Fairness of In-session Dropout Prediction

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Abstract: The increasing use of machine learning models in education is accompanied by some concerns about their fairness. While most research on the fairness of machine learning models in education focuses on discrimination by gender or race, other variables such as parental educational background or home literacy environment are known to impact children's literacy skills too. This paper, therefore, evaluates three different implementations of in-session dropout prediction models used in a learning platform to accompany German school classes with respect to their fairness based on four different fairness measures. We evaluate the models for discrimination of gender, migration background, parental education, and home literacy environment. While predictive parity and equal opportunity are rarely above the defined threshold, predictive equality and slicing analysis indicate that model quality is slightly better for boys, users with higher parental education, users with less than ten books, and users with a migrant background. Furthermore, our analysis of the temporal prediction shows that with increasing accuracy of the model, the fairness decreases. In conclusion, we see that the fairness of a model depends on 1) the fairness measure, 2) the evaluated demographic group and 3) the data with which the model is trained.

1 INTRODUCTION

Algorithmic decision-making processes are playing an increasing role in all areas of life. In addition to education, AI models are used in marketing, healthcare, human resources, and economics. However, the assumption that all decisions made by algorithms are fair and objective has already been refuted in numerous studies. One example for algorithmic bias is the application of a computer calculated score (risk assessment) to predict the likelihood of criminals to relapse that has been proven to be discriminatory against defendants of black skin color, mislabeling them as high risk almost twice as often as defendants of white skin color (Angwin et al. 2016). Experiments testing the performance of different face recognition algorithms have shown both the commercial and the nontrainable algorithms to be racially and sexually biased, having lower hit accuracies when it comes to certain cohorts (females, blacks, age 18-30) compared to the remaining cohorts within their demographics (Klare et al. 2012). A study using the Google Translate API to translate sentences from gender-neutral languages into English has shown the program's tendency to use male defaults, especially in sentences related to male dominated fields such as STEM jobs (Prates et al. 2020).

The growing use of machine learning models in educational contexts therefore goes hand in hand with concerns about their fairness. Many studies have already evaluated different applications and found discriminatory tendencies. For example, in (Gardner et al. 2019; Hu and Rangwala 2020; Riazy and Simbeck 2019). In their review, Baker et al. (2021) criticize the fact that most studies examine discrimination based on gender and race - other characteristics are considered much less frequently. However, especially in the case of discrimination by models in education, other factors are crucial. This is because many studies have already shown that educational success is strongly linked to the social background of the family (Carroll et al. 2019; Lee and Burkam 2007; Steinlen and Piske 2013). Bias in the educational context can become relevant, for example, when implementing dropout prediction models. Dropout prediction models in massive open online courses (MOOCs) or higher education have already been created extensively in many studies

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(Tasnim et al. 2019; Okubo et al. 2017; Stapel et al. 2016; Sun et al. 2019; Wang et al. 2017; Xing and Du 2019).

In our setting, we consider different implementations of a temporal in-session dropout prediction model that has been created in the context of an online learning platform for German spelling and grammar skills. The platform is mainly used in secondary school lessons and offers various exercises in all orthographic domains. Since the temporal in-session dropout prediction model we studied is applied in school lessons, it differs from MOOCs in some respects: the homework assigned there is obligatory for students and the time frame is also not individual, but set by the teachers. Dropouts in MOOCs also differ from dropouts on our platform, as in the German school system you cannot drop through a course, but only through the whole grade level. We therefore consider the in-session dropout, i.e. the early termination of a session without finishing the assignments. From a didactic point of view it is preferable that learners complete a set of excercises in one training session. Dropping out early, e.g. due to frustration, stops the learning process. Despite the differences to MOOCs, we believe it is useful to investigate platforms used in the school context to find out more about the integration of online learning in the classroom.

To evaluate the models in terms of their fairness, we consider not only classical variables such as gender and migration background, but also parental educational background and home literacy environment (HLE). For this purpose, we proceed as follows: first, we will summarize the theoretical foundations of algorithmic bias and fairness and of dropout prediction. Then, we will describe the study setting, including the data set, the in-session dropout prediction models and the different groups for whose discrimination the model is examined. The selected fairness measures will then be calculated per group and model and interpreted.

