Keep It Up: In-session Dropout Prediction to Support Blended Classroom Scenarios

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Abstract: Dropout prediction models for Massive Open Online Courses (MOOCs) have shown high accuracy rates in the past and make personalized interventions possible. While MOOCs have traditionally high dropout rates, school homework and assignments are supposed to be completed by all learners. In the pandemic, online learning platforms were used to support school teaching. In this setting, dropout predictions have to be designed differently as a simple dropout from the (mandatory) class is not possible. The aim of our work is to transfer traditional temporal dropout prediction models to in-session dropout prediction for school-supporting learning platforms. For this purpose, we used data from more than 164,000 sessions by 52,000 users of the online language learning platform orthografietrainer.net. We calculated time-progressive machine learning models that predict dropout after each step (completed sentence) in the assignment using learning process data. The multilayer perceptron is outperforming the baseline algorithms with up to 87% accuracy. By extending the binary prediction with dropout probabilities, we were able to design a personalized intervention strategy that distinguishes between motivational and subject-specific interventions.

1 INTRODUCTION

With the onset of the COVID-19 pandemic, many schools in Germany had to close on short notice and teachers were forced to switch to online formats. After more than a year of the pandemic, school closures continued for weeks at a time, resulting in distance formats becoming established in many schools. This may have been the starting point for the use of digital teaching methods, persisting even after the pandemic. The use of digital instructional offerings can reduce teacher workload and support internal differentiation (Gerick et al. 2016, Kepser 2018).

In online learning platforms, dropout prediction models are often used to provide early interventions for at-risk users. Many studies are particularly concerned with MOOCs, as dropout rates of up to 90% are found (Kloft et al. 2014, Xing and Du 2019). However, dropout prediction models in MOOCs have quite different requirements to dropout prediction in online learning platforms that support school teaching:

(1) **Voluntariness:** most people in MOOCs participate voluntarily, while completing homework in school is usually mandatory.

(2) **Time Frame:** MOOCs provide over several weeks with a defined end. It is up to the users how quickly they complete the course. The use of a learning platform that accompanies school lessons, on the other hand, depends primarily on how the curriculum is defined as a whole.

(3) **Drop Out:** In the German school system you cannot fail a single subject, but only a entire class level. Thus, the definition of dropping out as it is defined in MOOCs cannot be applied to school settings.

(4) **Integration:** In school the subject matter is not taught exclusively via an online course. Rather, lessons are taught in the classroom, and accompanying exercises and homework take place on the online platform.

Dropout prediction for a school assignment platform is therefore in many respects different from MOOC dropout prediction. The goal of this paper is to translate existing research on dropout prediction to

the reality of blended learning scenarios.We therefore consider the early termination of a single session instead of the dropout of the entire course. We define a session as a limited time interval during which the user is working on the completion of an assignment consisting of several exercises. Leaving a session early should be avoided, as the exercises of the assignments didactically build on each other. Predicting this dropout provides the opportunity for interventions in adaptive learning environments. These interventions can, for example, adjust task difficulty, display orthographic rules, or display motivational gamified texts. This increases the motivation of the user and leads to higher learning success. Therefore, the research questions are as follows:

RQ1: How effective are machine learning models in predicting dropout within a session?

RQ2: How can the predicted dropout probabilities be used for in-session intervention to prevent early exit?

To this end, we first summarize the current research on dropout prediction and learning analytics intervention. Then we describe the underlying dataset and the feature engineering of our study and the used orthografietrainer.net platform. Next, the results of the different models are compared using different metrics for evaluation. Finally, the results are interpreted and discussed

2 RELATED WORK

2.1 Dropout Prediction in Online Learning Environments

There are numerous studies on dropout prediction in online learning environments. Many of these studies examine dropouts in MOOCs (Dalipi et al. 2018, Kloft et al. 2014, Xing and Du 2019). MOOCs do offer many advantages, however, they have dropout rates of up to 90% (Kloft et al. 2014, Xing and Du 2019). Dalipi et al. (2018) present several factors responsible for the high dropout rate. These include person-related factors, such as a lack of motivation and time, and course-related factors, such as poor course design, too little interaction, and hidden costs. Dropout prediction models therefore show great potential to define at-risk students and prevent dropout through appropriate intervention measures (Xing and Du 2019).

