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Research article

Unsupervised machine learning approach for tailoring educational content to individual student weaknesses

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ABSTRACT

By analyzing data gathered through Online Learning (OL) systems, data mining can be used to unearth hidden relationships between topics and trends in student performance. Here, in this paper, we show how data mining techniques such as clustering and association rule algorithms can be used on historical data to develop a unique recommendation system module. In our implementation, we utilize historical data to generate association rules specifically for student test marks below a threshold of 60%. By focusing on marks below this threshold, we aim to identify and establish associations based on the patterns of weakness observed in the past data. Additionally, we leverage K-means clustering to provide instructors with visual representations of the generated associations. This strategy aids instructors in better comprehending the information and associations produced by the algorithms. K-means clustering helps visualize and organize the data in a way that makes it easier for instructors to analyze and gain insights, enabling them to support the verification of the relationship between topics. This can be a useful tool to deliver better feedback to students as well as provide better insights to instructors when developing their pedagogy. This paper further shows a prototype implementation of the above-mentioned concepts to gain opinions and insights about the usability and viability of the proposed system.

1. Introduction

The spheres of education and technology have become intertwined in recent years. The development of various e-learning systems over the past few decades has greatly increased the usage of computers in learning and teaching. The global health crisis accelerated the global education sector's transition to Online Learning (OL), shedding light on the vast potential and capabilities of this field [1]. Beyond this emergency shift, OL has been trending upward in terms of participants for the past few years as technology has become more accessible to the general populace. With over 150 million users partaking in OL, this field of education is also bound to produce massive amounts of data. As students engage in learning, explore various subjects, complete tests, and submit projects and assignments, they leave behind a sea of information. Hence this prompts the question: *How can we leverage these extensive data archives?* This brings us to the concept of Educational Data Mining (EDM).

To explore data from educational contexts, EDM emerges as a paradigm focused on designing models, activities, methodologies, and algorithms. EDM seeks to identify trends and forecasts that represent learners' actions and accomplishments, as well as assessments, educational features, and applications [2]. In recent times we can identify several trends in EDM. Some of these trends include the inclusion of EDM modules as a standard component of computer-based educational systems. The use of EDM at various stages of the teaching and learning process is another trend. EDM assists in the initial stage's customization of the learning environment based on the profile of the student. EDM analyzes data as the student interacts with the system and offers suggestions in real-time. The success of the education delivered, including services, results, user happiness, and resource usefulness, is assessed at the final step by EDM.

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1.1. Motivation

With the standards of education moving away from preparing students for the job market and more towards critical thinking and adaptive learning we must keep our tools for education up-to-date as well [3]. We must further ensure that educators and instructors have better resources which in turn can influence better feedback to students. These tools can also lead to a better presence of instructors in OL [4]. As the world's landscape constantly changes it becomes imperative to have evolving pedagogical tools as well. Previous research has shown these factors to be of huge importance when it comes to user satisfaction with an OL learning environment and has consistently been the issue that most students raise when asked about the challenges of OL [5]. As most OL learning models are variations on the mastery model of learning and teaching, it is high time we incorporate more modern algorithms to aid in further developing the models being applied to different OL platforms [6].

Therefore, efforts should be made in the creation of novel, intuitive, and simple-to-implement software solutions. Such software can be essential in promoting online learning and encouraging efficient teaching methods by utilizing the large data reservoirs and patterns generated through EDM. Literature from 2022 reveals the myriad of techniques and algorithms, such as Self-Organization Theory, Concept Mapping, Immunological Algorithms, Hybrid Approach, etc [7]. However, they do not implement a data mining approach and thus our proposed method of content recommendation could fill that gap in the literature. Adopting this strategy has the potential to bring about changes in the online educational scene by equipping both educators and students with a new module to be adopted alongside a main recommender system to gain insightful knowledge and effective tools for improved learning experiences.

1.2. Research aim

OL has been a large part of the education sector since networking and computation have been readily available, [8]. Besides its myriad of features, [9] OL also provides educators and learners with precisely calculated and curated data for further evaluation and subject recommendation. The paper focuses on specifically Apriori Algorithm, [10] and F-P Growth Algorithms as association algorithms for educational data mining alongside K-means clustering, [11] as a clustering algorithm. Based on the data mining results, we suggest creating a recommendation system that makes use of the identified association rules to provide students with pertinent learning resources based on previously discovered trends of weakness. In addition, the research paper also showcases a prototype implementation of the above-stated module to a volunteer group of students and instructors to gain insights into the viability, effectiveness, and usability of the proposed model. By contributing to the broader field of educational data mining, our research seeks to advance knowledge and understanding of the effective implementation of EDM in an educational content provider module which can be applied to other OL platforms.

1.3. Research contributions

Our paper makes three significant contributions to the sphere of OL and EDM. They are as such:

- The methodological landscape of educational data mining and recommendation systems is improved by this study. Our novel use of the Apriori and F-P growth algorithms to analyze historical educational data offers a novel method for identifying undiscovered correlations in student learning patterns.
- We develop a module for a recommendation system that directs students toward specific remedial content and resources based on their shortcomings by utilizing the insights we learned from our association algorithm study. We outline the viability of our prototype in enhancing students' learning outcomes through A/B testing.
- Our study advances the use of relatively more tailored instruction in online education. We create the foundation for a more individualized and adaptive educational experience by utilizing data-driven insights to detect and address topic shortcomings. This is especially important when it comes to OL, where a variety of student demographics need individualized help to succeed.

1.4. Organization

The structure of the paper is as follows. Section 2 reviews related studies pertinent to our research study. In Section 3, we delve into the background, examining algorithmic structures and approaches and conducting comparisons among various association algorithms. Section 4 expounds on our dataset and the data collection process. Section 5 reveals our methodology, providing valuable insights into our ongoing research. We also elaborate on the applied methodology, encompassing all techniques employed in our paper, alongside detailed information about our prototypes. Section 6 presents and analyzes the outcomes derived from our applied methodology. Here, we scrutinize conclusions, implications, and the results of rigorous validity checks. Finally, in Sections 7 and 8, we examine our findings, draw conclusions, and outline our future research plans.

2. Related work

The boom of technological advancement during the early 2000s, study [12] greatly fueled the usage of computers and the Internet in learning environments. E-learning or Online Learning is described as the use of information and communication technology in the education sector to enable the provision of services aimed at improving academic results [13]. When the issues and challenges of implementing OL started to be overcome as time passed [14], we began to see more and more users subscribing to the idea of OL. As suggested by the Technology Acceptance Model (TAM) [15], the younger generation initially looked through unofficial lectures on various topics mainly on video-sharing platforms such as YouTube [16].

One of the biggest and most popular channels on YouTube (in the context of OL) was known as "Khan Academy" [17]. "Khan Academy" had recorded lectures explaining various topics on a broad spectrum of difficulty levels, thus pioneering the 'e-learning' (EL) model. Khan Academy eventually grew into its website, adding the next most important feature in the OL: *testing*. Testing allowed the advent of OL to venture into the mastery model of learning, [6]. The mastery model can be described as a learning model that expects users to show a certain acceptable level of competence on a certain topic/subject before they are allowed to delve further into the learning materials. This was of course not just limited to Khan Academy but other learning models also followed this formula for OL.

The type of OL described so far can be categorized as asynchronous learning [18]. Asynchronous learning has two main advantages [19]:

- Flexibility: Since this type of learning takes advantage of recorded lectures and videos, students and learners can choose to view these lessons at their convenience instead of in real-time. This allows learners to absorb the materials at their own pace, whenever they want.

