

## *Retraction*

# **Retracted: Predicting Course Grade through Comprehensive Modelling of Students' Learning Behavioral Pattern**

## **Complexity**

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This article has been retracted by Hindawi following an investigation undertaken by the publisher [1]. This investigation has uncovered evidence of one or more of the following indicators of systematic manipulation of the publication process:

- (1) Discrepancies in scope
- (2) Discrepancies in the description of the research reported
- (3) Discrepancies between the availability of data and the research described
- (4) Inappropriate citations
- (5) Incoherent, meaningless and/or irrelevant content included in the article
- (6) Manipulated or compromised peer review

The presence of these indicators undermines our confidence in the integrity of the article's content and we cannot, therefore, vouch for its reliability. Please note that this notice is intended solely to alert readers that the content of this article is unreliable. We have not investigated whether authors were aware of or involved in the systematic manipulation of the publication process.

Wiley and Hindawi regrets that the usual quality checks did not identify these issues before publication and have since put additional measures in place to safeguard research integrity.

We wish to credit our own Research Integrity and Research Publishing teams and anonymous and named external researchers and research integrity experts for contributing to this investigation.

The corresponding author, as the representative of all authors, has been given the opportunity to register their agreement or disagreement to this retraction. We have kept a record of any response received.

## **References**

- [1] D. Hooshyar and Y. Yang, "Predicting Course Grade through Comprehensive Modelling of Students' Learning Behavioral Pattern," *Complexity*, vol. 2021, Article ID 7463631, 12 pages, 2021.

## Research Article

# Predicting Course Grade through Comprehensive Modelling of Students' Learning Behavioral Pattern

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While modelling students' learning behavior or preferences has been found as a crucial indicator for their course achievement, very few studies have considered it in predicting achievement of students in online courses. This study aims to model students' online learning behavior and accordingly predict their course achievement. First, feature vectors are developed using their aggregated action logs during a course. Second, some of these feature vectors are quantified into three numeric values that are used to model students' learning behavior, namely, accessing learning resources (content access), engaging with peers (engagement), and taking assessment tests (assessment). Both students' feature vectors and behavior model constitute a comprehensive students' learning behavioral pattern which is later used for prediction of their course achievement. Lastly, using a multiple criteria decision-making method (i.e., TOPSIS), the best classification methods were identified for courses with different sizes. Our findings revealed that the proposed generalizable approach could successfully predict students' achievement in courses with different numbers of students and features, showing the stability of the approach. Decision Tree and AdaBoost classification methods appeared to outperform other existing methods on different datasets. Moreover, our results provide evidence that it is feasible to predict students' course achievement with a high accuracy through modelling their learning behavior during online courses.

## 1. Introduction

Higher education establishments play a key role in today's world and contribute immensely to people's lives by training highly skilled students. While these institutes successfully graduate thousands of students across the world, they also face the issue of student's failure in courses, leading to delay in their graduation or their dropout. Such problems can damage both students and our society, for example, resulting in students loss of confidence and depression which in some cases may lead to deferring their studies or their drop out from universities [1]. Needless to mention that such issues can increase university staff's workload and thereby raise universities' expenditure [2]. Taking Estonia as an example, while the average drop out of higher education students was about 19% in 2016, almost one third of students majored in IT dropped out in the first year [3, 4].

Multiple studies have reported that detection of students who are going to do poorly in courses and informing their teachers and themselves to take necessary actions is among the most crucial steps toward boosting their academic success (e.g., [5–7]). Student's grade—which usually indicates their ability to comprehend the conveyed knowledge—is considered as one of the main indicators of their success in the course [8]. Therefore, predicting students' grades or achievement in courses could be one way to identify students at risk of failure (e.g., [9, 10]). Such predictions would enable teachers to provide students with timely feedback or additional support. Consequently, it can be argued that equipping online educational systems (such as learning management systems, LMSs) with automated approaches to predict students' performance or achievement in a course is crucial.

Educational data mining (EDM) seeks ways to understand students' behavior in such learning environments and

accordingly enable students and teachers to take initiatives, where and when necessary [11, 12]. For instance, it can offer individualized learning paths, recommendations, and feedback by predicting students' performance or risk of failure in courses, contributing to their academic achievement [5, 7].

Basically, such prediction systems or approaches require different amounts of data, depending on the complexity of the parameter being predicted, if they are to make a good, highly accurate prediction. Many systems (or EDM approaches) require a large amount of data to develop high-performance and accurate prediction systems. However, accessibility of big loads of data does not guarantee a highly accurate prediction. One crucial task in achieving a decent prediction system is identifying and properly modelling the variables and their effect size on the parameter that is to be predicted. In other words, the key challenge is to find the relevant dynamic characteristics of an individual student for a specific prediction task which would later help properly adapting the learning object for them [13]. Among the most important dynamic characteristics of students in a course are their learning behavior or preferences with regard to accessing learning resources, engaging with peers, and taking assessment tests [14]. Multiple research has concluded that students' activity data logged in different LMSs (like Moodle) could be used to represent their learning behavior in online courses (e.g., [14, 15]). Furthermore, they also found that students' academic performance in terms of grades is highly correlated to their level of activities in online environments [16]. Simply put, it was found that different types of students' online activities could indicate their performance in online courses. However, many studies surprisingly take into account non-academic-related data or data related to students' past performance while developing predictive models for online learning environments. Unfortunately, some of these studies ignore the fact that neither students nor teachers have control over the majority of these factors (e.g., [15, 17, 18]). More importantly, if students find out such factors are used in predicting their performance in courses, they may feel despaired as they think their performance or circumstances in the past predispose them to failure in the present or future. Thus, similar to some recent studies, this study argues that more studies should consider employing students' activity data during courses to develop predictive models.

