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Exploring the Correlation Between Attention and Cognitive Load Through Association Rule Mining by Using a Brainwave Sensing Headband

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ABSTRACT In recent years, Internet of Things (IoT) technology has brought many applications and developments for wearable devices, and the use of non-invasive electroencephalography (EEG) instruments to measure attention has been a topic of discussion. However, the correlation between attention and cognitive load has rarely been analyzed by data mining. For this reason, this study used head-mounted non-invasive EEG instruments based on IoT technology to collect attention values related to two courses and extracurricular activities and used a cognitive load questionnaire to investigate the cognitive loads of subjects. Correlation analysis was carried out through data mining technology to find the correlation between attention and cognitive load. In addition, six short-term experiments and relaxation experiments were designed to measure the subjects' maximum attention and minimum attention values, so as to propose a strategy for setting the attention baseline. According to the results of the various experiments, subjects suffering from overload showed a state of inattention during the whole activity while subjects suffering a high load showed low sustained attention; only subjects with a medium load showed high sustained attention. Subjects with a low load showed inattention for nearly the entire activity. In this study, a strategy for setting an attention baseline was proposed to normalize the attention values from different EEG instruments. The correlation between attention value and cognitive load is analyzed using association rule mining technology so that the change of cognitive load could be effectively estimated by measuring the attention value instead of using questionnaire in the future.

I. INTRODUCTION

In an era of booming information, IoT technology enables independent subjects to communicate with each other through the Internet. Meanwhile, it has also been applied to the issue of Smart Cities for extensive research [1], making IoT one of the important developments in the information technology era [2] and a hot topic of academic research in recent years [3], [4]. The technology of IoT is not yet mature, and the physiological signal tools for measuring electroencephalography (EEG) are mostly conductive jelly, electrode caps, amplifier unit, and other equipment [5], thus limiting the methods of measuring EEG. However, today's

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IoT technology can be used to develop mobile wearable instruments through the Internet or wireless transmission. Wearable EEG instruments could solve many equipment and environmental limitations and provide many potential benefits when measuring brain wave signals [6]. In addition, some researchers have shown the feasibility of using low-cost wearable EEG to measure brain wave signals [7]. These wearable EEG instruments measure five wavelengths in the human brain with different channel numbers and contact points. The most commonly used EEG measurement topic is attention [8]. Apart from measuring attention through EEG, previous researchers also explored the relationship between attention and cognitive load [9].

This study found that in previous studies, attention was mostly measured by EEG instruments, while cognitive load

was studied through questionnaires. The association between attention and cognitive load was rarely studied through data mining. In addition, most studies only measured the attention value or calculated average value, but there was no research definition on how to measure attention and inattention. Since the values obtained by different wearable EEG instruments will vary slightly, this study used six mini-games and a one-minute relaxation experiment to measure the maximum attention and minimum attention of the subjects. Through this experimental design, it could be ensured that when different instruments were used, the maximum attention and minimum attention measured by each wearable EEG instrument could also be accurately determined. According to the maximum attention value and the minimum attention value, this study defined the attention baseline of a used wearable EEG instrument. Based on this baseline, the standards for ''attention'' and ''inattention'' could be defined. In addition, this study analyzed the association between attention and cognitive load through data mining based on association rules mining technology. In this study, cognitive load was divided into low load, medium load, and high load. Through two courses, multiple classroom experiments were conducted, and data were collected to analyze the association rules between attention and three different levels of cognitive load. Apart from exploring the association between attention and cognitive load, this study also designed an overload experiment to explore the change of attention and the association rules when a subject was faced with higher pressure caused by teaching materials.

This study held that although expensive EEG instruments can measure brain wave signals more accurately, the measurement will be limited to a fixed environment due to large-size instruments, meaning that subjects cannot be measured in a real classroom or study environment. Undoubtedly, it is difficult to replicate various stimuli in a real environment when conducting experiments in laboratories, and the measured attention value may be different from that in a real environment. IoT technology enables wearable EEG instruments that could solve the problems of environmental limitation and high price. However, in order to avoid variations in the measured values of different wearable EEG instruments, this study proposed a strategy to establish a baseline of attention. Through this strategy, the attention values obtained by different wearable EEG instruments could be normalized to avoid the influence of different instruments.

Moreover, most of the current methods for measuring cognitive load are based on a cognitive load questionnaire, and no instrument can directly measure cognitive load. However, the use of cognitive load questionnaires will vary depending on the responses of different respondents. In the process of an event, cognitive load may not maintain a fixed load, therefore subjects will be unable to answer a cognitive load questionnaire carefully at each time interval. If the association between attention and cognitive load can be analyzed, the change of cognitive load may be inferred from the change of attention value in the future. Therefore, this study used data mining based on association rules mining technology

to identify the association between attention and cognitive load. In the future, the association rules after mining could be used to predict cognitive load at different time intervals, which could indirectly enable cognitive load to be objectively quantified instead of relying on the subjective measurement method of a cognitive load questionnaire.

