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RESEARCH ARTICLE

A New Hybrid Approach to Detect and Track Learner's Engagement in e-Learning

KHALID BENABBES[1], KHALID HOUSNI[1], BRAHIM HMEDNA[2], AHMED ZELLOU[3], AND ALI EL MEZOUARY[4]

[1]LARI Laboratory, Faculty of Sciences, MISC Team, Ibn Tofail University, Kénitra 14000, Morocco
[2]IMIS Laboratory, University of Ibn Zohr, Agadir 80060, Morocco
[3]SPM Research Team, ENSIAS, Mohammed V University, Rabat 10000, Morocco
[4]IRF-SIC Laboratory, EST, University of Ibn Zohr, Agadir 80060, Morocco

Corresponding author: Khalid Benabbes (khalid.benabbes@uit.ac.ma)

ABSTRACT Learner engagement is a critical concept that can lead to satisfaction, motivation, and success in e-learning courses. It covers contextual, emotional, behavioral, cognitive, and social aspects. The instructors have difficulties identifying who is involved in the courses and the lack of face-to-face interaction with a learning resource to act upon and reduce the dropout rate. This paper presents a novel approach that aims to predict learner engagement in online courses and to quantify the relationship between learners' success and their engagement. For this purpose, we used the traces gathered from 1 356 learners' reactions in e-learning courses during the winters of 2020, 2021, and 2022 to implement this approach. To model learning engagement, a variety of features were considered, such as the total number of posts made in the forums and the total time spent on the e-learning platform. This study used the BiLSTM method with FastText word embedding to detect learners' emotions in forum discussions. Then, an unsupervised clustering technique based on the new dataset was used to cluster the learners into groups according to their engagement level. Several supervised classification algorithms were trained, and their performances were evaluated using cross-validation techniques and diverse precision metrics. The findings indicated that the decision tree rule model was more relevant than the other models, with an accuracy of 98% and an AUC score of 0.97. The conclusions of this research reveal that most learners are observers, and that there is a nonlinear correlation between learning success and learning engagement.

INDEX TERMS BiLSTM, e-Learning, emotion recognition, learners' engagement, learners' context, learner's behaviors.

I. INTRODUCTION

The e-learning environment was designed to offer learners an effective, flexible, and accessible online learning experience. This allows learners to study anytime anywhere [1]. However, the learners may have difficulties getting involved and keeping themselves motivated in the learning process, which can lead to high dropout, low performance, and low success rates [2]. The majority of learners enroll in browsing through course support and videos but never finish them. Consequently, learner activities are often lower than the recommended thresholds [3]. Most studies suggest that the lack of human interaction, emotional support, and attention problems in e-learning can explain this issue [4]. This can also result from technical problems or an unfriendly user interface [5]. The instructor's limited intervention is often identified as one of the main reasons for the lack of learner engagement in e-learning [6]. In a formal classroom, instructors deploy a variety of measures to check students' engagement levels, performance, and motivation, such as the learner's regular attendance, exams, and study monitors using security cams [7]. Unlike face-to-face learning, in which learners interact directly with teachers and other learners, e-learning allows them to feel alone and less emotionally

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supported, which can affect their motivation and involvement. Therefore, learners may have difficulty keeping up with e-learning activities, leading to dropout [8].

To reduce dropout rates, ongoing research has focused on automatically identifying engaged and non-engaged students at an appropriate time and effectively. This is particularly crucial during the first two weeks of training, when students are exploring available courses. At this stage, their understanding of the subject matter may not be fully developed or well-formed. Additionally, it is important to note that students have diverse enrollment objectives. While some students may be motivated to complete the course and obtain a certificate, others may have a specific interest in acquiring a deeper knowledge of particular topics.

Recommendation and customization approaches have been suggested as the best solutions [9]. The exploration and analysis of the enrolled learners' activities, who connect and interact with the e-learning environment, can help understand the learners' learning process, allowing instructors to efficiently gain insight into the learning process of each of them. Learners' engagement is related to their emotions and behaviors (cognitive), which is considered a useful solution for improving learning quality, because it is part of their personality predictions [10]. Emotions can be detected through blood pressure, body movements, voice, heart rate, and text [11]. Learner behavior may also be tracked through the analysis of learning traces from e-learning platforms, such as time spent on a learning task, quiz completion rates, and participation rates in discussion forums [12]. The text is comparatively suitable for detecting behaviors and emotions evoked in wordless situations [13]. Instructors encouraged learners to use e-learning platforms because they provided higher educational personalization. Within platforms, students can express their emotions and social and cognitive behaviors using text posts through online collaboration tools, discussion forums, and instructional videos, which can make learning more interactive and engaging [14].

It is essential to identify and track the social, emotional, and cognitive behaviors of learners, as these factors can indicate their likelihood of dropping out. However, tracking these behaviors manually can be time-consuming and often inaccurate. Machine learning algorithms can provide powerful solutions in this regard because they can quickly and accurately analyze large amounts of heterogeneous data to identify patterns and predict outcomes.

In contrast to traditional approaches that primarily focus on learner profiles and activities, our new approach considers learners' contextual factors to identify and measure their engagement. In addition to analyzing learner traces and activities, we integrated various contextual factors, such as mobility, brightness, weather, physical environment, location, noise, and health status. The integration of contextual elements is essential for enhancing the efficiency and operability of the model.

Therefore, we suggest using three machine learning techniques, each of which complements the others.

The first is the Bidirectional Long Short-Term Memory (BiLSTM) method with word embedding FastText to detect learner emotions using six emotional labels (sadness, fear, anger, disgust, happiness, and surprise) based on learning traces applying the Ekman model [15]. These moods were then categorized as positive, negative, or confused. The second technique is unsupervised; it uses the K-means++ [16] method to split learning within a consistent involvement cluster [17] attached to the given course, reflecting learners' autonomy. The third method uses the new dataset from the second experiment and provides an engagement decision-making model based on learners' classification using a trained decision tree [18] technique based on adaptation rules designed for the learner's context.

The main contributions of this paper are as follows. First, we identify the feature list that indicates the learner's engagement level, especially the significant features for grouping and reclassifying learners. Second, we conducted a comparative study of machine learning algorithms to select the best one for clustering and classifying learners based on their engagement levels. Third, we recommend a methodology to track learner engagement more accurately and in real-time.

This study aims to address the following research questions: How can learner emotions be automatically detected? How can learner engagement be predicted automatically using contextual, emotional, behavioral, cognitive, and social features? What variables influence a model's ability to accurately predict learner engagement?

The paper is organized into three parts, in addition to the introduction and conclusion. The first section outlines the concepts, features, and approaches adopted to identify learners' engagement. The second section presents the methodology in five phases, each of which is described in detail. The final section of this article discusses the results.

II. RELATED WORK

E-learning systems have introduced many opportunities for instructors and researchers interested in learning analytics. Through learning analytics techniques, educational data can be used to precisely identify student engagement levels and learning outcomes [19]. Various studies have been conducted on learners' engagement and performance in e-learning. According to Trowler et al. [20], a learner's investment or involvement is a reliable indicator of successful learning outcomes. In this study, emphasis was placed on learners' involvement within a web-based learning environment rather than on the traditional educational engagement approach (i.e., the learner's engagement in classroom teaching). Engagement in e-learning is a challenging concept that includes several different indicators such as interaction, success, and participation; however, it is not defined properly and sufficiently. According to El-Sabagh [21], engagement in e-learning is defined as an important determinant of learning success, which means that learners spend time and energy learning materials and skills, interact meaningfully with other classroom members, and emotionally involve themselves in the learning process. However, involvement comprises individual attitudes, behaviors, and beliefs as well as communication with others [22]. Khaleel et al. [23] define engagement as the degree to which college students exhibit attention, curiosity, interest, optimism, and enthusiasm while learning or being taught. Such engagement levels also impact their drive to learn and overall educational development.

There are three types of learning engagement in the literature, as designed by Fredricks et al. [24]: emotional involvement, cognitive involvement, and behavioral involvement. Emotional involvement depends on learners' feelings about the learning process, such as joy, curiosity, sadness, boredom, frustration, and anxiety. On the other hand, cognitive involvement refers to a learner's psychological investment, such as engagement in apprehending a given task. Behavioral involvement is related to effort, persistence, attentiveness, and participation. Furthermore, Padilla Rodriguez et al. [25] identified the e-learning learners as "engaged learners" or "navigators." He also categorized engaged learners as active, passive, or community contributors. Active contributors were the most engaged students who completed all peer reviews, assignments, tests, and quizzes. While passive contributors regularly watch video-based courses, they rarely attend course forums, quizzes, and exercises. The contributors were also actively involved in the course, showing a particular interest in forum discussions and sharing benefits with the community. On the other hand, browsers search for the information they need quickly. They autonomously explored different online course sections to make the best available features and services. Molinari et al. [26] believed that learners are socially engaged as they attempt to build positive interpersonal relationships and lean on the contributions of others in the LMS by using the social plugin for social collaboration between learners. Other researchers [11], [14] have explored learners' engagement in an e-learning course in an Indonesian school using a descriptive survey. The measure included four categories: behavior, emotion, involvement, and cognition of learners' engagement while learning English in e-learning. The results show that using an e-learning language platform can offer learners significant implications. Nawi et al. [12] conducted a research study on student engagement in both distance and open learning systems. This study was conducted at two higher education institutes in Malaysia and involved 132 English language learners. The results of the descriptive analysis indicated a high level of engagement, suggesting a positive perception of Open and Distance Learning (ODL). However, the reviews uncovered several concerns regarding peer interaction, faculty pedagogical methods, and access, which affected students' ability to achieve success and quality in their learning experiences.