Although modelling students' learning behavior and preferences act as a key indicator in their course outcome or grade—one that is based on current behaviors, not prior history—very few research studies have modelled students' learning behavior using their activity level to predict their course grades. Furthermore, the related research often ignores building students' model considering different aspects of students' learning behavior during a course (e.g., students' behavior with respect to content access, engagement, and assessment during courses), development of simple yet generalizable EDM approaches for prediction of course grade, and prediction of course grade using students' models derived from their activity data. Furthermore, some models are too complex and difficult to use or interpret for

practitioners. In this study, we aim to improve the existing works by developing an EDM-based approach that consumes students' activity data during online courses to model their learning behavior and accordingly predicts their course achievement or grade.

Contributions of this work include the following: (1) to provide educators with opportunities to identify students that are not performing well; (2) to take into account comprehensive students' learning behavioral pattern (in terms of their content access, engagement, and assessment during courses) in prediction of their course grade by developing students learning behavior model for each student in a course; (3) to develop an easy to implement and interpret student modelling approach that is generalizable to different online courses; and (4) to employ a multiple criteria decision-making method for automatically evaluating various classification methods to find the most suitable one for various datasets in hand (different courses with different feature numbers).

## 2. Related Research

*2.1. Prediction of Students' Performance.* One of the most important areas of the EDM is prediction of learning behavior and outcome of students (e.g., [19, 20]). This can further be categorized into three forms of predictive problems [21], including prediction of students' performance (e.g., [19, 20]), prediction of students' dropout (e.g., [22, 23]), and prediction of students' grade or achievement in a course (e.g., [24]).

There exist several research studies revolving around the prediction of students' achievement, performance, or grade in online courses. For example, Parack et al. [25] used previous semester marks of students, Christian and Ayub [26] and Minaei-Bidgoli et al. [27] used prior GPA of students, Parack et al. [25] used previous semester marks of students, Li et al. [28] used students' performance in entrance exams, Kumar et al. [29] used students' class attendance, and Natek and Zwilling [30] employed data related to demography of students (e.g., gender and family background) in their predictive models. Furthermore, Gray et al. [31] focused on psychometric factors of students to predict their performance.

Obviously, the majority of these studies either ignore that students have no control over such factors and informing them about such predictors may have destructive effects on them or do not consider that such indicators might be unavailable due to multiple reasons (e.g., data privacy) [17, 18, 32]. More research should alternatively concentrate on using data related to students' online learning behavior that are logically the best predictors of their performance in courses.

*2.2. Prediction of Students' Grade.* Several EDM approaches have been applied to educational data for prediction of students' achievement or grade in a course. For instance, Elbadrawy et al. [33] employed matrix factorization and regression-based approaches to predict grade of students in

future courses. More specifically, they used course-specific regression models, personalized linear multiregression, and standard matrix factorization to predict students' future grades in a specific course. According to their findings, matrix factorization approach has shown a better performance and generated lower error rates compared to other methods.

In another study, Meier et al. [9] proposed an algorithm to predict students' grade in a class. The proposed algorithm learns in a timely manner the optimal prediction for each student individually by using different types of data, for example, assessment data such as quizzes. The authors evaluated their proposed approach using datasets obtained from 700 students, and their findings reveal that for around 85% of students, their approach can predict with 75% accuracy whether or not they will pass the course. In a different attempt, Xu et al. [34] took into account the background and performance of the students' existing grades and prediction of future grades so as to predict their cumulative Grade Point Average (GPA). To do so, a two-layer model was proposed, wherein the first layer considers graduate students' performance in related courses. A clustering method was used to identify related courses to the targeted courses. In the second layer, the authors used an ensemble prediction method that by accumulating new students' data improves its prediction power. The proposed two-layer approach appeared to have outperformed other machine learning methods, including logistic and linear regression, Random Forest, and k-Nearest Neighbors. Strecht et al. [35] also proposed a predictive model to predict students' grade using different classification methods such as support vector machines, k-Nearest Neighbors, and Random Forest. Their findings show that support vector machines and Random Forest are among the best and most stable methods in their predictive model. The problem of prediction of students' performance was also formulated as a regression task by Sweeney et al. [36]. The authors in their work employed regression-based methods, as well as matrix factorization-based approaches. Findings from this study showed that combination of Random Forest and matrix factorization-based methods could outperform other approaches. Different from other related studies, a semi-supervised learning approach was used by Kostopoulos et al. [37] to predict students' final grades. The proposed approach applied the Random Forest method with k-Nearest Neighbor to different types of students' data. The findings from this study showed that the hybrid approach outperforms conventional regression methods.

Despite positive results reported in these studies, some have weaknesses. For instance, some suffer from being too complex for practitioners to interpret or use (e.g., [9]), while others might be unsuitable for being used in courses with small amounts of data. Moreover, most of the existing works ignore properly modelling student learning behavior or preferences during a course to predict their final grade [38]. To build on the existing works in prediction of grade, this work proposes a simple, generalizable (yet practical) approach to develop student models, including students' behavior regarding accessing learning resources, engaging with peers, and taking assessment tests. In other words, the

proposed approach aims to predict students' course grade or achievement by considering both students' actions logged to the system and modelling their behavior or preferences in a course using various machine learning algorithms.

### 3. Methods

*3.1. Description of Problem.* We assume that there exists a set of students' actions logged to the system referred to as  $X = \{x_1, x_2, \dots, x_{|X|}\}$  wherein each feature includes activity data of a set of students referred to as  $S = \{s_1, s_2, \dots, s_{|S|}\}$  that are aggregated to the system during a course. A set of students' features are further used to model their learning behavior in each course, represented by  $M = (m_1, m_2, m_3)$ . More specifically,  $m_1$  denotes students' behavior with regard to accessing content of online learning materials contents—CA (like course view, resource view, URL view, and so on) and  $m_2$  revolves around modelling students' engagement behavior with other class members—EN (e.g., forum view discussion, add discussion, add comments, and so forth), while  $m_3$  represents students' assessment behavior during a course—AS (such as quiz view, quiz attempt, assignment view, and so on). Each student  $s$  is associated with a pair of features  $X_s$  and  $M_s$ . Given the aforementioned information, we seek to predict students' course achievement categories (or grades), i.e.,  $A, B, C, D, E$ , and  $F$ . In doing so, this study considers whether students will have had required learning activities regarding the course materials content access, engaging with other class members, and assessment during a course (see Table 1 for notations).

