Developing SAMM: A Model for Measuring Sustained Attention in Asynchronous Online Learning

Shiow-Lin Hwu

Abstract: There is a strong relationship between sustainability and equality education, as it is emphasized in the United Nations’ Sustainable Development Goals (SDGs). To maintain learning effectiveness, learning attention is a valuable consideration. By continuously monitoring learners’ attention, the teaching and learning process can be measured and adjusted as needed. However, it poses a challenge for measuring attention in online learning environments where all participants do not interact face-to-face. To address this concern, this paper proposes a sustained attention measurement model (SAMM) that establishes attention tests to gauge learners’ sustained attention levels during asynchronous online learning. SAMM presents learners with real-time questions based on course content, collecting both their response time and accuracy. In an experiment conducted over an academic semester, we recruited 213 students from a private Taiwanese university of technology and analyzed their response time and accuracy rate to identify attention patterns in the online learning system. This analysis can provide valuable feedback for instructors to adjust their teaching methods.

Keywords: asynchronous online learning; pedagogical theory; sustained attention theory; sustained attention measurement

1. Introduction

In the fields of psychology and education, attention is a fundamental and essential concept [1,2]. Recent studies [3,4] have observed a significant increase in research related to attention, due in part to advancements in brain science technology, including electrophysiology, neurophysiology, positron emission tomography (PET), and functional magnetic resonance imaging (fMRI). These sophisticated techniques, however, are generally expensive and primarily intended for medical purposes, despite their potential for investigating attention-related approaches.

Since the outbreak of the COVID-19 pandemic, education has rapidly transitioned to online learning on a global scale. The use of e-learning technology has increased dramatically, as it offers greater interactivity and productivity in the teaching and learning process [5]. Even elementary school students have had to participate in online learning due to unprecedented circumstances. To ensure effective instruction, teachers must monitor the attention of all learners, particularly young students who are more susceptible to distractions. This monitoring helps teachers ensure that students are engaged and receiving the content being delivered.

Online learning, also referred to as e-learning, is an integrated technique that relies on advanced information systems and networks. The use of novel technology in the education field can improve access to quality education and communication between learners and educators. From the perspective of ESG (Environmental, Social, and Governance), online learning has gained significant popularity due to its multitude of environmental benefits. With the rapid growth of sustainable investment, ESG has gained importance for the educational industry, and the demand for education and training in this field has also increased. It has emerged as an efficient and flexible way to provide ESG education and
training to a wider audience, including professionals, students, and the general public. The United Nations’ Sustainable Development Goals (SDGs) emphasize the importance of quality education and lifelong learning as Goal 4 out of 17 interconnected and integrated goals [6]. This goal is to ensure that all individuals have access to inclusive and equitable education and opportunities. It also establishes access to a wealth of learning resources on the internet, catering to the unique needs and characteristics of both instructors and learners. Therefore, online learning provides a suitable solution for this goal since it can effectively overcome the limitations of physical space and time.

Online learning can be delivered synchronously or asynchronously. In synchronous applications, all participants, including instructors and learners, interact with each other in real-time through a teleconference system. In contrast, asynchronous classes are not performed at the same time and are usually implemented on a Learning Management System (LMS), which is a computer application with various tools to support specific instructional tasks such as assessing students’ knowledge, answering their questions, conducting exams, providing feedback, facilitating student discussions, and more [7]. Authenticated learners can access the LMS via an internet connection and perform instructional tasks at any time and from any location.

With the increasing ease of access to information technologies, online learning has become a popular choice for individual learners [8]. To ensure effective online learning, it is essential to establish a well-designed learning environment that can enhance learners’ motivation and interest [9]. Additionally, when developing an online learning system, the interaction functionality should be carefully considered, particularly for hands-on courses. The interaction between teachers and learners is crucial since instructors must observe learning performance and provide essential feedback on the learning situation [4,10].

The advancement of online learning has brought about many benefits; however, online teaching and learning systems face a unique challenge that traditional classrooms do not encounter. In a physical classroom, all participants are present in the same place, making it easy for instructors to observe learners’ responses, such as eye contact and body language. If a learner becomes distracted, the instructor can quickly identify the issue and implement strategies to help the learner refocus. In online learning, instructors lack the ability to monitor learners’ attention levels, making it challenging to adjust teaching methods accordingly. As a result, it is difficult for instructors to determine whether their current teaching strategies are effective or not.

