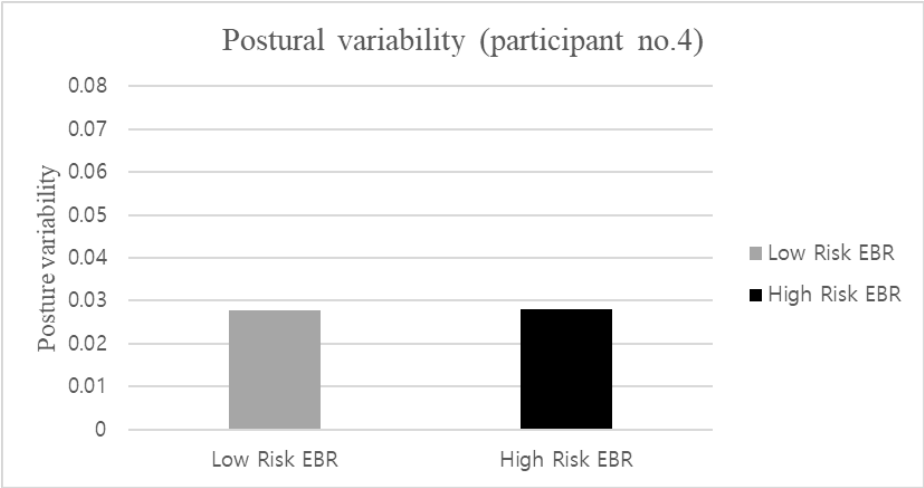
Posture variability
0.08
0.07
0.06
0.05
0.04
0.03
0.02
0.01
0
Low Risk EBR
High Risk EBR
Low Risk EBR
High Risk EBR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Posture variability
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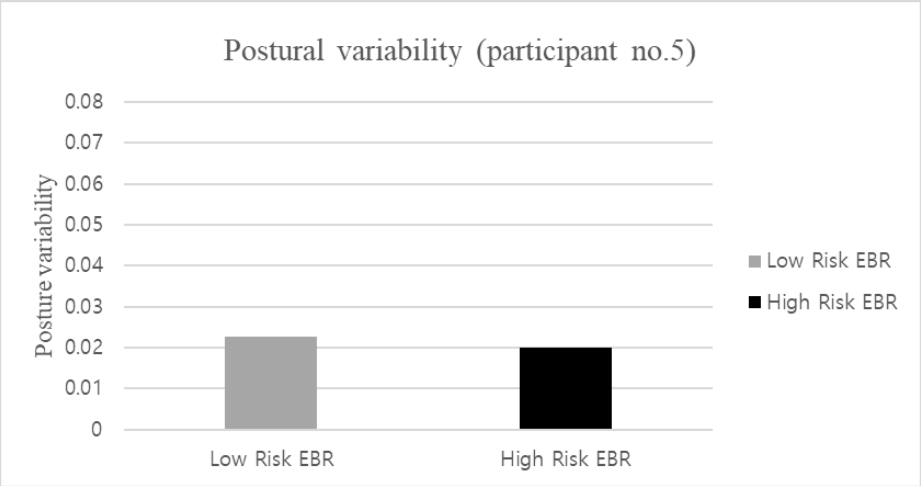
0.06
0.05
0.04
0.03
0.02
0.01
0
Low Risk EBR
High Risk EBR
Low Risk EBR
High Risk EBR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Posture variability
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0.02
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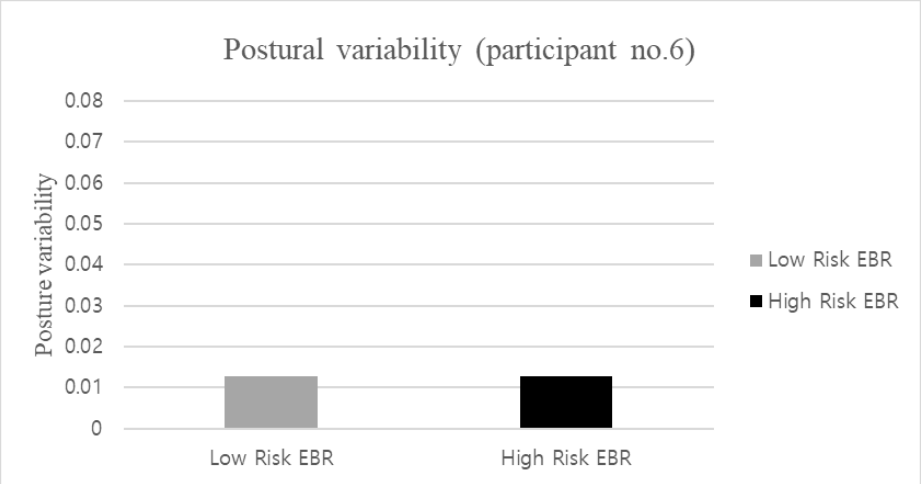
0
Low Risk EBR
High Risk EBR
Low Risk EBR
High Risk EBR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Posture variability
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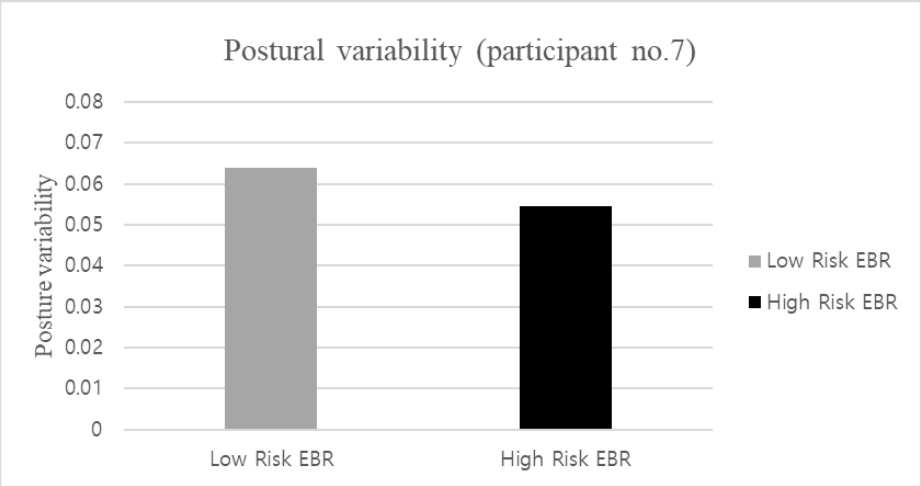
Low Risk EBR
High Risk EBR
Low Risk EBR
High Risk EBR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0.07
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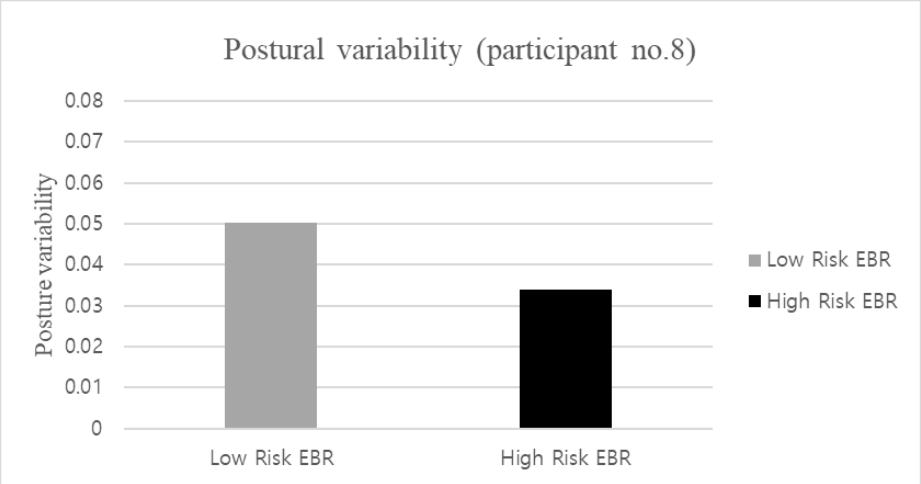
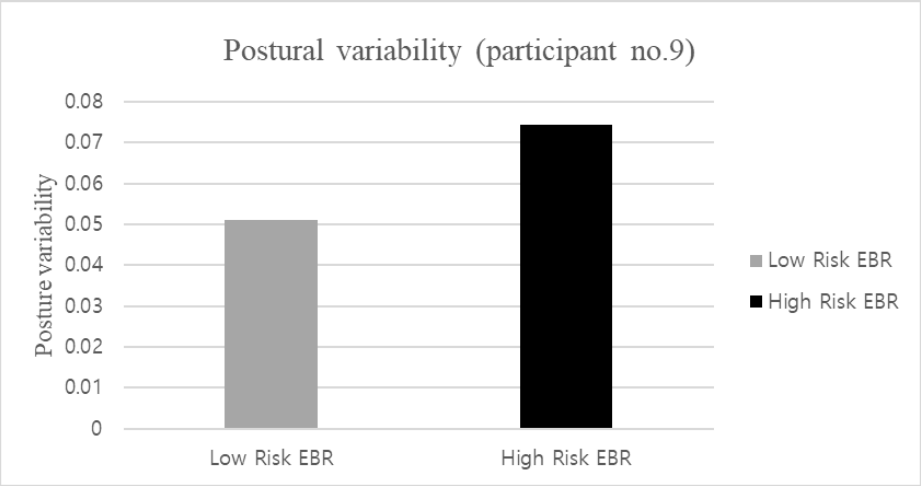
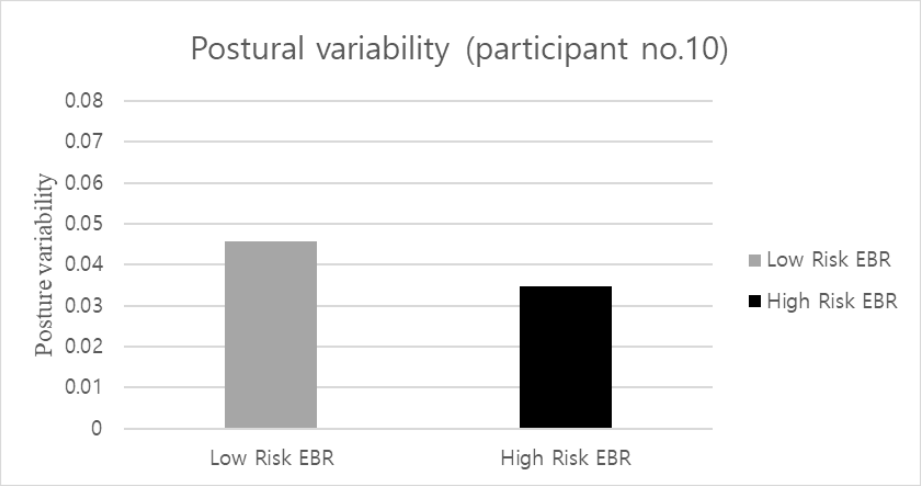
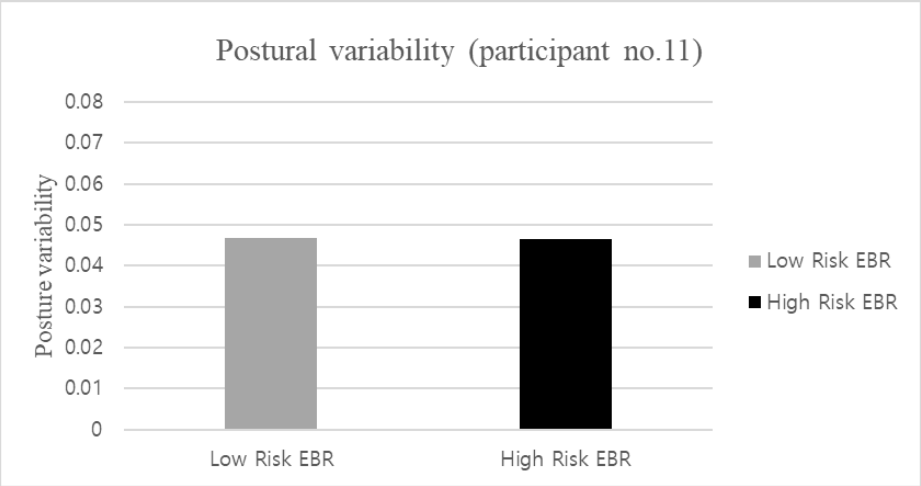
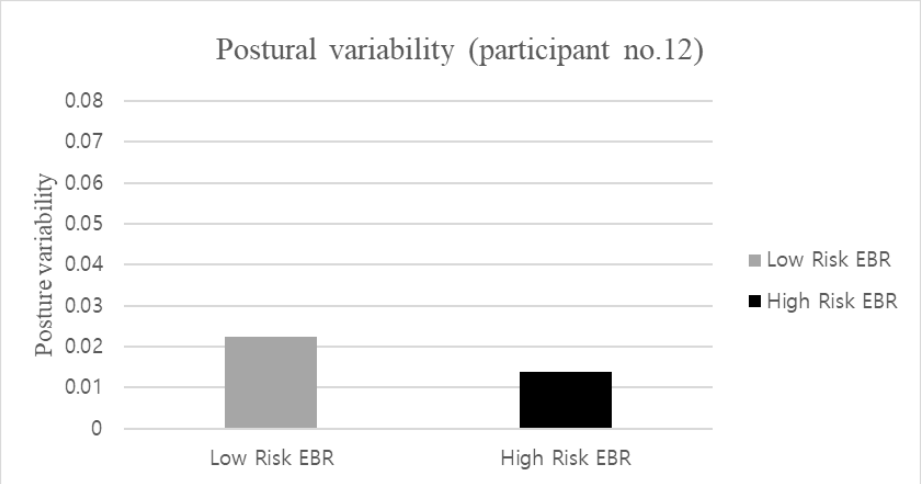
Low Risk EBR
High Risk EBR

