Modeling the e-Inclusion Prediction System

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Keywords: e-Inclusion, Machine Learning, Predictive Analytic.

Abstract: e-Inclusion aims to provide the benefits of digital technology for every member of society. Digital skills and their meaningful use are a prerequisite for everyone to be e-included. The improvement of learning outputs of online and blended courses on digital skills is therefore an important aspect of ensuring an e-included society. Due to the use of learning management systems and their ability to collect data on students, different types of student data become available for analysis. We proposed the data-driven approach which uses student data and machine learning algorithms to predict learning outcomes. The goal of this article is to present the conceptual architecture and prototype of the e-inclusion prediction system which is based on a combination of several algorithms and uses a machine learning approach.

1 INTRODUCTION

E-inclusion aims to provide the benefits of information and communication technology (ICT) for every member of society. Digital skills and their meaningful use are a prerequisite for everyone to be e-included. E-inclusion means both inclusive ICT and the use of ICT to achieve wider inclusion objectives. The development of ICT is ongoing, so it should be ensured that the acquisition and application of digital skills are also in line with ICT innovation (EC, 2020).

Nowadays, acquiring skills through online and blended courses is one of the learning opportunities. However, research shows that only a small percentage of people who take online courses complete them (Eurostat, 2020). The second problem with skills acquisition is related to scrap learning. According to a CEB Global (2014) study, for the average organization, 45% of learning investments are scrap learning - learning that is delivered but not applied back on the job. The improvement of learning outputs of online and blended courses on digital skills is therefore an important aspect of ensuring an e-included society. It is important to find out how to predict students' learning outcomes, especially their use of newly acquired digital skills, which would indicate that students will be e-included.

The data-driven approach, which uses student data and machine learning algorithms to train models, has been widely used in the education sector. Nafukho et al. (2017) examined factors related to training design, training delivery, student motivation, and the workplace environment to predict how these factors impact skill usage in a work placement. Testers et al. (2020) concluded that motivation to learn, expected positive personal outcomes, and learner readiness were predictors for training transfer in workplace.

However, there is little evidence that the current application of learning analytics in education improves students' learning outcomes, learning support, and teaching (Viberg et al., 2018). Prediction models are without a mechanism that assists the interpretation of machine learning results. An essential issue is to find out how to deliver the results of analytics corresponding to the expectation of learners and instructors to improve the learning process (Miteva, & Stefanova, 2020).

This article continues the presentation of our previous research related to e-inclusion prediction. The contribution of this study is to address the e-inclusion prediction problem and to provide the concept of the e-inclusion prediction system and prototype. The goal of this article is to present the conceptual architecture and prototype of the e-

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Vitolina, I., Kapenieks, A. and Grada, I.
Modeling the e-Inclusion Prediction System.
DOI: 10.5220/0010458302580265
In *Proceedings of the 13th International Conference on Computer Supported Education (CSEDU 2021) - Volume 2*, pages 258-265
ISBN: 978-989-758-502-9

inclusion prediction system which is based on a combination of several algorithms and uses a machine learning approach.

2 METHODOLOGY FOR BUILDING PREDICTIVE MODELS

Predictive modeling is a process of building models for predicting the future behavior of our data. It includes: understanding the data and defining the objective of the modeling; collection, pre-procesing and splitting of data; model building and evaluation, deployment of the selected model (Kuhn & Johnson, 2013). These phases are iterative and incremental.

The process of building the e-inclusion prediction system corresponds to the following processes: (i) problem definition, (ii) data analysis for feature selection and (iii) model training and validation iterations. These processes have been presented in our previous research (Vitolina, and Kapenieks, 2013; Vitolina, and Kapenieks, 2020).

In this article, the main focus is on the model deployment phase. According to Maskey (2019), in order to deploy the model, it is necessary to: (i) evaluate the model's performance in production, (ii) collect and store additional data from user interactions, (iii) interpret numerical outputs from the model, (iv) plan retraining frequency.

