Abstract—The field of e-learning has emerged as a topic of interest in academia due to the increased ease of accessing the Internet using smart-phones and wireless devices. One of the challenges facing e-learning platforms is how to keep students motivated and engaged. Moreover, it is also crucial to identify the students that might need help in order to make sure their academic performance doesn’t suffer. To that end, this paper tries to investigate the relationship between student engagement and their academic performance. Apriori association rules algorithm is used to derive a set of rules that relate student engagement to academic performance. Experimental results’ analysis done using confidence and lift metrics show that a positive correlation exists between students’ engagement level and their academic performance in a blended e-learning environment. In particular, it is shown that higher engagement often leads to better academic performance. This cements the previous work that linked engagement and academic performance in traditional classrooms.

Keywords—e-Learning, Association Rules, Apriori Algorithm, Support, Confidence, Lift

I. INTRODUCTION

With the proliferation of technology and the expanding use of smart devices, the field of e-learning has grown in popularity in recent times. E-learning can be defined to be the use of electronic devices and technology for learning new information and skills [1]. Such environments allow individuals to learn new skills without having a physical mentor teaching them face-to-face. In layman’s terms, e-learning can be defined to be the use of electronic technologies to access to educational curriculum outside of a traditional classroom [1]. Many e-learning platforms have been proposed such as Coursera, edX, and OWL in which courses are offered fully online. Moreover, several prestigious universities such as Stanford University and Massachusetts Institute of technology have also started offering online courses through their own platforms known as Stanford Online [2] and MIT OpenCourseWare respectively [3].

One of the challenges an e-learning environment faces is how to keep students motivated and not allow them to become isolated. This is particularly of importance in online courses since statistics have shown that on average only around 15-25% of students complete online courses they registered for [4] [5]. Therefore, keeping students motivated is crucial. This is because students might feel discouraged if they perceive that their learning pace is slower than others, especially with little to no face-to-face interaction with instructors or fellow students. Moreover, studies have shown that engagement with course material has an important impact on future career decisions taken by students [6]. Therefore, teachers need to find a way to keep students engaged and motivated [7]–[9]. Furthermore, many literature works have shown a positive relation between student engagement and academic performance with higher engagement level associated with better grades [10] [11].

In this paper, the relationship between the students’ engagement level and their academic performance is studied. Despite there being a few literature works that study this relationship [12] [13], none of the previous works consider a comprehensive set of engagement metrics and their impact on academic performance. This paper studies the impact of both the frequency-related and time-related engagement metrics as well as the overall engagement level on the academic performance of students using Apriori association rules algorithm.

The remainder of this paper is organized as follows: Section II gives a brief background about the field of e-Learning and the association rules. Then, Section III presents some of the related work from the literature. Section IV gives overview of the system model considered in this work. That is followed by Section V which describes the dataset available and its transformation into the considered features. Section VI discusses the experiments conducted and the resulting rules obtained based on two evaluation metrics. Finally, Section VII concludes the paper.

II. BACKGROUND

A. E-learning:

E-learning has become more popular in recent times due to the proliferation of technology throughout the world and the boom in information access. This is because it allows individuals to learn new skills without having to engage in a physical face-to-face teaching environment. In layman’s terms, e-learning can be defined to be the access to educational curriculum outside of a traditional classroom by utilizing electronic technologies [1]. Several more complex definitions have been given for e-learning [14]. However, they all agree on one common point which is the use of technology and technological devices such as computers and handheld devices as a means to access and share information [14].

This can shown how the field of e-learning can significantly contribute to the notion of big data. With increasing number of students accessing educational material online, more data flows are generated. Thus, machine learning and data analytics also become crucial in order to make use of the growing amount of collected data generated in the field of e-learning. In particular, the sub-field of educational data mining has emerged which focused on analyzing educational data to better understand and
improve students’ performance as well as enhance the learning and teaching process [15] [16].