The remainder of this paper is organized as follows. Section 2 reviews and discusses the relevant theoretical background; Section 3 introduces the research methods, including the wearable EEG instruments used in this study, the experimental design of maximum attention and minimum attention, the definition of attention baseline, the design of the classroom experiment and overload experiment, and the analysis and design of association rules mining; Section 4 describes the analysis and interpretation of the association rules and rules data after mining and analysis using association rules; and Section 5 is the discussion and summary of this study.

II. LITERATURE REVIEW
A. INTERNET OF THINGS IN ELECTROENCEPHALOGRAPHY

IoT consists of a variety of objects which are interconnected through either wired or wireless networks [10]. There are several interesting applications to extract information from the massive raw data captured by IoT devices [11]. In recent years, because of the rise of IoT technology, wearable devices for measuring EEG physiological signals have been developed. Xu et al. used sample entropy algorithm to analyze the EEG signals in both sober and fatigue state. In this research, mental fatigue is measured by filling out the subjective fatigue scale [12]. Li et al. introduced an attention-controlled wrist rehabilitation method to realize active rehabilitation training using a low-cost EEG sensor [7]. Kuo et al. used MindSet headset for detecting attention to investigate the participants' learning achievements and learning attitudes in an English listening course [13]. However, Tsai et al. indicated that the massive data captured by IoT becomes a serious problem. Data mining will no doubt play a critical role to provide more convenient services and shift to the next generation internet environment [14].

B. ASSOCIATION RULES MINING

Association rules are frequent patterns occurring frequently in massive data and satisfy a user-specified minimum support and a user-specified minimum confidence. In Agrawal et al.'s study, the authors introduced Apriori algorithm to discover association rules between items in a large database of sales transactions [15]. In addition to widely applied in e-commerce, association rules mining also has been adopted to other research areas in recent years. Cheng el al. proposed association rule-based similarity (ARBS) for a plant search system and proved that calculating the similarity among plant features through association rules can greatly increase accuracy [16]. For the discovery of contextual association rules, Luna et al. proposed a grammar-based

genetic programming methodology that automatically identifies context-aware associations in the application of educational data mining [17]. Simon et al. applied association rule mining to electronic medical records (EMR) to discover sets of risk factors of developing diabetes and proposed new patterns of conditions for prevention, management, and treatment approaches [18]. To extract frequent paths during the whole time period from massive taxi trajectory data, Yu et al.'s study proposed the techniques of network analysis and association rules [19]. Moreover, many other researches implement association rule mining to extract valuable information from massive data [20]–[25].

According to the above, it can be known that the application of the association rule mining is very common. However, it is found that the correlation between attention and cognitive load are rarely investigated by wearable devices. In this research, an association rule mining approach to explore the correlation between attention and cognitive load is proposed using a brainwave sensing headband. Using the explored association rules, one's cognitive load can be inferred by measuring his/her attention.

III. RESEARCH METHOD

Current technology can measure the attention value with instruments, however there is no instrument that can directly measure cognitive load level. Relevant researches have measured the cognitive load level of subjects through a cognitive load questionnaire. In this study, attention values obtained by wearable EEG instruments were collected, and attention baseline was defined by the experimental design for the maximum attention degree and minimum attention degree. The cognitive load of students in different tasks was collected through a cognitive load questionnaire, and the association rules between attention value and cognitive load were analyzed through association rules mining technology, including the association rules between attention and overload.

A. RESEARCH INSTRUMENTS

The types of brain wave signals were divided into five wavelengths [26]. Casson et al. pointed out that wearable EEG will be one of the necessary instruments for measuring EEG in the future [27]. This study used BrainLink Lite, a head-mounted non-invasive EEG instrument – BrainLink Lite (as shown in Figure 1) [7]. This instrument can capture brain wave signals (as shown in Figure 2) through a Bluetooth transmission module and a non-invasive dry electrode sensor on the forehead, and it can process and output the attention index and relaxation index of brain waves. Every brain wave signal received per second is received as a record, and the processed values of the attention index and relaxation index range from 1 to 100. The head-mounted non-invasive EEG instrument measures and records the attention value every second. In addition, Picton pointed out that with the occurrence of different events, the measured EEG signals will also show fluctuations in potentials with time, which are called event-related potentials (ERPs) [28]. In the measurement process

FIGURE 1. Schematic diagram of wearable Brainlink Lite.

FIGURE 2. Head-mounted non-invasive EEG instrument-BrainLink Lite.

of this study, it was seen that the attention value showed different responses per second along with the thinking activities of the brain, therefore the attention value would not be maintained continuously at the same value. Since this study did not focus on studying the changes and significance of the subjects' brains in a short time but rather explored the attention value and load of the subjects' learning process, the duration of the task and the degree of attention could not only be discussed using seconds as the time unit. Hence, this study took every minute as an interval, and calculated the attention value every 60 seconds to reach the average attention for each minute. Figure 3 illustrates the system architecture in this study. The wearable BrainLink Lite transmits data to a laptop via Bluetooth and then the laptop uploads the collected data to the server for data pre-processing and association rule mining.

