Inconsistencies in Measuring Student Engagement in Virtual Learning – A Critical Review

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Abstract—In recent years, virtual learning has emerged as an alternative to traditional classroom teaching. The engagement of students in virtual learning can have a major impact on meeting learning objectives and program dropout risks. There exist many measurement instruments specifically geared to Student Engagement (SE) in virtual learning environments. In this critical review, we analyze these works and highlight inconsistencies in terms of differing engagement definitions and measurement scales. This diversity among existing researchers could potentially be problematic in comparing different annotations and building generalizable predictive models. We further discuss issues in terms of engagement annotations and design flaws. We analyze the existing SE annotation scales based on our defined seven dimensions of engagement annotation, including sources, data modalities used for annotation, the time when the annotation takes place, the timesteps in which the annotation takes place, level of abstraction, combination, and quantification. One of the surprising findings was that very few of the reviewed datasets on SE measurement used existing psychometrically validated engagement scales in their annotation. Lastly, we discuss some other scales in settings other than virtual learning that have the potential to be used in measuring SE in virtual learning.

Index Terms—Modeling from video, Affect sensing and analysis, E-learning tools, Computer vision.

1 INTRODUCTION

Virtual learning programs are becoming more ubiquitous and mainstream as internet services become more widely accessible and adopted [1]. Compared to traditional in-person learning programs, virtual learning programs offer many advantages, including better accessibility, lower costs, and more personalization. However, virtual learning programs bring their unique challenges. In a virtual learning setting, in which students and tutors are separated by a "virtual wall", it is very difficult for the tutor to assess the engagement level of students. A large group of students further intensifies this problem. Student Engagement (SE) is directly related to meeting learning objectives [2]. Therefore, it is important for a tutor to objectively assess SE to provide students with real-time feedback and take necessary actions to maximize SE.

In recent years, advances in Artificial Intelligence (AI) have led to the successful development of algorithms to objectively and automatically measure SE in virtual learning environments, especially in academia and the online classroom [3]. However, majority of the published results in this area rely on supervised machine learning approaches [4], requiring annotated ground-truth data to train models and to provide different types of outputs related to SE (e.g., engaged versus not engaged, or different levels of engagement). A significant concern is that most of the datasets used non-standard definitions of engagement; thus, the labels in many of these datasets are annotated differently. Unless a standardized SE definition and measuring scale is in place, collecting labeled data to train AI algorithms is very challenging, thus, constraining the development of systems to objectively quantify and fairly compare SE measurement algorithms.

The objective of this critical review is to investigate existing SE datasets in order to identify inconsistencies in the definitions of SE and the various SE annotation scales used in these datasets. The SE annotation scales are analyzed based on our defined seven dimensions of engagement annotation, including sources (the observers performing the annotation), data modality (the information that is observed by observers for annotation), timing (the time when the annotation takes place), temporal resolution (the timesteps in which the annotation takes place), level of abstraction (whether engagement is defined and annotated as a single-dimensional variable or a multi-dimensional variable), combination (the way the dimensions of engagement are combined to create one value for engagement), and quantification (the way the engagement is represented numerically). Our research focuses on the datasets collected from students watching and interacting with educational materials on computers in virtual learning and computer-based settings. The educational materials may be interactive or non-interactive, online or offline, and in a variety of formats, including live and recorded lectures and educational software. The data extraction procedure of this review includes characteristics of the collected datasets for AI model development, and it focuses primarily on how the
datasets were annotated. Several inconsistencies have been identified in the existing SE annotation scales, and it has been concluded that very few of them have been specifically designed and suitable for virtual learning. Most of the existing SE annotation scales are not designed based on the definition of SE in educational psychology. Finally, we discuss some of the existing SE scales in non-virtual learning environments that have the potential to be modified and to serve as a standard scale for annotating the engagement of students in virtual learning settings.

This paper is structured as follows. In Section 2, we study the definition of SE in educational psychology and introduce dimensions of SE annotation. In Section 3, we critically review and analyze the existing papers introducing a new dataset for SE in virtual learning, focusing on their engagement annotation scales. Section 4 involves studying some of the SE annotation scales and protocols that have the potential to be modified and used for SE annotation in virtual learning. In the end, Section 5 presents our conclusions and directions for future works.

2 Definitions of Student Engagement

Researchers have identified SE as involving three primary dimensions [5], [6] – behavioral (e.g., attendance, involvement, and being On-Task), affective (e.g., emotional reactions of excitement and desirability), and cognitive (e.g., invested in learning, relish challenge). Reeve and Tseng [7] posited a fourth dimension of SE - “agentic”, where a student constructively contributes to the flow of instructions.

SE in a learning environment is driven by learning objectives and outcomes [5], [8] in addition to the retention of participants in the educational program [9]. Here, the term “education” is not only limited to academic education but extends to include healthcare, counselling, and self-management. Therefore, fostering engagement in a virtual learning setting is a key factor in reducing program dropouts. Virtual learning sessions bring different types of challenges, the most important being the perception of connection, or lack thereof, between the instructor and learner and the difficulty for the instructor to attend to a learner’s behaviors [10].

Most of the virtual learning platforms use video and audio mediums for content delivery and communication between instructor and student. However, there is a limit to the amount of informative features that can be extracted from video and audio data. These features (e.g., body pose, affect, audio pitch) can then be used to build AI models to measure engagement. These features can also be learned through deep learning approaches [11], but due to limited modalities (i.e., video and audio), the extent of information captured is restricted. In theory, other types of sensors can also be employed, for example, electrocardiogram (ECG), electroencephalogram (EEG), and wearable devices to collect other physiological information (e.g., electrodermal activity, skin temperature, heart rate). However, in a real-world scenario, the use of many sensors in the educational environment and on the body of a student is impractical. Therefore, the key question to consider is whether these features (extracted or learned) from a sensing modality correspond or correlate to a measurement scale. Recent advancements in AI, especially deep learning, have allowed for the extraction of temporal affective and behavioral information from video and audio data for various tasks in the field of affective computing. However, in the context of SE, many virtual learning datasets use different types of observational scales for collecting ground truth labels (as discussed in Section 3).

Sometimes these scales are arbitrarily contrived, invented, or based on general knowledge rather than complete psychometric analysis. Therefore, there appears to be no direct concordance between the measurement scales and the information extracted from the videos, audio, or other sensing modalities. In such cases, it is very hard to establish a clear interpretation between what we wanted to train our algorithm on and what we actually trained our algorithm on. In many AI-driven engagement measurement approaches, the focus is on building sophisticated AI models without as much emphasis on the correctness of labels upon which they are trained. The outcomes of a successful AI model are as good as the quality of ground truth labels assigned to it. This further leads to questions around the validity of performance values reported by those methods for measuring SE.

2.1 Student Engagement Annotation

The meaning of engagement may vary from both the theoretical perspective and the “grain size” of the context [12]. A grain size can be defined as micro-level or macro-level, representing the resolution at which engagement is measured or observed. The former may relate to an individual’s engagement in the moment, task, or learning activity. In contrast, the latter may relate to a group of students in a class, group, or community. For instance, the National Survey of SE scale [13] is best suited for institutional level evaluation and inadequate to identify insights on finding correlations between a student’s engagement and the learning activity. In traditional learning settings, several methods exist to measure SE – self-reporting, observational, experience sampling, instructor/teacher rating, and interviews [14]. Appleton et al. presented a review on measuring SE in technology-mediated learning [15], where they covered several self-reporting and observational (qualitative and quantitative) scales.

Sinatra et al. [12] highlighted the challenges in the measurement of SE that includes: i) construct definition; ii) grain size of measurement; iii) individual and developmental differences of participants; iv) use of only single method for engagement measurement; v) in situ (in the moment measurement) problems, and vi) problems pinpointing the source of engagement.