Lu and Cutumisu [27] addressed overall students' engagement levels during their learning process and their preferences for the intelligent classroom. This study was conducted at the University of China using 148 learners' traces for one semester, and the results proved that students' engagement was enhanced in the smart classroom. Moubayed et al. [13] conducted a study to assess learners' levels of involvement in an online learning environment. Based on their interactions and behaviors, learners were grouped using unsupervised learning algorithms. For a more accurate estimation of learners' engagement, interaction and effort-related criteria were considered to differentiate between active, passive, and observant learners. Thus, it is easy to dissociate them from the disengaged learners.

These studies are listed in Table 1 to evaluate the effectiveness of various approaches implemented in e-learning environments.

Each study employed a diverse range of features and techniques to address the challenge of predicting learners' engagement. Gupta et al. [10] suggested a new approach for analyzing the affective content of learners in a smart classroom environment using deep learning techniques. This approach is based on maximum margin face detection to analyze the content using facial expressions.

To address learners' engagement in e-learning systems, Huang et al. [28] used multimodal analysis techniques such as platform log analysis, learner sentiment analysis, and learners' feedback analysis. The results demonstrated that engaged learners were more willing to interact with the course content, attend activities, and provide positive feedback. Similarly, Sowmia et al. [29] used data analysis techniques based on Recurrent Neural Networks (RNN) to model learner engagement in a learning management system (LMS). The results of this study illustrated that RNN-based models were more effective in predicting learners' engagement than those based on traditional statistical methods. Aldhafeeri and Alotaibi [30] suggested a conceptual framework for analyzing learners' engagement in e-learning. This framework incorporates indicators, such as the time spent on the platform, interactions with the content, and learning outcomes. Thus, the authors used data gathered from surveys and interviews to identify the factors that influence learners' engagement in e-learning. Dickinson et al. [31] showed that there is a high correlation between learners' engagement and their e-learning outcomes, such as grades and course completion.

III. METHODOLOGY

This section describes the methodological approach using a 12-step process (Figure 1). It starts with the extraction and preprocessing of raw data to make each learner composite. Then, the unsupervised clustering algorithm [32] was applied to cluster the learners based on their engagement level for each course, develop the prediction model, and analyze and visualize the findings.

A. DATA COLLECTION

In our study, learner data on 'plant production,' 'descriptive statistics,' and English for engineering and technology

TABLE 1. Synthesis of studies on engagement detection in diverse environments.

Reference	Dataset	Methodology	Engagement Features	Environment	Accuracy (A)/Engagement Level (EL) (%)
[23]	48 students were analyzed using their activities logs and knowledge tests	Moodle, Microsoft excel, data collection	Behavioral engagement, personality traits, gamification	Programming environment	EL = 93
[25]	617 students were analyzed	Mooc, surveys, learning analytics	Social engagement, behavioral engagement, modeling, motivation, interactions, retention active learner, passive learner, and community contributors	E-learning system	EL = 80
[26]	70 surveys,12 interviews, 21 participants	Mooc, surveys make up the instruments used, educational data mining	Social engagement, behavioral engagement, engagement in serious games, motivations, emotions	Collaborative e-learning	A = 92
[11]	120 English language undergraduates from Malaysia class	A survey instrument known as Learner-Engagement Technology (LET), qualitative data collection	behavioral engagement, cognitive engagement, emotional engagement, social engagement	Open and Distance Learning (ODL)	EL = 71
[27]	367 undergraduate students' log files	Moodle, Self-Determination Theory (SDT), formative assessment,	Student engagement level, learning outcome, Attendance, performance, prior knowledge, activity context	E-learning courses	A = 90
[2]	601 learners were analyzed,	LSTM, GRU, and RNN, deep learning techniques, learning analytics data	Learner perception emotions, understanding, student engagement, peer collaboration, learning outcome, classification accuracy	Classroom and e-learning system	81<A<94

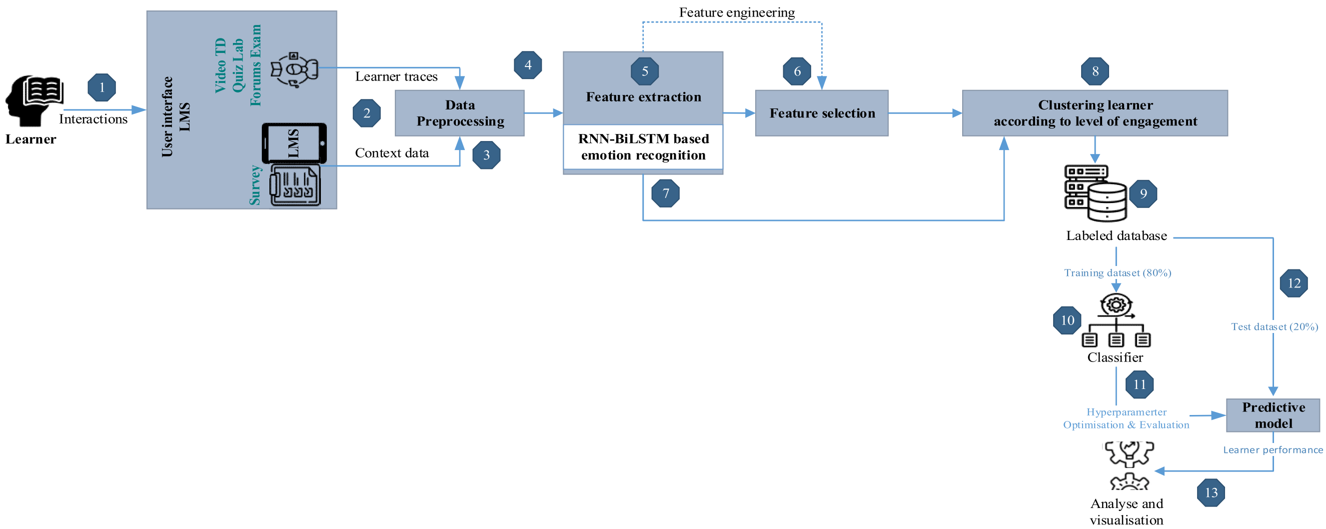

FIGURE 1. Our proposed approach for level engagement detection.

TABLE 2. Some processing of traces related to the relevant activities.

User_id	Event	Event_type	Date	Time_start	Time_end	Number of attempts	Score	Max_score	Week
53637	Forum	Forum_post	2018/07/12	3:34 PM	3:51 PM	2			1
53637	Forum	View_post	2018/07/13	10:15 AM	11:17 AM	3			1
53637	Quiz	Submit_quiz	2018/07/13	10:12 PM	10:42 PM	1	5	8	1
53637	Video	Seek_video	2018/07/15	2:19 PM	2:21 PM	4			1
53639	Video	Play_video	2018/07/15	5:24 PM	2:59 PM	1			1
53639	TD	Upload_td	2018/07/16	12:28 PM	12:48 PM	1	7	10	1

courses were gathered from an e-learning platform available at the Hassan II Institute of Agronomy and Veterinary Medicine (IAV Hassan II). The courses are outlined by chapters, 7 chapters for the first one, 4 for the second, and six chapters for the third course. These courses are spread over 12 weeks, and most learners taking courses are from outside IAV Hassan II through the LMS platform. The dataset contains 1356 enrolled learners, distributed by gender, as 54% male and 46% female. Approximately 63% of the students were between 18-25 years old, 19% were between 26-30 years old, 11% were between 31-38 years old, and 7% were older than 38 years. The learning system was testing for a duration of three years to assess its effectiveness and efficiency. To gather feedback on the functionality and user-friendliness of the learning system, a survey was conducted with both the students and teachers. However, it is important to acknowledge that test results may be subject to potential unreliability. This uncertainty arises from the possibility of imprecise responses from some learners as they may struggle to accurately recall and report their learning actions.

To enhance the evaluation of the learning system, we utilized the functionality index (IF), which measures the ratio of offered functions to required functions [33]. The IF index is typically equal to or less than 1 because non-required functions are not considered. In other words, an LMS with an IF index equal to or close to one is regarded as more effective.

To gather additional information, a specific process involving feedback and contextual surveys was implemented. When learners reached 50% completion of their courses, they were explicitly requested to complete a feedback survey (Figure 13 in Appendix A). Furthermore, after each new login, the learners were explicitly prompted to complete a contextual survey (Figure 14 in Appendix A). Gradually, the traces left open throughout the day during all sessions were implicitly collected for a more in-depth understanding of learner behaviors and engagement.

In addition, our context-aware learning system can identify and respond to specific environments in which learners operate. By considering a wide range of contextual factors, learners can obtain more personalized and adaptive learning experiences. These contextual factors may include location, mobility, luminosity, noise, and connectivity, which can be captured using physical or virtual sensors. The system records and associates these contextual factors as traces of each learner at a particular moment.