This study referred to cognitive load theory to design a cognitive load questionnaire [29]–[31]. The cognitive load questionnaire consisted of four items, each of which was given a score of one to seven points, in order from simple (one point) to difficult (seven points). After collecting the questionnaire data, the cognitive load degree was divided into three levels: low load, medium load, and high load.
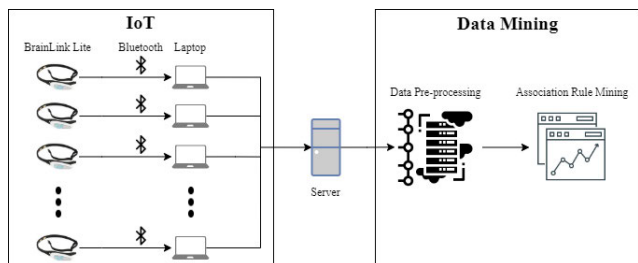
FIGURE 3. System architecture diagram of this study.

B. EXPERIMENTS DESIGN

Since the values measured by different wearable EEG instruments may vary slightly, two short-term experiments were designed in this study, corresponding to the maximum attention degree and the minimum attention respectively, to measure the maximum attention value and the minimum attention value using BrainLink Lite. This study defined the attention baseline according to the maximum attention value and the minimum attention value measured in the two experiments. According to this attention baseline, if the average attention value of the tested data was greater than the attention baseline, this interval would be defined as ''attention''. On the contrary, if the average attention value was less than the attention baseline, this interval would be defined as ''inattention''. In this way, the level of attention could be normalized without being limited by the fact that the values measured by different instruments could not be directly compared with each other. Besides, in order to widely collect the data of subjects with different loads, this study collected the attention data of two different courses and the data of the cognitive load questionnaire, as well as overload data during off-class periods. The following section introduces the different experimental designs in sequence.

1) THE MAXIMUM ATTENTION VALUE AND MINIMUM ATTENTION VALUE

To explore the maximum attention value and minimum attention value measured by BrainLink Lite, six short-term experiments were designed to measure the maximum attention value of the subjects. The minimum attention value was measured by a short-term relaxation experiment. Table 1 shows the six short-term tasks used to measure the maximum attention value. Each experiment lasted for one minute.

Each of the above experiments separately measured the subjects' attention value for one minute, and each subject completed six experiments. This experiment measured the maximum attention that the subjects could achieve in a short time. The short-term relaxation experiment was intended to measure the minimum attention degree of the subjects when they were not stimulated by the external environment and were not conducting any thinking activities, including not reminding themselves to relax. The time of the relaxation experiment was one minute.

TABLE 1. Introduction to the maximum attention experiment.

#	Experiment introduction
Experiment 1	This experiment included five questions. Each question consisted of ten consecutive English letters, such as CDEFGHIJKL, or OPQRSTUVWX, etc. Each item was read by subjects one time. They read the English letters of each question in sequence from the first letter to the tenth letter, and then read backwards in sequence to the first letter from the tenth letter. After completing one question, the subjects moved on to the next question in Experiment 1, until the end of one minute.
Experiment 2	This experiment included five questions. Each question included two groups of seven-digit numbers. For example, 6554321 + 8867999, or 5668745 + 7857966, etc. During the experiment, one question was randomly selected. As the addition was simple, two groups of numbers were separated when the question was given. The subjects were required to add the two groups of numbers on the left and right respectively. After completing one question, the subjects moved on to the next question in Experiment 2, until the end of one minute.
Experiment 3	This experiment included five questions. Each question was taken from Chinese Tang poetry and each question included ten Chinese characters. The subjects were only allowed to read it once. Then, they were required to read the Tang poetry of each question in sequence from the first Chinese character to the tenth Chinese character, and from the tenth Chinese character to the first Chinese character in reverse sequence. After completing one question, the subjects moved on to the next question in Experiment 3, until the end of one minute.
Experiment 4	This experiment included three questions. In each question, the subjects were required to multiply three groups of two-digit numbers, such as: 15 x 19 x 34, or 24 x 21 x 32, etc. During the experiment, one question was randomly selected. The subjects were required to multiply three groups of numbers by mental calculation within one minute. After completing one question, the subjects moved on to the next question in Experiment 4, until the end of one minute.
Experiment 5	This experiment consisted of a small computer game. As shown in Figure 4, the subjects were required to move the yellow circle through the computer mouse to continuously avoid arrows (blue circles) from all directions until the end of one minute.
Experiment 6	This experiment consisted of a small computer game. As shown in Figure 5, questions (red circle) were listed above the figure. The subjects were required to choose the answers to math problems (yellow circle) within one minute.

According to the measurement results of BrainLink Lite used in this study, the maximum attention value measured in the six short-time experiments was 100, and the minimum attention value measured in the short-time relaxation experiments was 11. This showed that the maximum attention
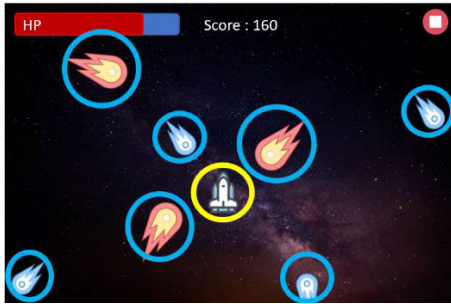
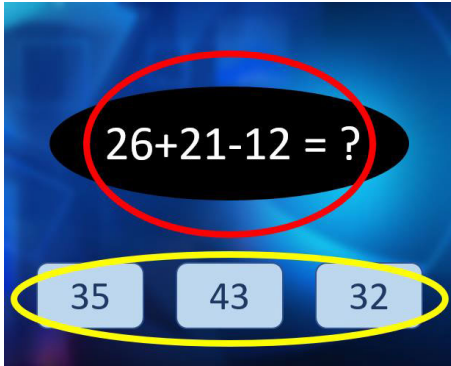**FIGURE 4.** Schematic diagram of the game for Experiment 5.