D’Mello [16] identified five dimensions of affect annotation for developing supervised machine-learning models for affect detection: sources, data modality, timing, temporal resolution (timescale), and level of abstraction. There are two major differences between affect detection and engagement measurement: (i) Affect is only one of the three primary dimensions of engagement, as engagement also consists of behavioral and cognitive dimensions [5]. (ii) Contrary to the affect “detection”, an annotation for engagement “measurement” must not only identify engagement versus
disengagement, but also determine the “level” of engagement. According to these differences and inspired by the challenges of SE measurement cited by Sinatra et al. [12], we conducted this review based on a modified version of the above five dimensions and by adding two more dimensions, combination and quantification (scale), described below. The engagement annotation scales used in the existing datasets are analyzed according to seven dimensions of engagement annotation.

The first dimension of annotation, sources, refers to the types and number of individuals performing the annotation [16]. Observer-based annotation is the most common approach in the reviewed SE datasets (see Section 3.2), which is categorized into expert (trained) observers and non-expert (or novice) observers. An example of the expert observers, which is considerably high cost per observer, would be a group of educational psychology experts who are asked to annotate students’ engagement in a dataset. Conversely, non-expert (untrained) observers would be students without any prior training in psychology who are asked to annotate engagement according to their perception of engagement.

Observer-based annotations do not interrupt the learning process of a student. However, they are time and labor-consuming [17], and can suffer from observation bias (such as seeing what one is looking for and missing what one is not [18]). These measures are hard to scale but can “measure SE as it occurs” [19], which can be used to annotate various segments or transience of a student’s engagement in an educational session. Moreover, trained annotators are required to gather high-quality labels for engagement [14]. The common methods for observational measurements are direct observation of students or videos, screen capture behaviour of students, interviews or focus groups, and analysis of discussion boards or other digital communication tools [19]. The observational measures are often used in conjunction with other measures for additional evidence rather than a stand-alone source of information [1], [20].

The annotation by non-expert observers is usually performed in crowdsourcing settings [21]. In crowdsourcing, a task is usually given over the internet to a less-specific and more-public oriented group of observers. This approach can yield a large number of annotations in a short span of time. However, due to the lack of expertise in observers, it could also lead to noisy annotations [1].

Annotations can also be performed by the person itself (student in our case), which is called self-observer or self-report. Collecting concurrent self-report data at regular intervals can be disruptive and disengage individuals during their task(s) [1]. Retrospective self-report also requires a student to reconstruct past states of engagement on a post hoc basis, which may be biased. Different students may also differ in their own sense of what it means to be engaged. Self-report surveys are a scalable format in a virtual learning setting in comparison to the observer-based approaches. However, they may not be the best mechanism to capture engagement [19], especially if they are presented to students after longer duration learning exercises or at the end of the semester. Since SE also encompasses cognitive and emotional components, it is argued that self-report is the most valid measure to capture aspects of engagement that focus heavily on students’ perception of their experience [15]. Furthermore, self-report surveys may not capture the transience of engagement experienced by students [19].

The data modality dimension [16] pertains to the information that is observed by observers for annotation, such as video, audio, computer screen recording, mouse cursor tracking data, or their combination.

Annotation timing [16] refers to when the annotation takes place. This can be done in the moment as when students in virtual learning sessions are shown pop-up windows on their computers to concurrently self-report their engagement. In observer-based annotation, observers may be asked to watch the recorded (e.g., audio-visual) data of students and perform annotation in an offline manner [36] or in online manner, e.g., live annotation of students’ engagement in a classroom [22].

Temporal resolution (timescale) [16] refers to whether the annotation is performed at frame-level (e.g., still images extracted from video frames), segment-level (e.g., pop-up window self-reports shown every x minutes in a session), or session-level (e.g., retrospective self-reports at the end of learning session). Majority of the existing engagement annotation datasets are recorded videos of students. Observers (self or external) have either annotated single-frames of videos, video segments of a predetermined length, or a video of an entire session. Some datasets have been annotated in an adaptive segment-level manner [22], [23] in which the length of video segments is determined according to the changes in the engagement states of the students.

Regarding the level of abstraction, engagement can be annotated at a high level, directly to the point, without considering the dimensions of engagement, e.g., into two classes of engagement and disengagement. In a different setting, the affective, behavioral, and cognitive dimensions of engagement are first separately annotated and then combined to result in a numerical value for engagement. In the field of affect annotation, Pomsta et al. [24] have defined the above two settings as discrete response, and dimensional response, respectively. Each of the affective, behavioral, and cognitive dimensions of engagement can also be annotated at different levels. To illustrate, behavioral engagement can be in two states of Off-Task and On-Task. The On-Task behavior itself can be in different categories of On-Task Conversation, On-Task Giving Answers, and so on [22].

An annotated dataset suitable for supervised machine learning requires a numerical value, a label, for each sample (e.g., an image, video segment, or entire video) in the dataset. The combination dimension is concerned with how the annotated affective, behavioral, and cognitive dimensions of engagement are combined to derive a numerical value for engagement. For instance, Aslan et al. in [23] the combination of the On-Task behavioral state and Highly-Motivated/Excited affective state results in the state of engagement (versus disengagement). Naibert et al. [25] proposed different architectures for the combination of affective, behavioral, and cognitive dimensions of engagement collected through self-report questionnaires. It should be noted that the practice of a combination of the multiple dimensions precludes examining distinctions among the dimensions, and important information may be lost [5].

In addition, a strategy for combination should take into
account the correlation between the affective, behavioral, and cognitive states of students [25]. As described for the level of abstraction, if one ordinal value is directly assigned to a specific level of engagement, without considering its different dimensions, no combination is required.

The *quantification (scale)* dimension refers to how engagement level is represented numerically, i.e., the type of the variable used for definition and annotation of engagement. The quantification of engagement level as a psychology term must ensure objectivity, precision, and rigor [27]. The engagement has been quantified and annotated as a dichotomous variable having two states of engagement and disengagement or as an ordinal variable representing ordinal levels of engagement. Another setting is to quantify individual dimensions of engagement and combine these to generate a numerical value for overall engagement level.

3 Student Engagement Datasets for Virtual Learning

In recent years, there has been a growing interest in measuring SE in virtual learning using various sensing modalities. As a consequence, many researchers collect-ed engagement measurement datasets, some of which are publicly available for research purposes. In this section, we discuss the existing SE datasets. We cover the majority of the works in which a single-modal or multi-modal dataset for engagement measurement in virtual learning has been proposed and used for AI model development. Despite the fact that affect is one dimension of engagement, we do not study the papers introducing datasets of general affect detection (such as basic affect state recognition or valence and arousal recognition datasets) as our focus is on engagement measurement datasets. This review may be limited in comprehensiveness despite a thorough review of the literature; however, it was not systematic in nature. This review is also not focused on analyzing the AI techniques for engagement detection. Other reviews are available for interested readers on engagement datasets with discussions regarding AI techniques [3], [28]. We also do not discuss publications on classroom-level engagement or the engagement of groups in a virtual learning setting, rather the focus is on individual-level virtual learning scenarios. In particular, we are interested in virtual learning datasets that were collected from students using computers to watch/interact with educational materials. These materials may be interactive or non-interactive, online or offline, and in different types of educational resources, including live and recorded lectures and educational software. Our intention is to synthesize knowledge and discover inconsistencies that will help guide future research in the field.