2 RELATED WORK

2.1 Algorithmic Bias

In education, machine learning based models are used for example in dropout- or at-risk predictions, adaptive learning environments which give personalized feedback and correction, automated scoring systems, or identification of struggling students (Kizilcec and Lee 2020). As interventions, feedback or scoring has a huge impact on the students' educational path, these applications and models should be evaluated regarding fairness. Algorithmic fairness, however, is discussed not only in educational contexts but in almost all aspects of our lives (Hajian et al. 2016; O'Neil 2016).

When talking about algorithmic fairness, the term algorithmic bias is often used as well. However, the terms are not synonymous: in the Merriam Webster dictionary bias is defined as "a tendency to believe that some people, ideas, etc., are better than others that usually results in treating some people unfairly" (Merriam-Webster Dictionary 2021a). Bias can occur in different stages of machine learning, and thus can lead to unfair models. Fairness is defined as "the quality or state of being fair; especially fair or impartial treatment; lack of favoritism toward one side or another." (Merriam-Webster Dictionary 2021b). We therefore start with the description of causes and origins of bias. Later on we introduce disadvantaged groups and describe different fairness metrics.

2.1.1 Causes and Origins of Algorithmic Bias

There are different attempts to define causes or to locate the sources of biases in machine learning models (Pessach and Shmueli 2020). Pessach and Shmueli for example differentiate between four causes. The first one derives from bias in the dataset which is replicated by the machine learning models. The second one describes bias origins from missing data or data selection biases which result in not representative datasets. Further, there could be proxy-attributes which are non-sensitive attributes that derive from sensitive attributes. Lastly, if the goal is to minimize the overall aggregated prediction error, a model could benefit the majority group over minorities (Pessach and Shmueli 2020). Mitchell et al. categorize two components of biased data, statistical bias and societal bias (Mitchell et al. 2021). Statistical bias occurs in the mismatch between the training sample and the reality, e.g., when the dataset is not representative. Societal bias, on the other hand, reflects the world as it is and replicates pre-existing discrimination in reality (Mitchell et al. 2021).

2.1.2 Disadvantaged Groups

There are several groups that can be discriminated against by machine learning model implementations. Some group characteristics are protected by law, such as gender, race, ethnicity, sexual orientation, religion, or disability (Baker and Hawn 2021). However, discrimination goes beyond that. Most research on educational practices focuses on fairness regarding gender, race, and nationality (Baker and Hawn 2021). Research on gender-related discrimination thus defines only two groups of gender (male and female) without considering non-binary or transgenders. Baker and Hawn (2021) argue that there is a huge research gap on bias in education considering other disadvantaged groups, such as urbanicity, socioeconomic status, native language, disabilities, speed of learning or parental education background.

2.2 Definitions and Measures for Fairness

There are various measures of algorithmic fairness, which are comprehensively described in (Kizilcec and Lee 2020; Mitchell et al. 2021; Verma and Rubin 2018). There is no ground truth in measuring fairness and different measures should be chosen based on the context, as they come with different advantages or disadvantages (Pessach and Shmueli 2020). All fairness criteria cannot be satisfied simultaneously (Pessach and Shmueli 2020). Most of the measures are statistical and rely on the confusion matrix: true positive (TP), false positive (FP), false negative (FN), true negative (TN). In their work, Verma and Rubin (2018) group fairness metrics into three categories: Definitions based on predicted outcome (1) focus solely on the predictions for different demographic distributions and do not consider the actual outcome. Definitions based on predicted and actual outcomes (2), on the other hand, consider both. Definitions based on predicted probabilities and actual outcome (3) use the predicted probability score instead of the binary prediction outcome. Kizilcec and Lee (2020) define three statistical notions of fairness: independence, separation, and sufficiency. Independence is satisfied if the protected and unprotected groups have the same opportunity for a predicted outcome. Separation and Sufficiency, on the other hand, go further and do not only consider prediction outcome but also actual outcome. Separation requires therefore that an algorithm's prediction is correct and incorrect at similar rates for different groups (Kizilcec and Lee 2020). Sufficiency is satisfied if the proportions of correctly predicted forecasts are equal across subgroups (Baker and Hawn 2021).