FIGURE 5. Schematic diagram of the game for Experiment 6.

degree of the subjects could be stimulated to the largest extent through the six short-time experiments. The maximum attention value of BrainLink Lite was 100 and could be measured through this experiment. Moreover, the minimum attention value of BrainLink Lite was one. The purpose of the short-term relaxation experiment was not only to measure the minimum attention value of subjects but to prove that even if subjects did not think at all, their brains would not be completely in a state without current, as found from the measurement results of this emptying experiment. As the minimum attention value measured by BrainLink Lite was 11, the attention degree of the subjects was greater than one, that is, the minimum attention value was not one under a normal relaxation state. Even if the values measured by different instruments varied, the attention value could be normalized to obtain the attention baseline through such experimental design.

2) ATTENTION BASELINE VALUE
In this study, the maximum attention value of 100 and the minimum attention value of 11 were obtained through the above six short-term experiments and a short-term relaxation experiment. Based on equation (1), as shown at the bottom of this page, this study defined the attention baseline and classified the average attention value into ''attention'' and

''inattention'', according to the attention baseline. According to equation (1), the baseline in this study was 55.5. Therefore, if every minute was taken as a time interval, and if the average attention value in this interval was greater than 55.5, the interval would be defined as ''attention''; if the average attention value in this interval was less than 55.5, then the interval would be defined as ''inattention''. This baseline could be used as long as the same instrument was used for experiments; if different instruments were used, the experimental design could be used to obtain the baseline of the instrument.

3) COURSES EXPERIMENT
This study collected the attention data of science and technology English and algorithm courses. The two courses were taught by the same university instructor and the subjects were from the same class. This experiment was a long-term task. The attention data of two science and technology English courses and three algorithm courses were collected every week. In addition, the cognitive load questionnaire found that students with a medium load were the majority, while students with a high load and low load were the minority, indicating that the teaching materials for students in the science and technology English or algorithm courses created loads that could be borne by students.

4) OVERLOAD EXPERIMENT
This study collected data on the overload attention value, which was measured for two minutes during an off-class period. Since the subjects were from information-related departments, non-information-related English academic journal papers were selected for the subjects to read in the overloaded teaching materials, and the teaching materials, as evaluated by experts, were more difficult than the learning materials provided by the classroom experiments.

5) EXTRACURRICULAR ACTIVITIES EXPERIMENT
This study collected the attention data of extracurricular activities. The data were measured in the daily activities of the subjects. The subjects chose the activities they wanted to engage in, such as writing programs, reading books, or playing games, etc. After the measurement, the subjects were asked to fill in the cognitive load questionnaire.

C. ASSOCIATION RULE MINING
This paper studied the association between attention and cognitive load through association of rule data mining. It employed the Apriori algorithm to analyze the association rules of the features shown in Table 2 and mined the association rules of attention and cognitive load to generate relevant combinations of various features. The association rules used

$$Attention\ baseline\ value = \frac{The\ maximum\ attention\ value - The\ minimum\ attention\ value}{2} + The\ minimum\ attention\ value \quad (1)$$

TABLE 2. Introduction to data feature.

Attribute	Description
Cognitive load level	1. Overload 2. High load 3. Medium load 4. Low load
Types of activities	1. Learning category 2. Leisure category
Total time length	1. Long activities (time length ≥30 minutes) 2. Short activities (time length <30 minutes)
Degree of attention	1. Attention (total average attention values ≥ attention baseline) 2. Inattention (total average attention values < attention baseline)
Level of sustained attention	1. High sustained attention 2. Medium sustained attention 3. Low sustained attention
The first inattention segment	Nth segment (average attention value of the segment < attention baseline)

TABLE 3. Overload association rules.

	A→B (A imply B)	Confidence(A→B)
1	Overload→The first segment	100%
2	Overload→Low sustained attention	97%
3	Overload→Inattention	92%
4	Overload→Low sustained attention, The first segment	97%
5	Overload→Low sustained attention, Inattention	92%
…	…	…

in this study are described as follows:

$$Association\ rule = \begin{cases} Support\ (A, B) = P(A \cap B) \\ Confidence\ (A \rightarrow B) = P(B|A) \end{cases} \quad (2)$$

The data feature values of Table 2 are described as follows:

- Cognitive load level: Cognitive load was divided into overload, high load, medium load, and low load, all of which were measured by the cognitive load question-naire.
- Types of activities: This study divided activities into learning category and leisure category.
- Total time length: This study divided the total time length of activities into long activities and short activities, with a length of 30 minutes as the dividing line.
- Degree of attention: This study divided the degree of attention into attention and inattention according to the average attention value.
- Level of sustained attention: According to the subjects' duration of sustained attention, this study divided sustained attention into the three levels of high sustained attention, medium sustained attention, and low sustained attention.
- The first inattention segment: This study divided the duration of each activity into several segments, and found that the first segment in which the average attention value was less than the attention baseline occurred in the Nth segment.