*3.2. Our Approach.* Figure 1 illustrates the summary of our proposed EDM approach. The subsequent subsections explain our approach in more detail.

To develop feature vectors and feature vector spaces, signifying students' level of activity and their learning behavior (student model) during online courses, various groups of students' activity data are used. These include aggregating the action logs of students to establish the students' feature vector, shown in equation (1), which was later quantified into three numeric values that can be used to model students' learning behavior through their activity levels (or to identify patterns of their online behavior), namely, accessing learning resources, engaging with peers, and taking assessment test, see equation (2). Each student is presented using continuous feature vectors which include multiple continuous values. Moreover, for each course, each students' learning behavior is modelled using a tuple of feature vector spaces, namely,  $m_1, m_2$ , and  $m_3$ , for their learning behavior with respect to content access, engagement, and assessment.

Both students' feature vectors and model later constitute a comprehensive students' learning behavioral pattern for a course. The main assumption here is that the action of students provides clues to their learning preferences as it implies intentionality. Therefore, the students' learning behaviors could be considered as a way to infer their study preferences, which is correlated to their course achievement

TABLE 1: Notations.

Notation	Explanation
$S, s$	A set of students and a specific student, $S = \{s_1, s_2, \dots, s_{ S }\}$
$X, x$	A set of features and a specific feature, $X = \{x_1, x_2, \dots, x_{ X }\}$
$M, m$	A set of model of learning behavior and a specific model of learning behavior, $M = (m_1, m_2, m_3)$
$U$	A pair of student models and features, $U = (X, M)$
Grade	The student's final grade
CA, EN, AS	The predefined list of feature associated with model of each learning behavior (content access, engagement, and assessment), $CA \subset X, EN \subset X, AS \subset X$ and $CA \cap EN \cap AS = \emptyset$
TOPSIS	The ranking method taking performance measure of classification method to produce the ranking of the best method for a current problem
$P$	The set of performance metrics
$C$	The classification methods

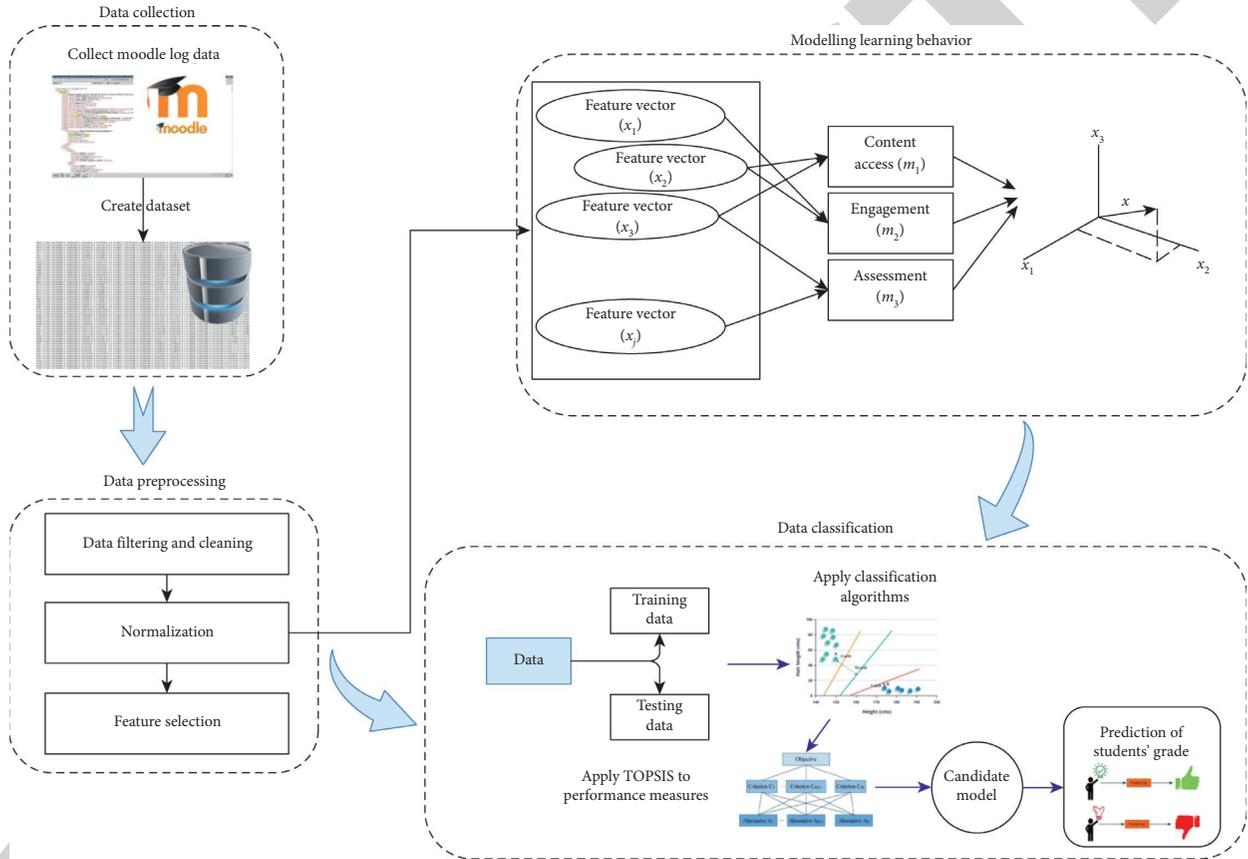


FIGURE 1: Framework of the proposed approach.