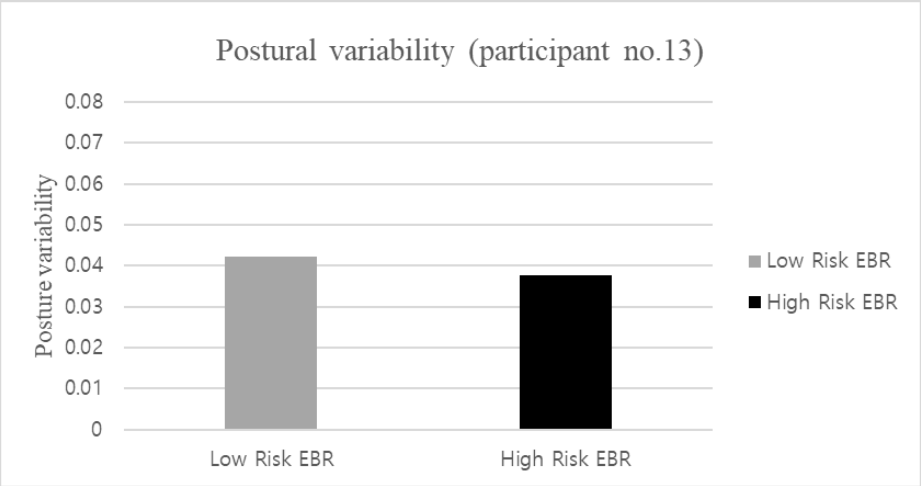

Postural variability (participant no.8)
Posture variability
0.08
0.07
0.06
0.05
0.04
0.03
0.02
0.01
0
Low Risk EBR
High Risk EBR
Low Risk EBR
High Risk EBR

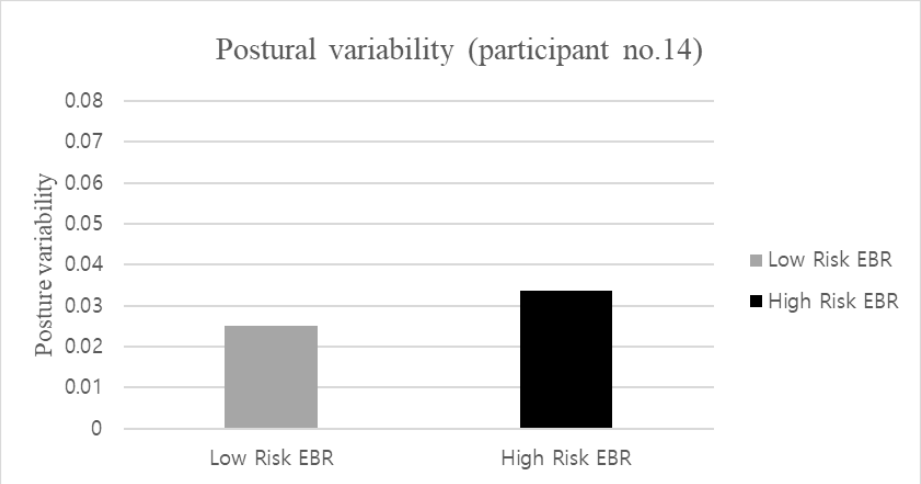

Postural variability (participant no.9)
Posture variability
0.08
0.07
0.06
0.05
0.04
0.03
0.02
0.01
0
Low Risk EBR
High Risk EBR
Low Risk EBR
High Risk EBR

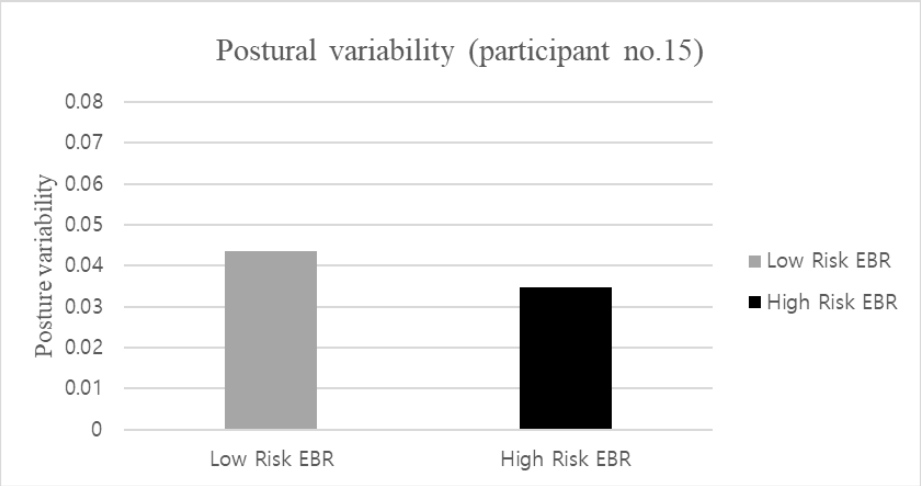

Postural variability (participant no.10)
Posture variability
0.08
0.07
0.06
0.05
0.04
0.03
0.02
0.01
0
Low Risk EBR
High Risk EBR
Low Risk EBR
High Risk EBR

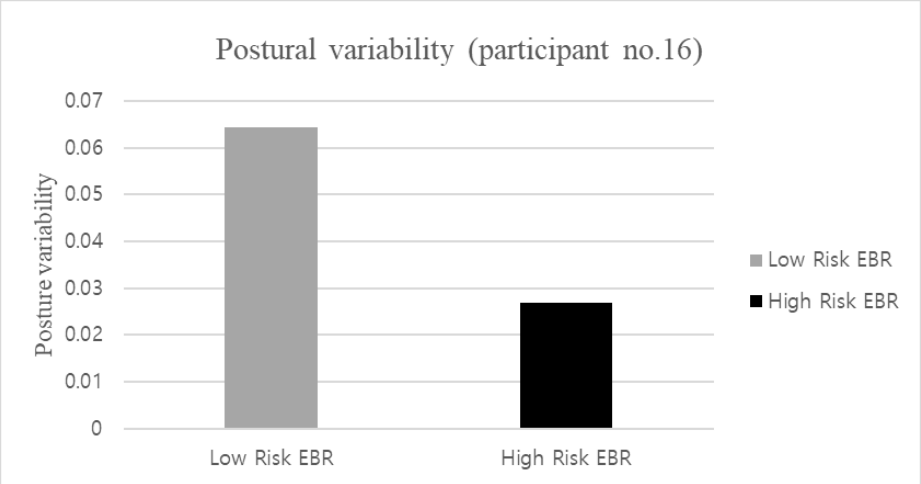

Postural variability (participant no.11)
Posture variability
0.08
0.07
0.06
0.05
0.04
0.03
0.02
0.01
0
Low Risk EBR
High Risk EBR
Low Risk EBR
High Risk EBR

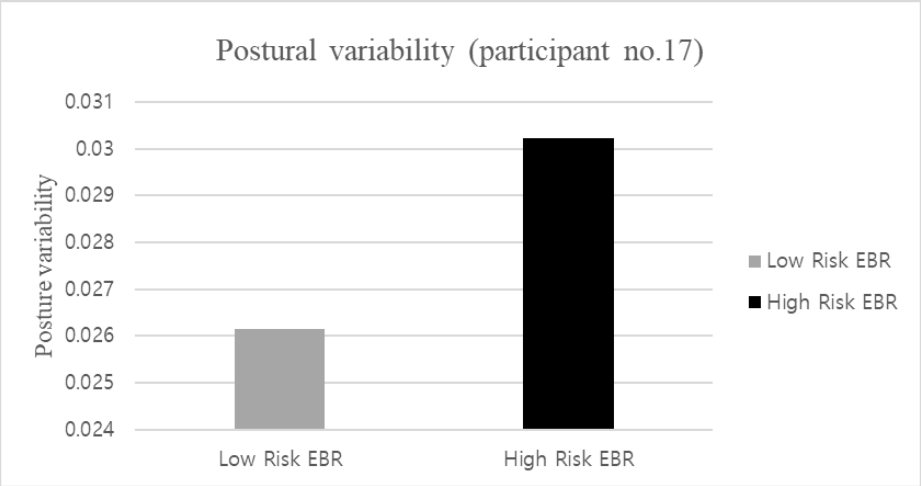

Postural variability (participant no.12)
Posture variability
0.08
0.07
0.06
0.05
0.04
0.03
0.02
0.01
0
Low Risk EBR
High Risk EBR
Low Risk EBR
High Risk EBR

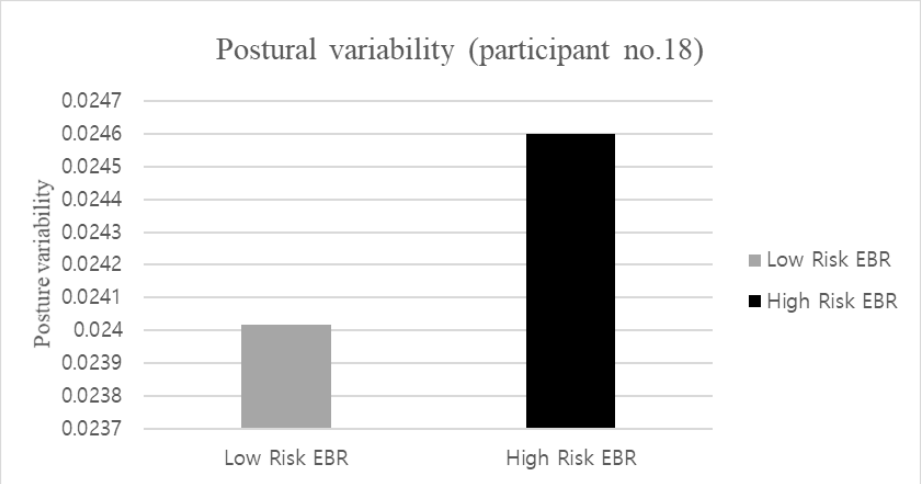

Postural variability (participant no.13)
Posture variability
0.08
0.07
0.06
0.05
0.04
0.03
0.02
0.01
0
Low Risk EBR
High Risk EBR
Low Risk EBR
High Risk EBR