The dataset was divided into two subsets for analysis. The first subset consisted of labeled data and included forum discussions and learners' emotions. On the other hand, the second subset is unlabeled and contains a substantial number of events, totaling approximately 678,278, which arise from learners' interactions within the e-learning system, such as participation in the discussion forum, reading text, watching course videos, the number of logins, submission of homework, learner' context, and participation in quizzes. Each event was identified by a set of attributes, including the event date and time, event type, and encoded learner name. All this information is thoroughly reported and saved in CSV log files.

B. DATA PRE-PROCESSING

Preprocessing was carried out on the raw data taken from the learners' traces produced during their e-learning activities for the 2020, 2021, and 2022 academic years. The raw data contain missing information, are sometimes redundant, and are not normalized. This noise affects the performance of the model. Therefore, it was necessary to improve the quality of the data before inclusion in the model.

1) DATA CLEANING USING ISOLATION FOREST

In the raw data-cleaning phase, we analyzed the activities of each session and eliminated fields containing redundant information. Subsequently, to segment Clickstream entries over a twelve-week period, we introduced a new feature called "week" that associates events with the corresponding weeks after the course of treatment. The events were afterward associated with a daily session up to 1 hour long computed using the difference between the two timestamps on each page (Figure 2). As a result, the number of event types was reduced from 6710 to 43. For anomaly detection, we adopted approaches to identify noncorrelated learners. There are several reasons for using anomaly detection: (1) it reduces model complexity, (2) it accelerates model training, (3) it improves overall model accuracy, and (4) it prevents overfitting of the model.

In this study, we employed the Isolation Forest algorithm (Iforest) [34] to address data anomalies in the dataset. This algorithm is based on the assumption that anomalies can easily be isolated from the rest of the normal instances in a dataset.

We created a feature vector for each student, incorporating several components: (1) Events as the list of traces generated by each student including contextual ones, (2) Certified as an indicator of whether the learner completed the course and obtained a certificate, and (3) Weeks that indicate the number of weeks spent on the training course.

This approach has several advantages: (1) a limited number of conditions are applied to differentiate normal instances from anomalies, (2) the algorithm exhibits linear time complexity and has minimal memory requirements, (3) the algorithm can be applied to even the most intricate problems and vast datasets, and (4) anomaly detection is independent of density or distance measurements. Following a thorough analysis, we discovered that a significant number of anomalies in the dataset were associated with recurring request bugs within the Moodle system. We identified 154 learners who were flagged as anomalous because their data exhibited patterns and behaviors that deviated significantly from the norm.

Furthermore, the Natural Language Toolkit (NLTK) and the Snowball Library (Slib) were applied for punctuation removal, capitalization folding, stop words, number removal, and the stemming process of text-based emotions. At the end of this step, most of the data processing is completed, leading to clean, filtered, normalized, and ready-to-use data.

In the following subsection, we briefly discuss how to extract learner features related to their engagement levels, normalize them, and reduce their dimensionalities.

C. FEATURE EXTRACTION

In this stage, we outline the process of extracting features to cluster learners based on their engagement level. This is a key step in our engagement detection model, as its performance is closely linked to the features that make up

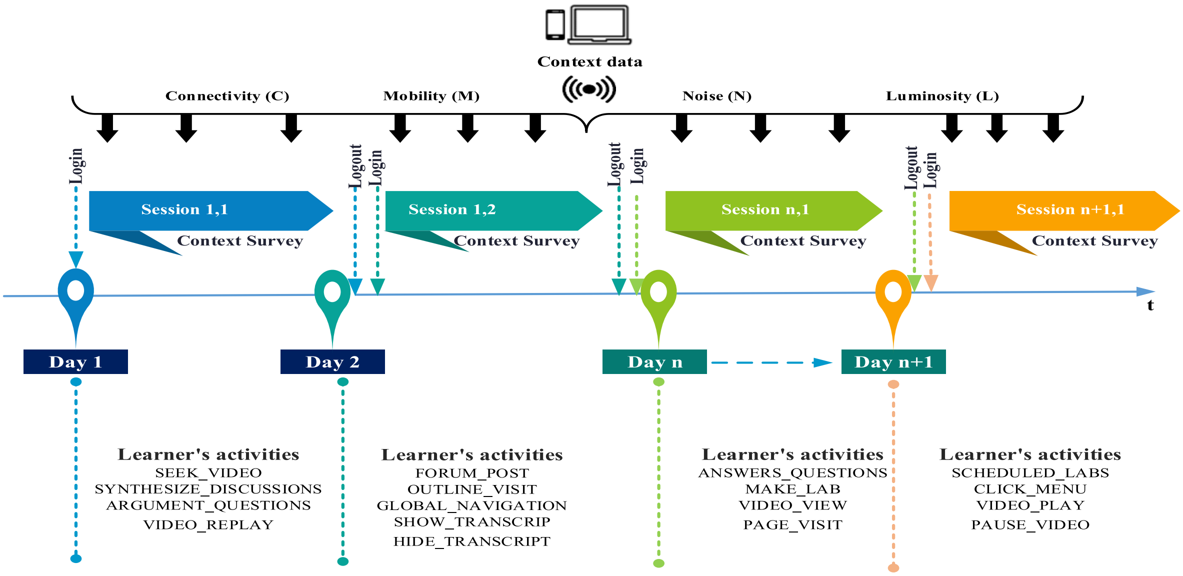

FIGURE 2. **Daily session stream of activities.**

a learner's profile. This profile is updated according to the current context. Therefore, we extract the most meaningful features of the learner's profile in a particular space at a given time, expressed as a set of contextual features, from which we draw feature vectors for each learner. Learning data are typically shown as a grid composed of instances or observations arranged in columns, each of which has a set of properties (attributes or variables) placed in the column. These features are mapped to various learning resources delivered in e-learning systems including synopses, examples, videos, exercises, quizzes, and forums. Navigational and contextual features are also introduced.

The raw data were transformed into significant features to explicitly describe the clustering model specification and enhance the performance of each model. Although several fields can be included directly in the dataset used to train a model, hidden and unused features must be extracted from the data to produce an enhanced learning dataset [35]. Using features such as Event (quiz, lab, forum, video), Event_type (paused_video, forum_post, view_post, etc.), User_id, time, attempts, score, max_score, we were able to determine whether each learner completed the self-evaluated activity, the number of attempts made, the maximum score achieved, and the duration of the activity. This was accomplished by extracting the times at the beginning and end of the activity. This procedure was performed in two stages. The first stage involved combining events based on their event_type, which enabled us to calculate the total number of each event type (Figure 1). In the second stage, utilizing the "time" column, we create a new "duration" column that measures the time taken by each learner to perform an activity or access a learning resource. The formula used to calculate duration is as follows:

$$\Delta t_i = t_{i+1} - t_i \tag{1}$$

where t_i is the event start time and t_{i+1} is the succeeding event time. The learners' events were arranged into sessions. Each session was defined as a series of events that occurred during the period of connection to the system. It starts with the connection and ends with disconnection from the system. To identify a session, we assumed that the retention time of a page did not exceed 1 h (Figure 2). This retention time is based on the difference between the two timestamps (t_{i+1} and t_i). For instance, if a learner has generated events in three different timestamps (t_1, t_2, and t_3), we use t_2- t_1 to calculate the first time event and then t_3-t_2 to calculate the second time event. We then calculated the sum of all results obtained for each "event_type" for each student.

Table 2 presents these values and displays an excerpt from the first feature extraction for the two learners with user_ids 53637 and 53639.

Motion is a key feature that is necessary for detecting learner engagement. To automatically extract these motions from discussion forums and address our initial research question, the following subsection focuses on designing a model that can deliver high-precision results.

1) EMOTIONS MINING

The forum posts were used to detect learners' emotions, classified according to the Ekman emotion model [15], into three modes: positive_motion, negative_emotions, and confusion_emotions. The first mode expresses the learner's satisfaction (happiness), the second mode (sadness, anger, fear, disgust) indicates the learner's dissatisfaction, and the third mode (surprise) is an unknown emotion caused by a particular situation without words. Several stages were executed to preprocess the labeled dataset, which aimed to remove irrelevant, uninformative, and noisy elements from the data to make the dataset suitable for creating accurate word vectors for classification. These stages involved case folding, number removal, punctuation removal, tokenization, stop word removal, and stemming.

Case folding was used to transform all characters into lower or upper cases to avoid matching errors caused by case differences. The removal of punctuation is the deletion of all punctuation marks (dots, commas, quotation marks, exclamation marks, question marks, brackets, and dashes) from a text before it is used for text analysis. Removing punctuation reduces text complexity and makes it easier to process. Tokenization is the process of dividing a text into process units called "tokens." The tokens are individual words or punctuation symbols. Stop removal is used to remove empty words such as "the," "and," "in," "on." This process focuses on words that reflect emotional intensity such as strong verbs, emotional adjectives, anger, and joy. Stop removal reduces the classification processing time, index size, and data noise. In this study, the Natural Language Toolkit (NLTK) library was used for punctuation removal, capitalization folding, stop words, and the number removal process during the pre-processing of text-based emotions. Stemming aims to reduce words to their basic form or root by removing affixes to facilitate text analysis and comparison between different sentences.