B. Association Rules:

Association rule learning is a type of rule-based machine learning algorithms that aims to discover interesting relations between items in large databases [17]. The idea is to produce rules that can predict the occurrence of an item based on occurrences of other items [18]. Agrawal et al. provide a more formal definition as follows [19]:

Let \( I = \{i_1, i_2, ..., i_n\} \) be a set of \( n \) attributes/items and \( T = \{t_1, t_2, ..., t_m\} \) be a set of \( m \) transactions forming a database. Each transaction \( t_i \) includes a subset of the items available in \( I \). A rule can be defined as \( X \Rightarrow Y \) where \( X, Y \subseteq I \), i.e. \( X \) and \( Y \) (known as itemsets) are a subsets of the items available. In other words, a rule can be thought of as a predictable transaction within the database. \( X \) and \( Y \) are commonly referred to as the antecedent and the consequent of the rule respectively.

Association rules can be beneficial in an e-learning environment as they can detect correlations between different features within the dataset. In particular, they can be used to correlate student behaviors with their performance to determine what is positively or negatively impacting their learning experience.

In order to evaluate the importance and interestingness of an association rule, several measures have been proposed. In what follows, three measures are presented.

- **Support**: Support of an itemset is an indication of how frequent an itemset appears in the transactions’ database. It can be thought of as the probability of occurrence of the considered itemset by counting the number of transactions in which the itemset appears relative to the total number of transactions. More formally, the support of an itemset \( X \) with respect to a set of transactions \( T \) is calculated as [18]:

\[
supp(X) = \frac{|\{t \in T; X \subseteq t\}|}{|T|}
\]

- **Confidence**: Confidence is a measure of how frequent the rule is within the transactions’ database. In layman terms, it is the portion of transactions that contain both itemsets \( X \) and \( Y \) forming the rule relative to the transactions that contain \( X \) in general. Hence, the confidence of rule \( X \Rightarrow Y \) can be defined as [18]:

\[
\text{confidence}(X \Rightarrow Y) = \frac{\text{supp}(X \cup Y)}{\text{supp}(X)}
\]

The confidence of a rule can be thought of as the conditional probability of the rule [20].

- **Lift**: The lift of a rule is a measure of how interesting the rule is. The lift determines the probability of the rule occurring relative to the probability of the antecedent and consequent being independent. Therefore, the lift of an association rule is defined as [21]:

\[
lift(X \Rightarrow Y) = \frac{\text{supp}(X \cup Y)}{\text{supp}(X) \times \text{supp}(Y)}
\]

A lift of 1 implies that the two itemsets comprising the rule are independent and hence the rule associating them together is not truly a rule. However, if the lift is > 1, it can be concluded that the two itemsets are dependent on each other. This makes the corresponding rule possibly useful in predicting future occurrences of the consequent if the antecedent occurs.

The significance of the lift is that it takes into consideration both the confidence of the rule as well as the overall transaction database [22].

Association rules are often used for categorical (non-numeric) datasets and have been considered for a variety of applications. This includes marketing and sales promotion, supermarket shelf management, inventory management [18], network intrusion detection [23], and health informatics [24].

Several association rules algorithms have been developed. In what follows, a brief description of three well known algorithms is given.

1) **Apriori Algorithm**:

Apriori algorithm is a breadth-first search-based algorithm that depends on the frequency of the itemsets to identify a set of association rules [25]. The algorithm identifies the itemsets that appear in at least \( C \) transactions within the database, where \( C \) is the minimum threshold chosen by the user. It adopts a "bottom up" approach where a frequent subset is extended by one item in each iteration. This means that the algorithm starts with itemsets of length 1 (i.e. only one item within the itemset) and determines the itemset that have a frequency higher than the considered threshold \( C \). This is repeated until no more new frequent itemsets are found. The length is then incremented by 1 and the same process is adopted again. This continues until there is no more possible extensions of the itemsets.