Several approaches have been proposed to enhance learning interaction and engagement by establishing systems that ask learners questions between teaching periods, such as personal response systems (PRSs) [11,12] and interactive lecture video platforms (IL-VPs) [13]. These solutions, which are derived from the principle of PRS, aim to enhance interactivity by promoting learners’ feedback and understanding of the discussion on a learning topic. In the study by [13], in-video quizzes were used for online learning, which facilitated interaction between learners and instructors. Furthermore, ref. [14] has also proposed similar solutions to enhance learners’ engagement and participation in class. These studies, however, may not fully account for the learners’ attentional situations, which could potentially act as a vital indicator for adjusting teaching methods effectively. It is crucial to include a theoretical framework to support such an implementation.

Sustained attention refers to the ability to become engaged in and maintain engagement in a task or activity over an extended period of time [15]. It is a fundamental aspect of human cognitive capacity and is essential for carrying out all cognitive activities and thoughts [16]. Cognitive load [17] refers to the amount of mental effort required to process and retain information during a learning task. Two main components are involved in cognitive load: intrinsic load, which arises from the inherent complexity, and extraneous load, which stems from factors unrelated to the learning content. If cognitive load is high, it can have significant effects on a learner’s attentional resources. The complex nature of the task, coupled with the need to process and integrate multiple pieces of information, can lead to
attentional strain. Therefore, learners may experience attentional lapses or decreased focus, so maintaining sustained attention for online learners becomes more challenging.

Signal Detection Theory (SDT) is a significant tool in cognitive science and is useful for applications involving human decision-making [1,18,19]. This theory provides a framework for evaluating mental processes in various contexts, including attention deficit hyperactivity disorder (ADHD) [19]. Furthermore, SDT serves as an effective manner for assessing and qualifying human attention in specific scenarios, offering valuable insights into attentional mechanisms and their implications [18,20].

This paper proposes a sustained attention measurement model (SAMM) for engaging sustained attention in asynchronous online learning. SAMM is based on the design of signal detection theory (SDT) and involves a series of questions based on the current course content to evaluate whether learners are paying continuous attention to the online course. These questions appear irregularly during each lesson chapter, and learners must respond instantly and correctly. Two factors—the time latency and correct rate of the answers—are collected to detect each learner’s attention level.

To evaluate the effectiveness of SAMM, we conducted an experiment involving 213 students from a private Taiwanese university of technology who participated in two general asynchronous online courses. We then analyzed the data and discussed the implications for the model and the corresponding experiment. Overall, the proposed SAMM shows promise for improving sustained attention in asynchronous online learning environments.

The remainder of this paper is organized as follows: Section 2 presents the theoretical foundation to facilitate the understanding of the sustained attention measurement model for online learning. In Section 3, the measurement model is presented, and its methodology is described to show how learners’ attention levels are collected during online learning. Next, an experiment conducted to simulate the model is depicted in Section 4, and a discussion is provided in Section 5 to illustrate the result of this research. Finally, conclusions and implications are stated in Sections 6 and 7, respectively.

2. Theoretical Foundation

To facilitate the understanding of the research, this section will provide a brief review of the key concepts related to sustained attention theory (SAT), signal detection theory (SDT), and the correlation between sustained attention and learning performance.

2.1. Sustained Attention Theory

Attention is a fundamental brain function that determines how we allocate cognitive resources. Sustained attention, a particular type of attention, refers to the ability to maintain engagement over an extended period without becoming distracted or losing focus until a task is completed or a predetermined period has elapsed [15]. Sustained attention is crucial for information processing and is essential for carrying out all cognitive activities and thoughts [16].

Sustained attention theory (SAT) [21] is a pedagogical theory that involves maintaining focused attention on an objective or activity for an extended period of time. Two common methods for assessing sustained attention and vigilance are the sustained attention to response task (SART) [22,23] and the Conners Continuous Performance Test (CPT) [24]. During these tests, a continuous series of images or letters is presented, and participants must provide feedback as long as the assigned result is displayed.

While SART and CPT are useful for specific diagnostic purposes, such as assessing brain damage or ADHD, they are not directly applicable to online learning scenarios, where maintaining the learner’s attention throughout a course requires more tailored methods. Establishing an attention measurement mechanism for asynchronous online learning environments requires considering relevant factors such as course content and response format. Therefore, it is essential to develop attention assessment methods that are specifically designed for the needs of online learners.
2.2. Signal Detection Theory (SDT)

Evaluating sustained attention is a crucial aspect, and it is essential to establish the correlation between attention levels and practical interactions in e-learning. In other words, it is necessary to transform learners’ responses to online learning materials into detectable signals that can indicate their sustained attention. Therefore, it is crucial to discuss how to properly detect and collect these signals.