- Deeper Learning: since asynchronous learning does not follow real-time lectures or have hard and fast traditional deadlines, learners are encouraged to research further into their materials and content. This can allow learners to identify further context and literature about their subjects.

The other type of learning that gained traction was synchronous learning. With Voice Over Internet Protocol (VOIP) technology advancing to enable low-latency communication, voice, and video calls started to become prevalent [20]. This allowed OL classes to be taken virtually and remotely, where learners and instructors could communicate in real-time. Hybrid classes became a possibility and thus another sphere of OL was created [21].

Synchronous OL has two significant advantages [19]:

- Interaction: Since lessons are being carried out in real-time, the instructor and learner may talk to each other, ask questions, and overall have a social presence in the classroom.
- Accountability: Since synchronous learning requires the learner to be online and active during a certain time of day, it fosters the feeling of being part of a regulated program which helps students with time management and maintaining a routine.

2.1. Trends of online learning

The landscape of OL has witnessed continual transformation, growth, and evolution, as noted by previous work [22]. One of the recent developments in OL is the integration of game-based learning (GBL) [23]. GBL employs diverse gamification strategies to create an engaging learning environment with reward systems. By awarding virtual points or badges upon accomplishing specific objectives, learners receive immediate feedback and positive reinforcement, a technique previously demonstrated to enhance the online learning experience and learning outcomes [24].

Besides, in light of technological advancements and emerging concepts such as GBL, it is essential to maintain an open mindset and recognize that continuous refinement and experimentation are key to enhancing OL. A promising avenue is the integration of machine learning into online learning [25]. Machine learning has the potential to unlock valuable features that can enrich online learning, as discussed earlier and explored in the solutions proposed below. For instance, clustering algorithms [26] can be employed, alongside association algorithms [27], to develop innovative tools and set new trends in the online learning sphere, ultimately enhancing the pedagogy of online learning environments.

Furthermore, many learning models utilized in online learning environments are based on variations of the Mastery model, often overlooking other essential aspects of learning, such as the forgetting curve [28]. Remarkably, online learning commonly neglects the Forgetting Curve (FC) [29], which suggests that we tend to forget information when not revisited over time. This theory can be applied to the realm of education [30]. Surprisingly, despite Hermann Ebbinghaus's foundational research on the FC, it has received limited attention in online learning pedagogy and applications. Nonetheless, some studies have delved into understanding how students forget and learn [31,32], and certain efforts have been made to address the effects of the forgetting curve in education.

One of the suggestions for mitigating the FC and OL pedagogy is making the content more engaging. If we look at recent research into OL pedagogy [33], we can see that more appropriate feedback alongside engaged and active instructor presence is a top priority. One factor that we believe to be a disadvantage of the widely adopted mastery learning model is that it does not promote revision of a topic [34]. Additionally, some learners may face more difficulty achieving the level of merit required by the model to move past a certain problem topic. The mastery model does not typically have any tools to address these issues.

2.2. User satisfaction with online learning

Prior research has sought to assess student satisfaction with online learning. An investigation conducted at Deakin University in Australia [35] discovered that the majority of students expressed contentment with the accessibility of course materials and the ease of assignment submission. However, they conveyed dissatisfaction with the feedback quality they received. In the context of Bangladesh, study [36] indicated that user satisfaction, particularly among public university students, was significantly influenced by the flexibility and quality of information and assessment. On the other hand, another study [37] reported widespread telecommunication problems during online learning, significantly diminishing student satisfaction. This study also highlighted issues such as inadequate feedback, limited interaction, and challenges in comprehending course materials during online learning.

Moreover, students seem to prioritize the instructor's capacity to operate the tools for an online class and engage with students even in an online environment as a big contributing factor to how effective online learning can be. The design of online learning has also evolved with the iteration and integration of new pedagogy and student needs in mind, such as gamification is one of the newer trends in online learning platforms [38].

2.3. Recommendation systems

Personalized recommendation systems are a key focus within the realm of OL, and they have seen significant contributions from researchers [39,40]. Notably, the work by Xiao et al. [41] greatly advanced this area. Subsequently, there has been a wave of innovative research and practical applications in recommendation systems. For instance, Xu and Zhou [42] proposed employing deep learning techniques to recommend courses based on a combination of course metadata and user content filtering. Furthermore, researchers such as Hua Wang et al. [43] have emphasized the utilization of association algorithms in recommendation systems, a concept also explored in a 2016 paper by Fang Liu et al. [44], where a variation of the Apriori algorithm was used for university course recommendations. These recommendation systems typically fall into two main categories: Content-Based Filtering and Collaborative Filtering.

In the realm of education data mining, Association Algorithms, including the Apriori [45] and F-P growth algorithms [46], have been employed to identify frequent itemsets and generate association rules using a minimum support threshold. Furthermore, clustering algorithms [47] have found application in educational data analysis, aiding in the identification of students facing similar challenges in specific subjects. It is crucial to note that the performance of these algorithms is highly dependent on the configuration of parameters and metrics. Properly tuning these settings is vital for optimal results.

3. Background

We mainly focus on using an unsupervised association algorithm, specifically, Apriori Algorithm and F-P Growth algorithm. Alongside that, we apply K-means Clustering and A/B testing as a validation technique. Here, in this Section, we present the necessary background information related to our study.

3.1. Clustering

Clustering is a machine-learning technique that involves grouping similar data points based on their characteristics or attributes [48]. The goal of clustering is to find patterns and relationships within the data, which can then be used to gain insights into the underlying structure and organization of the information. The fundamental idea of clustering is rather straightforward. The program analyzes a set of data points and groups them based on similarities it finds between them. Different criteria, such as distance metrics (such as the Euclidean distance), correlation coefficients, or other measurements, can be used by the algorithm to identify similarity.

The Euclidean distance is the distance metric that K-means clustering uses the most frequently. In a d-dimensional space, it calculates the straight-line distance between two data points. The Euclidean distance between two points x and y in a d-dimensional space is given by

$$distance(x, y) = \sqrt{(x_1 - y_1)^2 + (x_2 - y_2)^2 + \cdots + (x_d - y_d)^2} \tag{1}$$

Cluster centroid updates are necessary following data point assignment. The mean vector of all data points in a cluster makes up the centroid. The average of the coordinates of all the data points in a cluster, C, is used to determine the updated centroid coordinates. The formula for calculating the new centroid in k-means clustering is given by

$$\text{new\_centroid} = \frac{1}{|C|}\sum_i x_i \tag{2}$$

Here, $|C|$ represents the number of data points in cluster C, and $\sum_i x_i$ denotes the sum of the coordinates of all data points in the cluster.

To determine the optimal number of clusters in K-means clustering we can use the "Elbow Method" and "Silhouette Score". The Elbow Method is a heuristic method for determining the K-means clustering's ideal number of clusters (K). This is how it goes:

We calculate the sum of squared distances (SSD) between each data point and its designated cluster center for various values of K (often ranging from 1 to some upper limit). The "within-cluster sum of squares" (WCSS) is another name for this. The WCSS formula is

$$WCSS(K) = \sum_{i=1}^{N} \left(\text{distance}(data\_point_i, cluster\_center_i)^2\right) \tag{3}$$

Here, N represents the total number of data points,
$data\_point_i$ represents each data point.
$cluster\_center_i$ represents the cluster center to which
$data\_point_i$ is assigned.
distance($data\_point_i$, $cluster\_center_i$) represents the distance between $data\_point_i$ and $cluster\_center_i$. $data\_point_i$ represents a datapoint with its own set of coordinates in the designated space. Hence, in our 2-dimensional space, $data\_point_i$ is represented as (x_i, y_i). As for $cluster\_center_i$, the same coordinate system is utilized; hence, when calculating the distance, we utilize the Euclidean distance as described in Eq. (1). Plot the WCSS scores for various K values. The plot frequently resembles an "elbow", with the WCSS declining quickly at first (with a rising K) before beginning to level out. This is how the Elbow Method got its name.