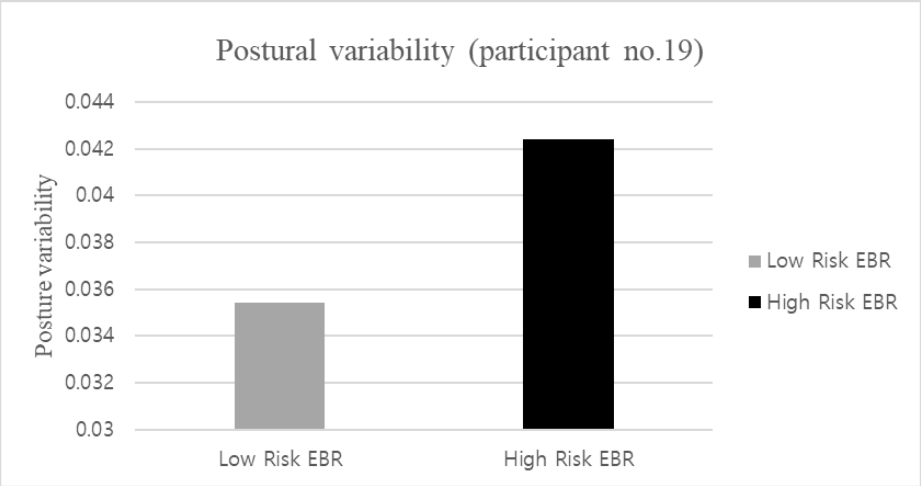

Postural variability (participant no.14)
Posture variability
0.08
0.07
0.06
0.05
0.04
0.03
0.02
0.01
0
Low Risk EBR
High Risk EBR
Low Risk EBR
High Risk EBR

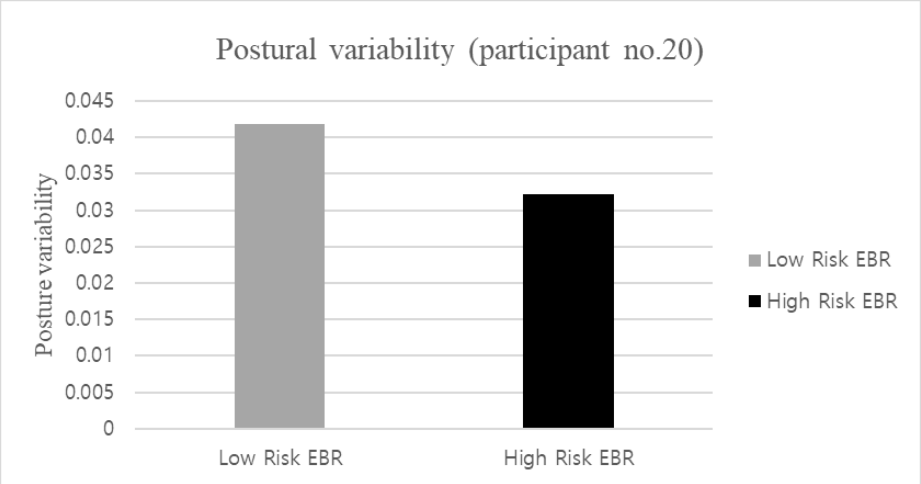

Postural variability (participant no.15)
Posture variability
0.08
0.07
0.06
0.05
0.04
0.03
0.02
0.01
0
Low Risk EBR
High Risk EBR
Low Risk EBR
High Risk EBR


Postural variability (participant no.16)
Posture variability
0.07
0.06
0.05
0.04
0.03
0.02
0.01
0
Low Risk EBR
High Risk EBR
Low Risk EBR
High Risk EBR

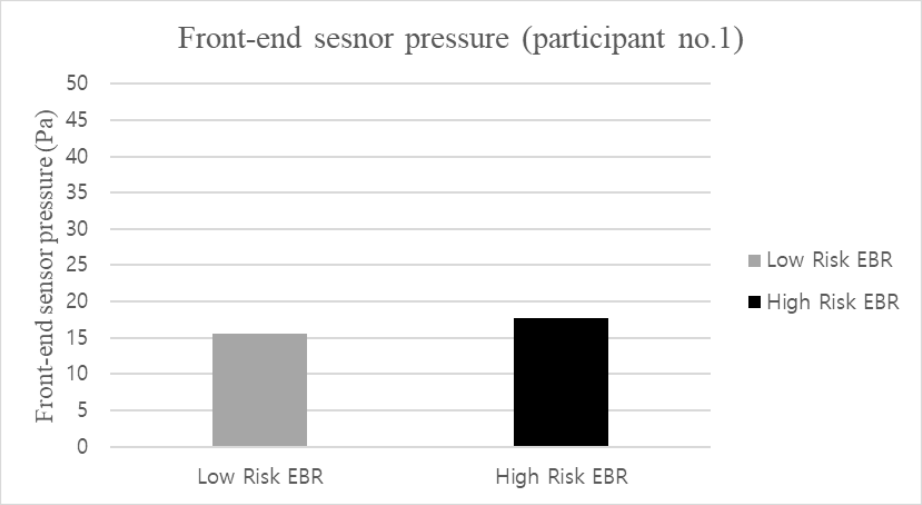

Postural variability (participant no.17)
Posture variability
0.031
0.03
0.029
0.028
0.027
0.026
0.025
0.024
Low Risk EBR
High Risk EBR
Low Risk EBR
High Risk EBR

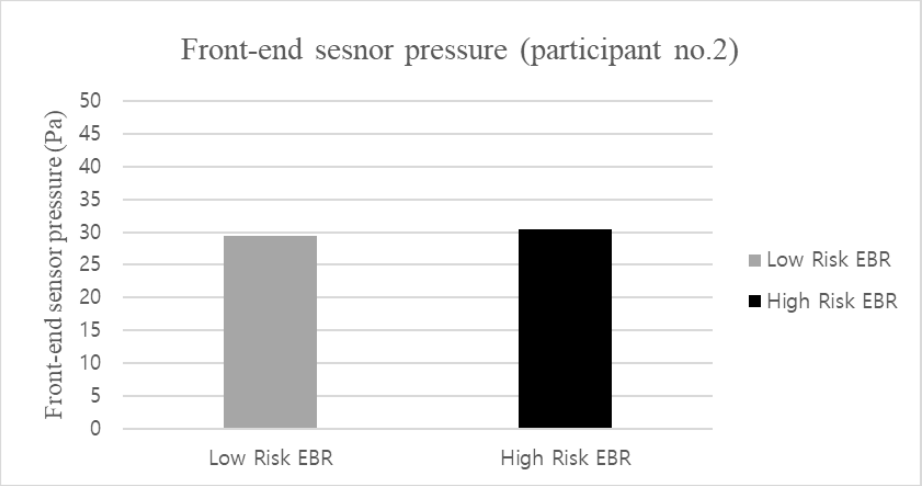

Postural variability (participant no.18)
Posture variability
0.0247
0.0246
0.0245
0.0244
0.0243
0.0242
0.0241
0.024
0.0239
0.0238
0.0237
Low Risk EBR
High Risk EBR
Low Risk EBR
High Risk EBR

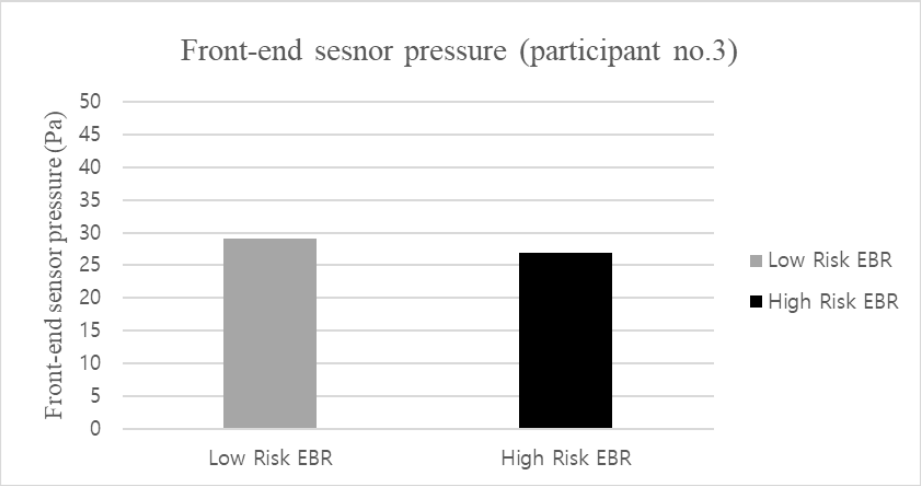

Postural variability (participant no.19)
Posture variability
0.044
0.042
0.04
0.038
0.036
0.034
0.032
0.03
Low Risk EBR
High Risk EBR
Low Risk EBR
High Risk EBR

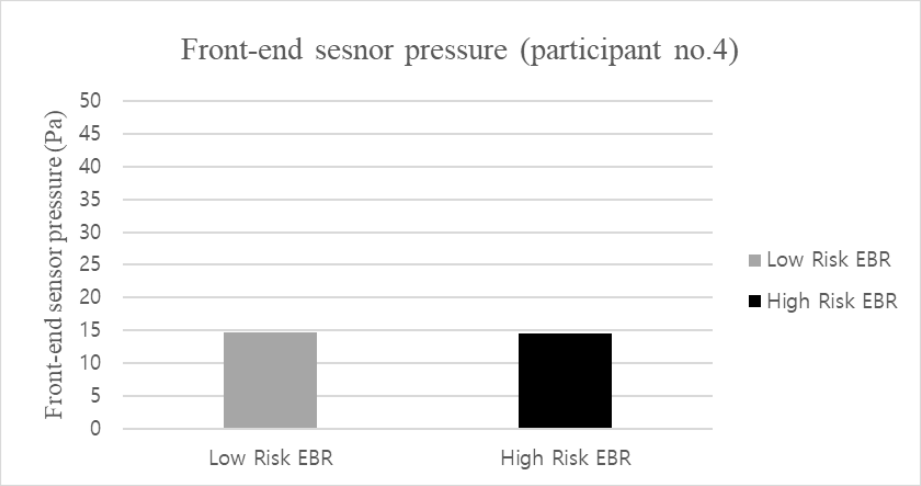

Postural variability (participant no.20)
Posture variability
0.045
0.04
0.035
0.03
0.025
0.02
0.015
0.01
0.005
0
Low Risk EBR
High Risk EBR
Low Risk EBR
High Risk EBR

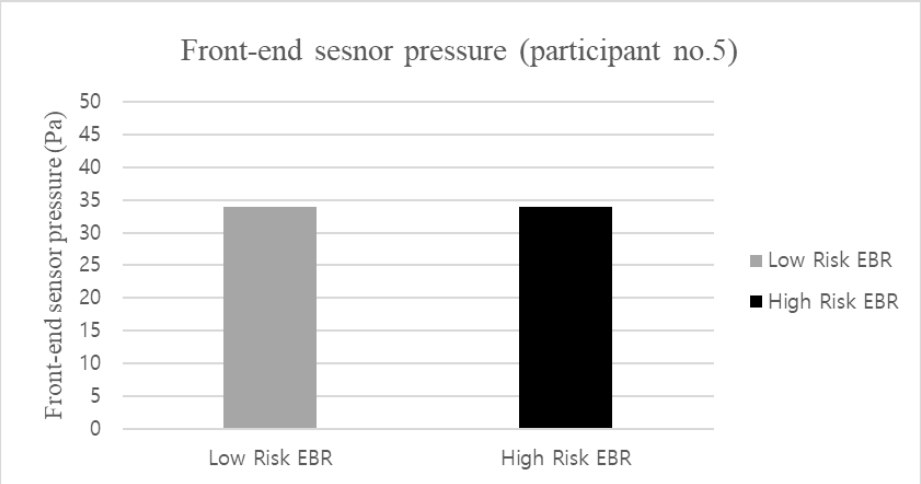
Appendix B: Front-end sensor pressure by participants