Signal detection theory (SDT) is a well-established methodology used to assess decision-making sensitivity. This technique enables researchers to analyze the role of human attention in perceiving signals [1,18,19]. SDT has been utilized to measure sustained attention by examining the mental processes involved in specific scenarios. In this methodology, a signal is presented as either present or absent, and the participant must respond accordingly by indicating whether they perceive the signal or not. The intersection of signal and response produces one of four outcomes: hit, false alarm, miss, or correct rejection. The details of each outcome are outlined below (Table 1).

1. Hit: The signal is presented, and the subject responds correctly.
2. False alarm: The signal is absent, but the subject responds, presenting a result.
3. Miss: The signal is presented, but the subject does not respond correctly.
4. Correct rejection: The signal is absent, and the absence of the target is responded to correctly.

Table 1. The four results of SDT.

<table>
<thead>
<tr>
<th>Response</th>
<th>Signal</th>
<th>Present</th>
<th>Absent</th>
</tr>
</thead>
<tbody>
<tr>
<td>Present</td>
<td>Hit</td>
<td>False alarm</td>
<td></td>
</tr>
<tr>
<td>Absent</td>
<td>Miss</td>
<td>Correct rejection</td>
<td></td>
</tr>
</tbody>
</table>

In an e-learning environment, various methods can be used to measure the sustained attention of learners. One commonly used method is question-answer processing, where a series of questions related to the course content are presented to the learner during the course viewing. The learner is then required to answer the question correctly within a predetermined time frame. In this scenario, two major factors need to be considered when measuring online learning attention, according to the framework of Signal Detection Theory (SDT). Firstly, the correctness of the question-answer can be transformed into a response, where a correct answer is considered a “Hit”. Secondly, the time taken to answer the question should also be considered. A longer time to answer may indicate that the learner is not familiar with the course content or is not fully focused on the study.

2.3. Correlation of Sustained Attention with Learning Performance

Previous relevant research [25–29] demonstrated a strong correlation between learning performance and sustained attention. In [25], the correlation is demonstrated in terms of reading test scores within a classroom environment. The approach [26] discovered a significant correlation between attention and reading comprehension scores in typically developing children, while [27] identified a positive association between sustained attention and reading comprehension of annotated English texts online. The authors of [28] conducted a study examining the correlation between low-attention periods during video lectures. The study [29] revealed a robust and positive correlation between learning performance and sustained attention. This correlation was linear and exhibited favorable predictability, indicating that learners with highly sustained attention attained superior learning performance.

Therefore, it is crucial to evaluate learning performance using diverse assessment methods [30]. The conventional approaches can be classified into participant assessment [31], file assessment [32], and paper assessment [33]. Moreover, many e-learning systems incorporate a “timeout logout” function to monitor the user’s online activity. If the user becomes
inactive for a certain period of time, the system logs them out. While this method helps to identify inactive learners in e-learning environments, it does not measure attention, which is crucial for adjusting teaching methods.

Summative assessment is a method that involves constructing a series of continuous and evolutionary steps for studying and generating qualitative feedback to help both the teacher and student understand the details of study performance [34]. By frequently assessing learners’ processes and the results of their practice, it enables learners to self-assess [35]. Additionally, the assessment results of each teaching phase can serve as indicators for instructors to understand how studying outcomes can be adjusted and strategies modified as necessary [36]. Continuously assessing learning efficiency can help better tailor teaching methods to learners’ interests and motivation, resulting in better outcomes.

Based on the approaches discussed above, we have identified three crucial considerations for attention in online learning. Firstly, it is paramount to grasp the essence of educational principles that guide the assessment of learning effectiveness. This consideration enables the effective management of teaching and learning processes within the online learning system, achieving alignment with educational goals and objectives. By incorporating these principles, educators can create a conducive environment that facilitates optimal learning outcomes and engagement for online learners.

Secondly, while developing question-driven learning engagement functions, it is essential to analyze the correlation between the questions presented and the subsequent responses. It is crucial to investigate whether the difficulty level of the questions has any influence on the quality and accuracy of the learners’ responses, considering the potential cognitive load involved. Moreover, it becomes necessary to integrate an attention measure into the design of this mechanism to effectively monitor and assess the learners’ sustained attention throughout the whole learning process. By incorporating such functionality, educators can obtain valuable insights into how fluctuations in attention may impact the learners’ overall performance, enabling them to adapt their instructional strategies accordingly and mitigate potential cognitive overload.