The details of the works reviewed in this section are presented in Table 1, containing the seven dimensions of engagement annotation (defined in Section 2.1): virtual learning setting, and the baseline information of the participants in the virtual learning setting. We report the following two characteristics: (i) virtual learning setting – in which student attends virtual classes where a teacher presents a course to the students in real-time, and (ii) computer-based setting – in which student watches an educational video, a recorded course, reads a document, writes an essay, or works with educational software on a computer screen in an offline manner. Any of the above settings can be non-interactive or interactive in which the student should interact with the computer in addition to looking at the computer screen. The data collection can happen in the wild, i.e., in real-world situations, e.g., for video datasets with different backgrounds and in different lighting conditions, or in the lab in which the data of all students are collected in a lab, e.g., with uniform background and ideal lighting conditions. We report the number of students in each dataset, sex, and age. For each dataset, Table 1 also contains the percentage of samples at different levels of engagement. In this section, the datasets are presented according to the sources, concurrent and retrospective self-reports annotation, observer-based annotation (categorized into expert observers, student observers, unknown observers, and crowdsourcers), and the combination of self-reports and observer-based annotation.

3.1 Self Reports

Vanneste et al. [10] collected data from 14 students of grade 12 who were followed for six lectures (duration 70 minutes each) on various subjects. These lectures occurred in a hybrid virtual setting, i.e., students attended the lectures both virtually and in class. A digital pop-up was sent to students at random time intervals (5 – 12 minutes gap). They could move the slider to any value from 0 (disengaged), 1 (neutral), 2 (engaged), and any other position to self-report their intermediate engagement level. Therefore, the scale used was quasi-continuous. Their study generated 580 digital self-reports with approximately 40 measurements per student. They also collected another dataset for estimating collective engagements in a classroom, which is beyond the scope of this paper.

Monkaresi et al. [29] collected a dataset from 23 students who were asked to write an essay in front of a computer. They were given feedback to improve the quality of writing while sitting at the desk. Colour and depth videos were collected using a Kinect camera. Two ECG electrodes were placed on students’ left and right wrists, and one was placed on their ankles. The system gave the students an audible probe every two minutes to verbally and concurrently self-report their level of engagement (engaged in writing or not). Their response was recorded using a Kinect microphone. After one week of the recording, the students retrospectively filled out a questionnaire after viewing each segment, which asked them, “Were you engaged in the task or not?” For these self-reports, 1,325 segments were extracted from all the videos. They found a high correlation between concurrent and retrospective engagement reports ($r = 0.82$).

De Carolis et al. [30] collected data from 19 students to measure and monitor engagement. They developed SE profile using video slides, video lessons, and TED-style video lessons. Each participant’s video was captured through a web camera to record face and gaze behavior. The average time of the video lessons was 9 minutes, following which they filled out a questionnaire of their “perceived” engagement using the flow process that accounts for challenge, skill, engagement, and perceived learning during the virtual learning process. They performed factorial analysis to extract the four factors and obtained Cronbach alpha = 0.70 to
test their reliability. The range of scale of engagement is not clear from their description, though they process the videos in 10-second windows and obtained engagement values in the continuous range between 0 and 1.

Chen et al. [32] collected video data from 88 college students studying general-topic books on a computer in two-minute reading sessions. Students were asked to rate their ordinal levels of three affective states of engagement, confusion, and frustration at the end of each two-minute studying session from 1 (very little) to 6 (very much).

Hutt et al. [33] collected a large-scale dataset from 69,174 high school students attending virtual mathematics learning sessions with an educational online interactive software facilitating communication between teachers and students. They collected activity features of students while working with the educational software, such as viewing video lectures, taking quizzes, and viewing discussion boards. Self-reports were displayed through pop-up windows, and the students were asked about their affect states. The pop-up windows asked for one of their 19 affect states (including affective engagement) at a time, e.g., “How engaged are you right now?” or “How content do you feel right now?”

In each pop-up window, students can order (one of) their 19 affect states from 1 to 5, e.g., Not at all engaged to Very engaged. The fact that students were able to opt-out of the self-report pop-up windows and that the pop-up windows were shown at random time intervals make it less distracting and light touch to students compared to the previous works. Since the self-reports were taken at random time intervals, the authors segmented the collected data of the corresponding students, 1, 3, and 5 minutes before taking the self-report to generate 1, 3, and 5-minute data segments.

### 3.2 Observer-based Engagement Annotation

Human annotators are required to observe videos/images data (or other sensing modalities) and label them so that AI algorithms can be trained to detect engagement. In the context of SE, these annotators were either students, experts, or unknown. A student annotator could be a research team member or a beginner in the field, whereas an expert annotator could be a highly qualified person in the field. Unknown annotators are those whose qualifications are not discussed in the papers.

#### Student Observers

Whitehill et al. [17] collected videos from 34 undergraduate students in an experiment to measure the importance of seeing the student’s faces in the teaching setting. The students from computer science, cognitive science, and psychology annotated the data for the appearance of engagement. The videos were labeled at frame level and video level on a four-point ordinal scale – 1 = not engaged at all, 2 = nominally engaged, 3 = engaged in the task, 4 = very engaged, and X = unclear. They labeled the video data at intervals of 10 and 60 seconds. They found that 10 seconds annotation was easier because, in longer video segments, it was hard to label if the person appeared engaged earlier and not engaged later or vice versa. This was demonstrated through higher inter-rater reliability (across two annotators) for 10-second segments \( (k = 0.68) \) in comparison to 60-second segments \( (k = 0.39) \). According to Whitehill et al. [17], the annotation instructions provided for observers correspond to all the affective, behavioral, and cognitive dimensions of engagement. For instance, the authors contended that the distinction between levels 3 and 4 is linked to the student’s motivational state. The reported inter-observer reliability for four levels of engagement (Cohen’s \( k = 0.56 \)) is, however, significantly lower than that for dichotomous low and high engagement (Cohen’s \( k = 0.96 \)).

Nezami et al. [34] presented an engagement recognition dataset consisting of 4627 images from 20 students who were learning scientific knowledge and research skills using an educational interactive software. Images were sampled at a fixed rate, then randomly shuffled and passed on to observers (graduate psychology students), who labeled 100 samples each using a customized software. Each sample was annotated by at least six observers, which shows Fleiss \( k = 0.59 \). The annotators were provided definitions of affective and behavioral dimensions of engagement as “inspired by the work of Aslan et al. [23]”. By combining the outcomes of affective and behavioral dimensions, each image was labeled as engaged and not engaged.

Booth et al. [35] collected front-facing videos of 12 students of a graduate-level course watching lecture videos of the computer science course. The minimum length of the lectures was 20 minutes. For each video, undergraduate and graduate students were recruited to provide engagement ratings based on their “perception of the student’s engagement” on a continuous \([0, 1]\) interval scale in real-time. Annotators were not provided clarifications or indications to interpret the term engagement. Each video session received approximately nine annotations. They fused separate annotations into one continuous time series, and then these values were further divided into binary, trinary, and others based on various thresholding techniques. In the end, annotators completed an exit survey about their confidence in annotation accuracy and any distractions during the annotation process. Inter-rater/intraclass reliability analysis suggested that a value above 0.6 was considered a good agreement between annotators.

#### Expert Observers

Aslan et al. [36] collected data from recording nine students that provided the following information: RGB and depth camera, facial motion, eye tracking, body posture, facial expression, and screen capture. They used a three-point categorical scale for labeling engagement: 1 = Not engaged, 2 = Engaged, and 3 = Unknown. The unknown labels were discarded during training their AI models, so the actual task is whether a person was engaged or not. Each 80-minute video was divided into four segments. Three trained annotators labeled 20 minutes of each video segment. They considered a Cohen’s Kappa value of 0.6 or more as good agreement and less than 0.2 as poor agreement.