3 e-INCLUSION PREDICTION SYSTEM

3.1 Context Level Data Flows of the e-Inclusion Prediction System

The main goal of the e-inclusion prediction system is to determine student with e-inclusion risk. Figure 1 presents a context-level data flow diagram for the e-inclusion prediction system. The main user of e-inclusion prediction system is an instructor who teaches students in the blended e-learning courses. The instructor sets values of the e-inclusion degree threshold level and receives information on risk students and risk factors. The e-inclusion prediction system receives student data and the topic from the learning management system (LMS). We decided to use Moodle as a LMS because Moodle is the default system in our university, and it is also one of the most widespread open-source platform in the world (Moodle, 2020). To get feedback from students on the usage of the learned skills, we decided to send SMS messages to students' smartphones. The decision to use the SMS approach for communication with students is based on our previous successful experience delivering blended learning courses by the multi-screen approach (Kapenieks et al., 2014) . Then the database is supplemented with data on the actual use of newly acquired skills.

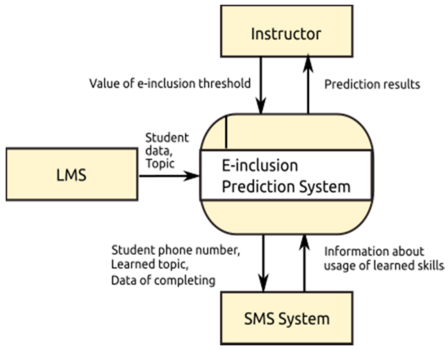


Figure 1: Context-level data flow diagram showing the relationship between the e-inclusion prediction system, instructor, LMS, and SMS system.

3.2 Basic Processes of the e-Inclusion Prediction System

As basic processes of the e-inclusion prediction system we determine (1) data pre-processing, (2) training and evaluation of the PREDICT model, (3) prediction of at-risk students, and (4) quality monitoring of the prediction performance.

3.2.1 Data Pre-processing

Data pre-processing for the e-inclusion prediction system includes data quality assessment, data cleaning, data transformation (García et al., 2015).

To ensure the quality of the data, we obtain the data as structured tables from the Moodle system. The data are students' answers to our pre-designed questionnaire questions. We based the Moodle survey questions on knowledge management theory to get students' answers and transform them as features for prediction (Nissen, 2006). During the data preparation step, the system maps the student data obtained from the LMS to the feedback data obtained from the SMS system. Incomplete data are cleaned out of the database when the training course is over.

In this pre-processing step, the system also calculates feature values from student data. The output of the data pre-processing is a student database that is used for model training and prediction.

3.2.2 Model Building Process

The second process of the e-inclusion system is training and evaluation of the prediction model.

Pachler (2010) reveals the diversity of factors that influence the choice to use ICT. Based on our previous research as input for training purposes the e-inclusion prediction system uses the following features: (I) student's motivation in learning; (ii) student's ability to learn; (iii) instructor's willingness to share knowledge; (iv) student's assessment of e-learning environment; (v) student's evaluation of e-learning materials; (vi) student's knowledge level before learning; (vii) student's digital skill level; (viii) student's predicted use of the newly learned skills (Vitolina, and Kapenieks, 2013; Vitolina, and Kapenieks, 2014).

We labeled each learner record of the data set as *e-included* or *not e-included*. We defined that the value is *e-included* if we observed that the learner uses newly learned skills. The value is *not e-included*, if we observed that the learner doesn't use newly acquired skills. The data set contains 435 *not e-included* learners and 493 *e-included* learners. We named this attribute as *observed usage of newly learned skills*. The dependent variable of the linear regression model is the numeric variable – the degree of e-inclusion which is a combination of the learner's predicted and observed usage of newly acquired digital skills. We merged data from the several blended learning courses and topics. The participants of the courses were teachers who were improving their digital skills in continual education courses.

After several iteration of model training and evaluation we concluded that student's e-inclusion can be predicted by combination of several prediction models (Vitolina and Kapenieks, 2020a).

Figure 2 presents an algorithm for e-inclusion prediction learned in the training phase. Three different prediction models M1, M2, and M3 are trained, then predictions of these models are combined and final prediction is calculated.

Model M1 is an ensemble classification based prediction model that combines predictions of lazy.LWL with Random Forest, LMT, and Simple Logistic algorithms using the majority vote approach. Prediction Model M2 is based on the K-means clustering algorithm, it divides students into 2 clusters, where each of the clusters corresponds to the *e-included* or *not-e-included* group. Prediction Model M3 is a multiple linear regression model that predicts that the learner is digitally excluded corresponding to the previously set e-inclusion threshold. Calculation of final prediction PREDICT is explained in more detail in section: 4.1.2.