IV. EXPERIMENTAL RESULTS

The experimental activities planned in this study were divided into learning category and leisure category. The learning category activities included science and technology English, algorithm courses, and non-class overload experiments.

The subjects were students from the information engineering department of a university. Two courses were taught by the same teacher. Data on the overload experiment were collected during non-class periods, while data on leisure category activities were collected during daily activities selected by the subjects. Upon completion of each activity, the activity content was recorded, and subjects were asked to fill in the cognitive load questionnaire to record their cognitive load level during the activity.

In this study, the attention data of different activities and the corresponding cognitive load levels were collected, and there were 2,546 items. According to the Apriori algorithm, the association rule was mined. The minimum support in equation (2) was set at 2%, and the minimum confidence was set at 80%. The longest sustained attention time of the subjects measured during the activities in this study was 12 minutes, while the shortest sustained attention time was less than one minute. For exploration, this study divided the time length of the activities into multiple segments, with each segment having a length of three minutes. In this study, if the attention level is greater than attention baseline value and can last for a period, the state of attention is defined as sustained attention. Furthermore, an attention state that lasted for more than six minutes was defined as high sustained attention, an attention state that lasted for three to six minutes was defined as medium sustained attention, and a sustained attention state that lasted for less than three minutes was defined as low sustained attention.

In this study, data mining technology was used to analyze the association rules of the features shown in Table 2 to combine all association rules. However, highly correlated association rules contain fewer valuable and evident rules, therefore this study only provided an analysis of the association rules based on the experimental results.

A. OVERLOAD ASSOCIATION RULES
Overload refers to the load caused by students' inability to understand the meaning of teaching materials with a level of difficulty that exceeds the load students can bear. In this study, an overload experiment was designed. During the experiment, difficult papers unrelated to the subjects' major fields were prepared for the subjects to read, and the changes of their attention values during reading were recorded.
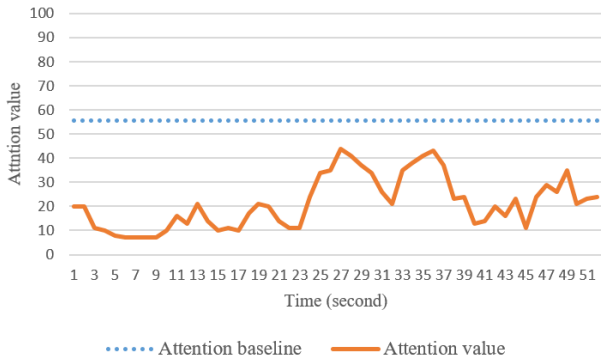
FIGURE 6. Overload attention value.

A number of highly relevant rules that had more than 80% confidence were selected from the results, as shown in Table 3. The analysis of the association rules between overload and attention values was as follows:

Rule 1: When the subjects suffered overload, the probability of occurrence of an attention value lower than the attention baseline in the first time segment was 100%, which indicated that the attention value of the subjects reading overloaded teaching materials was lower than the attention baseline in the whole process.

Rule 2: When the subjects suffered overload, the probability of low sustained attention was 97%, which indicated that the subjects were unable to read the teaching materials intently during the overload experiment. Only 3% of the subjects could temporarily maintain attention, because only a small number of students would focus on finding out the recognized words and try to understand them. In this regard, the subjects would not show a state of low sustained attention. However, this study observed the average attention value per minute and found that almost all subjects' average attention values were lower than the attention baseline in a very short period of time and they would enter a state of inattention.

Rule 3: When the subjects suffered overload, the probability of inattention was 92%.

Rule 4: When the subjects suffered overload, the probability of the simultaneous occurrence of a lower attention baseline and low sustained attention in the first time segment was 97%, which was consistent with Rule 1 and Rule 2.

Rule 5: When the subjects suffered overload, the probability of low sustained attention and inattention was 92%, which was consistent with Rule 2 and Rule 3.

Based on the above-mentioned correlation rule analysis and Figure 6, it was found that if the subjects read teaching materials that exceeded the load they could bear, the attention value would quickly appear to be lower than the attention baseline due to the lack of understanding of the content during the first few minutes. In addition, the subjects would continue to maintain a state of inattention. Therefore, teachers should carefully evaluate the difficulty of teaching materials during the teaching process so that students will not suffer excessive cognitive load and the decline of learning attention.

TABLE 4. High load association rules.

	A→B (A imply B)	Confidence(A→B)
1	High load→Learning category	100%
2	High load→Low sustained attention	88%
3	High load→Low sustained attention, The first segment	88%
4	Attention, High load→Low sustained attention	83%
…	…	…

B. HIGH LOAD ASSOCIATION RULES

This study collected the changes in the students' attention values in real learning environments measured using two courses and recorded their cognitive load.