After emotion data preprocessing (see the example in Table 3), the word-embedding process was performed. It is based on the use of numerical vectors to represent each word in a reduced-dimensional space. This vector mapping allows all semantic relations between words to be captured [34], which may help improve the performance and make the training of NLP algorithms [35] easier.

2) WORD EMBEDDING

The research conducted by Sivakumar and Rajalakshmi [36] concluded that using word embedding with the LSTM algorithm provided a high accuracy of 87.6%. In this study, the three most popular word-embedding algorithms, Word2Vec [37], GloVe (Global Vectors for Word Representation) [36], and FastText [37], were tested. Word2Vec generates word vectors using supervised and unsupervised learning techniques. It is well-known for its ability to extract the semantics of words and their syntactic relationships. Word2Vec uses two training methods: Continuous Bag-of-Words (CBOW), in which the model attempts to predict a target word from a given context, and skip-gram (SG), in which the model attempts to predict the context word from the target word. GloVe uses word co-occurrence to create word vectors. It merges the advantages of the co-occurrence matrix and matrix factorization to yield more accurate word vectors [37]. While, FastText divides each word into sub-words, or "n-grams," and uses these subwords to create word vectors. This method is particularly useful for languages with composite words and fluxional suffixes. The FastText model was applied to the same sentence derived from the preprocessing shown in Table 3, and is reported in Table 4.

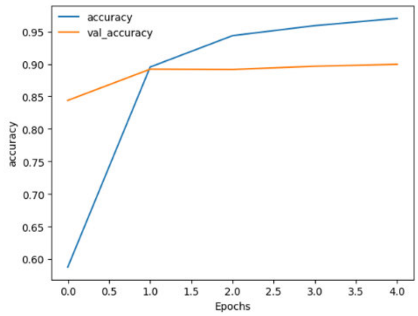

FIGURE 3. Accuracy and validation accuracy for FastText and BiLSTM.

The results obtained from word embedding are then integrated into the Long Short-Term Memory Modeling (LSTM) process using the Keras library, which will be introduced in the next subsection.

Long Short-Term Memory (LSTM) is a recurrent neural network (RNN) variant that handles long-term dependency problems better by storing information for an extended time. The LSTM utilized in this study was bidirectional and was considered more potent than the unidirectional model. By capturing contextual information in both directions, this overcomes the vanishing gradient problem, which can make training a dataset challenging. The model achieved this by incorporating gate units and memory cells (forget, input, and output gates). Several BiLSTM parameters, such as the activation function, unit/neuron number, dropout number, and epochs, were adjusted. In this study, the number of dropouts used was 20, 30, and 50, and the number of units/neurons rangeD between 64 and 156 units. The activation function used for the output dense layer was Softmax, whereas the activation function ReLU was used for the hidden layers. Dropout can help improve the model performance by reducing overfitting. Dropout was applied to the cross-layer BiLSTM links. Specifically, during each training stage, each BiLSTM unit has a probability p of not being updated. It is typically defined as a value between 0.1 and 0.5. The adopted optimization method was Adaptive Moment Estimation (ADAM). The loss function selected was the Categorical Cross-Entropy Loss function, because more than one class was used in this study. The number 50 was used for the epoch.

The dataset was then divided into 60% training data, 20% cross-validation data, and 20% testing data to identify the best model. Finally, the FastText BiLSTM architecture was adopted because it achieved a high accuracy of 89.1% (Figure 3) compared to the other architectures (Figures 4 and 5).

The BiLSTM test outcomes for each of the three-word embeddings (Word2Vec, GloVe, and FastText) are reported in Table 5 for comparison. The highest accuracies are indicated in bold.

After extracting features judged relevant to identifying the learner's engagement level, the data were normalized, as discussed in the following section.

TABLE 3. An example of preprocessing of a discussion forum post for emotions mining.

Preprocessing emotions process	Post
Post (before preprocessing)	"@switchfoot .com/2y1zl - Awww, that's a bummer you should, 3-5 !!"
Post after case folding	"switchfoot awww thats a bummer you should, 3-5!!"
Post after removing punctuation	"switchfoot awww thats a bummer you should 35"
Post after removing a number	"switchfoot awww thats a bummer you should"
Post after tokenizing	"switchfoot", "awww", "that", "a", "bummer", "you", "should"
Post after a stop word removal	"switchfoot", "awww", "bummer"
Post after stemming	"switchfoot", "awww", "bum"

TABLE 4. FastText model outputs on a preprocessed post.

Corpus	Dimensions				
	D1	D2	D3	D4	D5
switchfoot	0.062719	0.071826	-0.019263	0.092824	-0.067281
awww	-0.071426	0.052781	0.051728	-0.091652	0.081882
bum	-0.061582	-0.050921	0.082567	0.042371	-0.032157

TABLE 5. LSTM test outputs for a variety of word embedding.

Word2Vec			GloVe			FastText		
Unit	Dropout	Accuracy	Unit	Dropout	Accuracy	Unit	Dropout	Accuracy
50	20	0.821	50	20	0.275	50	20	0.848
	30	0.838		30	0.275		30	0.848
	50	0.831		50	0.275		**50**	**0.891**
100	20	0.875	20	20	0.275	100	20	0.882
	30	0.831		30	0.275		30	0.852
	50	0.840		50	0.275		50	0.868
150	20	0.858	100	20	0.275	150	20	0.805
	30	0.869		30	0.275		30	0.879
	50	0.859		50	0.275		50	0.842
200	20	0.841	200	20	0.275	200	20	0.887
	30	0.841		30	0.275		30	0.879
	50	0.876		50	0.275		50	0.842

TABLE 6. A comparison of diverse activities related to some studies based on the engagement dimension.

Engagement dimension	Features	Resources	Detail	Researches			
				[41]	[24]	[42]	[20]
Behavioral engagement	#NBR_CLICKS	TD, Lab, Video, Quiz, Exam, Forum	Number of cumulative clicks by a learner/Number of clicks by the most active learner	✓		✓	
	#NBR_ATTEND_WEEKS	TD, Lab, Video, Quiz, Exam, Forum	Cumulative number of weeks the learner was active/ Number of weeks of the most active learner	✓		✓	
	#NBR_ATTEND_DAYS	TD, Lab, Video, Quiz, Exam, Forum	Total number of days the student was active/Number of days the student was most active	✓		✓	
	#SEEK_VIDEO	Video	Number of searches within videos			✓	✓
	#COMPLE_RATE_VIDEO_VIEW	Video	Total of videos viewed/Total number of videos scheduled			✓	✓
	#CUMUL_TIME_VIDEO_VIEW	Video	Cumulative time spent viewing videos			✓	✓
	#COMPLE_RATE_QUIZ	Quiz	Cumulative number of quizzes taken/Total number of quizzes planned			✓	✓
	#TIME_SPENT_QUIZ	Quiz	Cumulative time spent on completed quizzes	✓		✓	✓
	##COMPLE_RATE_TD	TD	Aggregated number of performed TDs/total number of planned TDs			✓	✓
	#TOTAL_TIME_SPENT_TD	TD	Cumulative time spent on TDs			✓	✓
	#COMPLE_RATE_QLAB	Lab	Cumulative number of achieved Labs/Total number of scheduled Labs			✓	✓
	#NBR_DIST_PAG_UNIT_VISIT	Navigation	Number of distinct pages visited			✓	✓
	#NBR_TIME_SHOW_QUEST_ANSWER	Forum	Number of times the answers to questions were looked up	✓		✓	✓
	#TOT_PAGE_CLOSE	Navigation	Total of closed pages			✓	✓
	#CUM_TIME_SPENT_LAB	Lab	Accumulative time spent on the Labs			✓	✓
Cognitive engagement	#TOT_NBR_VIDEO_REPLAY	Video	Total number of video replaying			✓	✓
	#TOT_NBR_ATTEMP_QUIZ	Quiz	Total number of attempts made on the quizzes			✓	✓
	#TOT_NBR_ATTEMP_TD	TD	Total number of attempts made at the TD			✓	✓
	#TOT_NBR_ATTEMP_LAB	Lab	Total number of attempts made at the Lab			✓	✓
	#NBR_ARG_TO_QUEST	Forum	Number of times giving arguments for questions			✓	✓
	#NBR_WORDS_RESPONSE_TO_QUEST	Forum	Number of words in a response to the question (e.g., quick answer)			✓	✓
	#NBR_TIME_SYNT	Forum	How many times to Synthesize the discussions			✓	✓
	#TOT_NBR_ATTEMP_EXAM	Exam	Total number of attempts made on the final exam			✓	✓
	#POST_LENGTH	Forum	The post length by the number of words.			✓	✓
	#NUM_OF_POSTS	Forum	The number of posts made by a learner in the overall course.			✓	✓
Emotional engagement	#POSITIVE_EMOTION	Forum	The learner shows positive emotions like serenity, pleasure, hope, pride and curiosity.	✓		✓	✓
	#NEGATIVE_EMOTION	Forum	The learner shows negative emotions (like, shame, frustration, hopelessness, anxiety and anger).	✓		✓	✓
	#CONFUSION_EMOTION	Forum	The learner shows confused emotions like surprise, bewilderment, query doubt and conjecture.			✓	✓
Social engagement	#NBR_STATEM_FOURUM	Forum	Total number of statements made in the forums	✓		✓	✓

D. FEATURE NORMALIZATION

Scaling allows various machine learning algorithms to perform well [38]. Thus, their output model is strongly influenced by several features if the regular distribution of their values is not maintained. Consequently, before beginning the learning process, it is crucial to normalize the

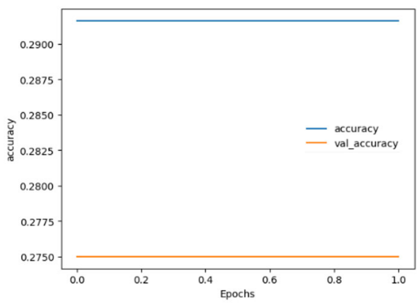

FIGURE 4. Accuracy and validation accuracy for GloVe and BiLSTM.