The decision for a more appropriate prediction model is based on training and model evaluation using open source data mining WEKA platform (Hall, 2009). For Model M1 and Model M3 evaluation, we used cross-validation, for clustering Model M2 we used WEKA mode – classes to clusters evaluation. Cross-validation is an appropriate validation method for a small data set (Yadav, & Shukla, 2016). In a binary classification problem, the performance of the classifiers is assessed using the standard measures of recall, precision, F measure (Seliya et al., 2009). We use the F2 measure in our study to emphasize the importance of recall. The F2 measure combines precision and recall, putting a double emphasis on recall.

Obtained values of performance metrics showed that Model M1 that uses ensemble approach for classification can predict 79.50% of at-risk students, Model M1&M2 where prediction is based on the combination of classification and clustering can predict 83.40% but Model M1&M2&M3 that supplemented Model M1&M2 with a linear regression can predict 95.60% of at-risk students. The values of the F2 measure for Model M1 is 0.800, for Model M1&M2 it is 0.824 and for Model M1&M2&M3 it is 0.863. The output of the model training and evaluation phase is trained Models M1, M2, M3, the e-inclusion threshold and the PREDICT model algorithm.

3.2.3 Prediction of At-risk Students

The third process of the e-inclusion prediction system is the calculation of student's learning outcomes in the context of usage of newly learned skills. In the prediction process, as the input data are student data, these have not been seen previously by training models. The second input data are pre-trained models that calculate the prediction for the student.

The output of the prediction process is the determination of students at-risk to be digitally excluded because they do not have the ability to use the newly learned skills in their professional or private life.

The prediction process includes the presentation of result to the instructor, in order to take action to decrease the risk factors. Results need to be presented to end-users in an intuitive form, and that is one of the challenges in the model implementation (Maskey, 2019).

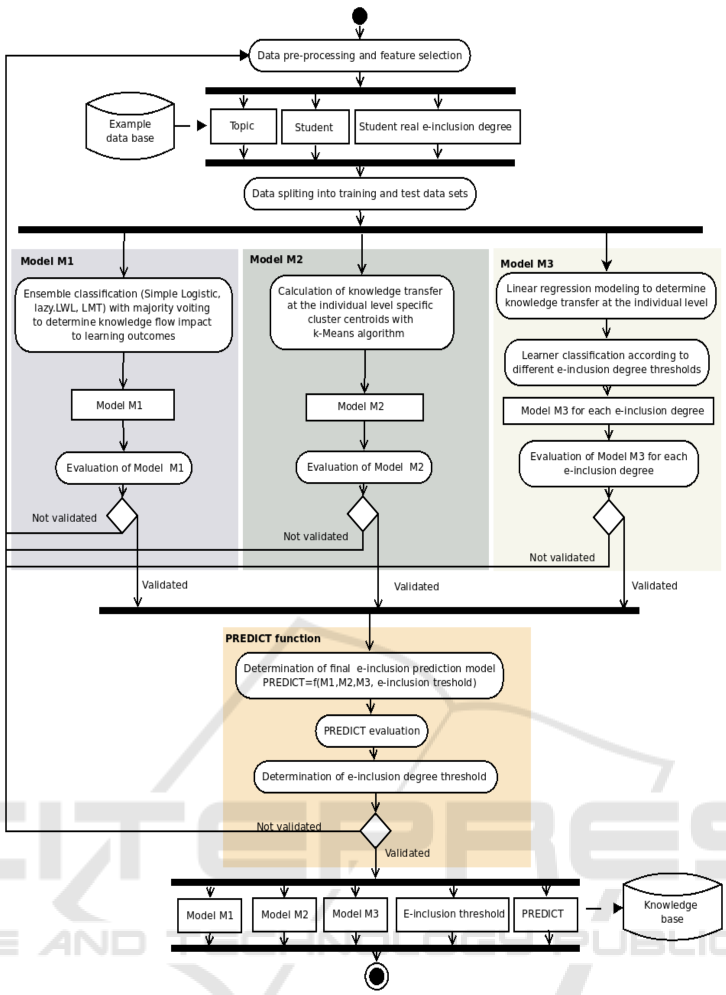


Figure 2: Algorithm for e-inclusion prediction based on training of three models and calculation of PREDICT function.