In case it is still unclear on the optimal number of clusters, we can further refer to the silhouette score method. The silhouette score is a measure to find the optimal number of clusters in K-means clustering. It quantifies how well-defined and separate the clusters are. Here's how it works:

- For each data point, calculate:
  - "a": Average distance to other points in the same cluster.
  - "b": Average distance to points in the nearest different cluster.
- Compute the silhouette score for each point: $\frac{b-a}{\max(a,b)}$
- Calculate the average silhouette score for all points in the dataset.
- Repeat this process for different cluster numbers (k) and choose the k with the highest silhouette score as the optimal number of clusters.

Higher silhouette scores indicate better-defined clusters, helping us find the best cluster count for our data.

3.2. Apriori association

This is a type of unsupervised machine learning that takes transaction data and sorts them according to the frequency of seeing items together [49]. In other words, it tries to find patterns of items occurring together. It is an iterative algorithm, it parses through the data and looks for frequent individual items. then, it parses the dataset again and looks for how often a pair of items from the frequent individual items appear together. It accepts or declines these itemsets based on a preset parameter such as "support". The iterations continue until no more frequent itemsets can be generated or all the generated itemsets no longer meet the minimum support threshold. The resulting frequent itemsets represent the associations that occur frequently in the dataset.

Association rules are also generated, which indicate exactly the conditional probability that has to occur to gain a certain frequent item set. The 'support' is calculated using Eq. (4) and Eq. (5).

The equation for calculating the support of an itemset in association algorithms is given by

$$\text{Support}(A) = \frac{\text{Number of transactions containing itemset } A}{\text{Total number of transactions}} \tag{4}$$

In this equation, A represents the itemset for which we want to calculate the support. Besides support, the "strength" of the association is measured using conditional probability using a parameter known as 'confidence'. Confidence in association rule is a measure of the accuracy of a rule. In simple terms, if items A and B are in the association rule, their confidence shows how often B is seen together with item A. The formula for confidence is given by

$$\text{Confidence}(A \rightarrow B) = \frac{\text{Support}(A \cup B)}{\text{Support}(A)} \tag{5}$$

Broadly, the Apriori algorithm functions like this:

- When a candidate item is created, it combines the item (k-1)-itemset that was obtained in the previous iteration. The availability of candidate k-itemset trimming with a subset comprising k-1 items but not in the high-frequency pattern with a length of k-1 is one feature of the Apriori method.
- The evaluation of each candidate's k-itemset's support. The number of transactions containing all the items in each of our candidate candidates is determined by scanning the database for each candidate. This is a characteristic of the Apriori algorithm as well, which necessitates calculation by thoroughly searching the database, starting with the longest items.
- Set a pattern with a high frequency. The candidate kitet with support larger than the minimal support is used to determine a high-frequency pattern with k items or itemset.

- The process is terminated if no new high-frequency pattern is discovered. If not, perform k plus 1 and go back to phase 1.

3.3. Frequent pattern growth algorithm (F-P Growth)

In the field of creating associations through item set mining, the Frequent Pattern Growth (FP-growth) algorithm is one of the fastest and most popular algorithms [50]. FP-growth algorithm is primarily based on FP-tree which is a prefix tree representation of the given database of transactions [51]. The FP-tree represents the dataset in the form of a tree where there is no need for candidate generation.

In the preprocessing of the FP-growth algorithm, all individually infrequent items are deleted from the transaction database before turning into an FP tree. This selection can be done with the help of a threshold value. In the FP-tree, each path represents a set of transactions that share the same prefix, each node corresponding to one item where all nodes referring to the same item are linked together.

To mine frequent itemsets from a database, the FP-Growth algorithm requires a few crucial steps. To show the frequency and relationships of these frequent itemsets, an FP-tree is first built. This tree provides a structured overview of the data. The system determines each item's frequency as it scans the incoming data, creating headers with tables that connect to each instance of the item. Then, for every individual item, sub-databases are built, creating a conditional pattern base for every often occurring item. Every sub-database only includes transactions related to a specific frequent item. The FP-Growth method then builds conditional FP-trees recursively for each common item using these sub-databases. Based on common frequent items in their routes, these conditional FP-trees are subsequently connected to the main FP-tree. Significantly, this method departs from the Apriori algorithm in that it does not require the generation of candidate itemsets.

The FP-Growth algorithm recursively mines common itemsets by examining the tree topology once the FP-tree has been fully constructed. Combining the prefix pathways in the main FP-tree with the suffix patterns (conditional FP-trees) yields frequent itemsets. The algorithm completes its duty after successfully identifying and extracting the desired patterns from the dataset until no more frequent item sets can be found.

3.4. A/B testing

A/B testing is a very highly used approach that many modern-day web-tech companies use for development [52]. The A/B testing framework consists of two steps: sampling and estimation. In the sampling step who gets to be the control (no change) and who gets to be the variation is determined and in estimation, a framework is provided to compute the average treatment effect. In the field of A/B testing, the fundamental process consists of a set of stages that are clearly defined and intended to extract meaningful verification from data. The main aim is to formulate precise objectives and hypotheses that will serve as the foundation for assessing the efficacy of any alterations or interventions. The crucial process of collecting samples from the user base is the primary phase, which must be completed with these goals in mind. To do this, users must be split into two groups: an experimental group that will be exposed to the suggested modifications, and a control group that will not receive any changes. The elements selected for testing are carefully chosen to ensure a representative sample of the user population.

The testing proceeds to the application of suitable statistical techniques when the data has been collected following these guidelines. These techniques are essential for contrasting the results and actions of the experimental and control groups. A crucial stage in the decision-making process is the study of the test results and statistical test findings. Here, the preliminary theories are either confirmed or refuted in light of the data's facts and conclusions.

4. Dataset

We have generated a new dataset specifically for testing algorithms and assessing their effectiveness using real-world data. To ensure the practical relevance of our evaluations, the dataset is sourced from online and hybrid learning classes.

4.1. Ethical considerations

As this study focuses on OL, we aimed to acquire student data from online learning environments. With the widespread shift to online learning during the global health crisis, a wealth of data should be available from the years 2019 to 2021. It is crucial to note that details about students in an institution are typically treated as sensitive and confidential, making such data not readily accessible to the public. Instructors and learners may also be hesitant to disclose personal information like names and emails due to privacy concerns.

Considering these challenges, we addressed instructors with letters from our supervisor and Institutional Review Board (IRB), assuring both learners and instructors that their information would remain confidential and solely used for research purposes. The letter explicitly mentioned that no personal information of the learners or instructors would be recorded or utilized during the research. Subsequently, this letter was submitted to several educational institutes, and two after-school coaching centers responded positively, agreeing to share data from their experiences teaching online and during hybrid classes.

4.2. Data collection

As mentioned earlier, our focus is on OL data, and we do not collect data from traditional in-person classes. To obtain relevant data, we opted for purposive sampling. We secured data from two after-school coaching institutions that willingly shared their online learning data during the pandemic period.

The data was organized into batches of 45 and 75 students, which were then merged into a unified dataset comprising 399 entries. Collection occurred in two phases: first on January 17th, 2023, and then on February 12th, 2023.