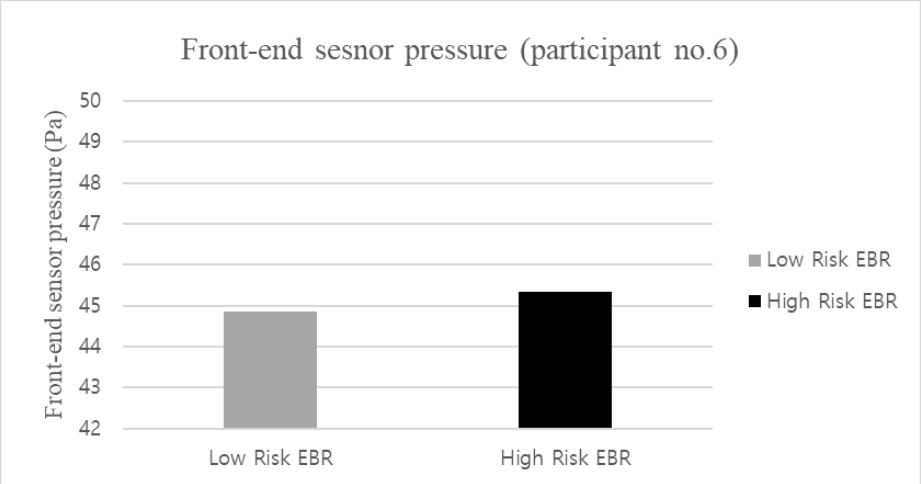


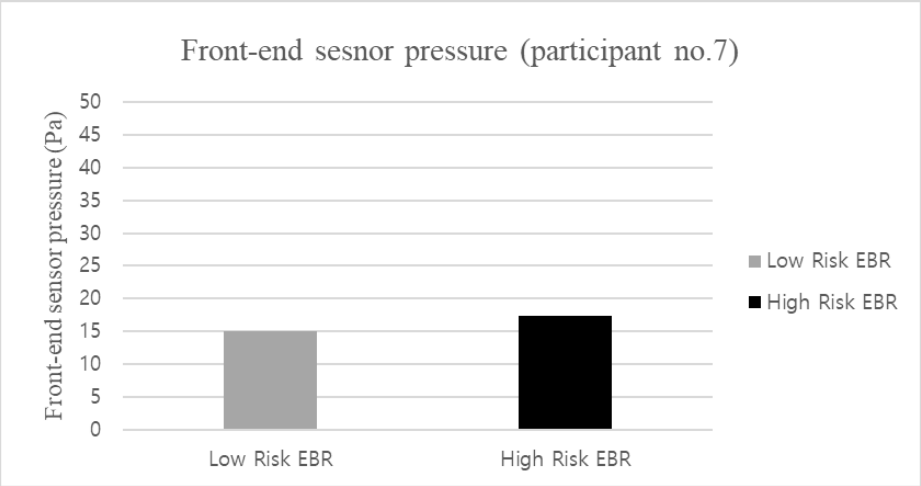


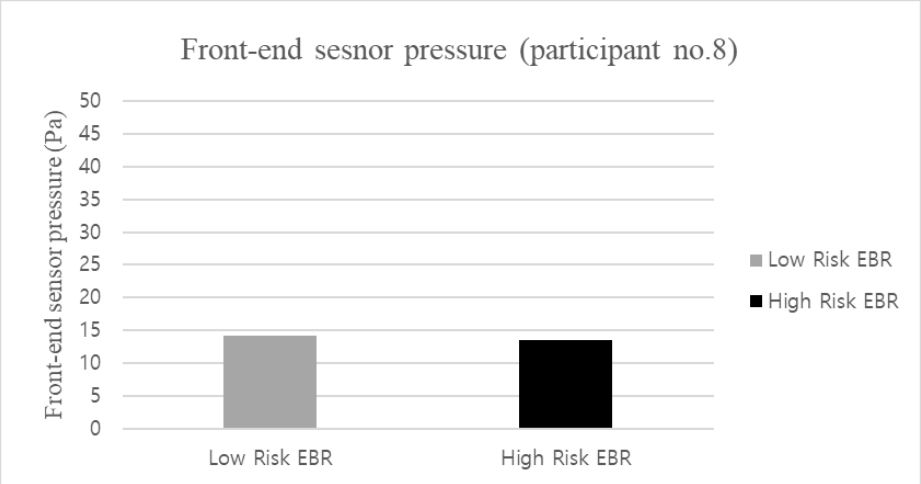

Front-end sesnor pressure (participant no.3)
Front-end sensor pressure (Pa)
50
45
40
35
30
25
20
15
10
5
0
Low Risk EBR
High Risk EBR
Low Risk EBR
High Risk EBR

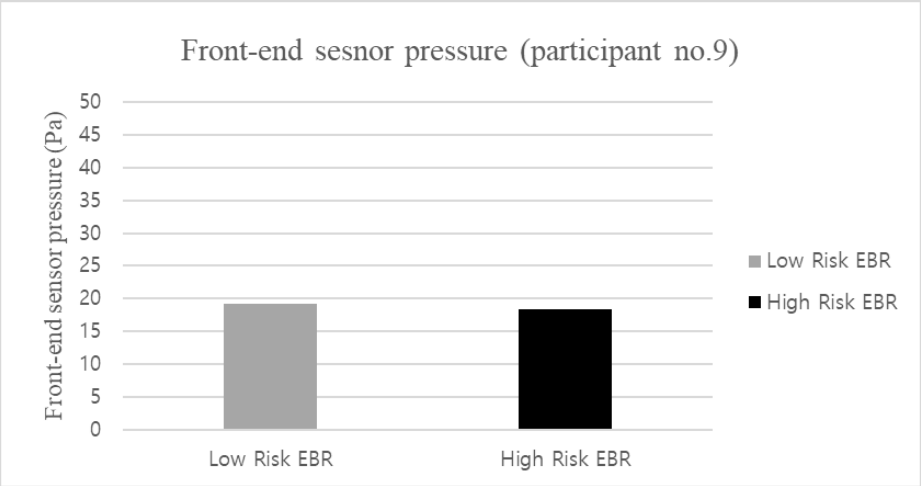

Front-end sesnor pressure (participant no.4)
Front-end sensor pressure (Pa)
50
45
40
35
30
25
20
15
10
5
0
Low Risk EBR
High Risk EBR
Low Risk EBR
High Risk EBR

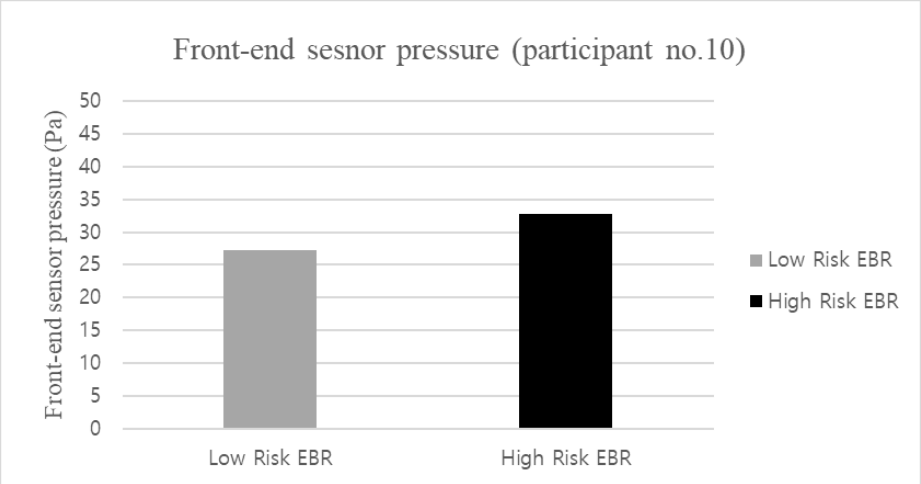

Front-end sesnor pressure (participant no.5)
Front-end sensor pressure (Pa)
50
45
40
35
30
25
20
15
10
5
0
Low Risk EBR
High Risk EBR
Low Risk EBR
High Risk EBR

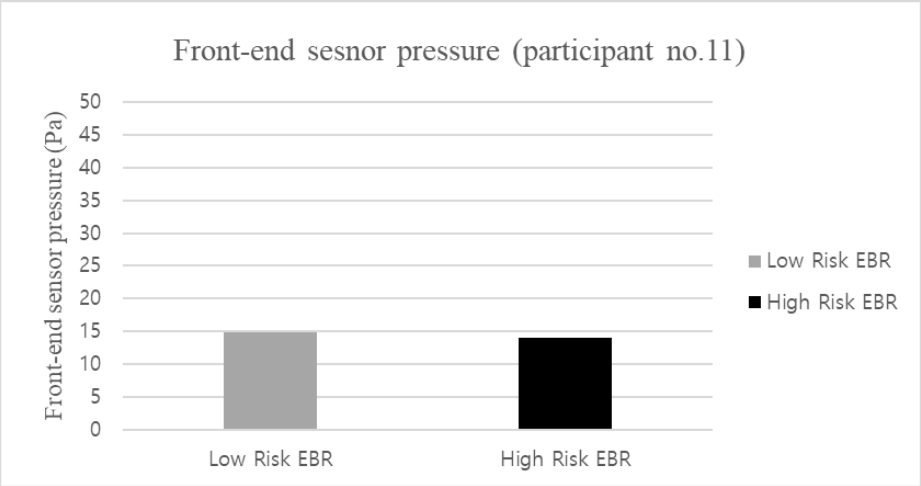

Front-end sesnor pressure (participant no.6)
Front-end sensor pressure (Pa)
50
49
48
47
46
45
44
43
42
Low Risk EBR
High Risk EBR
Low Risk EBR
High Risk EBR

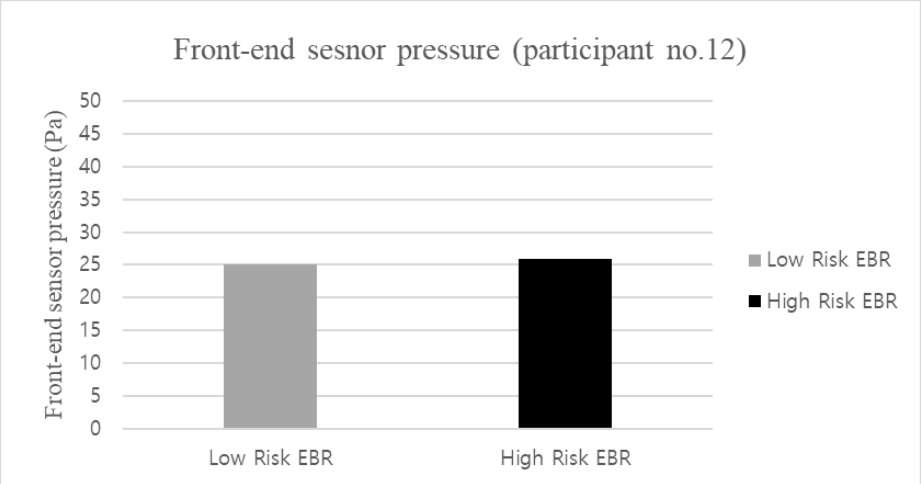

Front-end sesnor pressure (participant no.7)
Front-end sensor pressure (Pa)
50
45
40
35
30
25
20
15
10
5
0
Low Risk EBR
High Risk EBR
Low Risk EBR
High Risk EBR

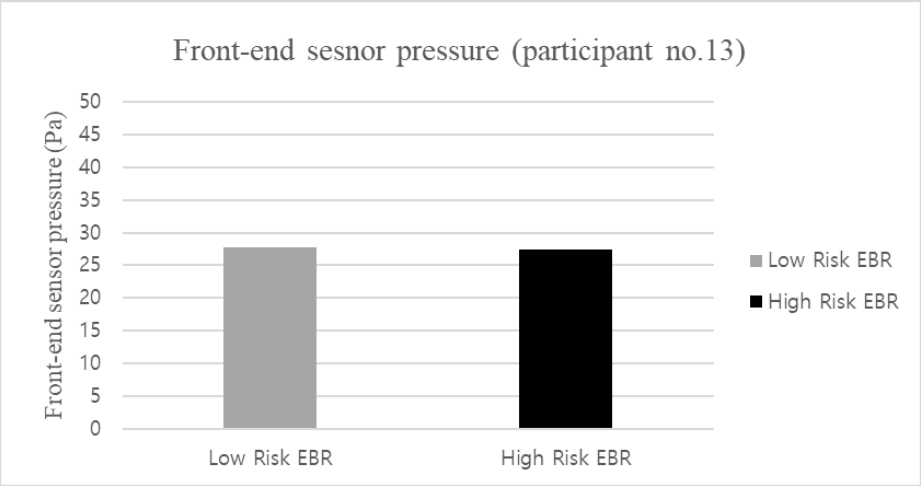

Front-end sesnor pressure (participant no.8)
Front-end sensor pressure (Pa)
50
45
40
35
30
25
20
15
10
5
0
Low Risk EBR
High Risk EBR
Low Risk EBR
High Risk EBR