3.2.4 Monitoring of Prediction Performance

The last process of the e-inclusion prediction system is system maintenance, especially quality monitoring. There is no common understanding as to what are the best key metrics for quality measurement of machine learning models (Schelter et al., 2018). The complexity of machine learning application management is higher due to the fact that performance of machine learning application depends on training data but during the production stage data can be changed. The quality and frequency of model retraining are impacted by the model drift (Lu et al., 2018). There are different approaches for adapting models to new data, including scheduled regular retraining, continual or online learning (Chen and Liu, 2018).

We decided to evaluate model quality based on models performance metrics such as the F2 measure, recall and precision, and to determine frequency of model retraining in line with receipt of new data. The output of the model monitoring process is the decision whether the model requires retraining.

4 PROTOTYPE OF THE e-INCLUSION PREDICTION SYSTEM

We have deployed the proposed model onto the prototype of the e-inclusion prediction system. The prototype is web-based software using the JAVA programming language and open source software WEKA libraries.

The prototype is an early version of the e-inclusion system and consists of the base functionality. The main task of the e-inclusion prediction prototype is to provide functionalities that inform instructors about at-risk students and evaluate the performance of the basic functionality of the e-inclusion prediction system.

The main functionality of the e-inclusion prediction system for the instructor: to set an e-inclusion degree threshold, to search for students, to display prediction results for students (e-included or not e-included); to display factors impacting the prediction result (for example, student motivation, student self-evaluation of learning materials or e-learning environment; download prediction results.

For prototype validation, we used 65 student data from the three blended learning courses: Video Technology and Design course, Mobile Technologies course, Robotics course. Teachers from vocational and secondary schools attended these blended learning courses.

4.1 Explanation, Visualization, and Interpretation of Prediction Results

4.1.1 The View of the Main Prediction Results

Figure 3 presents the view of the main prediction results for the instructor in the tabular form in the prototype. Each row of the table contains the following information about the student: what models (M1, M2, or M3) have been used for the prediction, what is the predicted value for the student's e-inclusion (at-risk or no risk) and what is the level of precision for the prediction (high, medium, low). This table presents four possible prediction and precision level combinations.

Video	Name	Submit date	M1	M2	M3	Prediction	Precision
Video	Jānis Bērziņš	2019-08-09				Risk	High
Video	Anna Liepiņa	2019-08-09				Risk	Medium
Video	Juris Ozols	2019-08-07				Risk	Low
Video	Eva Egle	2019-08-07				No risk	High

Figure 3: Prototype view of different types of the results predicting risk to be digitally excluded for learners and presenting the level of precision for the prediction.

To make the information easier to perceive, we chose to use red color tones as a warning of risk and green color for no risk (Silic, & Cyr, 2016).

4.1.2 Calculation of the Final Prediction

To calculate the final prediction, the prototype uses prediction results of Model M1, M2 or M3 based on the algorithm presented in the Figure 4.

If Model M1 predicts that the student will not be e-included, then the final result will be that the student is at risk. If Model M1 predicts that a student will be e-included, the next step is checking the prediction of Model M2. If Model M2 predicts that the student is not e-included, then the final result again is that the student is at risk. Similarly, M3 model is checked. This approach is chosen because we need to check as many students as possible who are potentially at risk.

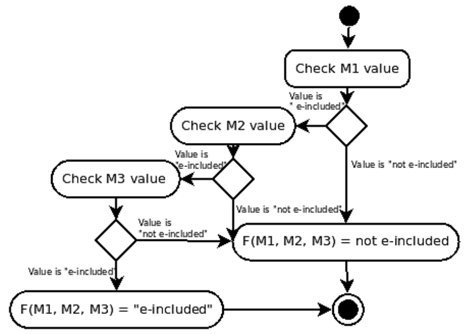


Figure 4: Process of determining the final prediction based on predictions of models M1, M2, M3.

4.1.3 Interpretation of the Extent of the Prototype Prediction Precision

To help the instructor to interpret prediction results, we supplemented the prediction with an indicator of the extent to which we consider the prediction to be precise. Model performance measurements showed that the precision is different for model combinations in case of the not e-included class.