Research on session dropout prediction, on the other hand, is found less frequently. Lee et al. (2020) investigated a session dropout prediction in an online learning environment and proposed the Deep Attentive Study Session Dropout Prediction (DAS) as a new Transformer based encoder-decoder model. In their work, Lee et al. (2021) combined knowledge tracing with session dropout prediction and were able to improve the area and receiving operator curve by 3.62% using Lee's DAS model.

Xing and Du (2019) define three different investigation paths that are often followed in prediction models: fixed-term dropout prediction, temporal dropout prediction, and dropout prediction model performance optimization. Fixed-term dropout prediction uses data from a defined period of time to perform the predictions. This comes with the disadvantage that interventions often cannot be applied early enough. Other studies only use data from the first week of the course to identify early dropouts. This makes it impossible to distinguish in which of the next weeks a person drops out. As a result, many students are classified at-risk, and no accurate intervention or personalized feedback is possible. Temporal Dropout Prediction models use data from all the previous weeks and are supposed to predict which user will drop out in the next week. This leads to a much smaller number of at-risk users, which makes it possible to focus on those users. To be able to plan personalized interventions, it would be appropriate to calculate the dropout probability. Dropout prediction model optimization deals with possibilities to improve the model performances, for example with approaches using sentiment features in comments or using deep learning algorithms (Xing and Du 2019).

For prediction, most studies mainly use clickstream data, which are calculated from log data in online platforms (Sun et al. 2019, Xing and Du 2019). They include all interactions a user has with the course and in temporal dropout prediction models, these must be considered individually for each week (Hagedoorn and Spanakis 2017). Since this is a binary classification problem, most models use supervised learning algorithms to build the models for dropout prediction (Liang et al. 2016). In a review by Dalipi et al. (2018), logistic regression was the most used machine learning model, followed by support vector machines (SVM) and decision trees. Hidden Markov models or survival analysis are used less frequently. Other studies use deep neural networks or recurrent neural networks (RNNs) which can outperform classical ML model (Sun et al. 2019, Dalipi et al. 2018, Xing and Du 2019). Deep learning models use neural network architecture with multiple hidden layers and

gain great results without the need for time consuming feature engineering processes before (Hernández-Blanco et al. 2019). In their review of deep learning in educational data mining, Hernández-Blanco et al. (2019) found that in 67% of the reviewed articles, the deep learning model outperformed traditional machine learning approaches.

Research on dropout prediction is therefore well advanced and has already been examined from various sides. However, the study of courses in MOOCs or universities, which are designed for longer periods of time, plays a particularly important role. In-session dropout prediction is less studied and especially online environments that support and supplement classroom learning have not been explored in studies to date. Yet the use of these environments has increased dramatically, partly due to the pandemic. With this work, we hope to make a valuable contribution to in-session dropout prediction in blended learning scenarios.

2.2 Learning Analytics Intervention

Insights and predictions in the learning analytics field allow strong conclusions to be drawn about student learning behavior. However, to have a real impact, the insights gained must also be meaningfully integrated within learning analytics interventions. The goal is to prevent academic failure at an early stage by monitoring progress data and providing personalized and appropriate support (Wong and Li 2020). Interventions are considered as the "biggest challenge in learning analytics" (Wong and Li 2018). Wise (2014) defines learning analytics interventions as "the surrounding frame of activity through which analytic tools, data, and reports are taken up and used. It is a soft technology in that it involves the orchestration of human processes, and this does not necessarily require the creation of a material artifact.". The design of learning analytics interventions thus plays a significant role in how helpful the use of information obtained through learning analytics is (Na and Tasir 2017).

Learning analytics interventions comes with different purposes: they can improve students' success and course performance, as well as retention, motivation, or participation (Na and Tasir 2017). Wong and Li (2018) categorized learning analytics interventions into four types: direct message, actionable feedback, categorization of students, and course redesign. In their review, most of the interventions used the method of direct messages, which includes telephone calls, emails or private messages to both, students at-risk and their tutors. These messages contain, for ex-

ample, information about additional help or counseling (Dawson et al. 2017, Milne 2017), encouraging messages to use online resources (Blumenstein 2017, Smith et al. 2012), or information to notify the tutor about students at-risk (Herodotou et al. 2017). The method of actionable feedback provides the students with their own performance data, for example via a dashboard that describes their learning behavior (Wong and Li 2018). Less common than direct message and actionable feedback are the intervention methods "categorization of students" and "course redesign". Categorization of students was done in various degrees to indicate risk levels. Interventions were then performed per category. Course redesign occurred very infrequently in the review and involved adjusting the course based on the information obtained. Information on dropout rates and at-risk students can also be used to evaluate instructors and course design.