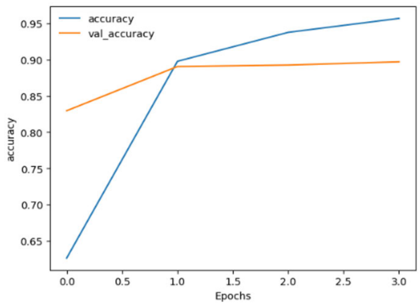

FIGURE 5. Accuracy and validation accuracy for Word2Vec and BiLSTM.

measurement units for these features [35]. Therefore, the MinMax method was applied to all values by fixing the minimum at 0 and the maximum at 1 in the [0, 1] range. Consequently, the normalized x value is formulated as follows:

$$V' = \frac{V - V_{min}}{V_{max} - V_{min}}$$

where $V_{\min}$ and $V_{\max}$ are the minimum and maximum values of V, respectively, in the dataset.

E. FEATURE SELECTION

In this section, we identify features likely to create a more robust model from the extracted features. Most methods proposed in the literature use a linear correlation between the features [39]. This takes time and requires multidisciplinary knowledge; therefore, we removed the least discriminating features [40]. This involves examining comparative studies conducted by other researchers to identify the types of learner engagement in e-learning environments. The resulting features can then be integrated into the learning algorithms, as listed in Table 6. Therefore, learner features related to engagement and disengagement were developed. As shown in Table 2, a forum is an indicator of learning involvement. Engaged learners are often posting homework and comments on discussion forums, they are interested to contribute in discussion topics, or reading them, and they often use the "Next" and "Previous" navigation buttons to move between course units. They also consulted their answers to their quizzes in more detail [41]. These learners frequently watch videos and take quizzes, exams, and peer reviews [26]. Even pausing a video could be a sign of a "more active engagement" with the content, and this action might also indicate specific checkpoints in the video where learners paused to have more time to apply what they had just learned [23].

By contrast, disengaged learners may not use the forum to learn a concept or spend little time participating in the forum discussion [42]. Thus, they may not be able to ask or answer questions. In addition, they rarely discussed ideas with others and did not help them solve their problems. Such learners may respond to a question superficially or reply without looking for details on the topic [20].

F. DIMENSIONALITY REDUCTION

Principal Component Analysis (PCA) was conducted to reduce the dimensionality of the original feature space of each engagement mode to two dimensions while retaining unchanged trends and patterns [43]. The output of the PCA was fed into the K-means algorithm to cluster the learners according to their involvement mode.

To address the second research question, we developed a comprehensive model that aimed to accurately predict learner engagement in an automated manner. This model was designed and trained using a wide range of carefully extracted features derived from the events generated within the e-learning platform. These features encompass various dimensions, including contextual, emotional, behavioral, cognitive, and social factors, which collectively contribute to a holistic understanding of learner engagement.

G. CLASSIFICATION OF LEARNERS BY CLUSTER ANALYSIS ENGAGEMENT

1) LABELING

In this section, a cluster analysis [44] was conducted to identify the types of learners in the e-learning system by examining their learning profile and engagement level with the proposed course based on the traces produced during the browsing of the learning resources. This analysis was carried out to identify consistent clusters in which individuals were similar, but differed from others in other clusters. Four cluster algorithms (K-means [45], agglomerative [46], Birch [47], and DBSCAN [48]) were assessed to select the most efficient and optimal algorithm based on the findings. These algorithms differ in feature clustering such as connectivity-based clustering [46], density-based clustering [48], and centroid-based clustering [45]. To assess the quality of the results, internal criteria were employed, specifically the Calinski-Harabasz index [35] and the Silhouette index [49]. Thus, K-means was selected as the preferred algorithm because it produced higher values for both performance indices than the other algorithms (Table 7).

The K-means clustering concept uses the cosine distance to group features together, such that the resulting features have a high impact on classification quality, with no redundancy, to achieve a high correlation between these features.

$$J = \sum_{j=1}^{k} \sum_{i=1}^{n} \left\| x_i^{(j)} - c_j \right\|^2 \qquad (2)$$

TABLE 7. Computed internal evaluation criteria for each course clustering (best results are in bold).

Index	Clustering algorithms	Plant production (course 1)	Descriptive statistics (course 2)	English for Engineering & Technology (course 3)
Calinski-Harabasz	K-means	**149287**	**163383**	**148163**
	Agglomerative	132931	156931	132931
	Birch	139523	161245	139523
	DBSCAN	148361	162169	143261
Silhouette	K-means	**0.92**	**0.85**	**0.89**
	Agglomerative	0.76	0.73	0.81
	Birch	0.82	0.79	0.80
	DBSCAN	0.72	0.61	0.68

TABLE 8. Hyperparameters optimized using the Grid-Search technique for each classifier algorithm.

Classifier Algorithm	Hyperparameters	Description	Type	Value's interval	Value assigned
DT [18]	Max_depth	Maximum depth of the tree from the root node to a leaf	Discrete	[1,18]	8
	Criterion	Function to measure the quality of a split	Categorical	['Gini', 'Entropy']	Entropy
	Max_features	Maximum number of features to be split	Discrete	None	None
LR [51]	C	Controls the regularization strength applied to the regression coefficients	Discrete	[0.1, 1, 10, 100]	10
	penalty	Regularization of the model and control over the influence of regression coefficients.	Categorical	['l1', 'l2']	l1
	solver	Optimization algorithm used to solve the logistic regression problem	Categorical	['liblinear', 'newton-cg', 'lbfgs', 'sag', 'saga']	saga
RF [54]	N_estimators	Number of decision trees to generate for the ensemble	Discrete	[4,18]	6
	Max_depth	Maximum depth of the tree from the root node to a leaf	Discrete	[1,18]	8
MLP [55]	Hidden_layer_sizes	The optimal number of hidden layers		[4-13]	9
	Max_iter	Maximum number of iterations allowed		[400,900,1300]	400
KNN [56]	N_neighbors	Number of neighbors	Discrete	[5,6,7,8,9,10,20,30,40]	40
	Leaf_size	Leaf size passed to the algorithm	Discrete	[1–4]	2
	Algorithm	The algorithm used to compute the nearest neighbors	Categorical	['auto', 'ball_tree', 'kd_tree','brute']	auto
SVM [57]	C	Penalty parameter applied to classification errors	Continuous	[0.2,20]	12
	Kernel	A tuning parameter to improve the classification accuracy	Categorical	['Linear', 'Poly', 'Rbf', 'Sigmoid']	Sigmoid

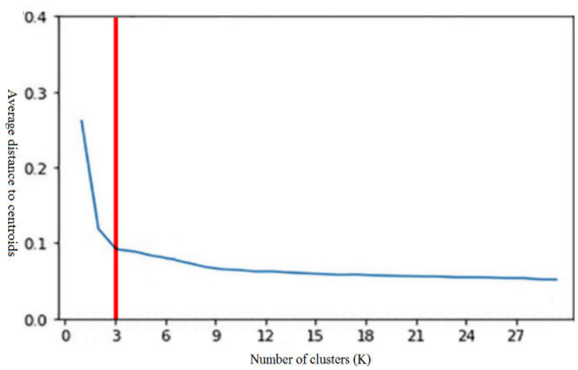

FIGURE 6. Elbow point for course 1.

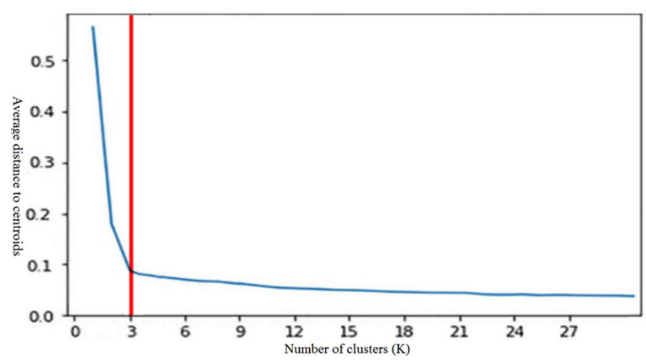

FIGURE 7. Elbow point for course 2.

where i is the observation, n is the set of observations, k is the set of clusters, cj is the cluster centroid and J is the target value.

The K-means algorithm optimizes the cluster centers and the individuals' distribution in clusters iteratively. To implement K-means in every proposed course, the number of clusters (k) is needed, so the elbow point method [32] is used for each course, leading to the outcome of three clusters (Figures 6, 7, 8).

Because K-means has some limitations, K-means++ [16], which is an improved version of K-means and is sensitive to the initial position, was utilized for each course.