(see Analysis of Correlation between Student Models and Course Grades section). In other words, students' actions or activity data help to infer whether the student's preference is to study by accessing learning materials (e.g., course view, resource view, and URL view), simply by taking assessment tests (e.g., quiz view, assignment view, quiz attempt, and assignment submission), by engaging with peers and/or the instructor (e.g., forum add discussion and forum view discussion), or maybe all. This would further help the learning system and educators to take necessary remedial actions, according to the students' model, during the semester to ensure that students' activities are kept within planned learning outcomes.

The process of developing students' model ( $M$ ), including content access ( $m_1$ ), engagement ( $m_2$ ), and evaluation ( $m_3$ ) behavior, is presented in Algorithm 1 (where CA, EN, and AS represent the set of features associated with students' learning behavior). More explicitly, students' feature vector ( $X$ ) is firstly inputted from our dataset. This feature vector is used to create three lists representing students' behavior of content access, engagement, and evaluation in a course. As the feature vectors mostly deal with attributes on a different scale, a Min-Max normalization was performed in this stage, mapping the minimum and maximum values in  $X$  to 0 and 1, respectively. Output of this algorithm is the student model ( $M$ ) for each course, which

```

Input: feature vector X, CA, EN, AS
Output: user model M
(1) Initialize  $n = |X|$ ,  $\text{sum}l1 = 0$ ,  $\text{sum}l2 = 0$ ,  $\text{sum}l3 = 0$ 
(2) while  $i < n$  do
(3)    $l_1 = \{x|x_i \in \text{CA}\}$ 
(4)    $l_2 = \{x|x_i \in \text{EN}\}$ 
(5)    $l_3 = \{x|x_i \in \text{AS}\}$ 
(6)
(7) For  $j$  in  $l_1$ :
(8)    $\text{sum}l1 = \text{sum}l1 + j$ 
(9)    $m_1 = \text{sum}l1/|l_1|$ 
(10) For  $j$  in  $l_2$ :
(11)    $\text{sum}l2 = \text{sum}l2 + j$ 
(12)    $m_2 = \text{sum}l2/|l_2|$ 
(13) For  $j$  in  $l_3$ :
(14)    $\text{sum}l3 = \text{sum}l3 + j$ 
(15)    $m_3 = \text{sum}l3/|l_3|$ 
(16)    $M = (m_1, m_2, m_3)$ 
(17) Return M

```

ALGORITHM 1: Modelling students' learning behavior.

shows the probability of students' learning behavior during the course.

$$X = \{x_1, x_2, \dots, x_{|X|}\}, \quad (1)$$

$$M = (m_1, m_2, m_3), \quad (2)$$

$$U_s = (X_s, M_s). \quad (3)$$

After modelling each student using their online learning behavior, derived from their activity data, a predictor is used to classify students into six different classes (i.e., grades A to F). To do so, each student's vector which consists of a pair of their feature vectors and models are used as an input to several classification methods. Multiple performance measures were employed to find the best performed classifier for prediction of students' course grade (see Algorithm 2). Once the performance measures are implemented, a multiple criteria decision-making method (i.e., TOPSIS) is used to rank the most suitable method for prediction of students' grade. The reason why we have modelled the classification evaluation task as a multiple criteria decision-making problem is that while some of these measures are closely related and belong to the same family, they possess some differences. For instance, they can act partial when it comes to classification of different class sizes in a partition (e.g., toward number of classes and features).

We employed the TOPSIS method for such ranking, underlining the most suitable approach for each dataset (course) [39].

The TOPSIS method firstly computes the normalized decision matrix using equation (4), which further allows comparing attributes.

$$r_{ij} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^n x_{ij}^2}}. \quad (4)$$

Secondly, it computes the weighted normalized decision matrix by constructing a set of weight ( $w_i$ ) for each criterion. The normalized value that is weighted ( $v_{ij}$ ) is calculated as

$$v_{ij} = w_i r_{ij}, \quad j = 1, \dots, n; i = 1, \dots, m. \quad (5)$$

Thirdly, it finds both ideal and negative-ideal solutions using equations (6) and (7):

$$A^+ = \left\{ \left( \max_i v_{ij} | j \in I \right), \left( \min_i v_{ij} | j \in J \right) \mid i = 1, 2, \dots, m \right\} \\ = \{v_1^+, v_2^+, \dots, v_j^+, \dots, v_n^+\}, \quad (6)$$

$$A^- = \left\{ \left( \min_i v_{ij} | j \in I \right), \left( \max_i v_{ij} | j \in J \right) \mid i = 1, 2, \dots, m \right\} \\ = \{v_1^-, v_2^-, \dots, v_j^-, \dots, v_n^-\}, \quad (7)$$

where  $I = \{j = 1, 2, \dots, n \mid j \text{ assocd. with benefit criteria}\}$ ,  $J = \{j = 1, 2, \dots, n \mid j \text{ assocd. with cost criteria}\}$ .

In our experiment which aims to evaluate classification methods, all metrics are considered as benefits requiring maximizing (with no cost criteria, requiring minimizing).

Fourthly, it calculates separation measures for both ideal and negative-ideal solutions. To compute these separation measures, the following equations are used:

$$S_i^+ = \sqrt{\sum_{j=1}^n (v_{ij} - v_j^+)^2}, \quad i = 1, 2, \dots, m, \\ S_i^- = \sqrt{\sum_{j=1}^n (v_{ij} - v_j^-)^2}, \quad i = 1, 2, \dots, m. \quad (8)$$

```

Input: U
Output: prediction of students' grade (A to F)
(1) classification algorithms C = {Nearest Neighbors, Linear SVM, RBF SVM, Gaussian Process, Decision Tree, Random Forest,
    Neural Net, AdaBoost, Naive Bayes}
(2) Evaluation measure P = {accuracy, precision, f1, recall, Jaccard, fbeta}
(3)
(4) for i in C
(5)   Learning classification algorithm i with U
(6)   for j in P
(7)     Evaluating the results of i with j
(8)   end
(9) end
(10) Choose the best classification algorithm by using TOPSIS
(11) Select classification algorithm with highest performance
(12) Use the algorithm to predict course grade
(13) return prediction of students' course grade

```

ALGORITHM 2: Prediction of students' course grade according to their model.