Thirdly, the PRS works [11,12,14] were specifically developed for the “Prolog” programming lesson, focusing on its implementation and effectiveness. Additionally, the utilization of ILVP (In-Video Learning and Video-Based Practice) [37] is showcased through in-video media. Thus, it is of utmost importance to conduct a comprehensive evaluation of the feasibility of integrating these tools into different courses, considering their compatibility with conventional LMS. By assessing the compatibility and feasibility, educators can assure the integration and optimize the learning experience for students across various courses while leveraging the benefits of these technologies.

3. The Sustained Attention Measurement Model (SAAM)

To collect sustained attention in asynchronous online learning, we have developed a sustained attention measurement model (SAMM) based on the framework of Signal Detection Theory (SDT). While SDT was originally used to analyze human perception signals, we have adapted it to measure attention in a learning context with specific teaching content.

Figure 1 illustrates the workflow of SAAM in asynchronous e-learning, encompassing five main steps with several individual sub-steps. Step 1 involves the learner logging into the system and accessing a series of pieces of content. In Step 2, a related question is presented to the learner. Step 3 expects the learner to provide an answer to the question. If the answer is correct, Step 4.1 follows, where the next content and its associated question are presented. However, if the answer is incorrect, the flow proceeds to Step 4.2, where it checks if the same question needs to be repeated. Steps 5.1 and 5.2, respectively, handle the learner’s three attempts to answer the question. Following an incorrect answer, the learner is required to review the content and provide a response with a higher likelihood of being correct. This comprehensive flow ensures a structured and interactive learning experience for the learner in the SAAM system.
The assessment process of this learning system considers two main factors: response correctness and perception time. In terms of response correctness, instructors prepare a set of questions related to the learning content in advance. Learners access the content through the LMS and provide their answers when a question appears. The system validates the correctness of the response, displaying “Correct” for accurate answers and “Incorrect” for incorrect ones. If the answer does not match the question’s intent, the same question is repeated until the answer is correct or the learner has exhausted three attempts. This approach helps mitigate the possibility of inadvertent responses by the user. Further details regarding these attempted concerns will be provided in Section 5, titled “Discussion”.

Reception, or the time required for a learner to complete an answer to a question, is another crucial factor. Time begins when a question-answer panel shows on the screen and ends when the answer has been entered or the time exceeds a pre-defined period for fulfillment. In the model, the reception field can be divided into two sections: “On time” and “Overdue”, which are respectively employed to depict whether the answer has been entered within the defined time period or not. In Table 2, four types of SAMM outcomes are summarized, and the intersection of response and reception is also provided. In the process, when a response is provided promptly and yields an accurate result, it is classified as a “Hit,” indicating an optimal outcome. On the other hand, if there is a delay in the response yet it still yields an accurate result, it can be referred to as a “Delay Hit,” reflecting the time lag in the response while maintaining accuracy. Conversely, if the response is incorrect, regardless of whether it is received on time or delayed, it is labeled as a “Miss” or a “Delay Miss,” respectively, indicating the absence of accuracy in the outcome.

Table 2. Four outcomes of SAMM.

<table>
<thead>
<tr>
<th>Response</th>
<th>Reception</th>
<th>On Time</th>
<th>Overdue</th>
</tr>
</thead>
<tbody>
<tr>
<td>Correct</td>
<td>Hit</td>
<td></td>
<td>Delay Hit</td>
</tr>
<tr>
<td>Incorrect</td>
<td>Miss</td>
<td></td>
<td>Delay Miss</td>
</tr>
</tbody>
</table>
In the measurement model, two functionalities, instructor management and a learning classroom, are deployed and shown on the main page. Instructors control video playback and evaluation by operating the management interface, and learners study the learning content by watching the content provided by the instructor.

As shown in Figure 1, the instructor sets up a series of content and questions, and then learners watch the content and input the answers when a question shows up. When a learner starts to watch study content, a series of questions appear sequentially at times predefined by the instructor; for instance, when a complete subject is finished, its question will appear. When a question derived from the current content shows up, the learner must fill in the answer in a text input box. Following that, the system checks the answer and pops up the question again if the answer is incorrect. In the design, three attempts for each question can pass the tests before entering the next content. As shown in Step 5.1 of Figure 1, when the answer for the question derived from content A is an error and the entering time is less than three times, the same question will be asked again until it reaches three times (as depicted in Step 5.2).