Table 4 lists a number of highly relevant rules with higher value and more than 80% confidence. The analysis of the relevant rules for high load and attention values was as follows:

Rule 1: When the subjects were under a high load, the probability of their activities falling into the learning category was 100%, which indicated that all the high-load data came from the learning activities. The results also implied that the subjects would not choose high-load leisure activities among the leisure category activities.

Rule 2: When the subjects were under high load, the probability of low sustained attention was 88%, which indicated that subjects under a high load could only maintain short-term attention during the learning process.

Rule 3: When the subjects were under a high load, the probability of low sustained attention and inattention during the first time segment was 88%, which indicated that 88% of the subjects under a high load were attentive at the beginning of the activity but could only stay attentive for a short time during the learning process.

Rule 4: When the subjects were attentive and under a high load, the probability of low sustained attention was 83%, which indicated that even if the subjects were likely to conduct high-load learning activities, they could not maintain long-term attention during the process.

Based on the above association rule analysis and Figure 7, it could be seen that the subjects suffering a high load were mostly inattentive during the first few minutes of the learning process and could not maintain long-term attention during the learning process. This may be because the understanding of the high-load teaching materials at the beginning would present a large processing load. Thus, the subjects suffering from a high load would be inattentive during the first few minutes. They had to spend more effort to understand this knowledge, and thus they could not maintain long-term attention. However, this study observed the average attention value per minute and found that, although the subjects could not maintain long-term attention and suffered fluctuations of attention compared with the attention baseline, they showed different performance levels regarding the absorption of high-load teaching materials after being taught by the teacher.
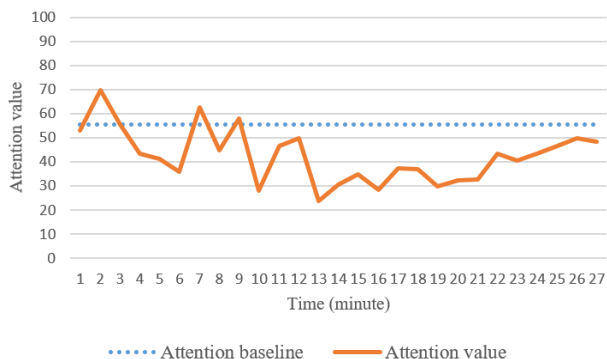
FIGURE 7. High load attention value.

TABLE 5. Medium load association rules.

	A→B (A imply B)	Confidence(A→B)
1	Medium load, Leisure category→The first segment	100%
2	Medium load, Low sustained attention →The first segment	100%
3	Medium load, Low sustained attention, Leisure category→The first segment	100%
4	Medium load, Medium sustained attention, Leisure category→The first segment	100%
5	Medium load, Low sustained attention, The first segment→Inattention	99%
6	Medium load, Medium sustained attention→The first segment	91%
7	Medium load, Medium sustained attention, The first segment→ Inattention	99%
8	Long activities, High sustained attention→Medium load	85%
9	Long activities, High sustained attention, The first segment→Medium load	85%
10	Medium load、The third segment→ Learning category, High sustained attention	100%
…	…	…

The two courses were taught by the same teacher, and the difficulty and content of the teaching materials were adjusted to cover all students. Among the collected data, the amount of high-load data was less than that of the medium-load data and low-load data, which showed that the teacher's teaching design and teaching materials could effectively reduce the students' cognitive load.

C. MEDIUM LOAD ASSOCIATION RULES
The analysis of the association rules between medium load and attention value is shown in Table 5.

Rule 1: When the two conditions of a medium load and leisure category occurred simultaneously, the probability of inattention during the first time segment was 100%, indicating that when the subjects were engaged in leisure category activities with a medium load, they would be inattentive from the beginning.

Rule 2: When the two conditions of a medium load and low sustained attention occurred simultaneously, the probability of inattention during the first time segment was 100%, indicating that if the subjects' sustained attention time was short during medium-load activities, they would be inattentive from the beginning.

Rule 3: When the three conditions of a medium load, leisure category, and low sustained attention occurred simultaneously, the probability of inattention during the first time segment was 100%.

Rule 4: When the three conditions of a medium load, leisure category, and medium sustained attention occurred simultaneously, the probability of inattention during the first time segment was 100%.

Rule 5: When the three conditions of a medium load, low sustained attention, and inattention during the first time segment occurred simultaneously, the probability of inattention was 99%.

Rule 6: When the two conditions of a medium load and medium sustained attention occurred simultaneously, the probability of inattention during the first time segment was 91%. Even if the duration of sustained attention was at a medium level, 91% of the subjects would become inattentive within a few minutes from the beginning when they were performing medium-load activities.

Rule 7: When the three conditions of a medium load, medium sustained attention, and inattention during the first time segment occurred simultaneously, the probability of inattention was 99%. This indicated that although the subjects with a medium load could maintain attention for a certain period of time, there was a 99% probability that the average attention value of the subjects during the whole activity would be lower than the attention baseline in the state of inattention at the beginning of the experiment.