Fifthly, it calculates the ratio measuring the relative closeness to the ideal solution:

$$C_i^* = \frac{S_i}{(S_i^+ + S_i^-)}, \quad 0 < c_i^+ < 1, \quad i = 1, 2, \dots, m, \quad C_i^* = 1 \text{ if } A_i = A^+, \quad C_i^* = 0 \text{ if } A_i = A^- \quad (9)$$

Finally, using maximization of ratio of  $C_i^*$ , it ranks alternatives.

## 4. Experimental Results

**4.1. Dataset.** To evaluate our approach, we created twelve datasets of different sizes from three courses in the Moodle system. The courses are “Carrying out and writing a research,” “Digital writing skills,” and “Teaching and reflection.” Datasets with different sizes would help finding the most optimum number of features for each course to better predict the course achievement. To create the datasets, for each course, we extracted different types of action (activity) data, such as number of times course resource viewed, course modules viewed, course materials downloaded, feedback viewed, feedback received, forum discussion viewed, quizzes answered, discussion created in forum, book chapters viewed, book list viewed, assignment submitted, assignment viewed, discussion viewed in forum, post created in forum, comments viewed, posts updated in forum, and of posts, assignment grade, quiz grades, and final grade. More details on the number of features for each dataset are given in Table 2.

**4.2. Analysis of Correlation between Student Models and Course Grades.** Before proceeding with the analysis, it is essential to investigate whether there exists a relationship between students' learning behavior model (derived from their activity level) and course grades. The main aim of this investigation is to attain a clear perception of how different types of students' activity data (actions) in the online

environment correlate with their course grades. To this aim, students' final grade is considered as an indicator of course achievement that is capable of reflecting both students' level of engagement and knowledge. Table 3 illustrates descriptive statistics of students' model for accessing learning materials, engaging with peers, and assessing their knowledge and final grade of the courses called “digital writing skills” and “carrying out and writing a research” (see Table A1 in Supplementary Materials for statistical analysis of the teaching and reflection course). As the table shows, there exists a positive correlation between content access, engagement, and assessment, with the course grade in both courses. This shows that there are correlations between students' model of learning behavior and the final grade of the course.

**4.3. Classification and Performance Measures.** After modelling each students' learning behavior, a pair of students' features and the model are used to train a predictor for classifying students into six different classes (see Algorithm 2). Nine different classification methods were implemented on different courses (datasets) using six performance metrics. Table 4 shows performance measures of classification methods, in 10-fold cross-validation, for a course called “digital writing skills” with different feature numbers.

According to this result, for the course, in 12 (i.e.,  $12 + m_1, m_2, m_3$ ), 15 (i.e.,  $15 + m_1, m_2, m_3$ ), 18 (i.e.,  $18 + m_1, m_2, m_3$ ), and 21 (i.e.,  $21 + m_1, m_2, m_3$ ) features, Decision Tree method outperforms other algorithms with accuracy and precision of 98% and 93% in 12, 15, 18, and 21 features, respectively. Regarding other performance measures, similarly, Decision Tree seems to have a superior performance than other methods in all four different features (similar findings are presented in Table A2 in Supplementary Materials for the teaching and reflection course). Interestingly, performance of Decision Tree, L-SVM, and AdaBoost is similar regardless of feature numbers, while performance of other methods appear to be affected by increment or decrement in number of features.

TABLE 2: Datasets.

No	Course name (short name)	Number of features (attributes)	Number of students (instances)
1	Carrying out and writing a research (CWR)	12	75
		15	75
		18	75
		21	75
2	Digital writing skills (DWS)	12	182
		15	182
		18	182
		21	182
3	Teaching and reflection (TR)	12	98
		15	98
		18	98
		21	98

TABLE 3: Statistical analysis.

	Digital writing skills			Final grade
	Content access ( $m_1$ )	Engagement ( $m_2$ )	Assessment ( $m_3$ )	
Content access ( $m_1$ )	1	0.5585	0.6237	0.5010
Engagement ( $m_2$ )	0.5585	1	0.7771	0.7429
Assessment ( $m_3$ )	0.6237	0.7771	1	0.9322
Final grade	0.5010	0.7429	0.9321	1
Count	182	182	182	182
Mean	0.0936	0.1721	0.3018	2.1154
Std	0.1139	0.1715	0.2279	2.3746
Min	0	0	0	0
Max	0.6108	0.6382	0.8049	5

	Carrying out and writing a research			Final grade
	Content access ( $m_1$ )	Engagement ( $m_2$ )	Assessment ( $m_3$ )	
Content access ( $m_1$ )	1	0.5719	0.2434	0.2881
Engagement ( $m_2$ )	0.5719	1	0.2930	0.3369
Assessment ( $m_3$ )	0.2434	0.2930	1	0.4855
Final grade	0.2881	0.3369	0.4855	1
Count	75	75	75	75
Mean	0.2027	0.2460	0.4710	1.24
Std	0.1257	0.0935	0.1102	0.7505
Min	0	0	0	0
Max	0.7833	0.7	0.7054	5

TABLE 4: Performance measure of classification methods for course “digital writing skills” with different feature numbers.