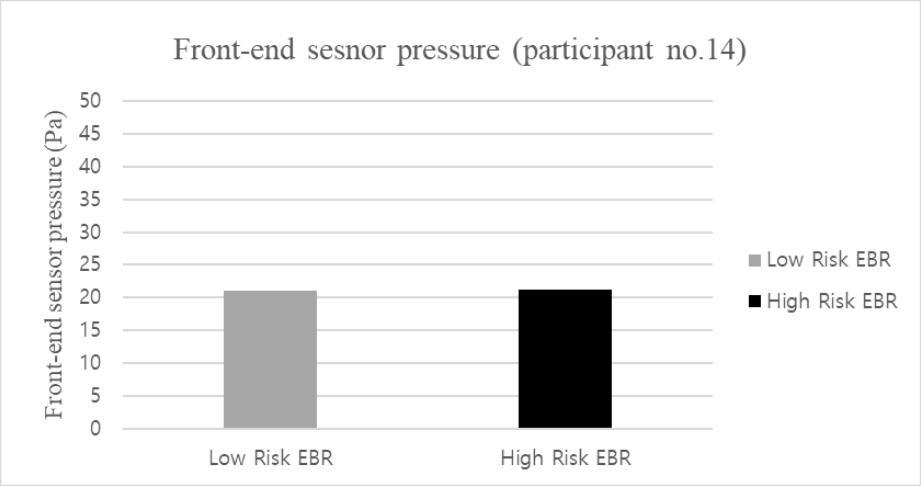

Front-end sesnor pressure (participant no.9)
Front-end sensor pressure (Pa)
50
45
40
35
30
25
20
15
10
5
0
Low Risk EBR
High Risk EBR
Low Risk EBR
High Risk EBR

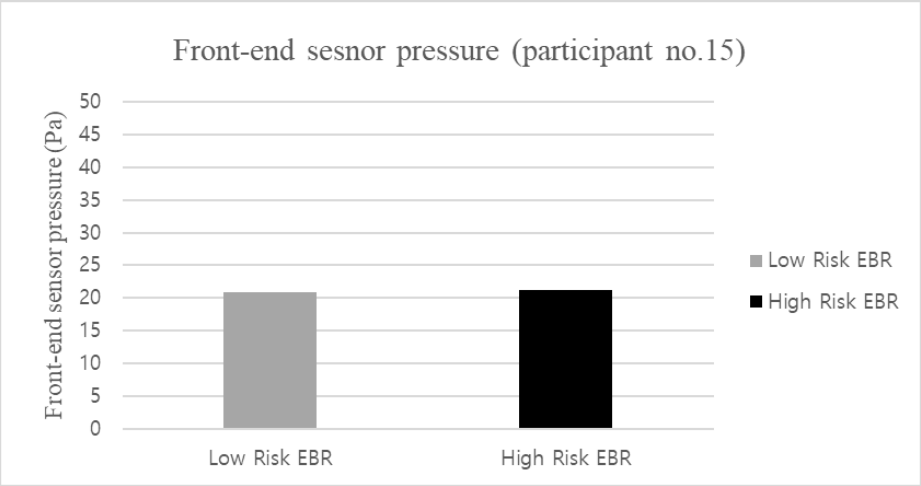

Front-end sesnor pressure (participant no.10)
Front-end sensor pressure (Pa)
50
45
40
35
30
25
20
15
10
5
0
Low Risk EBR
High Risk EBR
Low Risk EBR
High Risk EBR

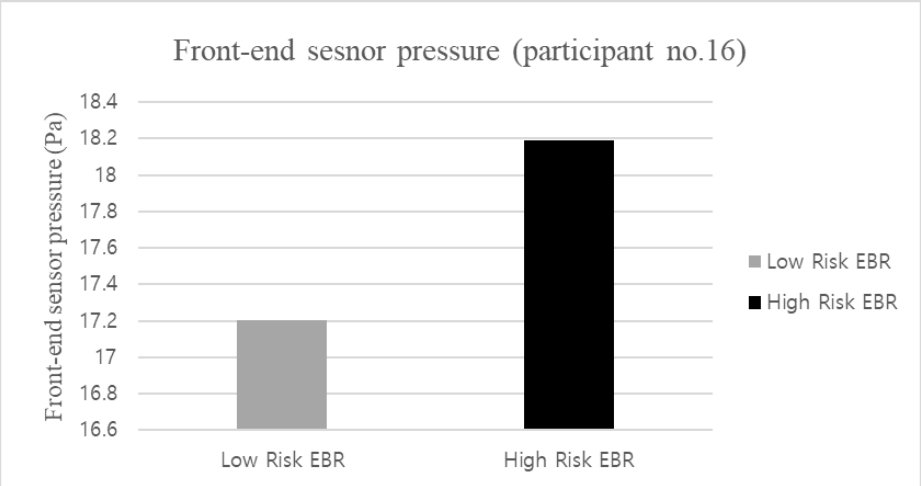

Front-end sesnor pressure (participant no.11)
Front-end sensor pressure (Pa)
50
45
40
35
30
25
20
15
10
5
0
Low Risk EBR
High Risk EBR
Low Risk EBR
High Risk EBR

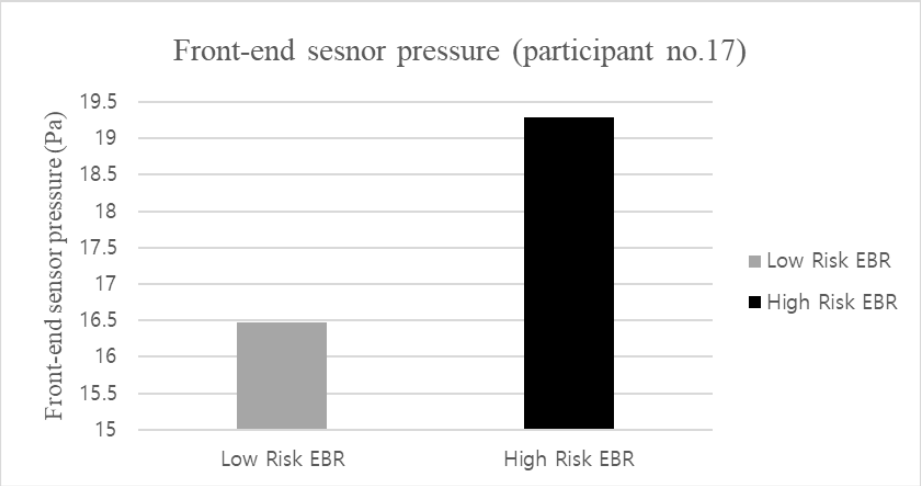

Front-end sesnor pressure (participant no.12)
Front-end sensor pressure (Pa)
50
45
40
35
30
25
20
15
10
5
0
Low Risk EBR
High Risk EBR
Low Risk EBR
High Risk EBR

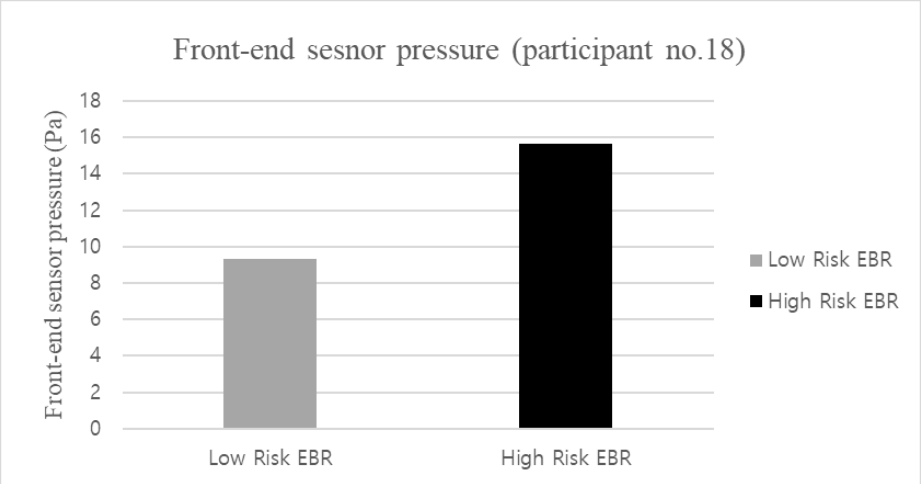

Front-end sesnor pressure (participant no.13)
Front-end sensor pressure (Pa)
50
45
40
35
30
25
20
15
10
5
0
Low Risk EBR
High Risk EBR
Low Risk EBR
High Risk EBR

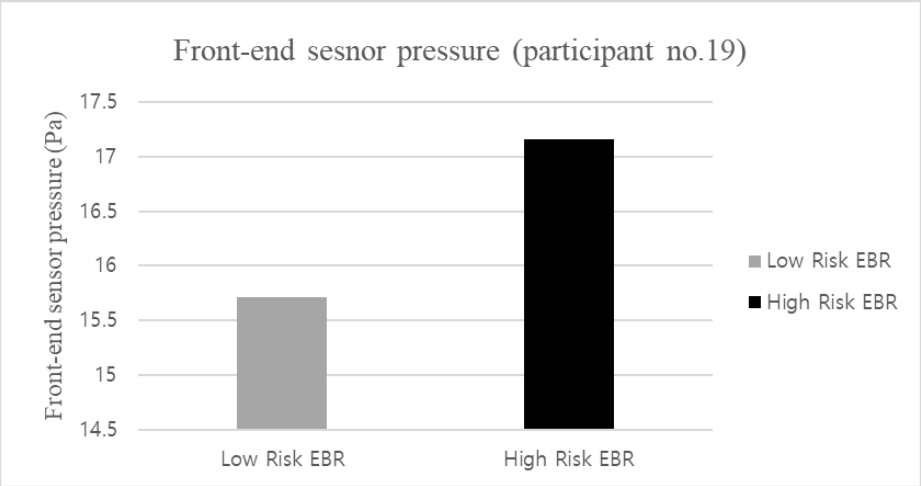

Front-end sesnor pressure (participant no.14)
Front-end sensor pressure (Pa)
50
45
40
35
30
25
20
15
10
5
0
Low Risk EBR
High Risk EBR
Low Risk EBR
High Risk EBR

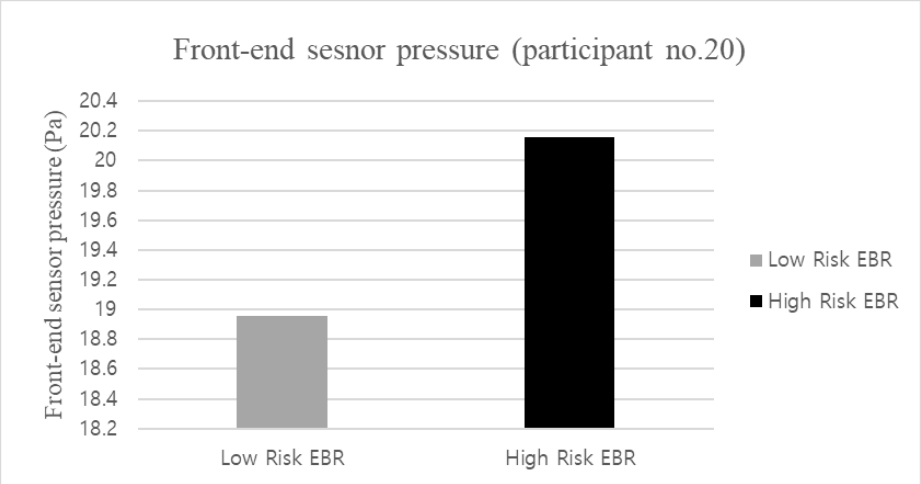

Front-end sesnor pressure (participant no.15)
Front-end sensor pressure (Pa)
50
45
40
35
30
25
20
15
10
5
0
Low Risk EBR
High Risk EBR
Low Risk EBR
High Risk EBR