To validate a machine learning model for fairness, accuracy metrics are used to evaluate how much the effectiveness of the predictive model differs between the respective subgroups. Once the difference in accuracy of a predictive model from two groups exceeds a threshold, the algorithm is considered discriminatory because demographic parity is no longer ensured (Riazy and Simbeck 2019).

In the following, we describe four notions of fairness that will be used in the later model evaluation. Note, however, that there are much more measures of fairness extensively described in other work, for example in (Verma and Rubin 2018). We define S as the protected variable, Y as the attribute to be predicted and R as the prediction outcome.

One definition based on predicted and actual outcomes is **predictive parity (PP)**, which is satisfied if both subgroups have equal predictive positive value (Verma and Rubin 2018). Predictive positive value is defined by

$$PPV = \frac{TP}{TP + FP} \tag{1}$$

and often referred to as precision. Formally, predictive parity is defined as:

$$P(Y=1|R=1, S=s1) = P(Y=1|R=1, S=s2) \tag{2}$$

Predictive Equality (PE) is a classifier satisfied if both subgroups have equal false positive rates (Verma and Rubin 2018). False positive rate is defined by

$$FPR = \frac{FP}{FP + TN} \tag{3}$$

Respectively, predictive equality is defined as:

$$P(R=1|Y=0, S=s1) = P(R=1|Y=0, S=s2) \tag{4}$$

Equal Opportunity (EO) is satisfied, if both groups have equal false negative rates (Verma and Rubin 2018). False negative rate is defined by

$$FNR = \frac{FN}{TP + FN} \tag{5}$$

Subsequently, equal opportunity is defined by:

$$P(R=0|Y=1, S=s1) = P(R=0|Y=1, S=s2) \tag{6}$$

Slicing Analysis (SA) demands equal AUROC. The receiver operating characteristic curve plots TPR against FPR at different thresholds. From that the area under the curve can be calculated using an integration process.

2.3 Dropout Prediction

Predicting students' dropout is one of the major research interests in educational data mining (Dalipi et al. 2018; Luan and Tsai 2021). Many investigations focus on student dropout in MOOCs and higher education (Dalipi et al. 2018; Prenkaj et al. 2020). The huge dropout rates can either be student-related, MOOC- related, or both (Dalipi et al. 2018). Student-related reasons for dropping out are especially lack of motivation, but also lack of time or insufficient background knowledge and skills (Dalipi et al. 2018). Course design or lack of interactivity, as well as hidden costs, are MOOC-related reasons for dropping out (Dalipi et al. 2018). Other than in MOOCs, dropout in higher education is defined differently, for example by learning behavior, by passing a course, or earning a certificate (Sun et al. 2019).

The data for dropout prediction models is mostly student engagement data, clickstream data (Dalipi et al. 2018), or student behavior data (Jin 2020). Other features can describe the student demographic, assignment grades, or social network analysis (Sun et al. 2019). Liang et al. (2016) define the data flow in dropout prediction models in eight stages. First, there is the user raw behavior log containing raw data. After that, the data is cleaned and pre-processed which results in a user table and action table. Then, feature engineering is performed and, if necessary, the predictors are labeled. The data is subsequently split into training and test sets and a binary classification model is tuned. As a result, and the last stage of data flow, the predictive model is calculated.

Prenkaj et al. (2020) differentiates between two cases of dropout prediction: plain dropout formulation and recurrent dropout formulation. While the plain dropout formulation is independent in time, the recurrent dropout formulation uses information from previous phases/ weeks to predict the dropout status of a student. Xing and Du (2019) define similar categories which they call fixed-term and temporal dropout prediction. Temporal models are modeled for each week separately and use data only until the current week. The advantage of this is that developments during the course are considered and interventions can be made each week. In temporal dropout prediction, course activity features change within each week whereas profile data or course data features are static (Hagedoorn and Spanakis 2017).