In our article, we propose the prediction of students' early termination to gain valuable insights that will enable these interventions to be designed and applied in a personalized way.

3 METHODOLOGY

3.1 Orthografietrainer.net

The online platform orthografietrainer.net is a learning platform to acquire German spelling skills. It contains exercise sets on various aspects of the German language, such as capitalization, comma formation, separated and combined spelling, and sounds and letters. Furthermore, exercises on German grammar are available. The platform is mainly used in blended classroom scenarios. The teacher registers the entire class on the platform and then assigns tasks as homework from the spelling area that was discussed in class. This is the most common form of use of the platform. During the COVID-19 pandemic, the access rates have risen sharply as many new teachers started using the platform. The platform addresses mainly school classes from fifth grade to graduating classes. The data set consists of 181,792 assignments, 164,580 sessions and 3,224,014 answered sentences. These were completed by 52,032 users in the period 03-01-2020 to 04-31-2020. There are different terms to be defined before explaining the didactic structure of the platform:

(1) Exercise Set: A set of sentences, consisting of 10 sentences. Further sentences are added automatically if a sentence is not solved correctly.

(2) Sentence: One sentence containing one or several gaps to be filled in by the user.

(3) Assignment: Assigned exercise set which is displayed to the user as pending; generally as homework.

(4) Session: Period of time a user is working on the exercise set.

(5) Dropout: Termination of the session without completing the exercise set; after dropout, the assignment is still pending.

A peculiarity of the platform is the didactic structure of the exercise sets. The platform focusses less on learning German spelling rules and more on repeated practice. The typical exercise process is therefore as follows: the teacher teaches a sub-area of German spelling in traditional lessons and assigns exercise sets on the online platform to students as homework. The homework is displayed to the students as pending assignments. Each exercise contains ten different sentences. Each training sentence is available in at least three versions representing the same orthographical spelling problem in different verbal contexts and words. The program starts in the training mode (1) which shows sentence 1 of the exercise set. If sentence 1 is solved correctly, sentence 2 is displayed, then sentence 3 is displayed as well. The exercise set is successfully finished after 10 sentences if the user makes no mistakes.

If the learner has made a mistake, the program switches to version mode (2). Here the previously incorrect sentence is displayed again until the user answers it correctly. The solution is displayed and the previous incorrect sentence is tested again immediately after. If it has now been answered correctly, the other two versions of the sentence are displayed. If the versions have been answered correctly, the incorrect sentence from the beginning is displayed again and - if the sentence is now answered correctly - the version mode is terminated. The program then switches back to training mode.

At the end of the training mode the test mode follows (3), in which all sentences that were once answered incorrectly are displayed again. As a result, the assignment takes longer the more mistakes are made by a user. Figure 1 shows the process of an assignment at orthografietrainer.net.

The students have the possibility to leave the session at any time and continue working on the assignment at another time. After 45 minutes of inactivity, a user is automatically logged out. As described before, the task process is automatically extended if a user makes mistakes: before moving on with the next sentence, versions of the mistaken sentence are displayed, as well as the wrong sentence is tested again. A session is thus considered terminated if it is left without completing the exercise set. This can either be the case when the required 10 sentences have not been answered, or if there are more than 45 minutes between two sentences. If the latter is the case it is possible that the assignment is resumed later and finished successfully. In our data set, this is then defined as one assignment which is worked on in two sessions. The first session is considered dropped out, the second is considered as finished successfully.