Features	Methods	Accuracy	Precision	F1	Recall	Jaccard	Fbeta
12	NN	0.8956	0.5685	0.5856	0.6067	0.5685	0.5750
	L-SVM	0.8956	0.5775	0.5977	0.6233	0.5775	0.5851
	R-SVM	0.8901	0.5766	0.5947	0.6193	0.5726	0.5832
	GP	0.8787	0.5712	0.5856	0.6050	0.5712	0.5766
	DT	<u>0.9889</u>	<u>0.9333</u>	<u>0.9360</u>	<u>0.9400</u>	<u>0.9333</u>	<u>0.9343</u>
	RF	0.8956	0.5775	0.5977	0.6233	0.5775	0.5851
	NeuralN	0.8956	0.5807	0.5996	0.6233	0.5807	0.5878
	AB	0.9564	0.7783	0.7938	0.8350	0.7783	0.7833
	NB	0.7681	0.5408	0.5278	0.5404	0.4903	0.5332
	15	NN	0.8956	0.5692	0.5859	0.6067	0.5692
L-SVM		0.8956	0.5775	0.5977	0.6233	0.5775	0.5851
R-SVM		0.8956	0.5775	0.5977	0.6233	0.5775	0.5851
GP		0.8678	0.5051	0.5237	0.5467	0.5051	0.5121
DT		<u>0.9889</u>	<u>0.9267</u>	<u>0.9267</u>	<u>0.9267</u>	<u>0.9267</u>	<u>0.9267</u>
RF		0.8956	0.5787	0.5985	0.6233	0.5787	0.5861
NeuralN		0.8956	0.5807	0.5996	0.6233	0.5807	0.5878
AB		0.9564	0.7783	0.7938	0.8350	0.7783	0.7833
NB		0.6026	0.5144	0.4197	0.4291	0.3668	0.4528

TABLE 4: Continued.

Features	Methods	Accuracy	Precision	F1	Recall	Jaccard	Fbeta
18	NN	0.8956	0.5712	0.5899	0.6133	0.5712	0.5782
	L-SVM	0.8956	0.5775	0.5977	0.6233	0.5775	0.5851
	R-SVM	0.8845	0.5745	0.5920	0.6168	0.5680	0.5808
	GP	0.8678	0.5273	0.5547	0.5900	0.5273	0.5375
	DT	<u>0.9889</u>	<u>0.9333</u>	<u>0.9360</u>	<u>0.9400</u>	<u>0.9333</u>	<u>0.9343</u>
	RF	0.8956	0.5787	0.5985	0.6233	0.5787	0.5861
	NeuralN	0.8956	0.5821	0.6005	0.6233	0.5821	0.5890
	AB	0.9564	0.7783	0.7938	0.8350	0.7783	0.7833
	NB	0.5971	0.5189	0.4269	0.4294	0.3735	0.4597
21	NN	0.8956	0.5787	0.5985	0.6233	0.5787	0.5861
	L-SVM	0.8956	0.5775	0.5977	0.6233	0.5775	0.5851
	R-SVM	0.8845	0.5745	0.5920	0.6168	0.5680	0.5808
	GP	0.8678	0.5264	0.5545	0.5900	0.5264	0.5369
	DT	<u>0.9889</u>	<u>0.9333</u>	<u>0.9360</u>	<u>0.9400</u>	<u>0.9333</u>	<u>0.9343</u>
	RF	0.8956	0.5775	0.5977	0.6233	0.5775	0.5851
	NeuralN	0.8956	0.5821	0.6005	0.6233	0.5821	0.5890
	AB	0.9564	0.7783	0.7938	0.8350	0.7783	0.7833
	NB	0.5974	0.5185	0.4238	0.4279	0.3698	0.4576

NN denotes Nearest Neighbors, L-SVM stands for Linear SVM, R-SVM denotes RBF SVM, GP stands for Gaussian Process, DT denotes Decision Tree, RF stands for Random Forest, NeuralN stands for Neural Networks, AB denotes AdaBoost, and NB stands for Naive Bayes.

Table 5 similarly illustrates the performance measures of classification methods for a course called “carrying out and writing a research” with different feature numbers. According to this result, for the course, in 12, 15, and 18 features, the AdaBoost method outperforms other algorithms with accuracy and precision of 95% and 88% in 12, 15, and 18 features, respectively. This method also appears to have the best performance in 21 features when it comes to accuracy, however, with precision about 89% tends to perform better than other methods (including AdaBoost).

Regarding other performance measures, similarly, AdaBoost seems to have a superior performance than other methods in 12, 15, and 18 features. Nonetheless, in 21 features, Decision Tree shows the highest performance in  $f1$ , recall, and  $fbeta$ , whereas AdaBoost slightly outperforms Decision Tree in Jaccard. Such differences in result of various performance measures usually make decision making on selection of the best method for the current datasets in hand challenging, and an impartial method such as multiple criteria decision-making method (e.g., TOPSIS) would help to pick the best methods.

Regarding different feature numbers, besides AdaBoost and L-SVM methods that show a similar performance regardless of feature numbers, our findings reveal that all other methods seem to be affected by increment and decrement in number of features. In other words, these methods appear to have a more stable performance among other methods when it comes to feature number changes. Overall, the smaller the number of features (15 in particular; it can be said that 15 is the optimum number of features for the current dataset), the better the performance of classification methods. Also, increment in number of features results in decrement in performance of classification methods (21 in particular). Table 5 shows performance measure of classification methods for course “carrying out and writing a research” with different feature numbers.

As mentioned earlier, the TOPSIS method is employed in this study to rank and highlight the most suitable classification method for each dataset. Even though some methods usually outperform others using some specific performance measures (e.g., see Table 4), in many real-world datasets, there exist cases in which more than one method achieves the highest performance in different performance measures (e.g., see 21 features in Table 5). This makes the decision making on which classification method to use a challenging task. For such reasons and to minimize the partiality, if not fully avoided, this study employs the TOPSIS method to rank and select the best method for each dataset (course). According to Table 6, for the digital writing skills course, Decision Tree and AdaBoost are ranked the best and second best methods for all different datasets, respectively (different feature numbers). Similar findings are presented in Table A3 in Supplementary Materials for the teaching and reflection course.

Table 7 shows TOPSIS ranking of classification methods for carrying out and writing a research course. As it is apparent, AdaBoost and Decision Tree are ranked the best and second best methods for all different datasets, respectively (different feature numbers). It is interesting that while AdaBoost showed a higher performance in only two metrics, namely, accuracy and Jaccard, than Decision Tree which has performed better in the other four performance measures, namely, precision,  $f1$ , recall, and  $fbeta$ , AdaBoost is still ranked the best method in 21 features. More explicitly, AdaBoost with 0.9947 earns the first best rank and Decision Tree with 0.9918 is ranked the second best for classification of the data with 21 features.