4.3. Description

The data was organized in an Excel format, with columns denoting distinct topics and rows corresponding to individual students. Derived from grade 10 physics instructors and learners, the dataset includes 16 physics topics and 4 mock exams. To ensure privacy, each student received a unique ID, resulting in a total of 399 identifiable entries.

The dataset was standardized to be marked out of 100 by the coaching institution for consistency. It is worth noting that the institutions did not collect or send missing data for students who did not take most of the tests. The dataset shows an average mark of 69.547 and a spread, with a standard deviation of 20.5. This highlights a limitation where most students did not get very high marks, and the data varies quite a bit (see Fig. 1).

1	Id	Motion - F	Units - Re	Units and	Measuren	Displacem	Measuren	Motion Eq	Hookes La	Motion Eq	Moments	Forces and
2	123abc	12	52	88	39	41	43	58	93	4	48	28
3	456def	78	83	24	18	90	18	15	13	58	8	47
4	789ghi	63	98	94	45	57	9	89	67	65	31	8
5	101jkl	67	92	58	15	16	5	26	98	55	32	81
6	112mno	93	97	15	22	50	10	40	10	38	8	96
7	123pqr	80	52	84	90	69	98	82	31	12	65	12
8	134stu	15	100	86	7	55	92	13	14	30	39	66
9	145vwx	8	2	47	39	2	55	33	27	31	53	52
10	156yz	15	97	85	37	55	38	9	97	22	34	51
11	167abc	45	100	31	66	76	52	51	80	36	78	98
12	178def	36	25	18	57	66	41	50	5	82	59	10
13	189ghi	58	91	25	34	29	31	15	11	36	65	77
14	190jkl	96	97	81	53	10	97	39	78	18	72	80
15	201mno	26	31	68	77	87	51	69	10	55	44	47
16	212pqr	97	59	35	31	42	82	83	29	10	33	20

Fig. 1. Dataset snippet.

5. Methodology

In this paper, our methodology commences with the collection of pertinent data, followed by the application of algorithms to preprocess this data. Subsequently, we implement a prototype, culminating in the testing phase involving relevant stakeholders.

5.1. Data pre-processing

In the dataset, there were 20 columns. The initial column served as a unique student ID, functioning as a "key" to preserve learner privacy. The remaining columns were labeled with specific topics for testing. Each row represented a distinct student. Rows with missing data were excluded, and no imputation was performed to avoid potential bias. Accurate prediction of a student's performance on a particular topic was deemed challenging without introducing bias. Additionally, columns containing marks for mock exam paper 6 were omitted, considering Cambridge IGCSE's emphasis on different skills compared to papers 4 and 2. Apart from these measures, no further preprocessing was considered necessary.

5.2. Experimental test-bed

The Apriori algorithm was first tested using the cloud-based development environment "Google Colaboratory", with allocated resources of 0.8 GB of RAM and 26.3 GB of solid-state drive space. This choice was influenced by the cloud technology's advantages and the suitability of Python, given its extensive libraries and resources for unsupervised algorithms and dataset handling.

To ensure the algorithm was producing the expected output a snippet of the original collected data was used for testing. We only utilized 7 students and 7 subjects to apply the algorithm. The code was iterated until the expected output of frequent itemsets was produced. Afterward, Jupyter Notebook running the Python kernel on our personal computers was utilized to run the algorithm that we have just tested online. This time, the entire dataset was utilized. The clustering algorithm was applied using the same methods. The local machine had the following hardware specifications:

- 16 Gigabytes of Random Access Memory
- AMD Ryzen5 5600G Graphical Processing Unit
- 500 Gigabytes Solid-State Drive Memory

5.3. System design

We have utilized the pandas and sk. learn libraries in Python 3.10.8. The dataset was stored locally as a .CSV file and turned into a Python data frame using the pd.read_csv function. The next step was to take the data frame and convert it into transaction data, so that we may apply the algorithm to them. All the column headings were stored in a list, alongside an empty list of transaction data. We took the unique identifier, (in this case the student IDs) and iterated over every column for each unique student.

While iterating, we only chose students who had marks below 60 (This was taken as the threshold for passing a topic). These chosen marks were then appended to the initially empty transaction data list. Then the transactions are fitted onto the transaction encoder essentially takes the transactions and assigns a unique binary value to each unique transaction. It is placed into a binary matrix, where each row is a transaction and each column is an item. This binary matrix is then transformed and stored as a data frame. Visual Studio Code was used to compile and run the algorithms, taking up 984 megabytes of memory with 5% Central Processing unit usage. This new data frame containing the transactions is then passed as the parameter onto the Apriori Algorithm, which produces frequent item sets. These item sets are generated based on conditional probability, with a minimum support threshold of 50%. This method was repeated to apply the F-P Growth algorithm as well. This workflow is presented in Fig. 2.

A similar approach was utilized when applying the K-means clustering algorithm, by loading the. CSV dataset into a Python data frame. Then, we took two subjects that our association algorithm had provided to be frequent itemsets and selected those columns only. So that we can gather some useful information from the clustering, we selected only the passing values from one subject and failing marks from another. This new filtered data was fitted onto the K-Means method and plotted to give us a clustering graph. Each point on the clustering graph represents a unique student.

The number of clusters was determined by the "Elbow Method" where the within-cluster sum of squares (WCSS) was plotted against the number of clusters. Since the graph did not have a clear "elbow", we also applied the "Silhouette" score graph to uncover the optimal number of clusters. A higher score is optimal, hence the number of clusters that produce the global maxima (in our it is 6) is to be chosen. We selected the value where the Silhouette score value seems to be at a global maximum, in our case this being 6. These can be seen in Figs. 3 and 4 respectively.

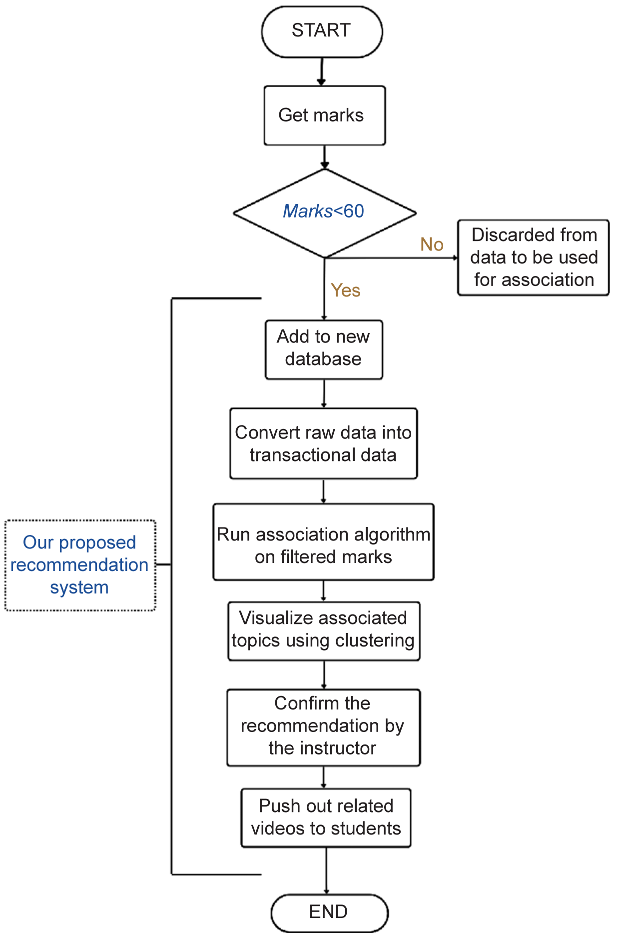

Fig. 2. Recommendation system workflow.