4. Experiment

To validate our research, an experiment was developed to evaluate the result of learning attention based on SAAM. The details of the experiment, which include participants, experiment design, and data analysis, are respectively described in the following paragraphs.

4.1. Participants

The proposed model is suitable for implementation in any general course that is designed for an asynchronous e-learning system. To evaluate the model, two courses were selected: English and Information Literacy and Cyberethics. English is a major second language taught in most schools in Taiwan, while Information Literacy and Cyberethics is a fundamental course for computer-science-related students, covering essential knowledge related to computer use. The experiment lasted approximately four months to ensure the collection of sufficient data.

A total of 213 students aged between 18 and 20 were recruited from a private Taiwanese university of technology to participate in this study. The students belonged to various departments, including information management, marketing and distribution management, landscape architecture, and early childhood education, and were enrolled in an English course. On average, they had studied English for 10 years. The Information Literacy and Cyberethics course was taught in departments related to information, such as information management and computer science, and the students were taking this course for the first time.

Prior to the experiment, the students were informed about the implementation of a real-time question-and-answer feedback system that would be utilized throughout the online course. This arrangement aimed to foster a greater emphasis on in-depth study and comprehension of the course content, which are essential for successful completion of the question-and-answer assessments. Additionally, the learner’s identifiable information is exclusively retained by the instructor for the purpose of evaluating learning performance. The question-and-answer results, presented in a basic data format, are collected and analyzed without containing any individually identifiable data in a way that ensures privacy.

4.2. Experiment Design

The aim of this experiment is to evaluate participants’ response time and answer accuracy in an e-learning setting. The study is guided by the principle of sustained attention theory, which emphasizes the importance of keeping learners engaged with course content. To achieve this, a set of questions was developed based on the learners’ curriculum. When a participant logs into the e-learning system and starts studying, the proposed model displays questions as part of the learning experience. The response time and accuracy of the participant’s answers are recorded for later analysis. By examining these factors, the
study seeks to understand how learners engage with the course material and whether the sustained attention theory is applicable in an e-learning environment.

The role of learning materials in teaching and learning is paramount [19]. It is essential to carefully choose materials that align with the course content in order to achieve the desired outcomes. The content of the lectures and the selection of questions within the learning materials are of paramount importance and are undertaken by an expert English teacher. Inappropriate question selection may impede the collection of learners’ performance data, resulting in prolonged response times on e-learning platforms and a higher frequency of incorrect responses. Thus, the expertise of professional English teachers in crafting and categorizing questions is essential for optimal learning experiences.

On the one hand, when a question is excessively challenging, learners may encounter difficulty answering it correctly, which can lead to frustration and demotivation. On the other hand, if a question is overly easy, learners may respond swiftly without engaging in substantial cognitive processing, resulting in superficial learning outcomes. Therefore, it is crucial to select questions that achieve a balance between difficulty and effectiveness, promoting meaningful engagement and optimal learning outcomes.

Considering the diverse knowledge backgrounds of learners within a course, the difficulty level of questions plays a significant role in influencing correctness and response time. Therefore, it is crucial to classify questions based on their difficulty to ensure that learners are presented with an appropriate level of challenge. Generally speaking, more experienced learners should be offered harder questions, unless the attempt rules can be dynamically adapted to match the current learner’s proficiency level.

Educators and instructional designers should exercise care during the question selection process to make sure that the chosen questions align with the learning objectives and provide an appropriate level of challenge. By carefully selecting questions, learners can actively engage in effective learning experiences that lead to optimal learning outcomes.

4.3. Data Analysis

In the experiment, learners are asked to watch course videos, which are divided into 3–5 min according to the content chapter arrangement. When a content segment is finished, a question related to the content just watched shows up, and the learner enters the answer before the system timeout is defined. To clarify the factors influencing the response time and correctness, two dimensions, the number of response attempts and the question content, were collected and analyzed. In addition, the answer result, including correctness rate, can also be a reference used to decide the learner’s study grades.

4.3.1. Response Attempts

First, the collected data were classified into three groups according to the number of response attempts. When an answer was incorrect, the question was asked again, up to three times. That is, if the number of response attempts was 2 or 3, the response to this question must have been incorrect at least once.