Alyuz et al. [37] collected an audiovisual data and screen capture dataset of 60 students in grades 1–12. The students attended computer-based non-interactive courses on math topics customized for their grades in a lab environment. In total, 60 hours of data were collected, one hour (two 30-minute sessions) from each student. The collected audio-
visual data and screen capture of students were used by three trained observers. The authors used the behavioral and affective dimensions of engagement as inspired by the work of Aslan et al.\[23\]. However, they did not combine the behavioral and affective dimensions and analyzed the dimensions of engagement separately. The behavioral states are On-Task and Off-Task, and the affective states are satisfied, bored, and confused. The author also allowed the annotators to select Can’t Decide, and Not Available in case they could not decide on a specific label, and if the student was not present or the learning session had not started yet, respectively. The authors did not specify a timescale for annotation, and the observers adaptively identified segments based on the observed state changes in students.

Okur et al.\[38\] collected around 170 hours of data from 28 students in computer-based classrooms using two different content platforms (one for Math and the other for the English language). Their task was to determine students’ behavioral engagement, i.e., On-Task/Off-Task. They collected contextual data from the URL logs and appearance data using a depth camera. If the student was not actively using the content platform on their device, they were labeled as “Off-Task”. If the content platform was active on the user’s device, appearance information was used to understand if they were consuming the content. Based on previous works by Alyuz et al.\[37\] and Aslan et al.\[23\], their temporal resolution is also adaptive based on the changes in the behavioral states of the students. However, for creating their dataset used for training AI models, they created 8-second video segments with 4-second overlap. Following Aslan et al.\[23\], they employed three observers with expertise in Education or Educational Psychology. The observers had access to students’ RGB video data, audio data, desktop recordings, mouse cursor location, and contextual logs. Observers were provided training about the process and shown examples before labeling the videos. The final ground truth labels were obtained by majority voting, and validity filtering was applied to discard videos with no majority vote. They obtained high inter-rater agreement for the three annotators (Krippendorff’s alpha = 0.82, 0.86, 0.87) and argued that behavioral engagement can be considered as an objective annotation scale for determining engagement.

Alyuz et al.\[39\] collected 113 hours of data from 17 school students who were consuming digital learning materials on laptops with cameras. Data was collected from video cameras, mouse movements, and students’ interaction and performance data related to learning content for 13 sessions of 40 minutes each. Three educational experts labeled the data using Human Expert Labeling Process (HELP) system\[23\] (described in Section 4). Their time scale is also adaptive based on the changes in the states of the students\[23\]. However, for creating their dataset used for training AI models, they created 8-second video segments with 4-second overlap. They used majority voting and validity filtering to obtain final ground truth labels.

Zaletelj and Košir\[40\] collected data from 22 undergraduate students using a Kinect Camera to record their video and depth information from a 25-minute lecture. Five human observers annotated the engagement level of students at a granularity of 1 second on a five points ordinal scale. To regularize fluctuations in annotations, median filtering was performed with a time window of 10 seconds and thresholding to three levels.

Kapoor et al.\[41\] collected video and screen recording data from eight 8-11 years old students. The students played an educational game for 30 minutes in a lab environment. By watching video and screen activities of students, teachers annotated the states of high, medium, and low interest, bored, and a state that they called “taking a break”. They report an average overall agreement (Cohen’s Kappa) of 78.6% between the annotations of the unreported number of teachers (observers). They did not report the temporal resolution of annotation; however, the duration of samples in the dataset was 8 seconds. According to the authors, due to the fact that they cannot directly observe the student’s internal thoughts and emotions, nor can children in the age range of 8 and 11 years old reliably articulate their feelings, they chose to focus on annotating affective states (affective dimension of engagement).

Bosch et al.\[42\] collected a dataset containing videos of 137 high school students working with an educational software about physics for 55 minutes. They used the Baker Rodrigo Ocumpaugh Monitoring Protocol (BROMP) observation system\[22\] (described in Section 4) for annotating the videos. Of all affective and behavioral states available in BROMP, they collected affective states of Engaged Concentration, Boredom, Confusion, Delight, and Frustration, and behavioral states of On-Task, On-Task Conversation, and Off-Task. As per in BROMP, the timescale of annotation was adaptive based on observing one student until visible affect is detected or 20 seconds have elapsed. They did not combine the affective and behavioral states to generate one numerical value as the engagement level, and different AI models were separately trained on the affective and behavioral states.

Unknown Observers

In many studies that we reviewed, information about the observers was either not provided or was not obviously clear. The EmotiW dataset\[43\],\[44\] contained video snippets from 78 subjects who watched an online educational video. In total, 262 videos, each of 5 minutes duration, were collected. A team of 5 observers annotated the videos for engagement level (from facial expressions) − 0 = disengaged, 1 = barely engaged, 2 = engaged and 3 = highly engaged. Weighted Cohen’s k with quadratic weights was applied to eliminate labels as less reliable (less than 0.4), and the remaining labels were averaged.

Alkabbany et al.\[45\] collected video datasets from 14 students who watched 10-15 minutes lectures followed by a quiz. Four observers labeled the data on a four-point scale: 0 = no face detected, 1 = behaviorally not engaged, i.e., looks outside the screen, 2 = behaviorally engaged, emotionally not engaged, i.e., looks inside the screen but with no sign of engagement, and 3 = emotionally engaged. After removing the "no face detected" category, they collected 109,325 frames. A frame was included in the dataset if three annotators used the same label for a frame. Therefore, the final number of frames selected in this dataset was 73,530. They obtained a pairwise Pearson correlation of 0.66, 0.71, 0.62, 0.72, 0.58, and 0.61 among different annotators, which
reflected relatively similar associations among observers. In defining engagement at the four levels above, the authors considered behavioral engagement to be a prerequisite to affective engagement and high levels of engagement, which is also implicitly considered by Aslan et al. [23].

Bhardwaj et al. [46] presented a tabular dataset obtained through a survey conducted on 1,000 students over a period of one week during online live classes. Ten observers were randomly selected who observed one student at a time in an online classroom while noting the SE on a scale of 0 to 5, and also engaged versus not-engaged. No further details regarding the engagement scale were provided by the authors.

Binh et al. [47] extracted 942 images from videos of students in a classroom. Based on “popular” postures, the images were labeled as interested (engaged) and non-interested (disengaged). The images were further labeled into granular activities within each of the two groups. No discussion on the annotation scale or annotators was provided in the paper.

Crowdsource Observers

Gupta et al. [5] created DAiSEE, a multi-label video classification dataset from 112 students, comprising 9,068 videos each 10 seconds long, containing labeled data for affective states of engagement, boredom, confusion, and frustration. They used crowd annotators to define each of these affective states into four levels – very low, low, high, and very high. The “wisdom-of-the-crowd” was relied upon to label subtle affective states, such as user engagement, that are “subjective and vary based on the viewer’s discretion” [3]. The data labels were obtained from non-experts by using a crowdsourcing application, CrowdFlower. For each video snippet, ten votes were obtained. Their general idea was that while the annotators are non-experts, “repeated labeling of examples by multiple annotators produces high-quality labels”. The Dawid-Skene [3] vote aggregation algorithm was used to obtain final labels from multiple human annotators for a given video snippet. However, contrary to their assertion, noisy annotations were generated due to high variability in engagement labels. To circumvent this issue, they created two teams of experts comprising a social, a clinical, and a behavioral psychologist to label a subset of videos. Each group worked on mutually exclusive videos from the subset of videos, and consensus from experts was used to create the final ground truth labels, which in turn led to the removal of noisy annotations. To measure the annotator’s inter-rater reliability, Cohen’s k was used. If the $k < 0.5$, those annotations were deemed unreliable and removed from the dataset.