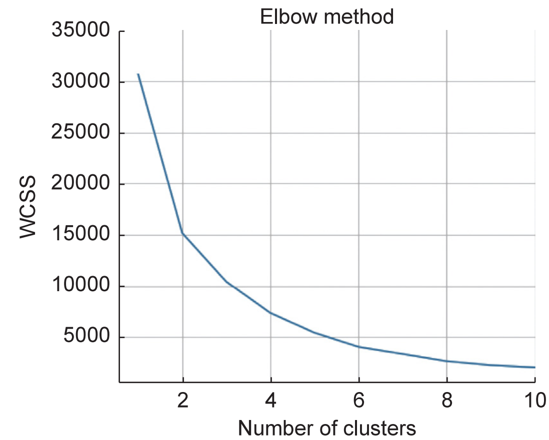

Fig. 3. Elbow method graph.

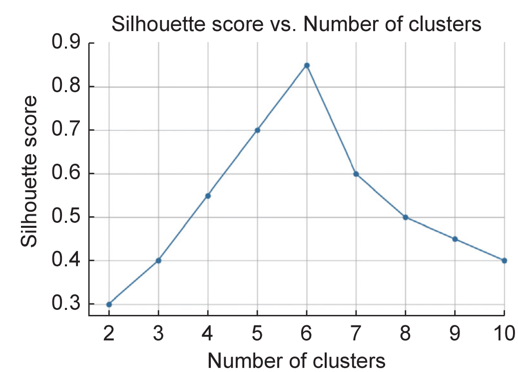

Fig. 4. Silhouette score vs. optimal cluster graph.

5.4. Prototype design

Additionally, using relevant generated output two high-fidelity, horizontal web application prototypes were generated [53]. These are categorized as such:

5.4.1. Instructor side

The instructor's portal allowed for the upload of a . CSV file database as showcased in this paper beforehand. The web application takes the dataset and generates a frequent itemset using the properties and constraints already described in this paper. This item is presented visually as a table, shown in Fig. 5, along with the support of each association. Furthermore, the clustering graphs from the associations are also shown. Two K-means clustering graphs are used to graphically depict the association analysis. We can better grasp the correlation between students' performance across several topics thanks to these graphs. In the first graph, we compare students who have scored over the cutoff in one subject to those who have fallen short in a different topic (As shown in Fig. 6). This enables us to determine whether the performance in these two subjects is related.

We can more easily spot trends and patterns thanks to the clustering algorithm, which pairs up students with similar performance patterns. The students whose scores fell short of the cutoff in both subjects are the topic of the second graph (As shown in Fig. 7). We can identify the students who struggle in both disciplines by grouping this subset of individuals. We can also visually see the number of cluster points on the second graph to be far larger, supporting our generated association. Instructors need this information to understand whether the number of students who are having difficulties in both topics is greater or smaller. These visualizations give teachers insightful information about how their students are performing on certain topics. They can modify their teaching methods based on this knowledge and offer more assistance to individuals who need it the most.

5.4.2. Student side

Based on the output of our algorithm, it can be seen that there is an association between Measurements Homework and Measurements - Cambridge Grade 9 exam, Moments – Worksheet and Measurements - Cambridge Grade 9 exam, Moments – Worksheet and Measurements Homework, and lastly between Moments – Worksheet and Static Electricity - Grade 10 Cambridge exam, all of these are discussed further into this paper. We are utilizing our database of videos and are not presenting any new algorithms. So, if a student does well (marks greater than 60) in all subjects, there is no suggestion for him as he did well in all subjects. Our algorithm only targets the students who got lower than 60 in any subject Secondly, if a student's marks are below 60% in a topic that has a known association with another, the system suggests a video for each of the associated topics. The prototype implementation is shown in Figs. 8 and 9.

These recommended videos can be taken from 2 sources.

- Platform's own database: in this method, if the recommendation system has already been applied to an OL platform, they can suggest the relevant videos from their own video bank.

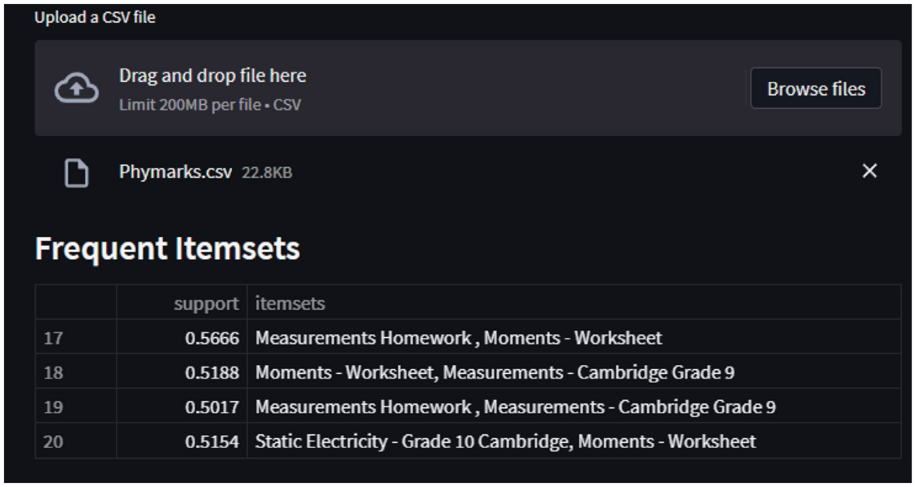

Fig. 5. Instructor portal 1.

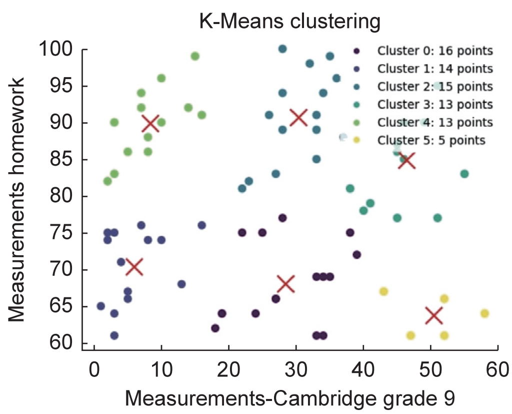

Fig. 6. Visualization for instructors 1.

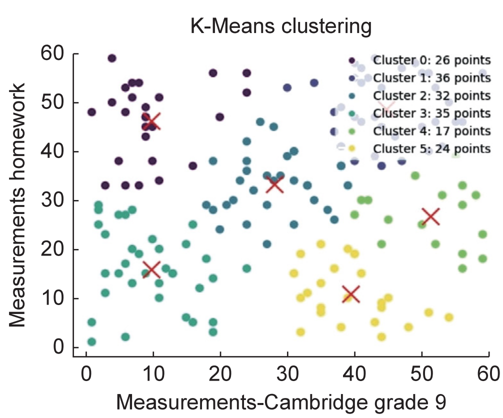

Fig. 7. Visualization for instructors 2.

- Key-word search: Alternatively, we can search the keyword of a specific topic on publically available video-sharing sites such as www.youtube.com.

5.5. Evaluation methods

To evaluate the effectiveness of our proposed content provider module, we use both qualitative and quantitative analysis.

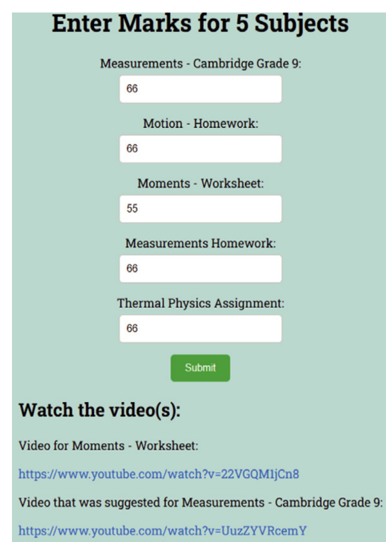

Fig. 8. Student portal example 1.