In Table 3, when only 1 response was made, the number of correct responses was 693, with the highest frequency (58%); thus, the attention of learners who responded correctly on the first try was excellent. The percentage of correct answers decreased as the number of response attempts increased. When the number of response attempts was 3, the percentage of correct answers was only 16%, which implies that the learners who answered incorrectly the first time did not focus on processing the course since most of them answered incorrectly more than once.

Response time is a critical factor in evaluating sustained attention. It refers to the time it takes for a learner to provide a response after a question appears. As shown in Table 3, the response time range peaked at 0–119 s for all response attempts, indicating that most learners were able to provide their answers within a short period of time. However, it is essential to note that a short response time does not necessarily indicate the correctness
of the answer. Therefore, it is imperative to consider both response time and correctness when evaluating sustained attention.

Table 3. A summary of the response results.

<table>
<thead>
<tr>
<th>Response Attempts</th>
<th>Response Time (Seconds)</th>
<th>Count of Incorrect Responses</th>
<th>Percentage of Incorrect Responses</th>
<th>Count of Correct Responses</th>
<th>Percentage of Correct Responses</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0–119</td>
<td>329</td>
<td>534</td>
<td>693</td>
<td>58%</td>
</tr>
<tr>
<td></td>
<td>120–239</td>
<td>129</td>
<td>134</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>240–359</td>
<td>28</td>
<td>15</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>360–479</td>
<td>7</td>
<td>5</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>480–599</td>
<td>5</td>
<td>4</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>600–719</td>
<td>3</td>
<td>1</td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Subtotal</strong></td>
<td></td>
<td><strong>501</strong></td>
<td><strong>42%</strong></td>
<td><strong>693</strong></td>
<td><strong>58%</strong></td>
</tr>
<tr>
<td>2</td>
<td>0–119</td>
<td>197</td>
<td>62</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>120–239</td>
<td>62</td>
<td>4</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>240–359</td>
<td>8</td>
<td>1</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>360–479</td>
<td>3</td>
<td>1</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>480–599</td>
<td>1</td>
<td>0</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>720–839</td>
<td>1</td>
<td>0</td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Subtotal</strong></td>
<td></td>
<td><strong>272</strong></td>
<td><strong>80%</strong></td>
<td><strong>68</strong></td>
<td><strong>20%</strong></td>
</tr>
<tr>
<td>3</td>
<td>0–119</td>
<td>113</td>
<td>28</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>120–239</td>
<td>38</td>
<td>1</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>240–359</td>
<td>3</td>
<td>0</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>360–479</td>
<td>1</td>
<td>0</td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Subtotal</strong></td>
<td></td>
<td><strong>155</strong></td>
<td><strong>84%</strong></td>
<td><strong>29</strong></td>
<td><strong>16%</strong></td>
</tr>
</tbody>
</table>

Furthermore, as demonstrated in Figure 2, the response time ranged from 1 to 3 min, regardless of whether the response was correct or not. This finding indicates that some learners may take more time to formulate their answers, but this does not necessarily mean their answers are incorrect. It is noted that an extended response time can also indicate a lack of sustained attention. Therefore, it is crucial to strike a balance between response time and accuracy when evaluating sustained attention in learners.

![Figure 2. The response time.](image)

4.3.2. Question Contents

Herein, we analyze the suitability of the questions used in the study and their inter-relationships. We also examine the average time delay in answering the questions and their accuracy levels. The study utilized a total of 28 questions, and Figure 3 illustrates the consistency of the correct and incorrect response rates across various response time levels.
Figure 3. The average response time and accuracy for each question.

Upon closer inspection, it is found that items 11 and 13, which had the highest response time, also had nearly identical rates of correct and incorrect responses. This indicates that the selection of questions had minimal impact on the model’s performance, as evidenced by the stable results in terms of response time and accuracy.

Therefore, based on the analysis of response time and correctness, we can conclude that the questions used in this study were appropriate and that their order had little effect on the overall performance of the model. These findings are important for future studies using similar methodologies and can serve as a basis for selecting questions that are both effective and efficient in obtaining accurate results.

5. Discussion

The main contribution of this paper is the development of a SAMM that measures sustained attention and its relationship to learning performance. To emphasize the significance of this model, several aspects are discussed below, including the Learning Management System (LMS) and video lecture presentation, biological signal detection for learning attention evaluation, and question level concerns. These considerations aim to provide a structured understanding of the revealed results and emphasize the achievements of this research.