Kamath et al. [48] collected data from 23 students who watched approximately 10-minute lectures on a computer screen. In total, 4408 images were obtained from the videos, sampled at a fixed rate, and uploaded to a crowdsourcing platform, CrowdFlower. The annotators labeled these images on a 3-point scale of not engaged, nominally engaged, and very engaged. At least 25 annotations were obtained for each image, and the majority vote aggregation technique was used to decide each image’s final ground truth label.

Delgado et al. [49] collected an image dataset of 19 students while solving math problems on an educational mathematics software. The students were provided with a piece of paper to take notes on. The videos of students were recorded with a front-facing camera, and 18,721 frames were extracted from the recorded videos for annotation. Three crowdsource observers annotated the frames in three classes of Looking at Their Screen, Looking at Their Paper, and Wandering. Majority voting was used to combine the three crowd-collected selections into a single vote for each frame. In the authors’ categorization, the first two classes correspond to engagement, and the Wandering class shows disengagement. Even though they did not clearly mention which affective, behavioral, and cognitive dimensions of engagement they detected, based on their definition, the first two classes appear to correspond to behavioral engagement.

3.3 Combination of Self Reports and Observer-based Annotation

Zheng et al. [50] collected video data from 19 participants using a built-in PC camera that faced the students, who were asked to answer a cognitive assessment battery test. Due to the different speeds of test completion by participants, the collected videos were of varying lengths. They collected both self-reports (from participants) and external observation results from other study members to label video samples to three levels of engagement.

Altuwairqi et al. [51] created an engagement dataset from students by recording their videos while working in a computer lab, along with their mouse and keyboard activity information. 164 videos of two minutes duration were collected from 110 students, and keyframes were extracted from videos. The engagement was labeled by observation, and student self-reports based on a 5-point engagement scale – Disengagement, Low, Medium, High, and Strong Engagement [52].

Ma et al. [53] collected 236 videos of length 30 minutes from 59 students watching recorded video lectures. The topic of the videos (on healthcare) was different from the major of the students (software engineering and digital media). Retrospective self-reports of the students, the annotation of three observers, and the answers of the students to the questions about the lectures were averaged to give an engagement level between 0 and 1. The authors did not provide details of their annotation scale. However, since the answers to the questions about the lectures were included in the final engagement level, the annotated engagement seems to contain the cognitive dimension of engagement.

Bosch [54] collected a dataset of 98 students reading books on computers. The students were instructed to concurrently self-report their mind wandering whenever they become aware that they have been mind wandering. Based on the self-reported data, 3,272 twelve-second video segments of Mind-Wandering and Non-Mind-Wandering were extracted from the video of students to be annotated by trained external observers. The observers annotated video segments in terms of the occurrence of mind-wandering. In addition to annotating mind-wandering in videos, annotators provided confidence regarding their annotation and described the reason why they annotated video segments as Mind-Wandering or Non-Mind-Wandering. Finally, maximum likelihood estimation was used to find the most consistent annotated video segments that were used for training.
AI models. Bosch hypothesized that mind-wandering and the cognitive dimension of engagement are correspondents. Chen et al. [55] collected data from 30 postgraduate students (17 females and 13 males) in a learning lab participating in an English as a second language class. Each student participated in two 50-minute sessions. The values of valence (positive/negative), arousal (high/low), and attention or engagement (on/off) of students were observed by a trained person together with the students’ self-reports. The data modalities collected from the students were videos, skin conductance sensor data, and computer log files. The authors did not provide any additional information regarding the annotation process, e.g., the time resolution of annotations.

3.4 Summary and Analysis

Table 1 summarizes our analysis of the papers reviewed in the previous sections. We organized the table to contain dimensions of engagement annotation, including sources, timing, temporal resolution, data modality, level of abstraction, combination, and quantification (scale), as well as brief demographic information of the students in the datasets, and baseline characteristics of the collected datasets. Based on our analysis, we observed several inconsistencies in the reviewed studies, which are described next.

Our review showed that the definitions of engagement used in previous studies were not consistent; they are primarily based on general observations of patterns and not based on psychometrically validated scales. Surprisingly, despite the availability of existing self-report and observational scales for SE [15], very few of the reviewed studies incorporated previously validated scales in their methodology. Bosch et al. [42] used BROMP (described in Section 4), and the authors in [37], [38], [39] used HELP [23] (described in Section 4) for engagement annotation. This further highlights the disconnect between computational and educational research streams and calls for a more interdisciplinary, collaborative approach to address the definition and measurement of SE.

Hutt et al. [33] stated that, as with any complex psychological construct, there is no direct way to measure affect, and it should be determined based on the operational definition of the construct. As affect is one dimension of engagement in learning environments, engagement measurement is more problematic compared to basic or non-basic affect state detection [33].

Appleton et al. [15] also mentioned that there is no “one-size-fits-all” measurement instrument for SE. Different instruments have their own strengths and limitations that need careful consideration before incorporating into a given study.

**Inconsistencies in Quantification (Scale)**

Few researchers (Vanneste et al. [10], Zaletelj and Košir [40]) have highlighted the lack of a “gold standard” in measuring engagement. A major issue among all the studies reviewed is the inconsistency in the use of scales for measuring SE. We observed that different studies used different quantification methods to represent different levels of engagement and used custom-made scales ranging from two to six points to continuous and quasi-continuous values. Moving forward, this can be a major constraining factor for progress in the field. In a simplified sense, the concept of an object, “X” must be consistently labeled as “X” based on a commonly accepted measurement instrument across multiple data sources. Otherwise, supervised AI models may not learn that concept effectively. Corresponding to the different types of engagement scales in the existing datasets, different types of supervised AI models were trained to solve binary or multi-class classification or regression problems [4]. In the definition of multi-level engagement, it is an ordinal (rank) variable [17]. Surprisingly, with the exception of Wang et al. [56], who used a rank loss for engagement level regression tested on the EmotiW dataset [43], all other works on SE considered ordinal levels of engagement as categories with no order and developed classifiers for categorical classification (see Table 1).

**Inconsistencies in the Level of Abstraction**

Despite the fact that engagement is a multi-dimensional state [5, 12], and considering that individual dimensions are also multi-componential [16], many authors have defined engagement as a single-component state without clarification on its dimensions. They defined different levels for single-component state of engagement, very low to very high levels of engagement, or some just defined presence or absence of engagement. A number of authors annotated engagement based on only one of its dimensions, e.g., affect or behavioral. Other works annotated engagement as a multi-dimensional state. No justification was provided in the existing datasets for considering only one or more dimensions of engagement in a particular learning setting (see Table 1).

**Inconsistencies in Combination**

In the works in which engagement was defined and annotated as a multi-dimensional state, some works combined the dimensions to generate one numerical value for engagement, as in HELP, in which various combinations of affective and behavioral dimensions result in a dichotomous engagement state [23]. In some other works, one dimension of engagement was taken into consideration as a prerequisite for other dimensions of engagement. For instance, in Alkabbany et al. [45], the presence of behavioral engagement (and the absence of affective engagement) corresponds to lower levels of engagement. Then, the presence of both affective and behavioral engagements corresponds to higher levels of engagement. In some other works, such as the datasets in which BROMP [22] was used for annotation, engagement (engaged concentration state in BROMP) is annotated as an affective state, and behavioral states are annotated separately and they did not combine the affective and behavioral dimensions. In a totally different engagement annotation method, Bosch [54], the occurrence of mind-wandering is considered as cognitive engagement, and mind-wandering has been annotated using video data modality along with concurrent self-reports (see Table 1).