The popularity of the apriori algorithm stems from the fact that it can be easily implemented and parallelized as well as makes use of the large itemset property [26]. However, the algorithm does suffer from some drawbacks. One of the main drawbacks is that it requires several database scans in order to produce the rules [26]. This is mainly due to the itemset extension property of the algorithm. Another drawback is the fact that it can be slow due to its dependence on the size of the database, number of items within it, and the choice of minimum support [18].

2) **Frequent Pattern (FP)-Growth Algorithm**:

Frequent pattern growth algorithm, also known as FP-growth algorithm, is an efficient and scalable alternative to the apriori algorithm [27]. The FP-growth algorithm also aims to find the frequent itemsets within the transaction database. However, it does so without using candidate generations, i.e. it doesn’t increment the itemset size by 1 in each round. This helps it outperform the apriori algorithm in terms of runtime as it significantly reduces the number of considered frequent itemsets. In essence, this algorithm adopts a divide-and-conquer approach to generate the association rules [27]. The algorithm is based on the use of a particular data structure named the FP-tree which conserves the itemset association information [27]. To produce the FP-tree, the transaction database is scanned once and the set of frequent items \( F \) is then determined and ordered in support-descending order. Then each transaction within the database is considered with the items in it sorted based on the order found in \( F \). The count of each item in the tree is updated with each new transaction studied. Hence, the FP-tree is produced using two scans of the database [27].
Despite its efficiency and runtime speed, this algorithm does suffer from one major drawback. That drawback is that all attributes of the database should be binomial, i.e. either it exists in the transaction or not [28]. Hence, it can’t be used in cases where an attribute/item can have multiple possible values.

3) Generalized Sequential Pattern Algorithm (GSP):

Generalized Sequential Pattern (GSP) algorithm is another association rule algorithm. It is mainly used for sequential mining. That means it looks for patterns in datasets in which values are given in a sequential manner [29]. The algorithm uses the apriori algorithm level-wise to discover the frequent itemsets within the corresponding level. The set of frequent itemset is then given to the GSP algorithm which makes multiple scans in order to determine the association rules. In each scan, a set of candidate sequences of length $k$ are formed using itemsets of length $(k-1)$. This continues until no more frequent sequences can be generated.

The GSP algorithm suffers from similar limitations as its apriori counterpart. One major limitation is that it needs multiple database scans to generate the association rules [30]. This is especially a concern when dealing with large transaction databases. Another limitation is the generation of non-existent candidates. This happens because the GSP algorithm generates candidate sequences by combining smaller ones without accessing the database. This can lead to time wasted when considering non-existent patterns [30].

III. RELATED WORK & CONTRIBUTION

A. Student Engagement:

Several works in the literature have explored the notion of student engagement levels and methodologies on how to define and determine these levels [31] [32]. Oriogun classified students based on their engagement into three levels, namely High, Nominal, and Low [31]. The authors used the SQUAD approach in which a student’s posts on a discussion forum were classified as one of five categories, namely: Suggestion, Question, Unclassified, Answer, and Delivery. Each post belonging to one of the aforementioned categories was given a score and the total score of each student was used to determine their engagement in the course. However, this study only focused on quality of forum posts to evaluate engagement without taking into consideration other possible metrics. Kamath et al. also classified students using a three-level model. However, the authors used image recognition as the basis of their classification by building a custom dataset of images portraying the different engagement levels and using support vector machines to classify new images [32]. Yet, this provides a limitation as not all students will have cameras in their devices. Moreover, this won’t be as beneficial in a non-real time scenario.

To be able to measure/identify the engagement level of students, different engagement metrics have been used and proposed in the literature [33]–[35]. Reid used the “Classroom Survey of Student Engagement (CLASSE)” model and proposed frequency-related metrics to determine the engagement level of the students [33]. The metrics considered were: number of questions asked, number of participations, number of interactions with instructor, and time spent on the course. On the other hand, Ramesh et al. used three main frequency-related features to determine the engagement level of students in a Massive Open Online Course (MOOC) setting [35]. The engagement metrics are number of posts in discussion forums, number of content views, and binary indicator of assignment completion. These metrics were used to determine the students’ engagement based on a three-level model. However, most previous works lack the use of a comprehensive set of engagement metrics that include both frequency-related and time-related metrics.