5.1. Learning Management System (LMS) and Video Lecture Presentation

A Learning Management System (LMS) is a vital component of online learning, serving as a kernel platform that facilitates the management, delivery, and tracking of educational content and activities. It provides educators and learners with a centralized hub where they can interact, access course materials, submit assignments, participate in discussions, and track their progress.

There are numerous LMS options available on the market, each with its own unique features, interface, and functionalities. Examples of popular LMS products include Moodle, Blackboard, Canvas, and Google Classroom. These products may vary in terms of user interface, customization options, integration capabilities, mobile accessibility, and pricing structures. It is important to consider the specific needs and requirements of the institution or organization when selecting an LMS that best aligns with the online learning goals.

Moodle [13] is a widely recognized and extensively applied LMS. As an open-source platform, Moodle provides a high degree of flexibility, making it suitable for various educational contexts. Its open-source nature enables users to freely access and modify the source code to satisfy specific customization needs. This contributes to its feasibility,
customizability, accessibility, interoperability, and ease of learning content management. The proposed SAMM is built based on the Moodle framework, and the question-answer interaction suite is integrated so that the interaction results can be collected via the system.

Furthermore, the video lectures utilized for delivering learning content can be categorized into three primary types [38]: voiceover video lectures, picture-in-picture video lectures, and screencast video lectures. Voiceover video lectures involve course narration that accompanies presentation slides; picture-in-picture video lectures feature the instructor’s image superimposed on the video content; and screencast video lectures demonstrate the content within a specific software or digital environment, such as a Python IDE environment. In the proposed model, voiceover video lectures are utilized to deliver the content in a chapter-wise format, as designed by the instructor.

5.2. The Utilization of Biological Signals for Evaluating Learning Attention

Biological signal detection systems are devices used to assess, extract, and analyze a variety of physiological signals produced by the human body for healthcare monitoring, mental status measurement, and attention measurement [29,39,40]. These are established to collect and record signal data that reflect the functioning of different biological systems, providing valuable insights into a realistic environment.

Some applications utilized for measuring attention in online learning, such as eye tracking, paper-and-pencil tests, electroencephalogram (EEG), heart rate (HR), Galvanic Skin Response (GSR), and others, have been explored. The multimodal approach, which combines eye tracking, HR, and GSR, has also garnered significant attention [41]. Additionally, in [25], the use of NeuroSky’s MindSet headset and earphones for EEG testing is a well-known application with validated signal collection. However, managing these devices poses challenges, including deployment, maintenance, and guidance for remote users. Moreover, establishing such devices can be costly, and ensuring a stable environment that does not impact signal collection is crucial.

While the numerical data derived from various biological signals can provide insights into individuals’ current sustained attention, the proposed attention detection model prioritizes reception and response. It offers seamless integration with LMS and can be implemented without the need for external devices beyond basic computer and network setups. This approach achieves feasibility and accessibility, ensuring a user-friendly experience.

5.3. Concerns Related to Question Level

With regards to the cognitive domain [42], which is an educational objective framework derived from Bloom’s Taxonomy, cognitive processes can be classified into six levels: remembering, understanding, applying, analyzing, evaluating, and creating. Considering the learners’ course experience, the questions included in the model primarily focus on the levels of remembering and understanding, constituting approximately 50% and 40%, respectively. The remaining levels are allocated for the remaining questions.

Figure 4 presents an example of the question-answer processing screen. The screen consists of multiple components, such as the list of learning materials, the list of online students, the main display area, an identity switch function, and the question-answer interaction area, with one question displayed as an illustration. When a question that corresponds to the current content is presented, the learner is required to answer it. If the answer does not match the question, the system offers the learner another chance to retry, allowing for up to three attempts. The attempt time is a flexible parameter within the model, allowing for adjustments as necessary. When determining the optimal attempt time, several factors can be considered, including the question’s difficulty level and the learner’s proficiency in the course. In cases where students possess higher skills and encounter more challenging questions, a slightly longer attempt time may be allocated to maintain a balanced outcome.
In addition, instructors can collect and refer to the response and reception results to enhance teaching contents and methods. As illustrated in Figure 5, instructor management consists of multiple components. The primary management area, labeled as number (1), encompasses multiple management functionalities of instructor including learner management, course administration, homework assignment, assessment tracking, score monitoring, questionnaire handling, and others. Areas labeled as numbers (2) and (3), respectively, display operational records and answer results, providing information on correctness or incorrectness along with the number of attempts made. The screen also includes the learner’s identity and the date and time of their responses. When an instructor needs the data on response and reception results for any objective, such as evaluating the effectiveness of teaching materials, it can be imported as an editable file, for example, in CSV format.
6. Conclusions and Future Work