Front-end sesnor pressure (participant no.16)
Front-end sensor pressure (Pa)
18.4
18.2
18
17.8
17.6
17.4
17.2
17
16.8
16.6
Low Risk EBR
High Risk EBR
Low Risk EBR
High Risk EBR

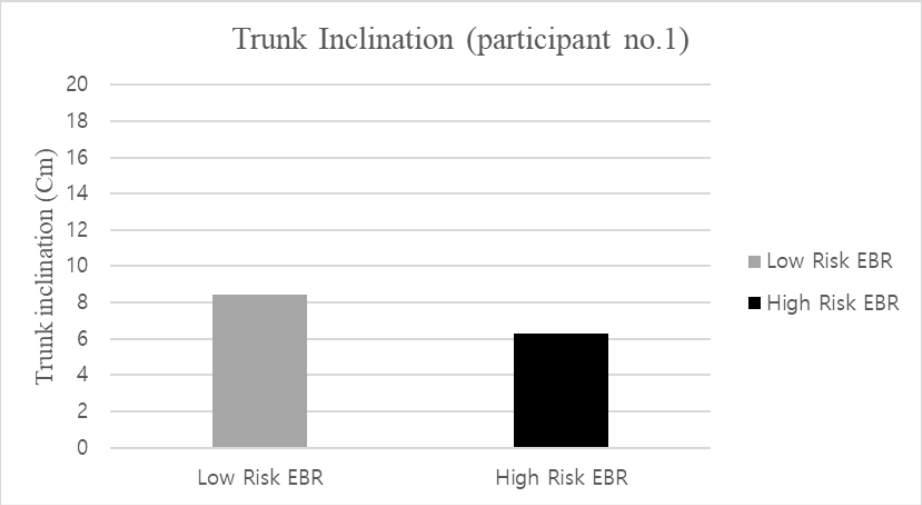

Front-end sesnor pressure (participant no.17)
Front-end sensor pressure (Pa)
19.5
19
18.5
18
17.5
17
16.5
16
15.5
15
Low Risk EBR
High Risk EBR
Low Risk EBR
High Risk EBR

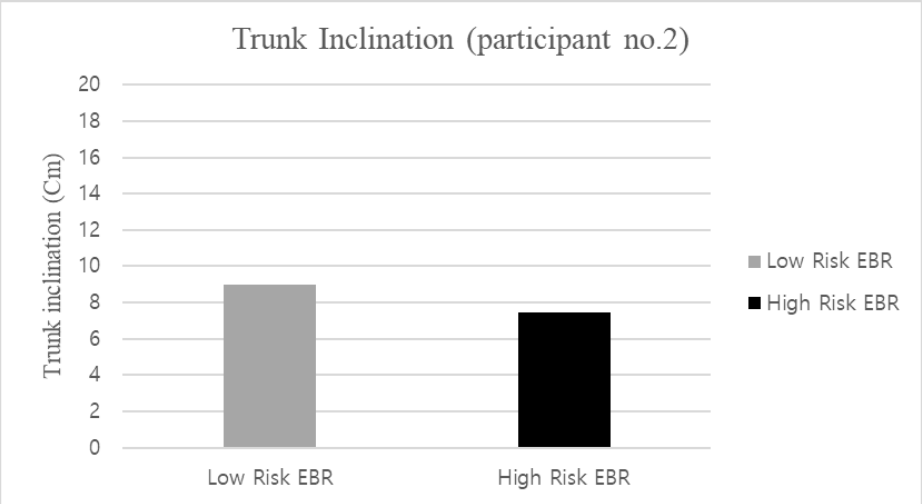

Front-end sesnor pressure (participant no.18)
Front-end sensor pressure (Pa)
18
16
14
12
10
8
6
4
2
0
Low Risk EBR
High Risk EBR
Low Risk EBR
High Risk EBR

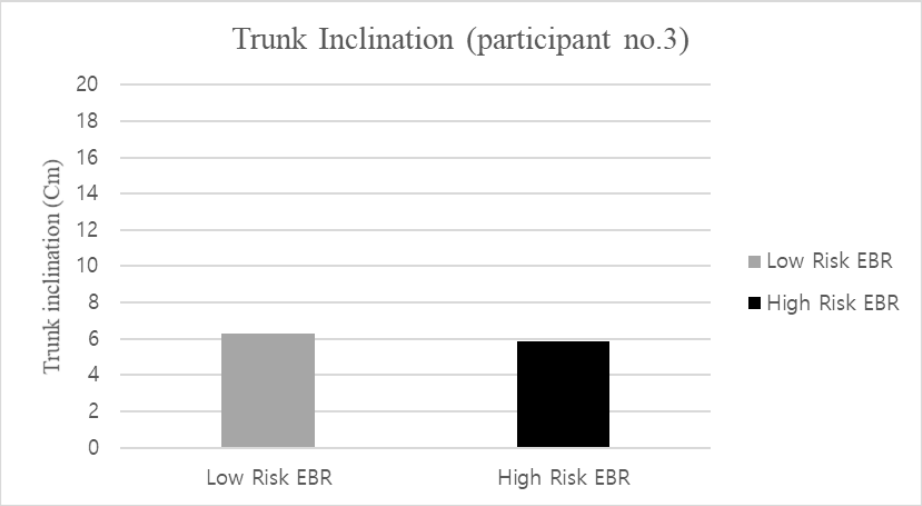

Front-end sesnor pressure (participant no.19)
Front-end sensor pressure (Pa)
17.5
17
16.5
16
15.5
15
14.5
Low Risk EBR
High Risk EBR
Low Risk EBR
High Risk EBR

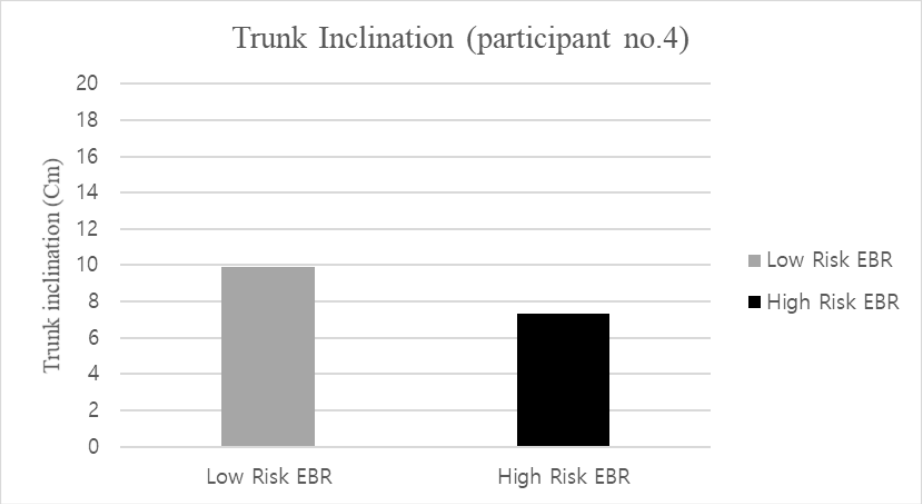

Front-end sesnor pressure (participant no.20)
Front-end sensor pressure (Pa)
20.4
20.2
20
19.8
19.6
19.4
19.2
19
18.8
18.6
18.4
18.2
Low Risk EBR
High Risk EBR
Low Risk EBR
High Risk EBR

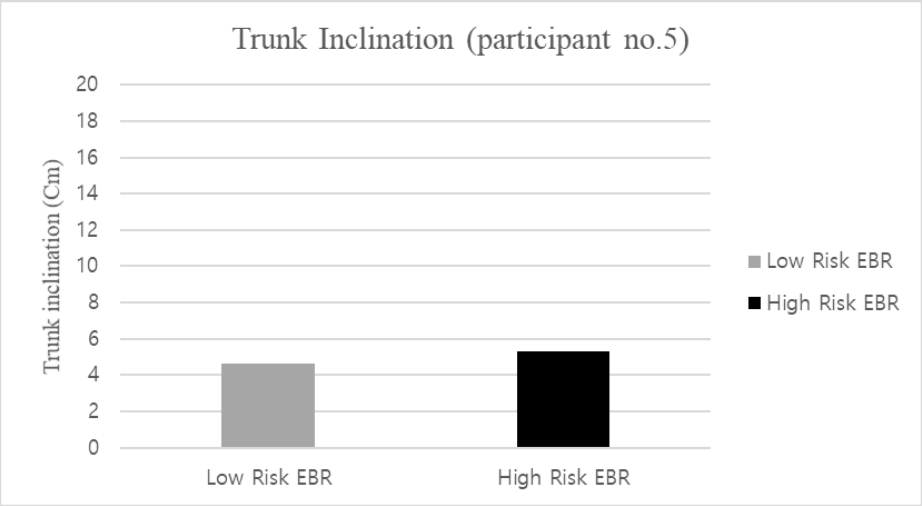
Appendix C: Trunk inclination by participants