This clustering methodology allowed us to classify the learners by describing their engagement in each cluster. 1356 learners were enrolled in three courses; 40 of them were assigned to the first cluster, 115 to the second, and 1201 to the third. Concerning the "Plant production" course, 15 learners were assigned to the first cluster, 45 were assigned to the second, then 691 were grouped in the third. For the "Descriptive statistics" course, there were 12 learners in the first cluster,

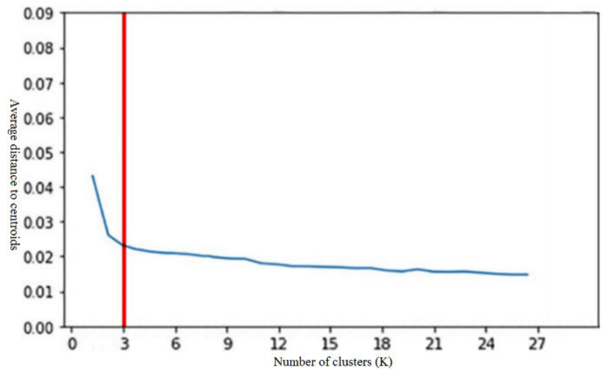

FIGURE 8. Elbow point for course 3.

14 learners in the second cluster, and 378 learners in the third cluster. The learners listed in Cluster 1 (active learners) were enthusiastically engaged in the learning process. The passive learners (less engaged learners) listed in Cluster 2 watched videos and performed few exercises or quizzes. The third cluster (observers' learners) was located outside the learning process as non-engaged; they were not interested in learning resources. Consequently, the new dataset was labeled using three labels (active learners, passive learners, and observer learners). As a result, this new dataset was used as input for the classifier algorithms to produce predictive models, as described in the following section.

2) CLASSIFIER MODELING

Because the predicted classes are already known to each learner, supervised machine learning algorithms seem to be the best alternative for creating a prediction model of the learner's level of learning involvement. All classifiers (Decision Trees (DT) [18], K-nearest neighbors (KNN) [50], Random Forest (RF) [50], Support Vector Machine (SVM) [52], Logistic Regression (LR) [51], and Multilayer Perceptron (MLP) [28] used in this study were trained to optimize the model parameters based on several criteria such as the learner's background, learning life cycle, learning style, skills, and learner tasks. Classifier analysis allowed us to select the most optimal one for our research. Therefore, K-fold cross-validation [35] with k = 10 was applied to train it to improve the performance of the model. The hyper-parameters were then defined using the grid search [52] technique applied to each model (Table 8). Finally, model overfitting and underfitting were evaluated using the learning curve technique [53]. Moreover, the classifiers were tested on separate datasets to ensure reliability of the results. As a result, the average of the true negative rate (TNR) and the true positive rate (TPR), which merely counts the number of instances correctly classified by the model, were used. To achieve the highest accuracy for the engaged and non-engaged classes, precision, the area under the ROC Curve (AUC), and recall were used. By analyzing the precision results shown in Table 9, we can conclude that DT had the highest precision value. The latter means that it is most appropriate for our purpose, yielding the best performance in predicting the learner's involvement level.

Algorithm 1: Set of learning context rules designed to deduce the learner's engagement level

Inputs: MS: Mood_status, HS: Health_status, M: Mobilty,C: Connectivity, L: Luminosity, N:Noise, C: Connectivity, Pr_EN: Engagement_level

Variables: MS, HS, M, C, L, N, Pr_EN, engaged_status: String

Initialization: engaged_status <- ""

Output: get the learner's engagement level related to the set contextual criteria

```
IF Pr_EN = "engaged" THEN

    IF L="yes" and C="high" AND M="NO" AND MS="happy" AND N="no" AND HS="High"
    engaged_status <- "enagaged"
    ELSE IF M="NO" OR C="low" OR  HS="low"
     engaged_status <- "nonenagaged"
    ELSE IF MS="angry" OR MS ="excited" OR  MS ="sad"
     engaged_status <- "nonenagaged"
    ELSE IF MS="angry" OR MS ="excited" OR  MS ="sad"
     engaged_status <- "nonenagaged"
ELSE
ENDIF
        ENDIF
Return engaged_status
```

FIGURE 9. Set of contextual learning rules used to infer the learner's engagement level.

H. CONTEXT DATA WITHIN THE DECISION TREE RULE

Building upon the research conducted by Xie [58], which emphasizes the significance of learners' personal context, including their experiences, expectations, motivations, and social relationships, in determining their engagement type when using e-learning systems, as well as the pedagogical model proposed by Xie et al. [59] that underscores the importance of considering learners' context, motivation, learning preferences, and technological skills to enhance their engagement in e-learning, we have incorporated these insights into our study. Additionally, the study conducted by Fredricks et al. [24] explores the concept of e-learning engagement and its potential in education. It highlights the influence of learners' personal contexts, encompassing their family experiences, peer relationships, and self-motivation, on their engagement with the e-learning environment. In our research, we have taken into account the contextual data collected in real-time by physical and virtual sensors, as well as questionnaire data gathered during each connection to the e-learning system.

Using the contextual data gathered, 62 combinations were drawn using the attribute values (pre-engagement type from the model in Section III-G.2, health status, mood status, connectivity, noise, mobility, luminosity) and were targeted as the contextualized final engagement type.

Subsequently, we used the classification and regression tree (CART) technique [60] to define the correlation between the learners' contexts and their final engagement type (engaged or non-engaged). It classifies learners based on a set of context attributes taken from the last established combination table. We then transformed the results obtained as a tree (root and leaves) into an algorithm format, as shown

TABLE 9. Results of the involvement prediction models (the best results are marked in bold).

Classifier algorithm	Train			Test		
	TNR	TPR	AVG	TNR	TPR	AVG
DT	**0.31**	**0.96**	**0.63**	**0.32**	**0.97**	**0.64**
SVM	0.84	0.64	0.74	0.89	0.51	0.70
RF	**0.34**	**0.94**	**0.64**	**0.31**	**0.89**	**0.60**
MLP	0.72	0.77	0.74	0.73	0.76	0.74
LR	0.79	0.75	0.77	0.62	0.68	0.65

in Figure 9. This algorithm is used to design a new approach based on a previous approach known as the tree decision rule.

IV. RESULTS AND DISCUSSION

In this section, the clustering results for the learner traces of each course using the K-means++ algorithm, as outlined in the data preprocessing section, are discussed. After preprocessing, the data rows were labeled as passive, active, or observer learners. Subsequently, the rows were labeled as engaged or non-engaged.

To train an involvement-level prediction model, the newly labeled dataset was used as the input for the classification algorithms (DT, SVM, RF, LR, and MLP). To achieve this, 80% of the labeled dataset was used for training, and 20% for testing. Afterward, ten-fold cross-validation [35] and grid search [52] were used to optimize the model, and the Learning Curve [61] was used to check for underfitting and overfitting. To measure the effectiveness of the machine learning model in predicting the learner's engagement levels versus the literature [20], [41], [42], each automatic learning model was evaluated separately using a variety of reliability metrics. Therefore, all the classifiers studied yielded good results (Table 10). However, the DT accuracy was the highest (98%) for all courses, which means that the algorithm seems to be the most accurate for our purpose. Consequently, it provides better performance in engagement level detection. In contrast, LR and MLP showed low performance because of overfitting, which was reflected by the algorithm's learning curve. In addition, MLP is a deep learning technique that requires a very wide dataset to process data efficiently [28], which was not the case in our experiment. Moreover, the TNR and TPR results for each classifier (DT, SVM, RF, MLP, LR), captured from the training and test data (Table 9), showed that the DT and RF classifiers outperformed the others. However, DT performs better than RF and is simpler to implement, but difficult to beat in terms of performance.

In contrast, the SVM classifier was excluded because of its lower performance, which is considered insignificant. The DT classifier also outperformed the precision, recall, AUC, and accuracy scores of other e-learning studies [62], [63].

Studies that applied DT have shown its best performance in identifying learners' engagement level when they interact with the e-learning platform [64]. Moreover, both the number of enrolled learners and their traces used in our study are sufficient to address the learners' involvement issue more accurately than in other studies that use a limited number of traces coming only from up to 694 enrolled learners [63], [65], [66]. Furthermore, the algorithms disclosed in this paper showed a correlation between the learning resource use rate and the final scores, along with learning engagement. Some learner engagement measures are efficient at gathering learner actions, such as automatic trace analysis [67], [68], while others may disrupt their engagement. For instance, in a self-assessment, learners are invited to complete a survey during their learning. Additionally, many pioneering approaches that use physiological sensors have been used in the literature to identify both the emotional and cognitive dimensions of learners' engagement, but they are difficult to implement and costly [69], [70].

Table 11 displays the number and proportion of the various learner types related to each of the three courses. Most learners were classified as observers, and only 6.5% were active, while 28% were considered passive. The "English for Engineering and Technology" course showed the most active learners (6.5%), while learners of the "Descriptive Statistics" course were predominantly observers (97%). Barely, 27.9% of passive learners were enrolled in the "English for Engineering & Technology" course, which means that most learners were disengaged. This is confirmed by world trends of Moodle LMS learning, where course completion rates are relatively low, typically between 5 and 15% of enrolled learners [71]. In this study, only about 7% of the learners completed their courses in an e-learning environment. The success rate was relatively low for "English for Engineering and Technology" course compared to the other two courses. Only 41 (20%) of the 201 enrolled learners completed their courses.