B. Academic Performance Prediction:

Similarly, several literature works tried to predict the academic performance of students based on a variety of factors. Yadav et al. studied the impact of previous or first year exams marks on the final grade of engineering students [36]. In their experiment, the authors used several classification algorithms and found that the C4.5 (also known as J48) algorithm gives the most accurate results. This was corroborated by Ramesh et al.’s work in [37] which also concluded that decision tree classification algorithm was the most suitable for predicting students’ performance. Moreover, it was shown that students’ previous data can be used to predict their final grade. Prasad et al. also considered the use of decision tree algorithms and found that the C4.5 (J48) algorithm is the most suitable algorithm to predict students’ grades because of its accuracy and speed [38].

C. Impact of Engagement on Academic Performance:

Some literature works have also studied the impact of student engagement on their academic performance [10] [11] [12]. Lee studied the relationship between student engagement and their academic performance using the data from 121 U.S. schools [10]. The study concluded that both behavioral and emotional engagement can be used to predict reading performance accurately. On the other hand, Casuso-Holgado et al. used a questionnaire that aims to measure the students engagement and investigated the relationship with academic achievement. The study concluded that engagement is positively related with the academic achievement of students. Similarly, Madar et al. aimed to study the relationship between the student engagement through the use of an e-learning platform and their academic performance. This was done using a survey questionnaire filled by postgraduate students. Results showed a positive correlation between engagement on the platform and the performance of students.

However, most works that studied this relationship didn’t consider it for an e-learning environment. Moreover, the few works that did investigate this relationship in an e-learning setting didn’t use a comprehensive set of engagement metrics to fully understand their impact on the academic performance of students.

D. Contribution:

The contribution of this work can be summarized as follows:

- Providing a comprehensive set of engagement metrics that include both frequency-related metrics and time spent on different tasks of the course.
- Studying the impact of the considered engagement metrics and levels on academic performance.

IV. SYSTEM MODEL

Figure 1 presents the overall system model considered in this work. The presented module is the general module that would be integrated into the LMS. It consists of the following modules:
• Data Collection Module: Collects the data from the LMS. This includes both the events and the grades.
• ML-based Student Status Predictor Module: Predicts the status of the students using different supervised learning algorithms.
• Engagement Metrics Module: Calculates the different engagement metrics using the collected events log data.
• Student Clustering Module: Clusters students into different engagement levels using the aforementioned engagement metrics by implementing unsupervised learning algorithms.
• Association Rule Generator Module: Takes the both the grades dataset and calculated engagement metrics as well as the resulting clustering decision to generate a group of association rules.
• Feature Selection Module: Selects the features that are most representative of the student performance.
• Performance Metrics Module: Generates a group of performance metrics that can be used to classify students.
• ML-based Classification Module: Classifies students by implementing different supervised learning algorithms.
• Set of Students Who May Need Help Module: Identifies the group of students who may need help in the course. This can be used as an initial step of the e-learning personalization process.

This work focuses on the association rule generator module. Within this module, several different association rule algorithms can be implemented. In this case, the apriori algorithm is used. This is because as discussed previously, the FP-growth algorithm only accepts binomial features. On the other hand, the GSP algorithm searches for association rules in a transactional dataset. However, the dataset considered here is not a transactional one, i.e. each record represents one student. Hence, the GSP algorithm can’t be implemented.