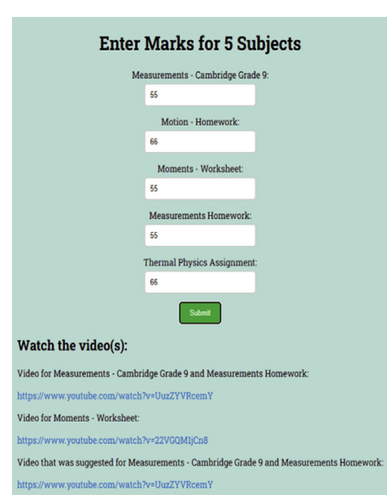

Fig. 9. Student portal example 2.

Table 1
Instructor feedback questions.

Questions	Contents
Open-ended questions	* How could the e-learning module improve your ability to deliver course content effectively? * In what aspects of your pedagogy would you find the e-learning module most beneficial?
Likert scale questions	* The e-Learning module has provided opportunities for new instruction. * The e-learning module can influence my assessment and feedback strategies. * The e-learning module can improve my ability to provide timely and constructive feedback to students. * (Follow up: If you have answered above a 3 in the previous question, can you explain a bit how?)

5.5.1. Qualitative analysis

Ten instructors were presented with the instructor-side prototype and were queried with a series of questions. The responses were scrutinized to extract insights into their opinions and concerns regarding the proposed module. The questions posed during the interviews are summarized in Table 1. It is noteworthy that the Likert scale employed consisted of five points: Strongly Agree, Agree, Neutral, Disagree, and Strongly Disagree.

5.5.2. Quantitative analysis

Seventy high school students volunteered for A/B testing, with Version A representing our innovative module and Version B the traditional approach. The test comprised two phases. In the initial phase, all 70 students took a test on the syllabus of a subject associated with our module, namely "Moment of a Force". Those scoring below the 60% threshold were invited to participate in Phase Two.

In the second Phase, 40 students were filtered as per the threshold. 10 students were asked to revise using Version A, the rest using Version B. After revisions, another test on the same topic was given to all 40 students. The results along with conversion ratios are discussed further in this paper.

$$\text{Conversion Rate} = \frac{\text{Number of Conversions}}{\text{Number of Visitors}} \times 100\%$$

was also calculated for each version, where the Number of Conversions was set to be the number of students who scored above the threshold, and the Number of Visitors was set to be the total number of students per version, to better understand the comparison.

6. Results and findings

In this section, we delve into the pertinent findings that we have uncovered.

6.1. Experimental findings

The Apriori algorithm produced frequent itemsets with the following metrics, as discussed earlier:

- The transaction data only included marks below 60
- The Minimum support was set at 50%
- The Minimum confidence was set at 65%

The F-P Growth algorithm, when executed with the same parameters, yielded identical results. Confidence assesses the frequency with which a specific association rule holds true, indicating the likelihood that when one set of items is purchased, another set is also purchased. On the other hand, support in association rule mining gauges how frequently an itemset appears in the dataset, representing the frequency of its occurrence among all transactions. High support suggests the itemset is common, while low support indicates its infrequency. Notably, there was a significant runtime difference between the two association algorithms, with the F-P Growth algorithm demonstrating a 3.7 times faster runtime, as illustrated in Table 2.

Table 2
Comparison of algorithm runtimes.

Algorithm	Runtime (s)
Apriori	0.06801557
F-P growth	0.018004179

Table 3
Association rules with multiple items, support values, and confidence values.

Association rules	Support	Confidence
Measurements Homework and Measurements Grade 9 Test	0.50	0.79
Moments Worksheet and Measurements Grade 9 Test	0.51	0.76
Moments Worksheet and Measurements Homework	0.56	0.74
Moments Worksheet and Static Electricity	0.52	0.76

Upon analyzing the results, notable findings emerge. Notably, items are separated by commas (,) rather than hyphens (-), and the comprehensive list of items is depicted in Fig. 10. Primarily, single transaction itemsets dominate the output, suggesting that poor results in these topics are often not associated or dependent on other topics. From an educational perspective, this aligns with the understanding [54] that reasons for subpar performance in standardized testing can be multifaceted and not always directly linked to other topics within the same subject.

Concerning associations with multiple items, there appears to be a relation between certain topics, providing valuable insights for instructors to enhance learner understanding of these connections. The association rules involving multiple items are detailed in Table 3. The frequency of items such as 'Measurements Homework' and 'Measurements - Cambridge Grade 9' to below-par marks is noticeable. This suggests that if a learner struggles with their homework, it is indicative of a likely poor performance in their class test.

The association of 'Moments - Worksheet' with 'Measurements Homework' and 'Measurements - Cambridge Grade 9' implies a connection between these topics. Instructors can explore the syllabus of these topics for deeper correlations, guiding improved instructional strategies. Similarly, learners can recognize the importance of focusing on these interconnected topics for overall success. Besides, the correlation between 'Static Electricity - Grade 10 Cambridge' and 'Moments - Worksheet' indicates an association, although the specific relationship in terms of syllabus content remains unclear. Despite this, both topics involve mathematical calculations and the application of formulas.

In our clustering analysis, we encountered a unique challenge. Since we selected subjects based on frequent itemsets from the Apriori Algorithm, applying clustering directly to all 399 rows of marks in the two columns resulted in too many data points. This made it challenging to generate a meaningful graph and extract valuable information (see Fig. 11).

To address this challenge, we decided to plot clustering based on only the failing marks in the two specific columns. However, this approach did not provide substantial insights as it primarily displayed students who had failed in both topics, limiting our ability to draw meaningful conclusions. Nevertheless, by plotting clustering with the marks of one subject where students had

	support	itemsets
0	0.645051	(Displacement - Construction)
1	0.655290	(Electrical Quantities Exam)
2	0.679181	(Forces and Moments - Cambridge)
3	0.587031	(Hookes Law - Graph)
4	0.682594	(Measurements - Cambridge Grade 9)
5	0.709898	(Measurements Homework)
6	0.593857	(Mock 1 - P4)
7	0.627986	(Mock 2 - P4)
8	0.723549	(Moments - Worksheet)
9	0.655290	(Motion - Homework)
10	0.627986	(Motion Equations and Graphs)
11	0.648464	(Motion Equations and Graphs - Exam)
12	0.638225	(Sound and Electromagnetism)
13	0.675768	(Static Electricity - Grade 10 Cambridge)
14	0.621160	(Thermal Physics Assignment)
15	0.627986	(Units - Recap Quiz)
16	0.645051	(Units and Prefixes - Grade 9 - Quiz)
17	0.501706	(Measurements Homework , Measurements - Cambridge Grade 9)
18	0.518771	(Moments - Worksheet, Measurements - Cambridge Grade 9)
19	0.566553	(Moments - Worksheet, Measurements Homework)
20	0.515358	(Moments - Worksheet, Static Electricity - Grade 10 Cambridge)

Fig. 10. All generated associations from our dataset.