The completion rate is under average for this course, which could be explained by the intense requirements for the final exam. In this particular course, 4 out of 13 active learners (21%), 11 out of 56 passive learners (14%), and no observer learner succeeded in the course; the mean scores of the active, passive, and observer groups were 54, 43, and 15, respectively. This implies that there was no longer a proportion between course completion and final scores in the active, passive, and observer groups.

Similar to the findings of Wihastyanang et al. [72], active learners demonstrated higher success rates and final scores than other groups of learners, indicating deeper engagement with the course material.

Passive learners attended the course periodically and achieved a mean success rate of 45%. These findings indicate that the behaviors of both groups may enhance the quality and efficiency of learning. These results depend on their involvement and contribution to the learning activities (Table 6). Otherwise, most of the e-learning learners belong to the "observer" category, where the completion rate was only about 3% of students in this group. To keep this learners' group engaged and motivated, further research should focus on early behaviors during the first few weeks by identifying those who are susceptible to dropping out of courses through their engagement profile (Figure 9).

TABLE 10. Progress of the different learner types in e-learning courses.

Classifier model	Metrics	Courses		
		Plant production	Descriptive statistics	English for engineering and technology
DT	AUC	**0.97**	**0.97**	**0.99**
	Accuracy	**0.98**	**0.98**	**0.96**
	Precision	**0.99**	**0.99**	**0.93**
	Recall	**0.98**	**0.98**	**0.96**
SVM	AUC	0.61	0.78	0.68
	Accuracy	0.65	0.76	0.63
	Precision	0.67	0.63	0.62
	Recall	0.68	0.69	0.68
RF	AUC	0.88	0.86	0.89
	Accuracy	0.87	0.97	0.81
	Precision	0.88	0.88	0.89
	Recall	0.84	0.84	0.89
LR	AUC	0.71	0.81	0.84
	Accuracy	0.81	0.71	0.82
	Precision	0.82	0.62	0.82
	Recall	0.83	0.82	0.86
MLP	AUC	0.79	**0.91**	0.89
	Accuracy	0.78	0.80	0.78
	Precision	0.88	0.72	0.78
	Recall	0.86	0.64	0.76

TABLE 11. Accuracy results on both training and test data for the five classifiers.

Courses	Total number of learners (%)	Engaged				Non-engaged	
		Active learners		Passive learners		Observers	
		Total number (%)	Completion rate (%)	Total number (%)	Completion rate (%)	Total number (%)	Completion rate (%)
Plant production (751)	**55.3**	**15 (2%)**	**74**	45 (6%)	52	**691 (92%)**	4
Descriptive statistics (404)	30	12 (3%)	**61**	14 (3.5%)	31	**378 (93.6%)**	6
English for Engineering & Technology (201)	7.4	13 (6.5%)	**31**	**56 (27.9%)**	21	**132 (65.6%)**	0

As shown in Figure 10, active learners participated in the discussion forums at a higher rate (49%), viewed more than half of the course videos, and submitted 19% of the TDs and quizzes. However, passive learners participated intermittently on the e-learning platform; they had a low participation rate in discussion forums and viewed a limited number of course videos. This may be explained by the overload of the course material or simplification of the classroom course [73]. According to Strømman [74], active attendance at discussion forums and the use of course videos could be the key to success in e-learning, but instructors' intervention is essential to address learners' feedback and answer their questions to guide them positively. To this end, we recommend implementing this newly proposed model in an e-learning system to analyze and visualize course involvement, learning time, and their correlation with the final grade. Such a system can be helpful in improving the learning process by means of the instructor's interference at a specific time to raise the engagement level in a particular learning resource.

Regarding the third research question, various studies have highlighted the importance of contextual features in the process of detecting learner engagement in e-learning [75], [76]. In line with this, our ablation study conducted in Section III confirmed that context significantly influences learner engagement. In Section III-G, the engagement outcome reported takes priority only when specific contextual attributes hold the following values: Mood_status = Happy, Health_status = High, Mobility = No, Luminosity = Yes, Connectivity = High, Noise = No. Identifying the current level of learner engagement enables the adaptation of learning resources to align with learners' preferences, ultimately enhancing their motivation within the specific learning environment.

As shown in Figures 11 and 12, the first two weeks were decisive in retaining the learners in the e-learning course. The instructors need to carefully tailor the course sections and concentrate on the learners' feedback at the beginning of the sessions. According to Raj and Renumol [67], learners may drop out of a course at several points, and they suggested that providing learners with regular support and guidance to progress could reduce dropouts, especially during the first and second weeks of training. Our analytics system was designed as an integrated extension of the LMS MOODLE system. However, the diversity of the learners' experience in our system makes it difficult for instructors to provide services of the highest quality. Our model efficiently captured changes in learners' involvement and identified their engagement levels on time and at the right place. This enables instructors to be more aware of learners' behavior, allowing courses to be developed and tailored according to their preferences [53]. Therefore, providing a higher online facilitation level can improve learners' learning experiences [77].

In this study, the size of the dataset was significantly small. A few features of participating learners were addressed. Such

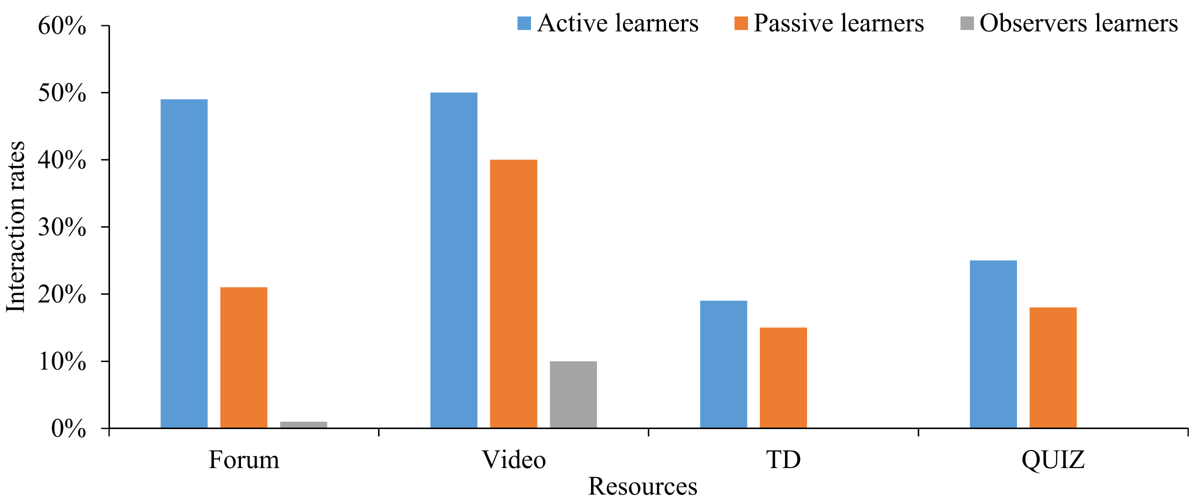

FIGURE 10. Distribution of the three learners' categories by learning resource engagement in e-learning.

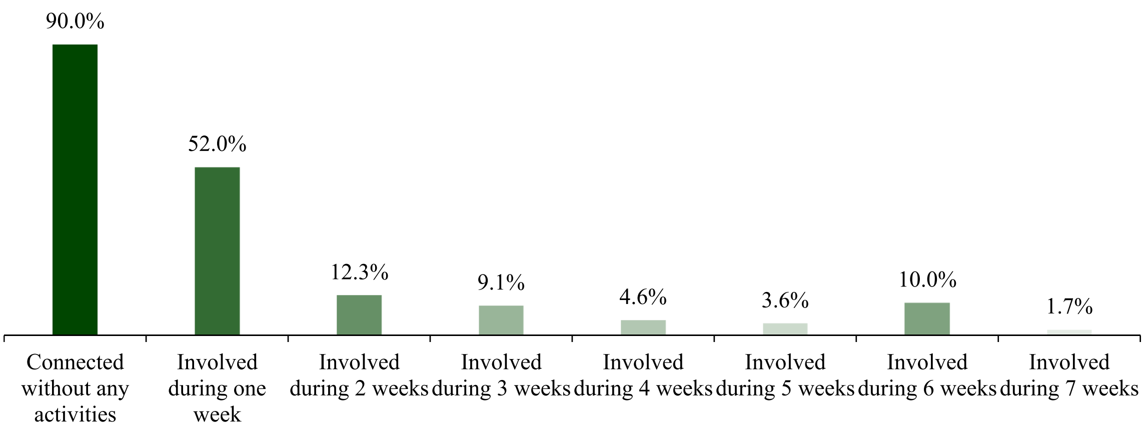

FIGURE 11. Learners' study time of e-learning.