**4.4. Statistical Significance.** To find out whether the differences between results of different classification methods were due to difference in the models or statistical chance, we

TABLE 5: Performance measure of classification methods for course “carrying out and writing a research” with different feature numbers.

Features	Methods	Accuracy	Precision	F1	Recall	Jaccard	Fbeta
12	NN	0.6250	0.3813	0.3888	0.4326	0.3297	0.3793
	L-SVM	0.6643	0.3382	0.3825	0.4583	0.3382	0.3537
	R-SVM	0.6786	0.3771	0.4089	0.4750	0.3605	0.3867
	GP	0.6786	0.4339	0.4445	0.4844	0.3993	0.4340
	DT	0.9071	0.8142	0.7943	0.7906	0.7656	0.8039
	RF	0.7304	0.4934	0.4947	0.5367	0.4434	0.4876
	NeuralN	0.7161	0.3917	0.4167	0.4667	0.3750	0.3990
	AB	<b>0.9464</b>	<b>0.8829</b>	<b>0.8835</b>	<b>0.8933</b>	<b>0.8663</b>	<b>0.8822</b>
NB	0.4375	0.3733	0.3154	0.3780	0.2222	0.3340	
15	NN	0.6946	0.4601	0.4572	0.4888	0.3996	0.4545
	L-SVM	0.6643	0.3382	0.3825	0.4583	0.3382	0.3537
	R-SVM	0.6911	0.4011	0.4210	0.4833	0.3678	0.4037
	GP	0.6929	0.4597	0.4732	0.5233	0.4228	0.4601
	DT	0.9339	0.8496	0.8435	0.8489	0.8218	0.8458
	RF	0.6768	0.3481	0.3850	0.4450	0.3418	0.3610
	NeuralN	0.7036	0.3996	0.4229	0.4750	0.3746	0.4059
	AB	<b>0.9464</b>	<b>0.8829</b>	<b>0.8835</b>	<b>0.8933</b>	<b>0.8663</b>	<b>0.8822</b>
NB	0.7089	0.4706	0.4637	0.4866	0.4008	0.4634	
18	NN	0.6768	0.3833	0.4080	0.4667	0.3607	0.3892
	L-SVM	0.6643	0.3382	0.3825	0.4583	0.3382	0.3537
	R-SVM	0.6643	0.3382	0.3825	0.4583	0.3382	0.3537
	GP	0.6786	0.3789	0.4106	0.4750	0.3623	0.3885
	DT	0.9196	0.8188	0.8058	0.8139	0.7743	0.8108
	RF	0.6500	0.3947	0.4052	0.4619	0.3463	0.3924
	NeuralN	0.7161	0.4021	0.4300	0.4833	0.3854	0.4105
	AB	<b>0.9464</b>	<b>0.8829</b>	<b>0.8835</b>	<b>0.8933</b>	<b>0.8663</b>	<b>0.8822</b>
NB	0.4268	0.3708	0.3085	0.3637	0.2171	0.3286	
21	NN	0.6375	0.3107	0.3334	0.3921	0.2783	0.3156
	L-SVM	0.6643	0.3382	0.3825	0.4583	0.3382	0.3537
	R-SVM	0.6643	0.3382	0.3825	0.4583	0.3382	0.3537
	GP	0.6643	0.3400	0.3841	0.4583	0.3400	0.3555
	DT	0.9339	<b>0.8854</b>	<b>0.8852</b>	<b>0.9000</b>	0.8604	<b>0.8838</b>
	RF	0.6643	0.3736	0.4026	0.4667	0.3509	0.3820
	NeuralN	0.6786	0.3374	0.3547	0.3938	0.3078	0.3419
	AB	<b>0.9464</b>	0.8829	0.8836	0.8933	<b>0.8663</b>	0.8822
NB	0.4429	0.3704	0.3275	0.3730	0.2451	0.3408	

NN denotes Nearest Neighbors, L-SVM stands for Linear SVM, R-SVM denotes RBF SVM, GP stands for Gaussian Process, DT denotes Decision Tree, RF stands for Random Forest, NeuralN stands for Neural Networks, AB denotes AdaBoost, and NB stands for Naive Bayes.

TABLE 6: TOPSIS ranking of classification methods for course “digital writing skills” with different feature numbers.

Features	Nearest Neighbors	Linear SVM	RBF SVM	Gaussian Process	Decision Tree	Random Forest	Neural Net	AdaBoost	Naive Bayes
12	0.1654	0.1878	0.1794	0.1612	<b>1.0000</b>	0.1878	0.1922	0.6561	0.0000
15	0.3429	0.3612	0.3612	0.2400	<b>1.0000</b>	0.3626	0.3649	0.7369	0.0081
18	0.3390	0.3512	0.3384	0.2752	<b>1.0000</b>	0.3525	0.3563	0.7225	0.0000
21	0.3549	0.3536	0.3409	0.2770	<b>1.0000</b>	0.3536	0.3587	0.7236	0.0000

TABLE 7: TOPSIS ranking of classification methods for course “carrying out and writing a research” with different feature numbers.

Features	Nearest Neighbors	Linear SVM	RBF SVM	Gaussian Process	Decision Tree	Random Forest	Neural Net	AdaBoost	Naive Bayes
12	0.1547	0.1663	0.1990	0.2490	0.8492	0.3358	0.2211	<b>1.0000</b>	0.0259
15	0.1640	0.0106	0.0881	0.1879	0.9231	0.0137	0.0908	<b>1.0000</b>	0.1767
18	0.2058	0.1742	0.1742	0.2087	0.8698	0.1932	0.2439	<b>1.0000</b>	0.0241
21	0.1039	0.1572	0.1572	0.1587	0.9918	0.1799	0.1356	<b>0.9947</b>	0.0481

performed statistical significance tests. This also helps to check the validity of results produced by TOPSIS. Signed-rank test and the  $t$ -test are among the most frequently used tests for this purpose [40, 41]. We selected to perform  $t$ -test, and results revealed  $P$  value of smaller than 0.01 for all methods. This implies that the differences between the methods were likely due to differences in the models, confirming findings of the TOPSIS method.