3.2 Feature Selection & Engineering

Our analysis is intended to predict whether a user will interrupt the session before completing the exercise set on the basis of the learning process data. Although these are text tasks, no text analysis is carried out. The tasks are either correct or incorrect, no further analysis (e.g. of the type of error) is done. The information as to whether the user terminates the exercise prematurely has not yet been stored in the database and is therefore calculated separately. In addition to the features of the learning process shown in table 1, features of the assignment and session are calculated (table 2).
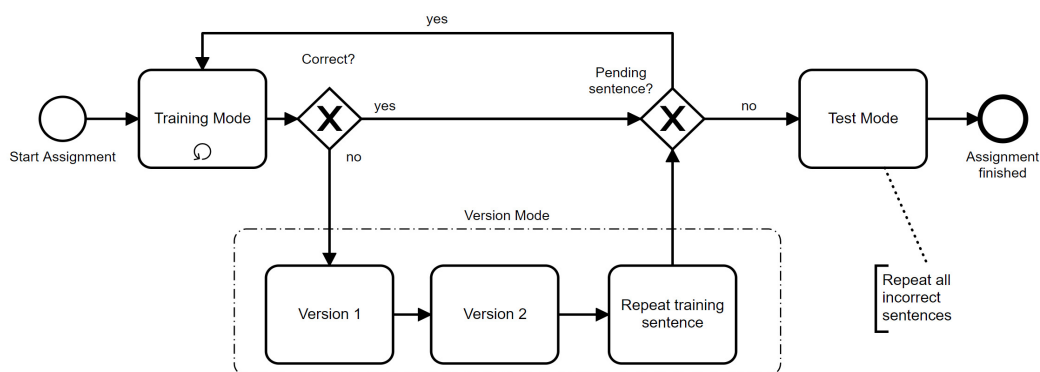

Figure 1: Task Process at orthografietrainer.net.

Table 1: User Features.

Name	Description
Field	Field of grammar
Class level	Class level of the user
Gender	Gender of the user
Test position	Mode in which the sentence is displayed
User Attribute	Group of users
First Reading	Describes, if the sentence is displayed for the first time to the user
Distracted	Describes, if the user submitted a task while missing a field
Success	Describes, if the answer is correct
Difficulty	Difficulty of the sentence
Years registered	Count of years the user is registered at the platform
Pending	Count of pending tasks
School	Describes whether the sentence was processed in school time
Multiple false	Describes, if the same sentence was answered incorrectly several times
Datetime	Date and time when the sentence was processed

Table 2: Session Features.

Name	Description
Break	Describes, if an assignment has more than one session
Session No.	Session number of the assignment
Order No.	Order number of the sentence
Previous Break	Describes, if this assignment was interrupted earlier
Steps	Describes the difference between the next possibility to finish an assignment and the current sentence number

The "Break" feature describes an exercise that has been interrupted. The exercise is then divided into two sessions, which are defined by the "Session No." feature. Each session contains N records of answered sentences, which are ordered by time by the "Order No." feature. The feature "Previous Break" shows if

and how often the assignment has been interrupted. Table 2 shows the session features.

The structure of the exercise process results in many exercises being completed at sentence numbers 10, 14, 18, or 22 sentences. A sum of 10 sentences occurs when the user does not make a single mistake. A sum of 14 sentences occurs when the user makes one mistake: Thus, each error adds 4 extra sentences that must be answered. While this is true for many assignments, it is not true for all. For example, if a user makes a second error in version mode, the loop becomes one level deeper. To explain this specific task structure in the model as well, the feature "Steps" is added. This feature describes the difference between the next possibility to finish an assignment and the current sentence number.

After preprocessing and feature engineering, the features were one-hot encoded. This led to a number of 24 input variables. As the successfully completed assignments outweighed the unsuccessful ones, the ratio of successfully / unsuccessfully completed assignments was balanced.

3.3 Matrices & Machine Learning Models

The goal of this research is to predict the dropout probability within a session. MOOC dropout predictions are usually estimated after several weeks of participation. In this case however, we re-estimate dropout prediction after every single sentence. Every time a user submits a sentence, the prediction model is updated using all sentences answered so far. Thus, the matrix used by the prediction model grows over the course of the session. The sentence position can take values from 1 (beginning of exercise) to 300 (if many mistakes were made). Since few sessions span more than 60 sentences, up to 60 matrices are created for every user. A matrix is defined by:

$$A: \{1, ..., m\} \times \{1, ..., n\} \rightarrow K, (i, j) \mapsto a_{ij}, \quad (1)$$