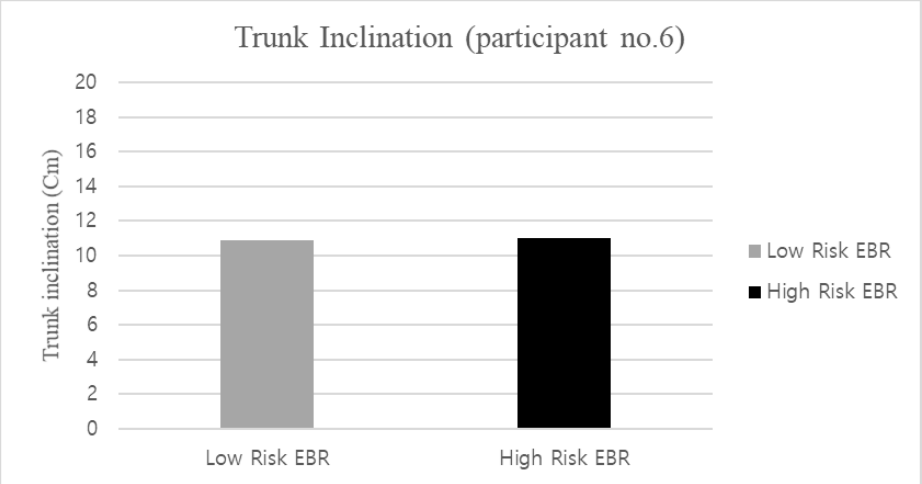


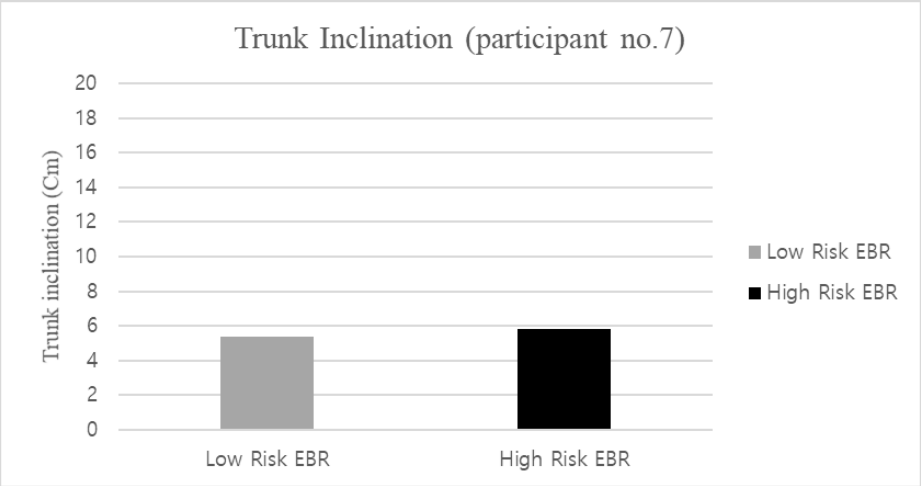


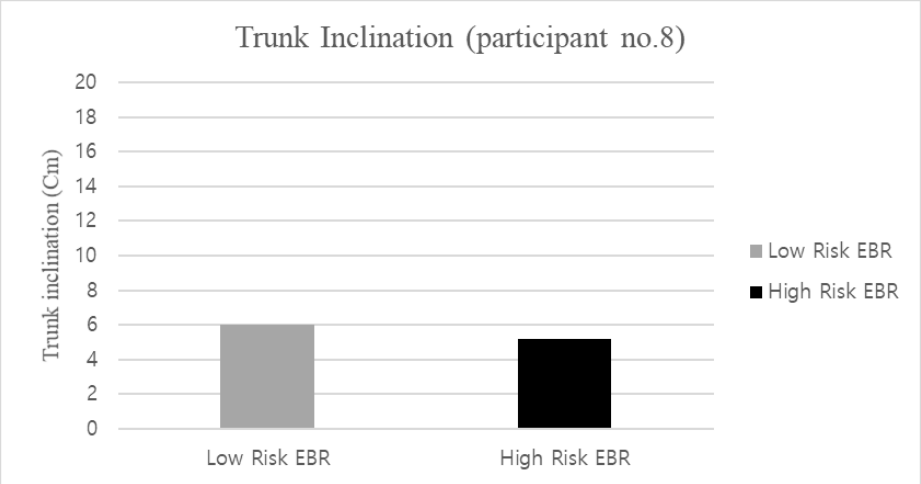

Trunk Inclination (participant no.3)
Trunk inclination (Cm)
20
18
16
14
12
10
8
6
4
2
0
Low Risk EBR
High Risk EBR
Low Risk EBR
High Risk EBR

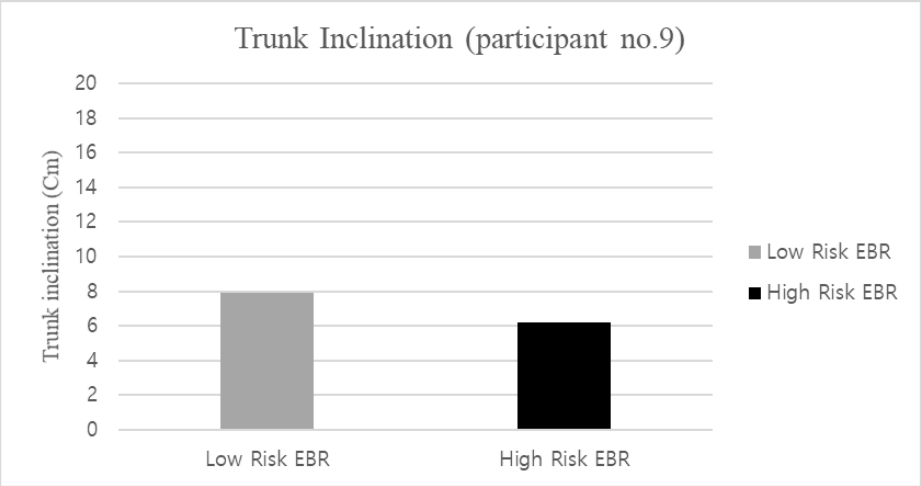

Trunk Inclination (participant no.4)
Trunk inclination (Cm)
20
18
16
14
12
10
8
6
4
2
0
Low Risk EBR
High Risk EBR
Low Risk EBR
High Risk EBR

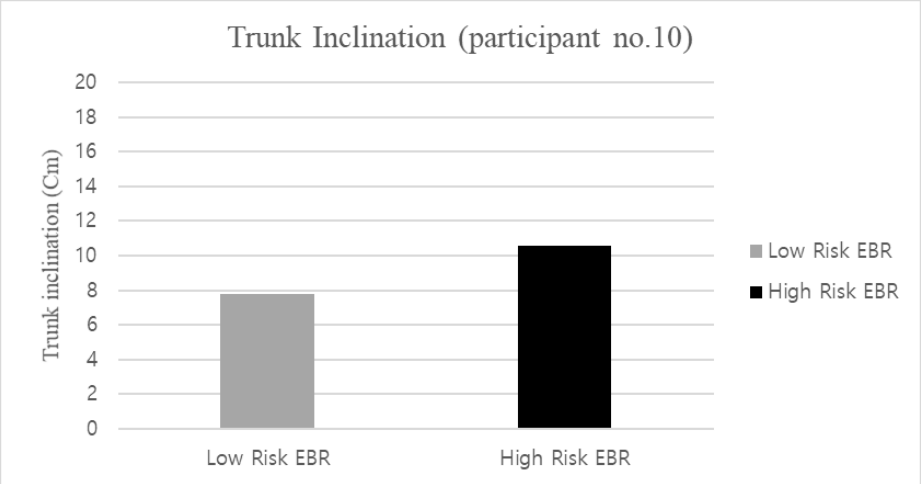

Trunk Inclination (participant no.5)
Trunk inclination (Cm)
20
18
16
14
12
10
8
6
4
2
0
Low Risk EBR
High Risk EBR
Low Risk EBR
High Risk EBR

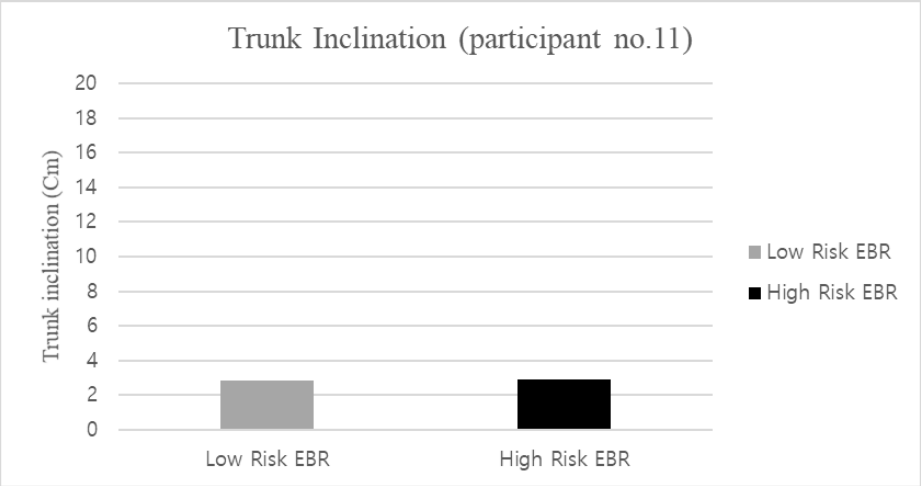

Trunk Inclination (participant no.6)
Trunk inclination (Cm)
20
18
16
14
12
10
8
6
4
2
0
Low Risk EBR
High Risk EBR
Low Risk EBR
High Risk EBR

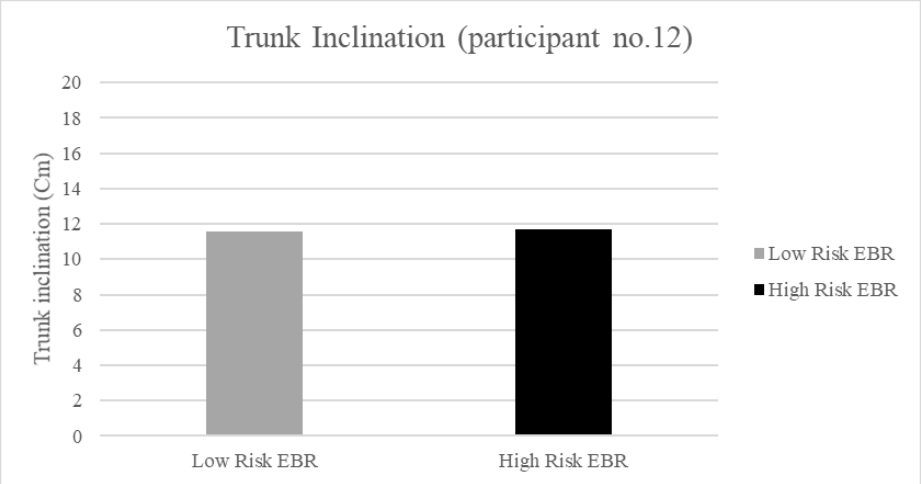

Trunk Inclination (participant no.7)
Trunk inclination (Cm)
20
18
16
14
12
10
8
6
4
2
0
Low Risk EBR
High Risk EBR
Low Risk EBR
High Risk EBR

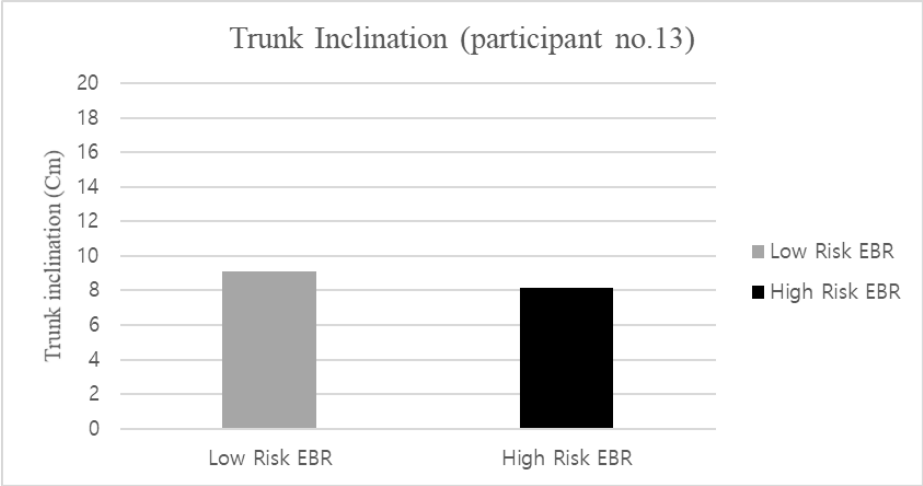

Trunk Inclination (participant no.8)
Trunk inclination (Cm)
20
18
16
14
12
10
8
6
4
2
0
Low Risk EBR
High Risk EBR
Low Risk EBR
High Risk EBR

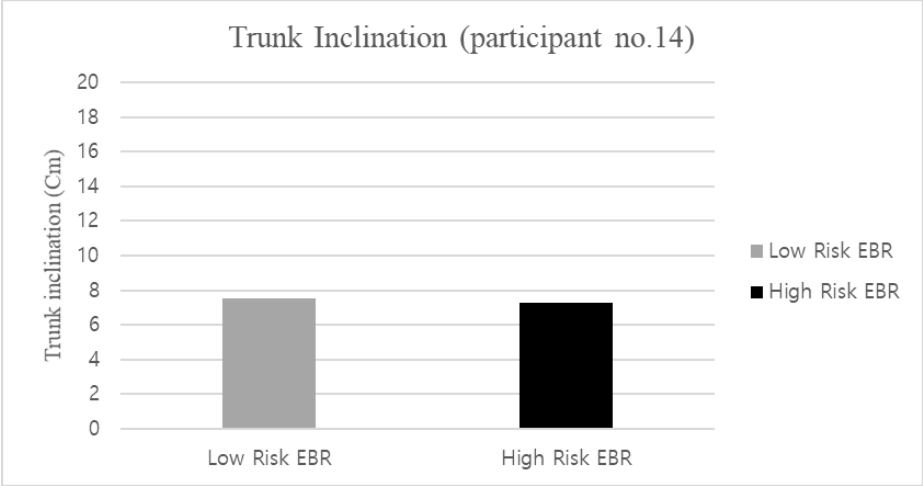

Trunk Inclination (participant no.9)
Trunk inclination (Cm)
20
18
16
14
12
10
8
6
4
2
0
Low Risk EBR
High Risk EBR
Low Risk EBR
High Risk EBR