The prediction strategy can be classified into three categories: analytics examination, classic learning methods, and deep learning (Prenkaj et al. 2020). Analytic examination describes the use of basic statistics while classic learning methods include traditional machine learning models. The most commonly used machine learning algorithms in student dropout prediction are logistic regression, decision tree classifier, and support vector machines (Dalipi et al. 2018). However, various models have been implemented to tackle different purposes of dropout prediction. Sun et al. (2019), for example, used a temporal model based on a recurrent neural network (RNN). This is advantageous because there is no need for feature engineering as the clickstream log data can be directly fed into the model. To perform a temporal prediction mechanism, Xing and Du's model is as well built using a deep learning algorithm, which calculates dropout probability rates to prioritize interventions for at-risk students (Xing and Du 2019). Wang et al. (2017) proposed a combination of a convolutional neural network and recurrent neural network for a dropout prediction model to be able to skip the manual feature selection process. Other researchers use Ada boost (Hagedoorn and Spanakis 2017), random forest (Del Bonifro et al. 2020), or survival analysis (Chen et al. 2018).

In their review, Shahiri et al. (2015) discussed important attributes on predicting student performance. One of the most frequent attributes is cumulative grade point average (CGPA), which has been shown to be the most significant input variable in a coefficient correlation analysis (Shahiri et al. 2015). Internal assessments, for example in a quiz or assignments are another valuable attribute to predict student performance. Attributes of students demographic include gender, age, family background, and disability and are as well often used (Shahiri et al. 2015). Further attributes are extra-curricular activities, high school background, or social interaction network (Shahiri et al. 2015).

3 RESEARCH QUESTIONS & STUDY SETTING

Although there are many articles on dropout prediction models, this paper explores some aspects that have not been studied before. We investigate the discriminatory potential of in-session dropout prediction models, not classical MOOC dropout predictions. Furthermore, we consider different fairness metrics and compare different ML implementations. We also consider rarely studied demographic features, such as HLE and parental education. Our research questions are therefore as follows:

RQ1: How fair are in-session dropout prediction models considering different fairness measures?

RQ2: What is the potential for discrimination by in-session dropout prediction models for different demographic groups?

RQ3: How do different ML implementations of prediction models differ with respect to their discrimination potential?

Our data is obtained from the platform orthografietrainer.net, an online learning platform for the acquisition of spelling skills of the German language. The in-session dropout prediction model was trained with learning process data from this platform and predicts whether a user will end a session early or not. A session is considered exited early, if the session is left without completing the assigned set of exercises.

The goal is to be able to intervene during the processing of an assignment to support the user in successfully completing the session. The evaluation of the model in terms of fairness will look at different demographic groups. To find out about the users' demographic characteristics, a survey is carried out. The prediction model is then applied to the different groups and the results are examined with different fairness metrics. In the following, the study is described by the data set, the prediction model, and the fairness evaluation method.

3.1 Data Set

The online learning platform orthografietrainer.net offers exercises for spelling and grammar skills, for example for capitalization, separate and compound spelling, or comma formation. The target group ranges from fifth grade to graduating classes, as well as users from adult education or students at university. The platform is mainly used by teachers to assign homework to students, which can then be solved on the platform. The users receive automated corrections, and the teachers can then view an evaluation. Due to the Covid-19-pandemic, access numbers have risen sharply, which shows that the platform was used in distance learning formats.

The data set consists of 181,792 sessions from 52,032 users and all assignments were performed between 1st of March and 31st of April 2020.

To measure fairness, we use both, variables that derive from the registration process such as gender, and variables obtained in a survey that could be answered voluntarily by users of the platform. The survey collects data on people's social background, the importance of school grades, interests and enjoyment of German lessons. It is automatically displayed to each user three months after registration on the platform. A total of 2749 people took part in the survey from March to June in 2020.