**Inconsistencies in Data Modality**

In the existing datasets, diverse types of information have
| Reference            | Setting                      | Participants          | Data Modality                    | Sources               | Timing  | Temporal Resolution | Level of Abstraction — Combination | Quantification or Scale — and distribution of measures |
|----------------------|------------------------------|-----------------------|----------------------------------|-----------------------|---------|---------------------|-------------------------------------|-------------------------------------------------------------|
| Vanneste et al. [10] | virtual learning, lecture,  non-interactive, in-the-wild | 14 students, 4 females, 16-20 y.o. | NA                               | self-reports          | concurrent | 5 ± 1.2 min         | engagement                          | interval, from 0 (totally disengaged) to 1 (neutral) to 2 (totally engaged) |
| Merkens et al. [27]  | computer-based, essay writing, non-interactive, lab | 9 students, 9 females, 16-60 y.o. | NA                               | self-reports           | concurrent and retrospective | 2 min                    | engagement                          | affective, cognitive, engagement, interest, and motivation: 85% and 26% |
| De Cauwer et al. [28] | computer-based, lecture, non-interactive, lab | 18 students, 9 females, 16-60 y.o. | NA                               | self-reports           | retrospective  | 5 min            | -                                   |                                            |
| Ozer et al. [29]     | computer-based, book reading, non-interactive, in-the-wild | 98 students, college  | NA                               | self-reports           | retrospective  | 2 min            | affective dimension                | ordinal, affective states of engagement, concentration, and frustration, from 1 (very little) to 6 (very much) |
| Hall et al. [30]     | virtual learning, lecture, interactive, lab | 67/74 students, high school | NA                               | self-reports           | retrospective  | random           | affective dimension                | ordinal, levels of emotions: engaged, disengaged, from 1 (not at all engaged) to 3 (very engaged) |
| Vuthikun and Wulff [31] | computer-based, software, interactive, lab | 38 students, 25 females, under graduate | video and image | observational data (6 trained students) | retrospective  | 10 sec and 60 sec | affective, behavioral, and cognitive dimensions — implicitly | affective, behavioral, and cognitive dimensions: 85% and 50% |
| Neumeister et al. [32] | computer-based, software, interactive, lab | 30 students, 11 females, 16-18 y.o. | video and image | observational data (6 trained students) | retrospective  | single-frame | affective and behavioral dimensions — tabular | affective, behavioral, engaged and disengaged: 85% and 50% |
| Redfyl et al. [33]   | computer-based, lecture, non-interactive, lab | 12 students, 20 y.o. | observational data (7 untrained students) | retrospective  | 20 min | engagement | affective and behavioral dimensions — tabular | affective, behavioral, engaged and disengaged: 71% and 29% |
| Asian et al. [34]    | computer-based, lecture, non-interactive, lab | 9 students, high school | observational data (7 untrained students) | retrospective  | 20 min | engagement | affective and behavioral dimensions — categorically: engaged, not-engaged, and unknown | affective, behavioral, engaged and disengaged: 68% and 32% |
| Aijazi et al. [35]   | computer-based, lecture, interactive, lab | 60 students, 20 females, grades 1-12 | audio, video, screen capture | observational data (3 experts) | retrospective  | adaptive and based on state change | affective and behavioral dimensions — tabular | affective, behavioral, engaged and disengaged: not applicable, can’t decide and not available: 72%, 17%, and 5% categorical; behavioral states of on-task and off-task: can’t decide and not available: 99% and 99% |
| Owe et al. [36]      | computer-based, lecture, interactive, in-the-wild | 28 students, 14-15 y.o. | video, audio, computer screen, mouse cursor, and URL bags | observational data (3 experts) | retrospective  | adaptive and based on state change | behavioral dimension | categorical: on-task, off-task, can’t decide, engaged and disengaged: 71% and 29% |
| Aijazi et al. [35]   | computer-based, lecture, interactive, in-the-wild | 17 students, 14-15 y.o. | video, audio, computer screen, and mouse cursor | observational data (3 experts) | retrospective  | adaptive and based on state change | behavioral dimension | categorical: on-task, off-task, can’t decide, engaged and disengaged: 68% and 32% |
| Zoloty et al. [37]   | classroom, lecture, non-interactive, lab | 22 students, 2 females, undergraduate | video and image | observational data (2 experts) | retrospective  | 1 sec | engagement | affective and behavioral dimensions — categorically: engaged, not-engaged, and unknown | affective, behavioral, engaged and disengaged: 68% and 32% |
| Kapoor et al. [38]   | computer-based, software, interactive, lab | 9 students, 8-11 y.o. | video and computer screen | observational data (trained annotators) | categorical  | 8 sec | affective dimension | categorically: 5 states of high, medium, and low interest, boredom, and taking a break: 45%, 30%, 20%, 5%, and 0% |
| Bosch et al. [39]    | computer-based, software, interactive, in-the-wild | 127 students, 37 females, 13-15 y.o. | video | observational data (trained experts) | concurrent | adaptive and based on state change or 20 sec | affective and behavioral dimensions — categorically: occurrence of affective states of boredom, concentration, delight, frustration, and engaged concentration: 4%, 2%, 2%, 14%, and 78% categorical; occurrence of behavioral states of on-task, off-task, and can’t decide: 71% and 29% |
| Kaur et al. [40]     | computer-based, lecture, non-interactive, in-the-wild | 36 students, 26 females, 19-27 y.o. | video | observational data (3 experts) | retrospective  | 10 min | behavioral dimension | affective and behavioral dimensions — categorically: levels of engagement: 7%, 2%, 5%, 43%, and 48% |
| Alkabbany et al. [41] | computer-based, lecture, interactive, in-the-wild | 14 students, undergraduates and postgraduates | video | observational data (4 annotators) | retrospective  | single-frame | affective and behavioral dimensions | categorically: engagement, disengagement, engagement, and disengagement: 7%, 2%, 44%, and 48% |
| Vuthikun and Wulff [31] | virtual learning, lecture, non-interactive, in-the-wild | 1010 students | video | observational data (10 annotators) | retrospective  | - | engagement | affective and behavioral dimensions | categorically: levels of engagement: 1%, 3%, 5%, and 40% |
| Bhal et al. [42]     | virtual learning, lecture, non-interactive, in-the-wild | - | video | observational data | retrospective  | single-frame | engagement | affective and behavioral dimensions | categorically: levels of engagement: 1%, 3%, 5%, and 40% |
| Gupta et al. [43]    | virtual learning, lecture, non-interactive, in-the-wild | 112 students, 52 females | video | observational data (10 untrained annotators) | retrospective | 10 min | affective dimension | categorically: levels of engagement: 1%, 3%, 5%, and 40% |
| Kaur et al. [40]     | virtual learning, lecture, non-interactive, in-the-wild | 25 students, undergraduates and graduate, 16-24 y.o. | video | observational data (25 untrained annotators) | retrospective | single-frame | engagement | affective and behavioral dimensions — categorically: looking at their screen, looking at their paper, and wandering: 75%, 2%, and 3% |
| Delgado et al. [44]  | computer-based, software, interactive, lab | 19 students | video | observational data (19 untrained annotators) | retrospective | single-frame | behavioral dimension | affective and behavioral dimensions — categorically: looking at their screen, looking at their paper, and wandering: 75%, 2%, and 3% |
| Zheng et al. [45]    | computer-based, software, interactive, in-the-wild | 19 students | video | observational data (19 untrained annotators) | retrospective | 14 min | - | affective and behavioral dimensions — categorically: levels of engagement: 3%, 4%, and 9% |
| Alkabbany et al. [46] | computer-based, lecture, non-interactive, in-the-wild | 110 students | video | observational data (110 untrained annotators) | retrospective | single-frame | engagement | affective and behavioral dimensions — categorically: levels of engagement: 3%, 4%, and 9% |
| Ma et al. [47]       | computer-based, lecture, non-interactive, in-the-wild | 59 students, undergraduates and graduates, 20-32 y.o. | video | observational data (59 untrained annotators) | retrospective | 30 min | engagement | affective and behavioral dimensions — categorically: levels of engagement: 3%, 4%, and 9% |
| Bosch et al. [39]    | computer-based, book reading, non-interactive, in-the-wild | 98 students | video | observational data (students annotations) | concurrent and retrospective | 12 sec | cognitive dimension | affective and behavioral dimensions — categorically: levels of engagement: 3%, 4%, and 9% |
| Ozer et al. [48]     | computer-based, software, interactive, lab | 30 students, 17 females | videos, skin conductance, leg files | observational data | retrospective | - | - | affective and behavioral dimensions — categorically: levels of engagement: 3%, 4%, and 9% |