Rule 8: When the two conditions of engaging in long activities and high sustained attention occurred simultaneously, there was an 85% probability that such activities would have a medium load, indicating that if the subjects could maintain longer attention during long activities, there would be an 85% confidence to infer that such activities would have a moderate load level.

Rule 9: When engaging in long activities, if high sustained attention and inattention during the first time segment occurred simultaneously, there would be an 85% probability that such activities would have a medium load.

Rule 10: When the two conditions of a medium load and ''subjects becoming inattentive during the third time segment'' occurred simultaneously, there was a 100% probability that the subjects would have high sustained attention and engage learning category activities. This indicated that if the subjects with a medium load could maintain their attention state for three time segments at the beginning, there would be 100% confidence to infer that the subjects had a high level of sustained attention.

Based on the above-mentioned association rule analysis, it could be seen that when the subjects were engaged in
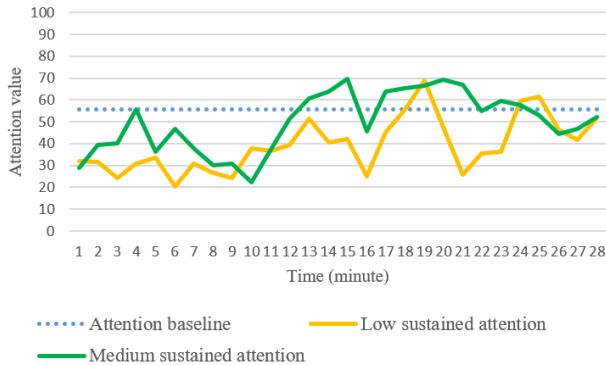
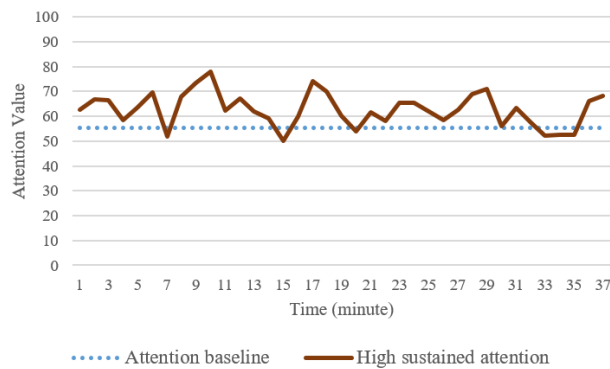**FIGURE 8.** Low/medium sustained attention of medium load.

FIGURE 9. High sustained attention of medium load.

medium load activities, whether they had low or medium sustained attention, and whether they were engaged in leisure or learning category activities, they would be inattentive at the beginning of the activities. From Figure 8, it could be seen that the attention values of the subjects for the whole activity were nearly all lower than the attention baseline. From Rule 10 and Figure 9, it could be seen that the medium load subjects who could maintain high sustained attention could maintain sustained attention for a long period at the beginning. However, fatigue could occur after a period of attention, and the state of inattention would then begin at a later stage. In addition, this study found that high sustained attention only occurred under the condition of a medium load, presumably because the subjects could not maintain long-term attention under the condition of a high load and would not need to spend much effort to understand teaching materials with a medium load, thus enabling them to understand those teaching materials and maintain a longer attention degree.

D. LOW LOAD ASSOCIATION RULES

The analysis of the association rules for a low load and attention values is shown in Table 6.

Rule 1: When the subjects were under a low load, the probability of falling below the attention baseline during the first time period was 81%, indicating that the subjects with a low load showed inattention from the beginning.

Rule 2: When the two conditions of a low load and low sustained attention occurred simultaneously, the probability

TABLE 6. Low load association rules.

	A→B (A imply B)	Confidence(A→B)
1	Low load→The first segment	81%
2	Low load, Low sustained attention→ The first segment	100%
3	Low load, Low sustained attention→ Inattention	98%
4	Medium sustained attention, Low load, Learning category→Long activities	83%
5	Medium sustained attention, Low load, Leisure category→Long activities	92%
…	…	…

of inattention during the first-time segment was 100%, indicating that if the subjects' sustained attention time was short during low load activities, they would be inattentive from the beginning.

Rule 3: When the two conditions of a low load and low sustained attention occurred simultaneously, the probability of inattention was 98%.

Rule 4: When the subjects were engaged in low-load learning category activities, if they had a medium sustained attention, there would be an 83% probability of such long activities. This indicated that if the subjects with a low load could maintain attention for a certain period of time, there would be an 83% probability that they could complete relatively long activities.

Rule 5: When the subjects were engaged in low-load leisure category activities, if they had a medium sustained attention, there would be a 92% probability of such long activities.

Based on the above-mentioned association rule analysis, it was found that the subjects engaging in low-load activities showed a state of inattention from the beginning. Figure 10 shows that the attention values for the whole activities of the low-load subjects were almost always lower than the attention baseline. This study found that if the subjects were engaged in low-load activities, they might be able to understand the contents of their study without spending much effort and would easily get distracted, making the overall attention value lower than the attention baseline. In addition, from Rules 4 and 5, it was known that when the subjects were engaged in low-load leisure category activities, whether they were learning category activities or leisure category activities, if the subjects could maintain their attention for a period of time, there would be a high probability of such long activities, which indicated that low-load activities could keep the subjects feeling relaxed and enable them to finish long activities while maintaining a medium level of sustained attention.