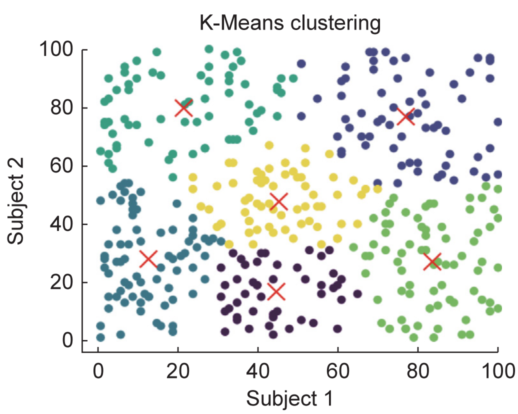

Fig. 11. All 399 points for 2 subjects.

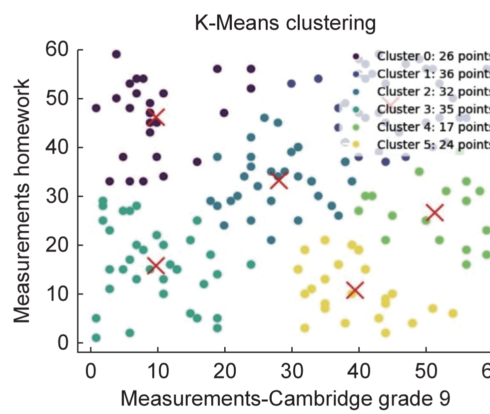

Fig. 13. Filtered data clustering 2.

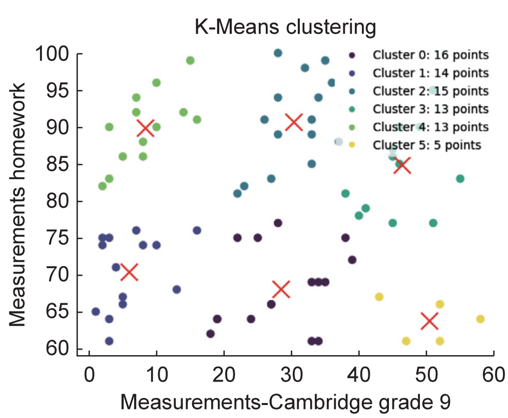

Fig. 12. Filtered data clustering 1.

failed against the other subject where students had passed, we were able to glean more useful information (see Fig. 12).

In this visualization, clusters 0 and 2 represent the majority of students, indicating that those who are just above the passing grades for 'Measurements Homework' tend to perform poorly in the 'Measurements - Cambridge Grade 9' test. This valuable information, not captured by the association algorithm, can be crucial for pedagogy design and content providers. Additionally, comparing this graph with the K-means Clustering graph using filtered marks where students failed both subjects provides further visual confirmation of the association (see Fig. 13).

6.2. Results from A/B testing

We conducted A/B testing to evaluate the effectiveness of our proposed module, involving real high-school students in two phases. In phase 1, 70 volunteer students from grades 10–11 took a Physics test on the topic "Moment of a Force". This topic was selected based on historical data indicating an association with "Measurements". Results showed that 55% of the students did not meet the pass threshold, set at 60% marks.

In phase 2, 20 students were exposed to one video (Version A), while another 20 students were exposed to two videos (Version B). Version A demonstrated a conversion rate of 20%, whereas Version B exhibited a significantly higher conversion rate of 70%. This suggests that Version B is a more effective method for student revision. These results are summarized in Table 4.

6.3. Analysis of interview

We interviewed 15 instructors to gather their views on the module, with a specific focus on the instructor portal. Due to

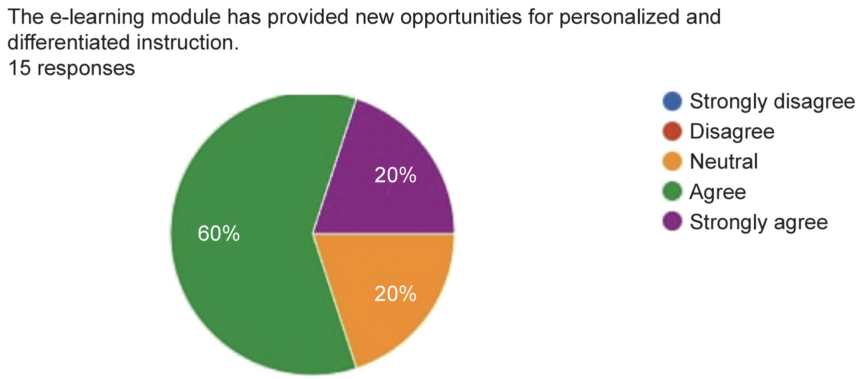

Fig. 14. Responses to the e-learning module have provided opportunities for new instructions.

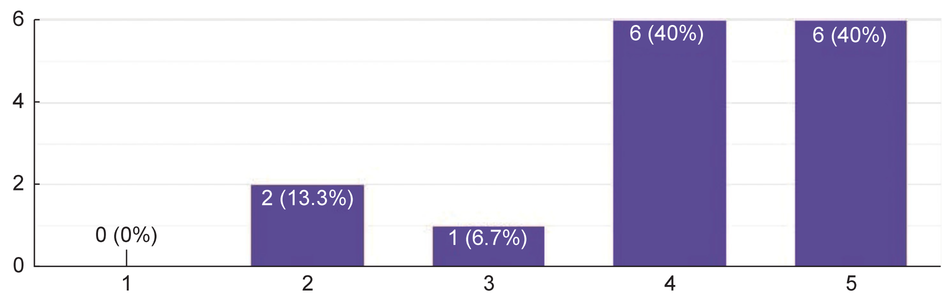

Fig. 15. Responses to the e-learning module can influence my assessment and feedback strategies.

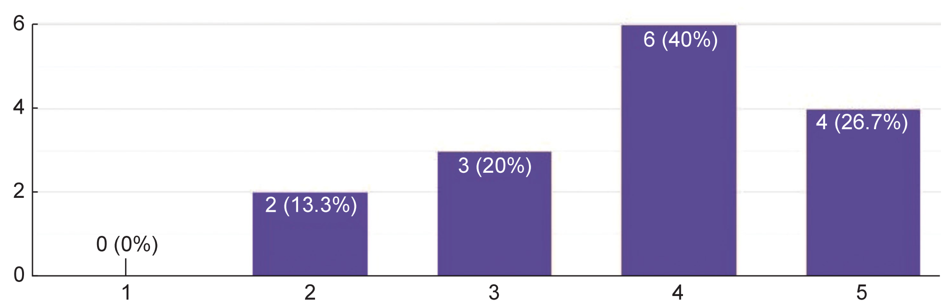

Fig. 16. Responses to The e-learning module can improve my ability to provide timely and constructive feedback to students.

Table 4
Comparison of pass and fail statistics.

Total students = 40	Number of students	
	Passed	Failed
Traditional method (One video)	4	16
Our proposed method (Two videos)	14	6

a request for anonymity, their names are not disclosed in this paper. The instructors mentioned that understanding correlations between topics and student performance influences how they teach those topics. They adapt their teaching approach from the start, addressing any syllabus content overlap to support students. Eight of the 15 participants indicated that they would place additional emphasis on related topics to ensure students build a stronger foundation. Dr. Navid Rahman(MBBS and PGT), an instructor of high-school chemistry for 14 years said -

"I can get the data from beforehand about the link of topics and be ready to give feedback when they do bad".

Additionally, Dr.Dewan Chowdhury a high-school physics instructor for over 10 years commented -

"I would make plans in my lesson plans knowing these links exist, so I can show them what the overlaps are in topic content".