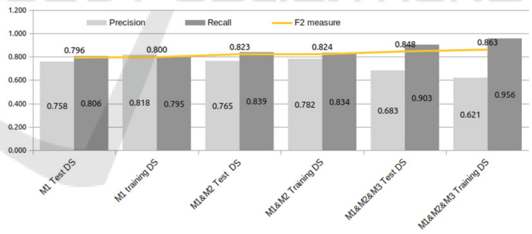


Figure 5: Comparison of models and their performance in the training and testing phase.

Figure 5 shows how the precision decreases and the recall increases for different model combinations in case of a training data set. For model M1, the precision is 0.818, for the combination of models M1&M2 it is 0.782, for the combination of models M1&M2&M3 the precision is lower - 0.621. We checked that the trend of decreasing precision remains with the test data also, the precision decreased from 0.758 to 0.683. It means that among the predicted students at-risk, there will be more who are actually e-included. So we decided to add a Precision column to the prediction table in the prototype. Based on the observed precision values, we divided it in three levels for not e-included or at-risk class: (1) high level - if the model makes a decision based on Model M1; medium level - if the model predicts based on the combination of models M1&M2; and low level - if the prediction is based on a combination of Models M1&M2&M3. We found that 80% in the test phase or 85% in the training phase not e-included students are predicted with Model M1.

In case of the e-included class, we determine that prediction precision is based on our calculations of correctly predicted e-included learners. We obtained that 92.63% of e-included learners are correctly predicted in case of the training data set and 87.50% in case of the test data set.

4.1.4 Detailed View of the Prediction Results

To ensure that the instructor has the possibility to understand more deeply the reasons that impact student learning outcomes the prototype has a detail view of prediction results in tabular form (Figure 6) or as a visual presentation (Figure 7).

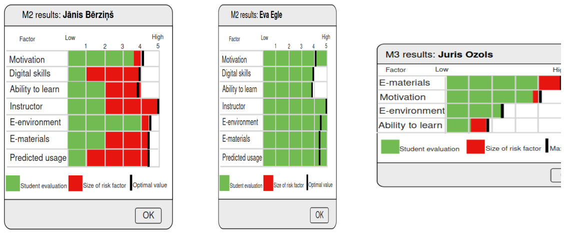
Name	Motivation	Digital skills	Ability to learn	Instructor	E-environment	E-materials	Prediced usage	M2
Jānis Bērziņš	3.5	1.0	2.0	2.0	4.0	2.0	1.0	Risk
Anna Liepiņa	4.0	5.0	1.0	5.0	4.5	4.0	5.0	Risk
Juris Ozols	4.5	4.5	3.0	5.0	5.0	4.0	4.0	Risk
Eva Egle	5.0	4.0	4.0	5.0	5.0	5.0	5.0	No risk

Figure 6: The view of student data and corresponding prediction results in tabular form in the prototype for Model M2.

To determine which features are most important to a particular student, the prototype offers to the instructor a visual view of the student's feature based on algorithms obtained during the training phase. Risk factors of the student are colored in red.

Figure 7 (a) and (b) present visualization of the results obtained from Model M2 that used clustering for predictions. To interpret prediction results of M2, we used values of the centroids calculated in the model training process, subdivided into two classes: "e-included" and "not e-included".

Figure 7(a) presents visualization of student's data which has prediction of the risk to be digitally excluded with high level reliability. Based on warnings about the student's weaknesses, the instructor can decide what actions to take. Information in this prototype view is visualized as follows: green bars show the extent to which a student has one of the specific features, while red shows how much it lacks to reach the feature. The factor having a longer red bar affects the student more and these are the main risk factors. The centroid values which are determined by the k-Mean algorithm are represented by a black vertical bar. They mark the boundary that a student feature should reach in order to avoid the risk of being digitally excluded.



(a) (b) (c)

Figure 7: Detailed view of the Model M2 and M3 results for an individual learner. (a) Model M2 prediction of the at-risk student; (b) Model M2 prediction of the e-included student; (c) Model M3 prediction of the at-risk student.

Figure 7(b) demonstrates the features of a student, who is predicted as e-included by the prototype. The instructor can see that all the features are green and have high values.