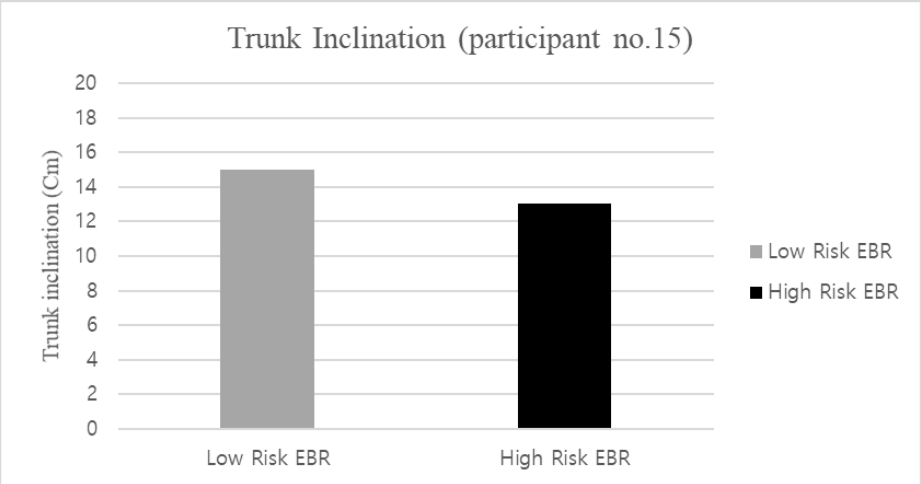

Trunk Inclination (participant no.10)
Trunk inclination (Cm)
20
18
16
14
12
10
8
6
4
2
0
Low Risk EBR
High Risk EBR
Low Risk EBR
High Risk EBR

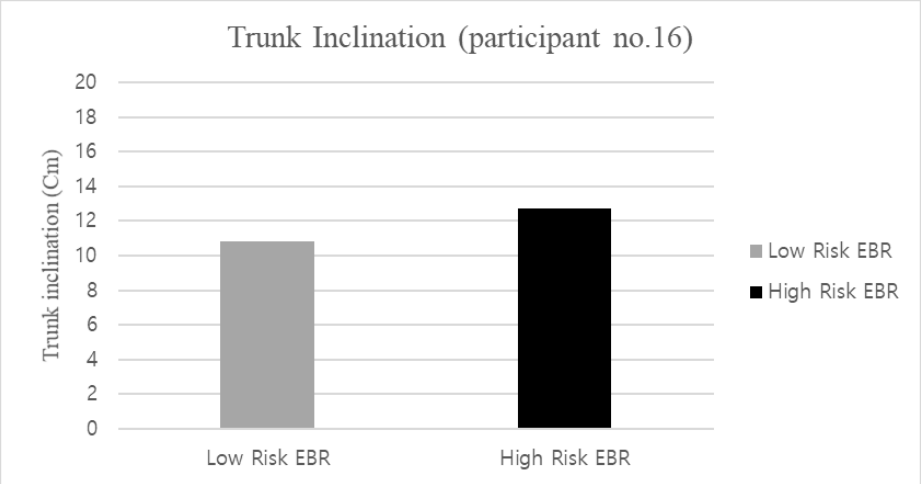

Trunk Inclination (participant no.11)
Trunk inclination (Cm)
20
18
16
14
12
10
8
6
4
2
0
Low Risk EBR
High Risk EBR
Low Risk EBR
High Risk EBR

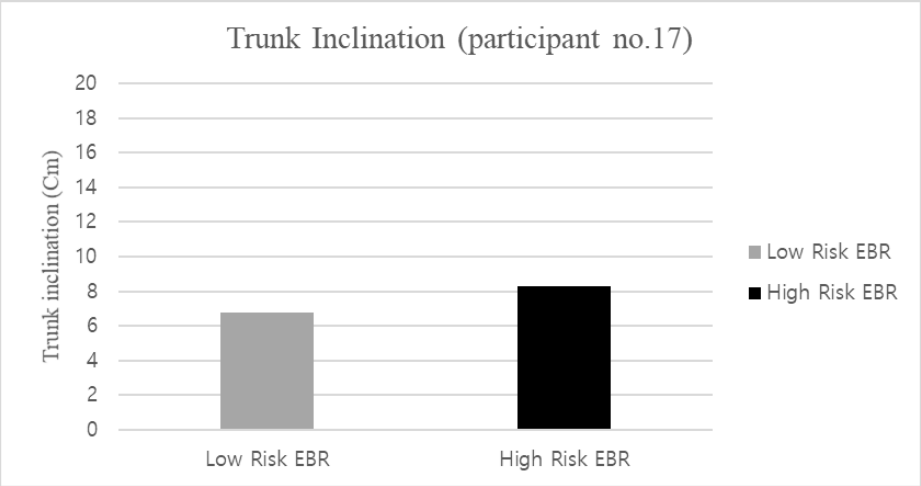

Trunk Inclination (participant no.12)
Trunk inclination (Cm)
20
18
16
14
12
10
8
6
4
2
0
Low Risk EBR
High Risk EBR
Low Risk EBR
High Risk EBR

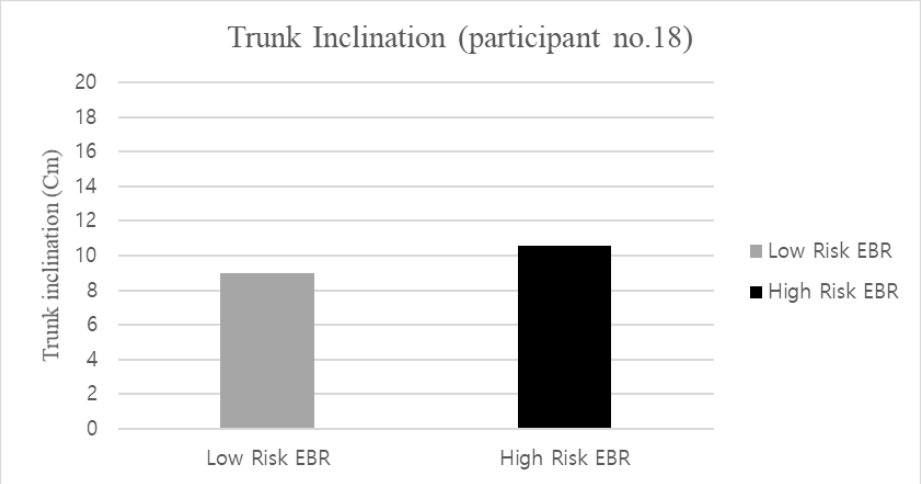

Trunk Inclination (participant no.13)
Trunk inclination (Cm)
20
18
16
14
12
10
8
6
4
2
0
Low Risk EBR
High Risk EBR
Low Risk EBR
High Risk EBR

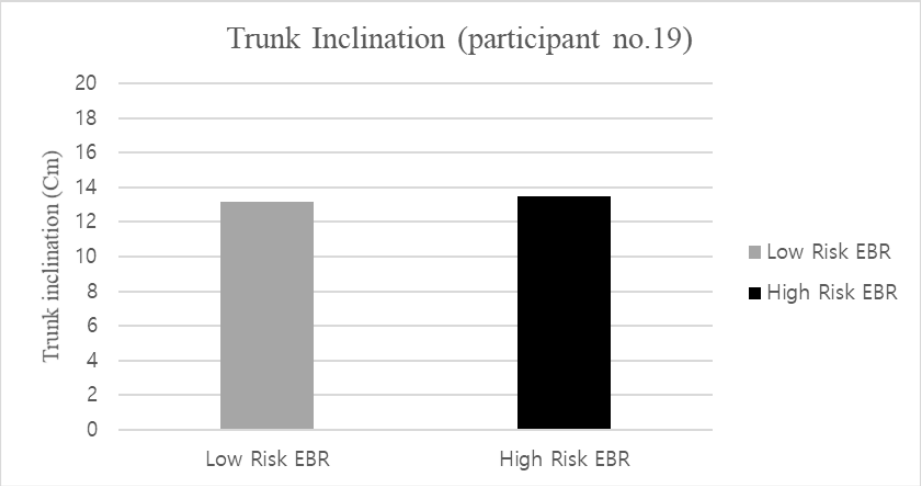

Trunk Inclination (participant no.14)
Trunk inclination (Cm)
20
18
16
14
12
10
8
6
4
2
0
Low Risk EBR
High Risk EBR
Low Risk EBR
High Risk EBR

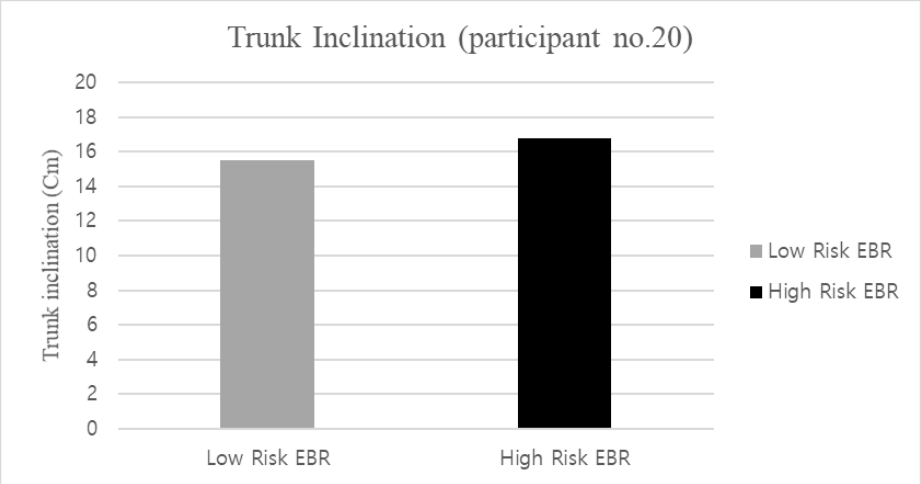

Trunk Inclination (participant no.15)
Trunk inclination (Cm)
20
18
16
14
12
10
8
6
4
2
0
Low Risk EBR
High Risk EBR
Low Risk EBR
High Risk EBR


Trunk Inclination (participant no.16)
Trunk inclination (Cm)
20
18
16
14
12
10
8
6
4
2
0
Low Risk EBR
High Risk EBR
Low Risk EBR
High Risk EBR


Trunk Inclination (participant no.17)
Trunk inclination (Cm)
20
18
16
14
12
10
8
6
4
2
0
Low Risk EBR
High Risk EBR
Low Risk EBR
High Risk EBR


Trunk Inclination (participant no.18)
Trunk inclination (Cm)
20
18
16
14
12
10
8
6
4
2
0
Low Risk EBR
High Risk EBR
Low Risk EBR
High Risk EBR


Trunk Inclination (participant no.19)
Trunk inclination (Cm)
20
18
16
14
12
10
8
6
4
2
0
Low Risk EBR
High Risk EBR
Low Risk EBR
High Risk EBR


Trunk Inclination (participant no.20)
Trunk inclination (Cm)
20
18
16
14
12
10
8
6
4
2
0
Low Risk EBR
High Risk EBR
Low Risk EBR
High Risk EBR

ABSTRACT

Determining Eye Blink Rate Level Utilizing Sitting Postural Behavior Data

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Dry eye syndrome (DES) affects many white-collars workers worldwide. Though it is known that low eye blink rate (EBR) is associated with the risk of DES, it is difficult to improve EBR through self-correction. One way to increase EBR is to warn the worker of low EBR using an external system. Existing EBR measurement devices have limitations, such as physical discomfort or invasiveness, which hinder their acceptance. For a solution that overcomes these limitations, this study aimed to develop a classification

system that differentiates the levels of EBR using posture and postural variability data obtained from chair-embedded distance and pressure sensors. Additionally, this study attempted to investigate the relationship between EBR, posture, and postural variability. Participants completed three seated computer tasks, in which eye blink and postural sensor data were collected. The EBR classification system was developed by using a machine learning method; the accuracy of the EBR classification system was 93% across the three task types and study participants. The low EBR level was found to be associated with smaller postural variability and a tendency for the worker to hold a forward-leaning sitting posture. The EBR classification system developed in this study is expected to contribute to the prevention of DES.

Keywords: machine learning, dry eye syndrome, eye blink rate, smart chair, posture

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