$$i = 1, ..., m \; and \; j = 1, ... n \quad (2)$$

The variables m and n define the number of lines and columns of the matrix. Here, i describes the lines of the matrix which represents one session. Further, j is defined as the columns of the matrix where each column is representing one feature. Each entry a_{ij} is thus representing a feature j in session i. Each matrix represents a sentence position and contains the answered sentence of the respective sentence position and all previous ones. Matrix 1 thus contains all the first sentences of the sessions, and matrix 2 contains the first two sentences.
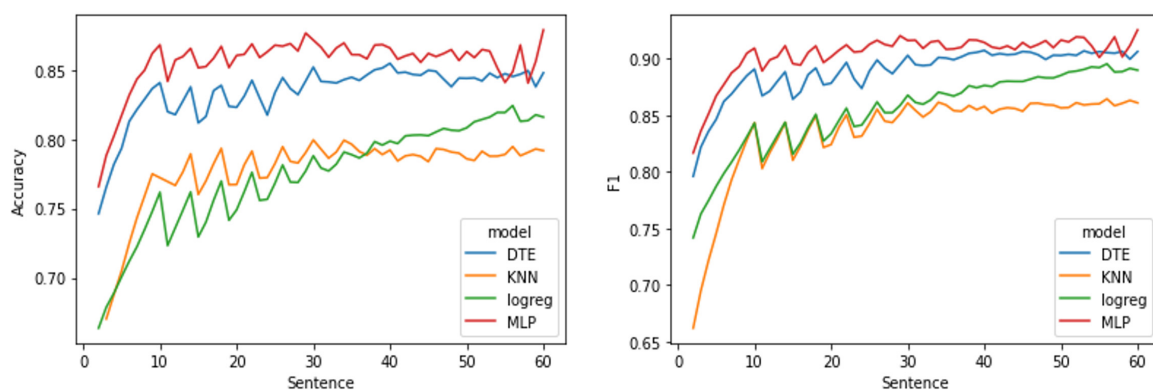
Figure 2: Accuracy and F1-Score per Sentence and Model (DTE=Decision Tree Classifier, KNN=k-Nearest Neighbor, logreg=Logistic Regression, MLP= multilayer perceptron).

In this study, three popular machine learning models were implemented as baseline algorithms to compare to the multilayer perceptron (MLP): logistic regression (logreg), decision tree classifier (DTE) and k-nearest-neighbor (KNN). We follow the selection of models by Xing and Du (2019) and the most frequent models found in the review by Dalipi et al. (2018). In our decision tree model (DTE), we use entropy as a criterion to measure the quality of a split and define the maximum depths of the tree as 5. The multilayer perceptron (MLP) consists of an input layer with 24 input variables. The three fully connected hidden layers (48, 24, and 12 nodes), as well as the input layer, apply the rectified linear unit function (ReLu). As we are facing a binary classification problem, the output layer applied the sigmoid function and as a loss function, we use binary cross-entropy. To reduce bias, we additionally apply 5-fold cross-validation.

The models described above are designed to predict whether a user will terminate the session prematurely. Most of the models are not only capable of making a binary statement, but also of estimating the probability of termination. Accordingly, we calculate the probability of early exit for each session in order to take appropriate interventions with this information. This way, interventions can be personalized: the higher the probability of termination, the stronger the interventions will be.

4 RESULTS

Figure 2 shows the performance of the different machine learning algorithms. Specifically, all models show an increasing accuracy over time. While the curve initially rises sharply up to sentence 10, it flattens out in the further course and approaches a peak

value. The MLP has the highest overall accuracy, up to 87%. The decision tree classifier is also very good, but is still slightly worse than the MLP at almost all points in time and reaches a maximum value of about 85%. The other models are closer together and reach up to 80% accuracy. The KNN model performs worst, remaining below 80%.

We furthermore calculated the importance of the features on the logistic regression model. Here we see that especially success and task difficulty have an influence. Other important features are previous break, i.e. whether the assignment has already been worked on in a previous session, the class level, the assignment type, capitalization and the user attribute. The most important feature in the Decision Tree Classifier is count wrong, i.e. the total number of errors. In the KNN model, it is as well count wrong, additionally to first reading, success and the three features indicating the testposition.

In addition to the binary statements as to whether a session is terminated prematurely or not, many models also calculate a termination probability. This does not apply to the KNN model and it is therefore not included in the further discussion. Figure 3 shows
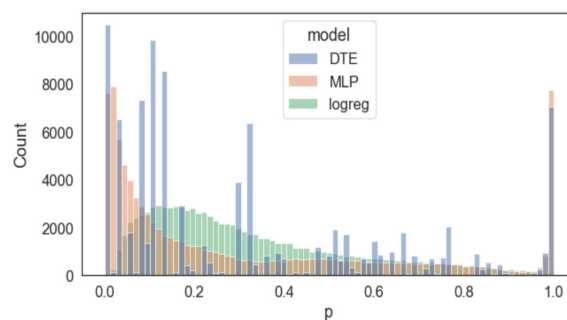