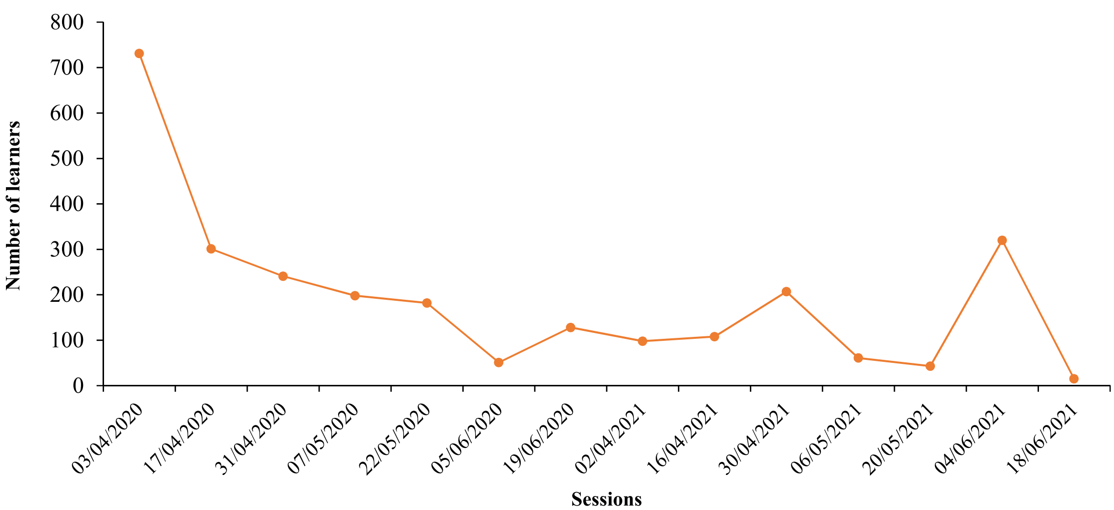

FIGURE 12. Evolution of the number of learners on the e-learning platform over time.

issues could be explored in future research in classrooms outfitted with cameras and computers, conducting conditions that can produce different student engagement levels. Future studies should also explore the relationship between the engagement levels measured, cognitive learning strategies, attitudes, and personal perceptions on the e-learning platform of many groups, and learning outcomes.

V. CONCLUSION AND FUTURE WORKS

Our research aimed to explore the ability to predict a learner's engagement based on the traces left during their interactions with the resource courses provided on the e-learning platform. Owing to the lack of learners' motivation to perform their tasks, instructors are expected to help them increase their motivation and reduce their dropout rates. In this study, an unsupervised K-means algorithm was used to cluster learners to label the dataset as engaged or non-engaged learners in the three courses offered by IAV Hassan II. Then, a context-aware feature vector is fed into the decision tree model, trained for adaptive rules that are used by this system to accurately assess engagement based on the learner's profile at the right time and location. The traces used are firstly quantified as Behavioral, Cognitive, Emotional, and Social engagement. They are processed using a variety of data preprocessing techniques such as deleting missing values, normalization, encoding, and outlier detection. Five classification algorithms are considered: Decision Tree, Random Forest, Logistic Regression, Multilayer Perception, and Support Vector Machines. Then, a cross-validation technique and a series of assessment metrics were used to evaluate each method. In this manner, GridSearch was used to tune each model and find the most efficient hyperparameters. Underfitting and overfitting were then checked using the learning curve technique. The results show that the decision tree rule implementation yields good performance in predicting the engagement level, with high accuracy, precision, recall, and AUC under heterogeneous learning environments. Using our machine learning model, we found that learner engagement can be predicted with an accuracy of 98%.

The findings of this study reveal that most learners are non-engaged and identified as observers. These observers had a course completion rate of less than 4% and displayed specific contextual features, including mobility, high noise levels, low brightness, persistent connectivity issues, sad mood status, or health status disability. It is noteworthy that despite their overall low engagement, these observers occasionally accessed discussion forums. Otherwise, only about 3% of the learners were highly engaged and classified as active. The latter showed a high success rate of 74% with a high final grade. It is also important to note that the use of discussion forums and course videos proved effective in enhancing learner engagement and success rate. Our model is easy to integrate into the e-learning system, and it can help instructors become aware of their learners' involvement level, so they can assist them through the customization of resources and content. This can lead to improved learning outcomes, learner satisfaction, and performance.

In our future work, we plan to explore additional aspects of learner engagement on different platforms, such as MOOCs, which were not addressed in our current approach. This includes examining course semantics to make the classification model more comprehensive.

Additionally, we recognize that many learners do not have access to high-speed Internet; thus, in our future research, we will consider learners' technological infrastructure and

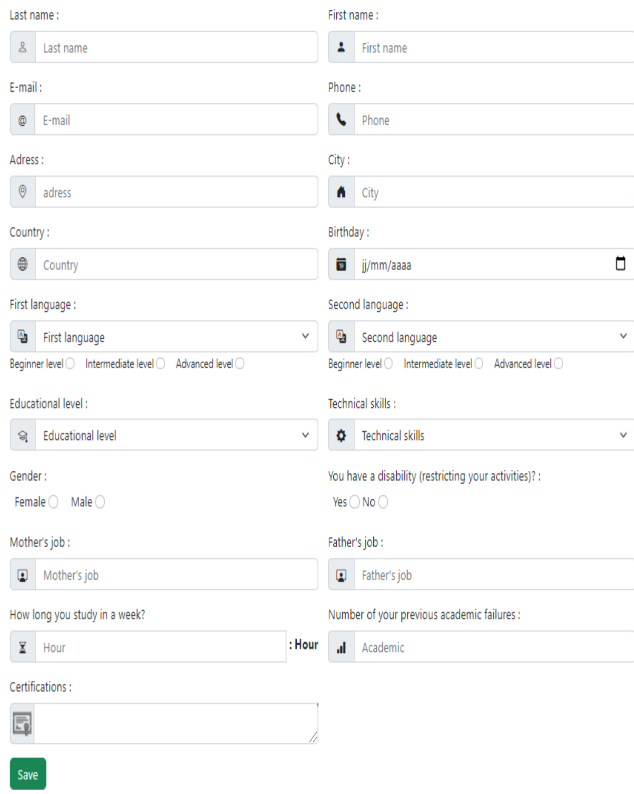

FIGURE 13. Learner registration form in Moodle.

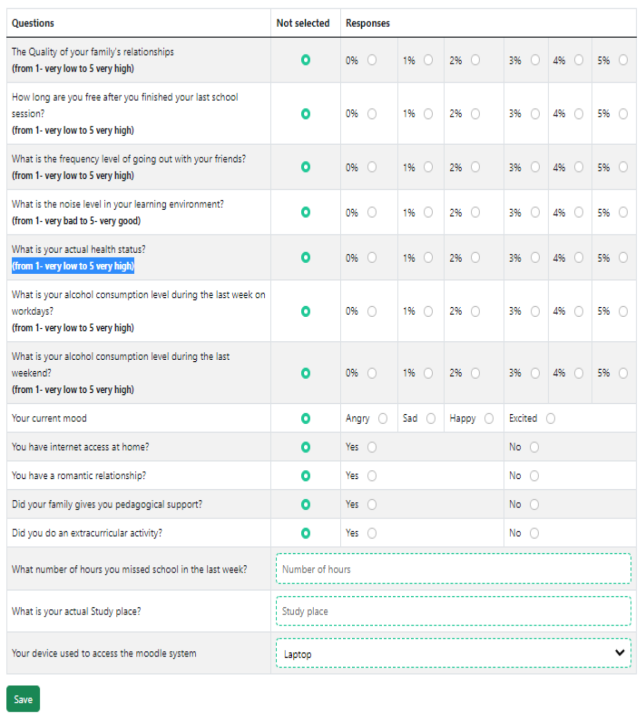

FIGURE 14. Contextual survey voluntarily filled in with each login.

context to provide them with learning resources that can enhance their engagement and lead to higher learning scores and fewer dropouts.

Finally, implementing a learning analytics system using our proposed model can help instructors identify areas where learners struggle, and develop more effective solutions to improve their learning performance.

APPENDIX A

See Figures 13 and 14.

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KHALID BENABBES received the engineering degree in computer science from ENSA, Agadir. He is currently pursuing the Ph.D. degree with the LARI Laboratory, Faculty of Sciences, MISC Team, Ibn Tofail University, Kénitra, Morocco. His research interests include data science, machine learning, MOOC, and recommender systems.

KHALID HOUSNI received the Ph.D. degree in computer science from the University of Ibn Zohr, Agadir, Morocco. His research interests include networks reliability and image/video processing. He has been a member of the Department of Computer Science, Faculty of Sciences, Ibn Tofail University, Kénitra, Morocco, since 2014.

BRAHIM HMEDNA received the Ph.D. degree in computer science from the University of Ibn Zohr, Agadir, Morocco, and currently holds the position of an Assistant Professor with the National School of Business and Management, Agadir. He is also affiliated with the IMIS Laboratory, University of Ibn Zohr. His research interests include machine learning, data science, MOOC, and learning styles.

AHMED ZELLOU received the Ph.D. degree in computer science from the Mohammedia School of Engineering, Rabat, Morocco. He is currently a Professor with the National School of Computer Science and Systems Analysis (ENSIAS). His research interests include semantic and fuzzy systems, information integration, hybrid systems, semantic P2P, and cloud integration and content integration.

ALI EL MEZOUARY received the Ph.D. degree in computer science from the University of Ibn Zohr, Agadir, Morocco. He is currently a Full Professor with ESTA, University of Ibn Zohr. His research interests include web semantic and adaptive learning systems.