Based on the analysis of the above experimental results, it was found that attention and different cognitive load levels could combine to form different association rules.
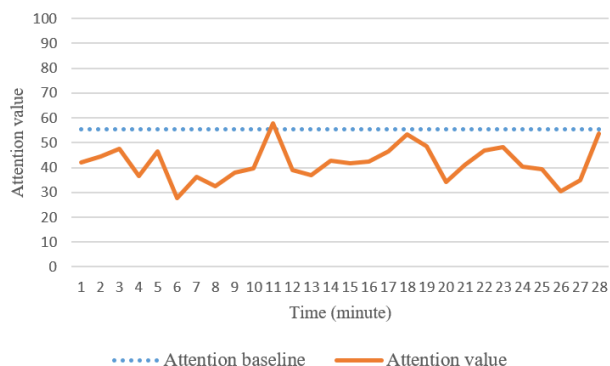
FIGURE 10. Low load attention value.

The following summarizes the analysis of attention and different cognitive load levels.

1) In the overload experiment, it was found that all subjects would immediately become inattentive when reading the overload teaching materials, which indicated that the subjects would maintain low sustained attention due to overload during the learning process.

2) In the high-load experiment, it was found that none of the subjects would choose high-load leisure category activities when choosing leisure activities. However, high-load learning activities were frequently accompanied by low sustained attention, which indicated that exposure to high-load knowledge would increase the processing load.

3) In the medium-load experiment, the subjects were found to be inattentive at the beginning of the activity, regardless of whether they had low or medium sustained attention or whether they were engaged in leisure or learning category activities. However, the medium-load subjects who could maintain high sustained attention were able to maintain it for a long period at the beginning. However, after a period of attention, fatigue would occur and attention would decrease. Moreover, this study found that only subjects with a medium load had high sustained attention. This result indicated that a medium load did not require as much effort as a high load, which enabled the students to maintain longer attention during long activities.

4) In the low-load experiment, it was found that the low-load subjects showed inattention for nearly the whole activity. This indicated that the subjects did not need to maintain a high level of attention to understand simple teaching materials. They would not concentrate on the teaching materials or courses, thus making the average attention value lower than the attention baseline.

Besides, this study investigated the final exam performance of the subjects and explored some association rules. It was found that the subjects classified in the high score group and under low-load showed inattentive at the beginning of the activity, while the subjects classified in the low score group and under either low or medium-load showed inattentive at the beginning of the activity.

Previous traditional experimental designs only used one experiment at a time to explore cognitive load or attention. This study used multiple experimental designs to explore the association between different cognitive load levels and attention values. In addition, this study used association rule mining technology to analyze the attention values measured by various experimental designs and the association rules of different cognitive load levels, which was different from previous studies. Previous studies found it difficult to imagine the association between data; however, association rules can effectively mine hidden associations.

V. CONCLUSION

In this study, a head-mounted non-invasive EEG instrument based on IoT technology was used to collect the attention values of the subjects, and the cognitive load of the subjects was collected using a cognitive load questionnaire. The association between attention value and cognitive load was explored through association rule analysis and data mining. IoT technology facilitates the use of wearable devices. The head-mounted EEG instrument used in this study was characterized by fast wearing, imperceptibility, a small size, and portability, which enabled this study to be carried out in various environments to effectively measure the attention value of subjects in the real learning environment of a classroom. As the attention values measured by different wearable EEG instruments could have relative variations, this study proposed a strategy to formulate an attention baseline to help normalize the attention values obtained by different wearable EEG instruments. Therefore, this study designed six short-term experiments to measure the maximum attention degree of the subjects, as well as short-term relaxation experiments to measure the minimum attention degree of the subjects. Through the range of the maximum attention degree and the minimum attention degree, the attention baseline was determined. Even if different instruments are used to measure attention values in future studies, the attention baseline of the instrument can be determined according to this strategy.

This study explored the association between attention value and the four cognitive load levels of overload, high load, medium load, and low load. In the overload experiment, it was found that all subjects would lose attention immediately after reading difficult teaching materials. In the high-load experiment, it was found that high-load learning activities were frequently accompanied by low sustained attention. In the medium-load experiment, it was found that only the medium-load subjects had the probability of high sustained attention; if the medium-load subjects had low sustained attention or medium sustained attention, they would be inattentive at the beginning of the activity. In the low-load experiment, it was found that the low-load subjects showed inattention for nearly the whole activity.

This study found that both overloaded and underloaded teaching materials could lead to inattention. In other words, medium or high-load teaching materials can make subjects be more attentive. Such results could provide teachers with

objective suggestions and references when choosing teaching materials or designing the proper level of difficulty for a curriculum. This study explored the association between attention and cognitive load, and the results could be provided as a reference for researches on the same topic. In future studies, the cognitive load of subjects can be inferred by just observing the change of their attention value. In this way, the cognitive load of subjects can be indirectly and objectively quantified, and subjective measurement methods based on cognitive load questionnaires can be abandoned.

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