Figure 3: Probability distribution per model (DTE=Decision Tree Classifier, logreg=Logistic Regression, MLP= multilayer perceptron).

the distribution of the probabilities per model. Here we can see that the distributions vary between the models. The distribution of the logistic regression model is denser and spreads mainly between 0.05 and 0.5. Few very low and few very high probabilities are predicted. The MLP model on the other hand predicts many low probabilities up to 0.1 and many high ones up to 1.0, but few in the middle of the distribution. The DTE model shows single high values and no smooth distribution.

5 DISCUSSION

Following our two research questions, we have shown that dropout prediction models can be applied not only in the context of MOOCs over multiple weeks, but also in the context of learning platforms that accompany classroom teaching. Instead of predicting over a period of several weeks, we were able to build models for local prediction, predicting early termination within a session and providing the opportunity to offer in-session interventions.

Previous studies on dropout prediction in MOOCs showed that the MPL outperformed the other models. This was also the case when transferring the research to our blended learning scenario. The accuracy of the in-session models was worse than that of the MOOC prediction models. Xing and Du (2019), for example, achieved an accuracy of 96% while our model could only reach up to 87%. This can be explained by the different data basis: in MOOCs, all clickstream data is used over several weeks, whereas in our models much less interaction takes place (namely only within one session). Our analysis also calculated feature importance and showed that the most important features for in-session dropout prediction are success, task difficulty, and count of wrong tasks.

In our study, we have also gone one step further and extended the mere prediction of early termination with specific termination probabilities to design personalized learning analytics interventions. The dropout probability allows us to better differentiate between different interventions, which vary depending on the level of dropout probability.

5.1 Outlook & Limitations

In this paper, we have shown that dropout prediction models can be applied to classroom supporting online learning. Using didactic and data-driven thresholds, we are now able to propose interventions for several probability domains that better match user needs. Moreover, session dropout prediction can be used not only to provide adequate interventions to learners but also to improve learning paths in the learning environment and to inform course creators about frequent obstacles to exercise completion. Learning analytics interventions can be designed on different bases (described in related work). However, the actual interventions are then highly dependent on the specific learning platform. In the case of the ortho-grafietrainer.net learning platform, which is used to acquire spelling and grammar skills, different interventions make sense based on the subject-specific tasks and the structure of the assignments:

- To increase motivation, basic motivational messages or a display of the number of sentences still pending can be implemented
- If users have problems with a certain sentence, they sometimes cannot get out of the loop of versions. In this case, it makes sense to release the user from the loop and continue with the next sentence once a certain probability has been reached.
- The difficulty of the sentences can be adjusted so that the user has a higher probability of solving the sentences correctly and thus completing the exercise.

Basically, interventions can be divided into motivational and subject-specific interventions. Motivational interventions only serve to further encourage users and to keep them engaged by means of displays or gamification elements. Subject-specific interventions, on the other hand, adapt the tasks, for example, the sentence sequencing or the difficulty. They thus have an impact on what is learned and therefore offer a stronger intervention method. The distinction between intervention types can be used to apply different interventions starting at different thresholds depending on dropout probabilities. Future research should implement and evaluate these very interventions in blended classroom scenarios to validate the effectiveness of this approach.

An important limitation in our study is the fact that the students do the homework at home and are confronted with other confounding factors there. Therefore, it can never be ruled out whether a dropout from the session is actually related to the learning experience or has resulted from the surrounding circumstances. Furthermore, we have no information about the way in which the platform is integrated into the school lessons. For example, it can make an enormous difference whether homework is graded or not. This information could be included in the future by, as an example, a survey for teachers using the platform.

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REFERENCES

Blumenstein, M. (2017). The Student Relationship Engagement System (SRES). In *Building an Evidence Base For Teaching and Learning Design Using Learning Analytics*, 31.

Sun, D.; Mao, Y.; Du, Y.; Xu, P.; Zheng, Q.; and Sun, H. (2019). Deep Learning for Dropout Prediction in MOOCs. In *2019 Eighth International Conference on Educational Innovation through Technology (EITT)*, 87–90.

Dalipi, F.; Imran, A. S.; and Kastrati, Z. (2018). MOOC Dropout Prediction Using Machine Learning Techniques: Review and Research Challenges. In *2018 IEEE Global Engineering Education Conference (EDUCON)*, 1007-1014. IEEE 2018.