## 5. Discussion

In the previous section, the results presented reveal that our proposed EDM approach is capable of automatically modelling students according to their learning behavior and preferences and predicting their achievements in different courses with high accuracy. This provides educators with opportunities to identify students that are not performing well and adjust their pedagogical strategies accordingly. The proposed EDM approach, see Algorithm 2, is generalizable and could be used on various online and blended courses. More specifically, any online learning environment that logs various students' actions (or activity data) during a course could benefit from our approach. In brief, students' aggregated action logs during a course will be used to build feature vectors for students (in other words, their logical representation), which would later be used to develop a three-layer student model for each student. In other words, some of the students' feature vectors that fall within the category of accessing learning resources during a course will be used to develop the first layer of the student model called "content access"; some other features that associate with students' engagement with their peers will be used to build the second layer of the model called "engagement"; finally, those features related to taking assessment test will be employed to develop the last layer of the model called "assessment." The rest of the features that are not used in developing the student model along with the three-layer student model constitute a comprehensive students' learning behavioral pattern which is later used for prediction of their course achievement. Finally, the TOPSIS method is used for evaluation of various classification methods.

The proposed approach and results reported in this study differ, to some extent, from several existing EDM approaches for prediction of students' final grade in a course. For instance, there exist several EDM-based studies developing student modelling for students to later use for prediction of their performance or achievement (e.g., [13, 42–44]). Most of these studies consider some specific type of collected data in the system that is related to students' learning style like Felder–Silverman Learning Style Model or try to involve data related to students' personality traits, e.g., Big Five Model into their student model [44]. Even though these attempts might result in a successful modelling of students, there is no guarantee that such student modelling that is occasionally built upon static characteristics of students (not their dynamic characteristics that project their actual learning behavior during a course) could always be useful to educators and instructors for identifying weak students, improving retention, and reducing academic failure rate. Moreover, although some of these student modelling methods consider both static

and dynamic characteristics of students, they require specific types of data or their development is complex. For instance, Wu and Lai [43] distributed questionnaires of openness for experience and extraversion among students to collect data about their personality traits (based on the Big Five Model) so they can accordingly model the students and predict their achievement based on personality traits.

Similarly, modelling students based on their learning style that is developed using some specific models, e.g., Felder–Silverman Learning Style Model [42], may require considering some specific types of students' data collected in the system (that may not exist in all online learning environments) and ignores some useful, informative students' activity data that can easily be found in all online learning environments. A generalizable approach should take into account requirements and data types of different online learning environments and be applicable to various learning systems on different platforms [45]. Our proposed approach benefits from a simple, yet accurate algorithm that considers various types of students' activity data during a course to build a multilayer student model so as to have a comprehensive students' learning behavioral pattern which can later be used for prediction of their course achievement. Unlike many existing works that require specific types of data to build their predictive model, our generalizable approach builds students' models according to three different categories of their actions during a course, learning resource content access, engagement with peers, and taking assessment tests. Besides these three categories, the proposed approach makes use of other important students' features that do not fall within these categories. This way comprehensive students' learning behavioral patterns are taken into account in predicting their course grades. As our findings show, our proposed approach can predict students' course grade in multiple courses with different sizes (courses with small and large number of students—around 70 to 180), showing the usefulness and accuracy of our approach even on less data. Besides the student model, different numbers of features in each course were taken into account in our experiment (ranging from 12 to 21), and regardless of the feature numbers, our approach appears to be highly successful, showing its stability. Furthermore, our generalizable approach benefits from a multiple criteria decision-making method to compare and identify the most suitable classification methods for predicting students' course achievement. This ensures that our proposed approach is impartial in selecting the most suitable classification method for each course with different number of features and students (as some performance measures can behave partially when it comes to classification of different class sizes in a partition or be biased toward number of classes and features).

## 6. Conclusions

This study has investigated the effectiveness of a student modelling-based predictive model for estimating students' achievement in a course. The proposed generalizable prediction approach includes both feature vectors that are

logical representation of students (derived from their activity data) and model of their learning behavior, namely, content access, engagement, and assessment, to constitute a comprehensive students' behavioral pattern which is later used for prediction of their course achievement. Furthermore, it employs the TOPSIS method to compare and evaluate various classification methods. Observe that some performance measures can behave partially when it comes to classification of different class sizes in a partition or act biased toward number of classes and features.

To evaluate our proposed approach, data from three different courses with different sizes at the University of Tartu's Moodle system are used. Our findings revealed that our proposed approach is capable of predicting students' course grade in multiple courses with different sizes, showing the generalizability and accuracy of our approach even on less data. Decision Tree and AdaBoost classification methods appeared to outperform other existing methods on 12 different datasets. Besides the student model, different numbers of features in each course were taken into account in our experiment, and regardless of the feature numbers, our approach appeared to be highly successful, showing its stability. One main reason for such success could be the proper identification and modelling of the variables and their effect size on the parameter that was predicted. Moreover, our findings show that it is viable to develop an easy to implement and interpret student modelling approach that is generalizable to different online courses.

### Data Availability

The data used to support the findings of this study were supplied by the University of Tartu in Estonia and cannot be made freely available.

### Conflicts of Interest

The authors declare that they have no conflicts of interest regarding the publication of this paper.

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### Supplementary Materials

Table A1: analysis of correlation between student models and course grades (teaching and reflection course). Table A2: performance measure of classification methods for course "teaching and reflection" with different feature numbers. Table A3: TOPSIS ranking of classification methods for course "teaching and reflection" with different feature numbers. (*Supplementary Materials*)

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