**TABLE 1**

Summary of Datasets for Student Engagement
been used for engagement annotation by observers, such as video, images, audio, screen capture, and mouse cursor tracking data, or self-report questionnaires by students. The diversity across datasets for data modalities used for annotation may not pose a problem; however, the inconsistencies between the data modalities used for annotating datasets and the data modalities used for training supervised machine-learning models are problematic. For instance, in Chen et al. [32], retrospective self-reports were used for annotation, but videos were used for model training. Retrospective self-report questionnaires are collected after the occurrence of engagement states. Therefore, compared to the ob-server-based engagement annotations, with appropriate time resolutions (e.g., 10 seconds), self-reports do not reliably reflect the in-situ state of the students, and supervised machine-learning models will have difficulty being trained on such data.

With respect to the relationship between the data modality and dimension of engagement annotation, it needs to be investigated what extent of each affective, behavioral, and cognitive dimensions of engagement can be annotated (and then be measured by the developed machine-learning models) from which data modalities. For instance, as implemented by Bosch [34], it needs to be investigated how much it is possible to collect cognitive engagement from video data.

According to Alyuz et al. [37], the distribution of affective and behavioral dimensions of engagement are different in students in different high school grades and in diverse ethnicities. The expression of emotions and affect also differs across genders [57]. This demographic information, such as sex, gender, age, ethnicity, students’ major, and the relevance of the virtual learning materials to students’ majors, should be taken into consideration in engagement data collection and annotation (see Table 1).

Inconsistencies in Timing
There are many inconsistencies in the existing engagement datasets in terms of the timing of self-reports, most of which were annotated retrospectively, and a few were based on concurrent self-reports. Moreover, Monkaresi et al. [29] used a combination of both. Apart from only one dataset [42], in which in-situ annotation was performed using BROMP protocol [22], all other observer-based annotations used retrospective annotation, which was performed using recorded data (see Table 1).

Inconsistencies in Temporal Resolution
D’Mello et al. [28] have differentiated between mood states and affect states. While moods, e.g., depression, have been defined for an entire learning session (several minutes or a few hours), engagement, defined as an affect state, arises and decays at much faster timescales (a few seconds).

According to the extensive experiments on the dynamics of affect states during learning [26], [58], and [59], there is an affect state transition approximately every 30 seconds, every 10-40 seconds, and every one minute. To illustrate, Disengagement to Engagement as an affect state transition, the temporal resolution of engagement annotation should be determined based on this affect dynamics (in different populations and in different learning situations). The existing datasets used inconsistent temporal resolutions for engagement annotation, starting from frame-level annotation, segment-level annotation with segments of 1-second length to 30-minute length, and session-level annotation. Temporal resolution in some of the existing datasets is close to the above-mentioned timescales, (e.g., 10 seconds and 60 seconds in Whitehill et al. and 10 seconds in Gupta et al.) [3]. Whitehill et al. [17] have also reported higher inter-rater reliability for annotation with 10-second segments compared to 60-second segments in a computer-based interactive learning setting. None of the annotation protocols in the reviewed datasets with high temporal resolution indicated how to annotate when there is a transition between different levels of engagement. In the datasets with a low temporal resolution, e.g., five minutes, more than one engagement state may occur in each timescale. Considering each data segment being annotated in the corresponding timescale as a multiset (or bag of words), none of the existing annotation protocols determined how many engagement or disengagement states (words) must occur in the timescale to be annotated as engagement or disengagement. The best solution is to have an adaptive timescale as performed in BROMP [22] and HELP [23] (explained in Section 4), (see Table 1).

Inconsistencies in Sources
In the studied datasets, the sources of annotation were expert, non-expert, or crowdsourcer observers or through self-reported questionnaires. In most of the studies, non-expert or crowdsourcer annotators were untrained students or freelancers. Aside from the EmotiW dataset [43], [44] and Vanneste et al. [10], no study mentioned training of their annotators for the task; however, that may be implicit in some of these studies. Booth et al. [35] outlined that no clarifications or indications were provided to the annotators to interpret the term engagement. If the annotators did not know what concept they were labeling, they may have used their uninformed definition of engagement, which could lead to inaccurate labeling. The AI models built on such a labeling strategy could learn erroneous concepts. A specialized concept of SE needs to be labeled by either experts or people with training in the field. Otherwise, the validity of these labels is doubtful. Gupta et al. [3] commented on noisy data after using a crowdsourcing platform for obtaining engagement labels. Other researchers reported conducting some type of noise filtering of labels [43], [44]. Such post-processing could be avoided by using expert annotators and a validated SE scale. Cost and time to annotate the data is a known challenge, but accurate labeling of data is paramount to build generalizable AI models. BROMP [22] and HELP [23] (explained in Section 4) are two engagement annotation protocols that are used in several studies, [36], [37], [38], [39], [42], where training is provided to observers (see Table 1).

Most of the questionnaires used in the reviewed datasets contained very few questions, sometimes including only one question [29], [35]. A short questionnaire could indicate a flawed data collection process that could influence the value of reported metrics [1].

Other Observations
Very few of the datasets reviewed in this paper were available in the public domain [3, 44]. The focus of researchers then turns to the development of new machine learning and deep learning models to improve performance. However, none of these studies performed descriptive analysis on the relationship between extracted features and the engagement labels. None of the reviewed papers conducted correlation analysis on the ground truth and predicted labels; the focus was predominantly on performance improvement. As noted by Vanneste et al. [10], the majority of work in this area does not address the strength of the association between features and engagement (self-reports or observations). The effect size of the data collected is not analyzed in any of the datasets reviewed. In these public datasets, very few researchers have analyzed and pointed out the problems in the labeling process. Abedi and Khan [60] indicated the labeling inconsistency in the DAiSEE dataset as a misleading factor in training temporal and non-temporal classification models. Liao et al. [61], and Mehta et al. [62] also discussed the annotation problems in the DAiSEE dataset by giving examples of videos and annotations of one person in different classes of engagement. They criticized annotating engagement levels in videos by discrete labels and proposed to use continuous values for engagement annotation in videos. Despite the fact that some of the engagement detection datasets are readily available for research in the public domain, they should not be used as-is, and a deeper level of scrutiny on the labeling mechanism may further be needed. This becomes more important in light of conflicting definitions and inconsistent scales for measuring SE.

Another important missing factor in the existing datasets is the characteristics of the virtual learning setting, in which the engagement annotation scale is designed to be applied. To illustrate, it is crucial to determine whether the virtual learning environment is interactive or non-interactive. In an interactive setting, the interaction of the student with the computer (e.g., mouse cursor movements) is much higher than in a non-interactive setting in which the student has to just watch a recorded or online video. It is important to consider whether it is: (i) an online course with live communication between students and their teacher, (ii) a recorded video of the teacher being viewed offline on a computer, (iii) a writing/interactive task on the computer screen, or (iv) a writing task on a piece of paper. As the affective, behavioral, and cognitive dimensions of engagement are different in the above exemplary settings, the characteristics of the virtual learning setting have to be included in the design of engagement annotation.