Nearly all instructors concurred that understanding the connections between topics aids in refining their teaching approaches to identify foundational topics for students. They responded to three open-ended questions and three Likert scale questions, employing a 5-point scale: Strongly Agree, Agree, Neutral, Disagree, and Strongly Disagree. The overall trend of positive responses indicates that the module is perceived as beneficial for pedagogical decision-making. The responses to the Likert scale questions are depicted in Figs. 14, 15, and 16.

7. Discussion

Machine learning algorithms have the potential to transform online learning by offering personalized feedback and optimizing resources. This study, conducted during the global health crisis, collected data from grade 10 physics students and professors to create a dataset comprising 16 physics topics and 4 practice exams. To address ethical concerns, data privacy was ensured, and preprocessing involved removing incomplete rows and irrelevant columns. The application of the Apriori and F-P Growth algorithms unveiled meaningful correlations between subjects and student performance. This information serves as a guide for teachers and students to focus on specific areas for improvement. The study highlights the promise of machine learning in enriching online education through tailored feedback and materials. Evaluating association and clustering algorithms requires real-world data. Future research could explore other unsupervised algorithms, such as hierarchical clustering and CNN architecture, to further enhance online learning models. Additionally, clustering can help group individuals, enabling the detection of similar behaviors among them [55]. The utilization of clustering methods can also provide more insightful visualizations of results [56].

7.1. Comparison of different association algorithms

In the realm of data mining, there are several association algorithms worth considering when establishing relationships between items.

7.1.1. Apriori and F-P growth

The F-P growth algorithm employs a prefix tree representation of the given database, creating an FP-tree of transactions. Initially, it determines the frequencies of individual items (support of single-element items) and discards item sets appearing fewer times than the user-set threshold. Unlike Apriori, FP growth addresses the challenge of generating numerous candidate frequent item sets in each iteration, offering a more efficient solution, especially as data size increases. Despite differences in their underlying mechanisms, both Apriori and FP growth algorithms yielded comparable associations in our dataset, showcasing their effectiveness in generating meaningful outputs through a threshold-based approach.

7.1.2. Equivalence class transformation (Eclat)

Eclat's output might not be as interpretable as Apriori's since it directly mines frequent itemsets without generating candidate itemsets explicitly. For closed itemsets with efficient filtering (in our case threshold filtering), the Apriori algorithm gains a clear edge over the Eclat algorithm [50].

7.1.3. Fuzzy association

In fuzzy association, determining the degree of membership that each leaf attribute belongs to of its previous parent [57]. Therefore, the fuzzy association rule deals with uncertain or fuzzy data where items have degrees of membership to itemsets rather than being strictly present or absent. However, in our case, we give every subject the same degree and itemsets the same confidence initially as every subject can have the same chance of being a weakness for another subject.

7.1.4. RuleGrowth

The RuleGrowth algorithm depends on a pattern-growth approach instead of a candidate-and-test approach for sequential pattern mining in datasets [58]. RuleGrowth takes as parameters a sequence database and the min-sup and minconf thresholds [58]. Sequential patterns often have temporal dependencies, where the order of items matters and sometimes makes it difficult to distinguish meaningful patterns from random occurrences.

7.1.5. Maximal sequential algorithms

Maximal sequential algorithms are primarily used for solving problems where patterns are too long which may generate an exponential number of results [59]. However, for our scenario where we are required to find the co-relations between subjects and find their weaknesses, finding the longest sequential patterns does not contribute much compared to other algorithms. Therefore, Apriori and FP-growth algorithms do not face this problem and are more applicable in our scenario. Table 5 presents the comparison of association algorithms.

A summary comparing and contrasting our proposed method with related research is presented in Table 6.

7.2. Limitations

The algorithms were executed on a restricted dataset, consisting of only 399 student records. While sufficient for a prototype, it may not provide conclusive results. Additionally, the data processing currently occurs on an offline local platform. However, considering the eventual application in online learning, it is crucial to explore how the implementation can seamlessly transition into a live, real-time online environment. The sample size for A/B testing with students was also relatively modest.

8. Conclusion and future work

The potential of machine learning algorithms in the context of online education has been examined in this research. A comprehensive dataset with 16 different physics topics and four practice examinations was produced by the study using information from grade 10 physics students and their lecturers. Importantly, this research put ethical concerns first and put strict safeguards in place to protect data privacy and security.

We discovered links between various subjects and student performance using the Apriori and F-P Growth algorithms. The way teachers and students approach online learning can be revolutionized by these correlations, which provide insightful information about areas that need to be optimized and improved. This personalized feedback can improve the educational process and ultimately result in more successful learning results. Our study emphasizes the value of assessing association and clustering algorithms using real-world data. This study essentially shows how machine learning can usher in a new era of individualized, data-driven online education. We can enable both instructors and students to make educated decisions, maximize their learning opportunities, and eventually pave the path for a more effective and interesting online educational environment by utilizing the power of algorithms and real-world data.

The study outlines a promising methodology for building a recommendation system module in Online Learning (OL) platforms using data mining techniques. However, further research and development are needed to enhance its feasibility and scalability.

- Integration with Online Learning Platforms and Cloud: The next research phase involves seamlessly integrating the recommendation system module into fully functional online learning platforms and sustainable cloud storage systems for own video contents [60–62]. Collaborations with educational technology companies and institutions are necessary to facilitate real-time data analysis and personalized recommendations for diverse students.
- Extensive Testing and Evaluation: To validate the recommendation system's utility and reliability, rigorous testing on larger datasets is essential [63,64]. Experimentation with a wide student population and various courses elucidates the system's adaptability and generalizability. Long-term studies should assess the impact of tailored recommendations on student engagement and performance.

Table 5
Qualitative comparison of association rule mining algorithms.

Algorithm	Key characteristics	Applicability
Apriori & FP-growth	Prefix tree-based FP-tree representation. Efficient for large datasets. Ideal for association rule generation with threshold filtering.	Effective for association rule mining, especially when dealing with threshold-based filtering.
Eclat	Mines frequent itemsets directly. May lack interpretability compared to Apriori.	Suitable for closed itemsets with efficient threshold filtering.
Fuzzy association	Considers degrees of membership for itemsets. Deals with uncertain or fuzzy data.	Effective for handling uncertain or fuzzy data, but may require specific scenarios for optimal performance.
RuleGrowth	Pattern-growth approach for sequential pattern mining. Depends on min-sup and minconf thresholds.	Appropriate for sequential pattern mining, especially when considering temporal dependencies.
Maximal sequential algorithms	Primarily used for long sequential patterns. May generate an exponential number of results. Limited applicability for finding correlations between subjects.	Less applicable for scenarios requiring identification of correlations between subjects compared to Apriori and FP-Growth.

Table 6
Comparison with related work.

Research	Dataset size	Method	Validation
Our proposed system	399 students with 16 topics	Apriori algorithm on filtered data based on threshold	A/B Testing and Instructor's Interview
[42]	1853 learners of 5479 courses	Deep learning with content and collaborative filtering by extracting watch time and video meta-data	AUC score (a metric for binary classification models)
[41]	–	Combination of sparsity,content and collaborative filtering	–
[43]	500 students	Improved apriori algorithm which process dataset vertically	Run-time comparison
[44]	–	Apriori Algorithm combined with collaborative filtering	–

- Pedagogical Impact Studies: Future work focuses heavily on integrating the recommendation system into institutions' and instructors' educational procedures. Studies should look into how teachers might use the system's findings to improve their instruction and modify their course materials to better suit the needs of certain students.

The projects listed above serve as a thorough roadmap for integrating and improving the suggested recommendation system for online learning platforms. By focusing on these crucial areas, we can open the door for more efficient and individualized online learning experiences, which is ultimately advantageous for both students and teachers.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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