V. DATASET DESCRIPTION

A. Data Preprocessing:
The collected dataset is from a second year undergraduate Science course offered in a North American University. The dataset consists of two parts. The first part is an event log of 486 enrolled students and has a total of 305933 records collected from the university’s learning management system (LMS). Each record has the following 6 fields:
• Event Date: The time-stamp of the event.
• Event Type: The type of action the student makes.
• Event Location: The directory in which the action was taken by the student.
• Session Start: The time-stamp signaling the start of the online session.
• Session End: The time-stamp signaling the end of the online session.
• Student ID: Student Identifier.
The dataset was sorted based on the “Student ID” first and then based on “Event Date”. This was done so that a chronological order of the events each student took is obtained.
The second part is the obtained grades of the 486 students in the different assignments, quizzes, and exams. Each record has the following 8 fields:
• Student ID: Student Identifier.
• Assignment 1: Grade obtained in Assignment 1.
• Assignment 2: Grade obtained in Assignment 2.
• Assignment 3: Grade obtained in Assignment 3.
• Quiz 1: Grade obtained in Quiz 1.
• Midterm Exam: Grade obtained in Midterm Exam.
• Final Exam: Grade obtained in Final Exam.
• Course Grade: Final Course Grade.

B. Data Transformation:
Using MATLAB, the event log dataset was transformed from its original state into a new dataset representing the students’ engagement metrics. This was done by searching the events’ column of the subset of data representing each student and calculating the engagement metrics accordingly. Moreover, each metric’s value was rounded to the nearest 10s to get a discrete set of values as per the requirement of the different association rules algorithms. Furthermore, the engagement level of each student is determined as per our previous work [39]. Based on the engagement metrics used in the literature and the original available dataset, Table I presents the calculated engagement metrics and engagement level which are considered in this study as well as their description, type, and range of values of each metric. Note that for the engagement level, L means Low while M means Medium and H means High.

Similarly, the grades of each student were rounded to the nearest 10s to get a discrete set of values as per the requirement of the association rules algorithms. The calculated engagement metrics dataset and the grades dataset were combined to form a new dataset consisting of eighteen features, namely the Student ID, nine engagement metrics, engagement level, and the seven grades.

VI. PERFORMANCE EVALUATION & DISCUSSION

A. Experiment Setup
As mentioned earlier, the experiment uses apriori algorithm to generate the association rules linking the students’ engagement metrics and level to their performance. To do so, the following settings were used:
TABLE I: Engagement Metrics Description

| Feature                   | Description                                      | Type         | Range of Values         |
|---------------------------|--------------------------------------------------|--------------|-------------------------|
| Student ID                | Student identifier                              | Numeric      | [0,...,485]             |
| Num. of Logins            | The number of times the student accessed the course site on the LMS | Numeric      | [0,10,...,650]          |
| Num. of Content Reads     | The number of times the student accessed/downloaded course material | Numeric      | [0,10,...,1010]         |
| Num. of Forum Reads       | The number of times the student posted on the discussion forum | Numeric      | [0,10,...,60]           |
| Num. of Forum Posts       | The number of times the student posted on the discussion forum | Numeric      | [0,10]                  |
| Num. of Quiz Reviews      | The number of times the student reviewed their quiz solution before final submission | Numeric      | [0,10]                  |
| Assign. 1 duration to submit (in hours) | The duration (in hours) between Assignment 1 posting and submission | Numeric      | [0,10,...,580]          |
| Assign. 2 duration to submit (in hours) | The duration (in hours) between Assignment 2 posting and submission | Numeric      | [0,10,...,300]          |
| Assign. 3 duration to submit (in hours) | The duration (in hours) between Assignment 3 posting and submission | Numeric      | [0,10,...,630]          |
| Average Assign. duration to submit (in hours) | The average duration (in hours) between Assignments' posting and submission | Numeric      | [0,10,...,500]          |
| Engagement Level          | Student engagement level using K-means Clustering | Categoric    | [L,ML,H]                |

1) Software:

The following software have been used to run the experiment and record the results:

- Operating System: Microsoft Windows 10 (64-Bit OS, X-64 based processor)
- MATLAB: MATLAB was used to transform the data from its original state to the new desired dataset that includes the engagement metrics as as the grades.
- Waikato Environment for Knowledge Analysis (WEKA) version 3.8: WEKA is a toolkit used for machine learning and data mining. It was developed using Java by the University Waikato in New Zealand.