This paper introduces the Sustained Attention Measurement Model (SAMM), derived from a modified Signal Detection Theory (SDT), as an approach for measuring sustained attention. The model incorporates perception and response factors to gather relevant information for assessing learners’ attention. By analyzing response time and the correctness of selected questions, SAMM provides a comprehensive assessment of sustained attention. The experiment conducted to evaluate SAMM focused on two crucial factors: the number of response attempts and question-response issues. The results highlighted the importance of evaluating response time and correctness together to obtain an accurate assessment of sustained attention.

Furthermore, the experiment revealed that most learners were able to respond quickly after a question appeared, indicating that SAMM is sensitive enough to detect even small variations in attention span. These findings emphasize the effectiveness and sensitivity of SAMM in capturing and measuring sustained attention in learners. In conclusion, the model’s incorporation of perception and response factors, along with the analysis of response time and correctness, allows for a comprehensive evaluation of sustained attention.

SAMM possesses certain limitations that can be addressed in future research. Firstly, this study lacks a more precise before-and-after analysis, despite the relationship observed through the evaluation of learner semester assessments and the level of reception and response. Previous relevant research [25–29,29,38–41] has employed various approaches, such as pretests, posttests, and biological signal detection systems, to enhance attention measurement. However, these mechanisms tend to be costly and may have extreme impacts. In our improved model, we aim to incorporate helpful techniques or mechanisms that can be seamlessly integrated at a minimal cost.

Secondly, the current model is designed for voiceover video lectures in a chapter-wise format. Nevertheless, when it comes to second-language courses, it is crucial to consider the learner’s practice and repetition of content. Incorporating the instructor’s face and oral presentation can be particularly helpful in facilitating speaking skills, as it allows learners to engage in repeated practice by following and even replaying specific sections of the learning video. Therefore, future enhancements should focus on incorporating learner practice and considering the implementation of picture-in-picture video lectures to further improve the teaching content.

7. Implications

In this section, an implication, including holistic, comparative, and implementation perspectives, is provided to figure out the broader significance of these research findings and insights for future research and practice.

7.1. Holistic Perspective

Monitoring the effectiveness of learning is essential for ensuring successful outcomes. The proposed model offers a means to measure real-time performance in terms of response time, accuracy, and number of attempts made. By analyzing the collected data, instructors can evaluate whether a learner’s overall achievement is above average, average, or below average. This information provides a method to assess learning effectiveness and enables adjustments to teaching policies, strategies, methods, and content to be made more effectively based on the actual learning situation revealed by the proposed model.

7.2. Comparative Perspective

Individualization is an essential consideration in designing effective e-learning systems. By comparing the response time and accuracy of each learner, it is possible to classify their correct/incorrect perception level. Ongoing measurement is also crucial to understanding how learners learn and what they gain from the learning process. With this information, instructors can comprehend how each learner learns and provide individualized tutoring when necessary.
Moreover, the proposed SAMM establishes a direct and straightforward method for gathering materials to design differentiated instruction. This process ensures that what a learner learns, how they learn it, and how they demonstrate their knowledge match their readiness level, interests, and preferred mode of learning. This is often difficult to achieve in conventional e-learning systems but can be implemented in the proposed model with the measuring functionality.

Attention is a critical cognitive process that impacts learning. According to research [43], sustained attention has a significant influence on learning outcomes and effectiveness. The attention levels of learners can benefit both instructors and learners. For instructors, precise information on learners’ interests allows them to adjust teaching strategies to maintain learners’ attention. For learners, feedback data helps them better understand their learning process, enabling them to adapt their learning strategies [44]. Therefore, collecting and measuring learners’ attention levels is crucial to designing effective e-learning systems.

7.3. Implementation Perspective

When developing a system with multiple functionalities, it is crucial to consider conformance. Asynchronous LMSs are commonly designed as web applications that can be accessed by both instructors and learners via web browsers. To ensure greater flexibility, the measurement model is implemented as a software package using an appropriate web programming language. This approach allows for the creation of a web program with built-in database operations. The developed model is then seamlessly integrated into the LMS without any external impact. Its functions are sequentially triggered based on predefined conditions and scenarios embedded in the code.

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