In Table 1, we have also reported the distribution of samples in different levels of engagement in the existing datasets. As can be observed, in almost all the existing datasets, the number of samples in disengagement or lower levels of engagement classes is much lower than the number of samples in higher levels of engagement. This highly imbalanced data distribution in these datasets should be taken into consideration while developing machine-learning models.

4 Student Engagement Scales

The definitions of SE presented in Section 2 and research in social science, education, and psychology have led to the development of several engagement scales used in various applications. It is to be noted that traditional SE scales meant for the classroom setting may not work well for virtual learning and are not discussed in this review. We also did not review engagement measurement instruments employed in gaming [63] and other fields as they may not be directly related to virtual learning. We now discuss some of the engagement scales that have the potential to be used in virtual learning settings.

Green et al. [64] presented a measure of engagement for media literacy interventions on the assertion that engagement (and not participation) can better explain and predict individual variations in the effects of these programs. This scale contained 16 items. They found four factors – involvement, perceived novelty, critical thinking, and personal reflection, that showed acceptable reliability. Deng et al. [65] presented a validated scale to measure student engagement in attending Massive Open Online Courses. Their 12-item scale includes the four dimensions of behavioural, cognitive, emotional, and social engagement. Dixson [66] presented the validation of an Online SE scale by correlating self-reports from students by tracking their data from an online management system. This scale consisted of 19 items and was found to be correlated with two types of students’ behaviors – observational learning and application learning. The temporal resolution in the above questionnaires is the entire semester. Regarding the level of abstraction, these questionnaires do not explicitly contain affective, behavioral, and cognitive dimensions of engagement but implicitly and in the semester level. For instance, they evaluate the behavioral engagement of students over the course of a semester, e.g., “I set aside a regular time each week to work on the MOOC.” Therefore, these self-reports need to be modified and evaluated to be applicable for engagement annotation in virtual learning for developing supervised machine-learning models.

BROMP [22] is an observation protocol for in vivo annotation of students’ affective and behavioral states. In the BROMP platform, observers (sources) are trained and tested on BROMP annotation protocol and achieved sufficient inter-rater agreement, Cohen’s Kappa $\geq 0.6$, in their observations and get a BROMP certification before participating in the annotation. Students in an in-person classroom working with educational software on computers are observed by the observer in-person by a side glance to make a holistic judgment of a student’s state based on facial expressions, speech, body posture, gestures, and the student’s interaction with the computer program (data modality). Observation is performed in a round-robin manner, observing and annotating one student and moving to the next. The frequency of observations per student varied between class periods depending on the number of students in the class (timing). Each student is observed for 20 seconds or until a visible state is detected (temporal resolution). The annotation is inserted in a mobile application. In BROMP, the affective and behavioral states of students are annotated separately (combination). Various affect states are included in the BROMP...
protocol; some of the commonly used are Boredom, Confusion, Delight, Engaged Concentration, Frustration, and Surprise. The main behavioral states are On-Task, and Off-Task (level of abstraction and quantification).

Aslan et al. [23] stated unaddressed challenges in BROMP as follows: (1) limited chance for revision as annotation is performed in vivo, (2) difficulty of making a decision about a student’s state in real-time, (3) fragmented annotation and disregarding state change in students due to the round-robin technique, (4) limited labels for model training, and (5) inevitable observer effect due to the presence of the observer in the learning settings. To address these challenges, they developed HELP annotation process. HELP has a systematic process of training and evaluation for observers (source). It contains an annotation software containing the recorded video, audio, screen capture of students’ computers and learning material contextual data, and demographic information of students (data modality). The timing is post facto as observers watch the recorded data of students retrospectively. Temporal resolution is similar to BROMP, after observing the first state change of the student. The annotation of the affect and behavioral states are separate. The discrete affective states are Satisfied, Bored, Confused, and the behavioral states are On-Task and Off-Task (level of abstraction and scale). Inspired by Woolf et al. [67], different combinations of affect and behavioral states result in the dichotomous state of engaged versus disengaged (combination). They evaluated their annotation process in different settings and achieved acceptable inter-rater agreement, especially for behavioral states. A number of studies have used HELP for engagement annotation with the same level of abstraction as in the original protocol [37], [38], [39]. Aslan et al. [23] failed to demonstrate how addressing the third challenge in BROMP regarding the ‘inevitable observe effect’ resulted in better annotation. It should be investigated which technique is optimal, observing one student throughout the entire time or using the round-robin technique.

Altuwairqi et al. [51] presented an affective model (not an annotation protocol) for engagement based on experiments with 50 students watching short computer-based courses and self-reported questionnaires about their emotions and their engagement levels and calculating matching scores and mismatching scores between them. In this affective model of engagement, different areas of the complex model of affect [68], corresponding to different values of valence and arousal, are defined as five ordinal levels of engagement: Disengagement, Low, Medium, High, and Strong Engagement. This affective model of engagement, in combination with self-reports, has been used for video-based engagement annotation by Altuwairqi et al. [51].

None of the above self-report or observer-based approaches are specifically designed for SE annotation in virtual learning settings. As is the case with the inconsistent engagement annotation scales in the existing virtual learning datasets, the annotation approaches in Section 4 are also inconsistent (as discussed in terms of the seven dimensions of engagement for BROMP [22] and HELP [23]). None of the observer-based approaches in Section 4 provide an ordinal multi-level scale for engagement.

Due to the variability of definitions, measurement scales, and other factors discussed in Section 3.4, it is a challenging task to build AI models on virtual learning datasets. A more pressing question is: “Can the technology/ algorithms measure what is being captured by the SE measurement scale?” For instance, from videos, we may be able to extract temporal behavioral and affect features, but it will be very hard to extract cognitive information. Sophisticated sensors can be used for capturing cognitive proxies, such as mind wandering using EEG; however, this may be impractical to adopt in practice. This further relates to the fact that the relationship between the subjective and objective measures is not always straightforward [69].

From the review of SE datasets in Section 3, observation scales appear to be the more widely used approach among computational researchers. Despite being labor-intensive, it can provide annotations at a lower granularity (i.e., in the moment). The finely labeled data can then be used to train various types of AI algorithms, especially based on deep-learning approaches, and can provide state-of-the-art results [11]. However, in the absence of a standardized and reliable annotation mechanism, it is very hard to ascertain if the best algorithms are only good for this particular labeling scheme or would be generalizable to other labeling schemes.

The majority of papers that we reviewed used either video or images to build AI models for detecting SE. Previous research shows that speech can also be a good indicator of human emotions [70], [71]. Speech analysis is especially useful in interactive virtual learning programs where both the instructor and student may participate. Therefore, we envision those future studies focusing on predictive modeling will also focus on speech along with videos/images and/or other physiological sensors.

5 Conclusions

In this critical review, we analyzed recent SE datasets and highlighted inconsistencies in terms of differing engagement definitions and measuring scales. Firstly, we defined seven dimensions of engagement annotation, then reviewed the relevant literature and identified inconsistencies in terms of observers, definitions of engagement scale or quantification, level of abstraction, combination, data modality, timing, and temporal resolution in the existing datasets and engagement student annotation protocols. We identified that there is no standardized psychometrically validated engagement annotation protocol that can be applied in virtual learning settings. We appreciate the previous work by researchers who collected these datasets in order to contribute to progress in the field. However, we also raised doubts on the comparability of labels of different engagement datasets and the generalizations of predictive algorithms across these datasets. We strongly recommend in future studies that both the observer-based and self-reporting scales should be used to provide better evidence of SE in virtual learning. Consistent approaches for observational and self-reporting measurement of engagement should be developed to make progress in the field of developing supervised AI models for SE measurement.
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