2) Experiment:

WEKA was used to run the apriori algorithm to generate the desired association rules. Apriori algorithm was used because it allows features to have multiple values rather than just binomial as is the case with FP-growth algorithm. Furthermore, apriori algorithm was used instead of GSP algorithm because the considered dataset is not transactional in nature, i.e. each student has only one record within the dataset. Hence, GSP algorithm can’t be implemented.

B. Rules:

To generate the association rules, the minimum support used was 0.1, i.e. the rule needs to have occurred at least 10% of the time to be considered. Moreover, the minimum confidence value assumed was 0.9, i.e. we would want to be more than 90% confident that the rule is applicable. These values were chosen to ensure that the rules are frequent and interesting enough to be considered in an educational setting [40]. Based on the aforementioned settings, the following rules have been generated:

- Engagement level=H & Quiz1≥90 ⇒ Course Grade≥90:
  The rule had a support = 0.2, i.e. 20% of all students were classified as highly engaged, had a grade higher than 90 in their quiz, and completed the course with a grade higher than 90. The rule had a confidence of 1 and a lift of 4.02. This means that all the students who were highly engaged and performed well in their quiz ended up excelling in the course. The high lift value shows that the components are highly correlated. This means that engagement level can indeed be used as a predictor for academic performance.

- Number of Logins≥60 & Quiz1≥80 ⇒ Course Grade≥80:
  The support of this rule is 0.61, which indicates that around 61% of the students logged into the system more than 60 times. This is an indication of being moderately or highly engaged as per the results obtained in [39]. The rule's confidence is 1 and the lift is 1.37, indicating that all students who were moderately or highly engaged and performed well in their quiz had a high final course grade. Moreover, the lift value indicates that there is a positive correlation between the antecedent and consequent of the rule.

- Engagement level=M & Quiz1≥70 ⇒ 70≤Course Grade≤90:
  This rule had a support of 0.4, confidence of 0.93, and a lift of 1.1. This shows again that there is a correlation between engagement and academic performance. This is because students that were moderately engaged tended to get a moderate grade in the course.

- Engagement level=H ⇒ 90≤Course Grade≤90:
  This rule had a support of 0.4, confidence of 0.93, and a lift of 1.1. This shows again that there is a correlation between engagement and academic performance. This is because students that were moderately engaged tended to get a moderate grade in the course.

In addition to the obtained rules, the average grade of the students is calculated based on their engagement. It can be shown that students with medium engagement had an average final grade of 77 while those that were highly engaged had an average final grade of 79. On the other hand, students that were lowly engaged had an average grade of 61. This cements the hypothesis that student engagement is highly correlated with academic performance even in a blended e-learning environment. Hence, it can be used as a predictor and identifier of students that may need help based on their engagement in the course.

VII. CONCLUSION

The field of e-learning has become more popular due to the proliferation of technology. Among the challenges facing e-learning is keeping the students engaged and motivated. This is especially important due to the impact that engagement has on academic performance. To that end, this paper proposed the use of apriori algorithm to investigate the impact of engagement on students’ academic performance in a blended e-learning environment. Nine engagement metrics that include
both frequency-related as well as time-related metrics were identified and calculated from the event log dataset available and combined with the grades to form a new dataset composed of eighteen features. Apriori algorithm was used to generate rules that studied the impact of students’ engagement level on their academic performance. Experimental results showed that there is a high positive correlation between engagement and academic performance. This was shown through the association rules generated which stated with high confidence and lift that students with higher levels of engagement tended to perform better in the course. Due to this positive correlation, engagement can be used as a predictor of the students’ academic performance. This in turn can be used to identify the unengaged students who may need help with the course and work with them to improve their engagement and possibly their performance.

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