Dawson, S.; Jovanovic, J.; Gašević, D.; and Pardo, A. (2017). From prediction to impact: Evaluation of a learning analytics retention program. In *Proceedings of the Seventh International Learning Analytics & Knowledge Conference.* ACM, 474–478. DOI=10.1145/3027385.3027405.

Gerick, J.; Eickelmann, B.; and Bos, W. (2016). Zum Stellenwert neuer Technologien für die individuelle Förderung im Deutschunterricht in der Grundschule. In *Individualisierung im Grundschulunterricht. Anspruch, Realisierung und Risiken*, 131–136.

Hagedoorn, T. R.; and Spanakis, G. (2017). Massive Open Online Courses Temporal Profiling for Dropout Prediction. In *2017 IEEE 29th International Conference on Tools with Artificial Intelligence (ICTAI)*, 231–238.

Hernández-Blanco, A.; Herrera-Flores, B.; Tomás, D.; and Navarro-Colorado, B. (2019). A Systematic Review of Deep Learning Approaches to Educational Data Mining. In *Complexity* 2019, 1–22.

Herodotou, C.; Heiser, S.; and Rienties, B. (2017). Implementing randomised control trials in open and distance learning: a feasibility study. In *Open Learning: The Journal of Open, Distance and e-Learning* 32, 2, 147–162.

Liang, J.; Yang, J.; Wu, Y.; Li, C.; and Zheng, L. (2016). Big Data Application in Education: Dropout Prediction in Edx MOOCs. In *2016 IEEE Second International Conference on Multimedia Big Data (BigMM),* 440–443.

Milne, J. (2017). Early alerts to encourage students to use Moodle. In *Building an evidence base for teaching and learning design using learning analytics*, 24–30.

Kepser, M. (2018). Digitalisierung im Deutschunterricht der Sekundarstufen. Ein Blick zurück und Einblicke in die Zukunft. In *Mitteilungen des Deutschen Germanistenverbandes* 65, 3, 247–268.

Lee, S.; Kim, K. S.; Shin, J.; and Park, J. (2021). Tracing Knowledge for Tracing Dropouts: Multi-Task Training for Study Session Dropout Prediction. In *Educational Data Mining Conference 2021*.

Lee, Y.; Shin, D.; Loh, H.; Lee, J.; Chae, P.; Cho, J.; Park, S.; Lee, J.; Baek, J.; Kim, B.; and Choi, Y. (2020). Deep Attentive Study Session Dropout Prediction in Mobile Learning Environment. arXiv preprint arXiv:2002.11624.

Kloft, M.; Stiehler, F.; Zheng, Z.; and Pinkwart, N. (2014). Predicting MOOC Dropout over Weeks Using Machine Learning Methods. In *Proceedings of the 2014 Conference on Empirical Methods in Natural Language Processing (EMNLP)*, 60–65.

Na, K. S.; and Tasir, Z. (2017). A Systematic Review of Learning Analytics Intervention Contributing to Student Success in Online Learning. In *Fifth International Conference on Learning and Teaching in Computing and Engineering - LaTiCE* 2017. 62–68. DOI=10.1109/LaTiCE.2017.18.

Smith, V. C.; Lange, A.; and Huston, D. R. (2012). Predictive Modeling to Forecast Student Outcomes and Drive Effective Interventions in Online Community College Courses. In *Journal of Asynchronous Learning Networks* 16, 3, 51–61.

Wise, A. F. (2014). Designing pedagogical interventions to support student use of learning analytics. In *Proceedings of the Fourth International Conference on Learning Analytics And Knowledge - LAK '14*. 203–211. DOI=10.1145/2567574.2567588.

Wong, B. T.; and Li, K. C. (2018). Learning Analytics Intervention: A Review of Case Studies. In *2018 International Symposium on Educational Technology (ISET)*. 178–182. DOI=10.1109/ISET.2018.00047.

Wong, B. T.; and Li, K. C. (2020). A review of learning analytics intervention in higher education (2011–2018). *Journal of Computers in Education* 7, 1, 7–28.

Xing, W.; and Du, D. (2019). Dropout Prediction in MOOCs: Using Deep Learning for Personalized Intervention. *Journal of Educational Computing Research* 57, 3, 547–570.