Model M3 is based on a linear regression, so the prototype visualizes the results of M3 according to the trained linear regression algorithm.

During the training and cross-validation process we obtained that the linear regression model uses only four attributes to predict the e-inclusion degree: Student motivation, student ability to learn, evaluation of e-learning materials, and e-learning environment. Linear correlation coefficients indicate that student features have different effects on prediction. The prototype visualizes and informs the instructor according to the coefficients determined by the algorithm on the effect on the prediction. For example, Figure 7(c) presents the size of risk factors according to the linear regression algorithm where the instructor can see that e-materials and ability to learn could be risk factors of the student.

4.1.5 The e-Inclusion Degree Threshold

We were challenged to determine at which predicted linear regression value to consider a student e-included and when the student is at risk.

To determine the e-inclusion degree threshold we calculated precision, recall, and F2 measure for different levels of e-inclusion degree. We observed that metrics have constant values if the e-inclusion degree is less than 60% from the maximum value in the case of training data and less than 65% for test data (Figure 8). F2 measure has the highest value when the e-inclusion degree is reached by 80% for both training data and test data. Based on this F2 measure value, we determined that a student can be considered e-included if he/she reaches at least 80% of the potential e-inclusion value.

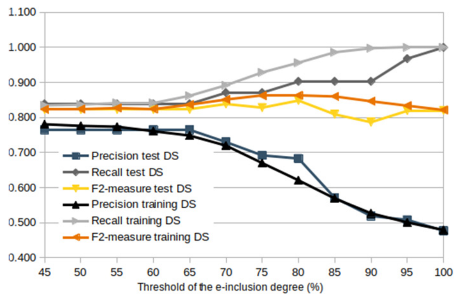


Figure 8: Metrics according to e-inclusion degree.

4.2 Evaluation of the Model Drift

To evaluate the prediction model drift, we compared performance metrics for training and test data sets.

The F2 measure was higher for the training data set but the difference was small. In the case of Model M1, the F2 measure of the training set is 0.798, but in the case of the test set it is 0.800. For the combination of M1&M2, the F2 measure of the training set is 0.823, for the test it is 0.824. For M1&M2&M3 the F2 measure of the training set is 0.863, for the test set it is 0.848. Model M1 in the prototype can predict 80.6 % of students at risk. It is possible to predict 83.9% of risk students in case of the M1&M2 combination model. Model M1&M2&M3 in the prototype can predict 90.3% of the student at risk.

As the differences in metrics are small, we assumed that the model has retained its accuracy. However, it should be noted that model quality monitoring is important and must be ensured on an ongoing basis.

5 CONCLUSIONS

The conceptual architecture of the e-inclusion prediction system was presented. The e-inclusion prediction model was developed by combining a classifiers (Simple Logistic, lazy.LWL, LMT), K-means clustering, and multiple linear regression algorithms. A data set of 65 learners records was used for testing and validating the e-inclusion prediction prototype. In a test condition the e-inclusion prediction recall, precision, F2 measure were found to be high. The recall value is above 0.806. It means that prototype can predict more than 80.60% at risk students from all digitally excluded students. The precision value is above 0.683, and the F2 measure is above 0.796. Comparing the model performance in the training phase and prototype testing phase the performance quality is stable. It is argued that the proposed e-inclusion prediction system could increase the number of e-included persons after they complete the digital skill improvement blended learning courses.

We concluded that it is possible to use the proposed prediction model for different digital skills improvement courses. It is possible to merge data from several courses or vice versa to predict for each course separately.

The prototype provides the main functionality for predicting digitally excluded students. Functionality includes data uploading, model training, and outcome predictions as well as result presentation.

A limitation in using the e-inclusion system is that the student should fill out questionnaires in the Moodle courses. In case the student has not submitted or has partly submitted the answers the system will miss data for predictions. Another limitation is the issue with the technical equipment. If the student does not have available software or any device for skill usage in the future then the instructor cannot impact the usage of the newly learned skills.

The plan for the future is to supplement the functionality of the prototype and to test it in production in cooperation with instructors of the blended learning courses.

ACKNOWLEDGMENTS

This work is supported by the EU ERANET FLAG ERA project 'FuturICT 2.0 - Large scale experiments and simulations for the second generation of FuturICT'.

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