A peculiarity of the platform is the structure of the exercises: If the teacher assigns an exercise to a class, this task is displayed to the students as pending. Exercises consist of 10 sentences devoted to a specific orthographic area, for example, capitalization. If a mistake is made while working on the task, new variations of the exercise sentences are added, and the task expands dynamically. Before a session is finished successfully, all previously wrong sentences are displayed at the end of the session again. As a result, exercises can consist of 60 or more sentences if many mistakes are made. Consequently, a session must at least consist of ten sentences if the assignment is finished without mistakes. It can thus be finished successfully with more than ten sentences if the previously wrong sentence is answered correctly later and the versions of this sentence are answered correctly too. Figure 1 shows the count of sentences an their sentence number. Some session have been exited before the tenth sentence and are thus unsuccessful. There is as well a drop after the tenth sentence, which shows all the sessions that are successfully ended without any mistakes.

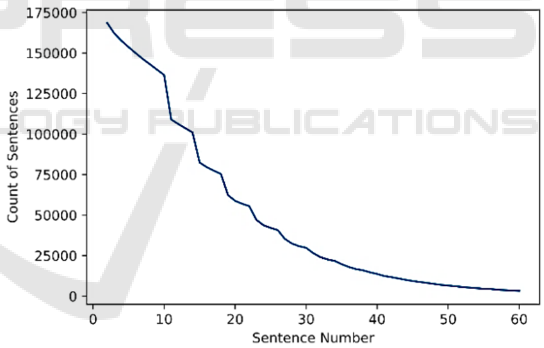


Figure 1: Count of Sentences and Sentence Numbers.

3.2 In-session Dropout Prediction Model

As stated above, the platform orthografietrainer.net is mostly used in blended-classroom scenarios, for example by assigning homework on the platform. Traditional prediction models cannot be applied on that case, as the whole setting is different: instead of a self-contained course, individual homework assignments and exercises are carried out on online platforms that accompany school lessons. A course dropout as in MOOCs or in higher education courses is therefore not as transferable. To deal with this scenario, an in-session dropout prediction model is applied. This is a temporal prediction model that predicts for each exercise sentence of an assignment whether a user will leave the session early or not. Instead of a course dropout, an early exit of the session is thus predicted. Herewith, different machine learning models have already been tested in previous studies to obtain a termination prediction within a session (Rzepka et al. 2022). The temporal dropout prediction model includes assignment and user features which are either obtained directly from the platform's log data or calculated in the feature engineering process. The model uses on the one end demographic attributes such as gender, class level, or user group and assignment features on the other hand such as count of correct processed tasks, field of grammar, difficulty of the sentences, or count of pending tasks. To construct a temporal dropout prediction, matrices are defined which include only the processed tasks until the current sentence position. Consequently, the prediction is re-run after each sentence is processed and improves as the number of sentences increases.

As a result, the Deep Learning Model (DL) showed the highest accuracy up to 87%. This is followed by the Decision Tree (DT) with a maximum value of up to 85%. Furthermore, k-nearest neighbor (KNN) and logistic regression (LogReg) were tested but showed lower accuracies (Figure 1). The F1-score shows best results for the deep learning model followed by the decision tree classifier. Lower scores are calculated for KNN and logistic regression. All models improve strongly during the first ten sentences and flatten out after. For the subsequent calculations regarding fairness, the best models (DL and DT) and one of the less good models (KNN) are considered.

3.3 Fairness Evaluation

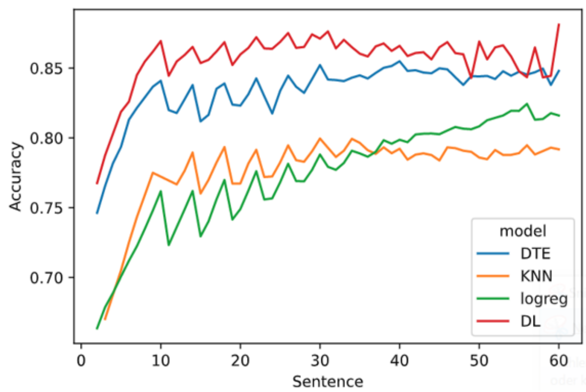
Our aim is to evaluate the in-session dropout prediction model regarding fairness. For our analysis, we therefore examine the performance of the predictive model on four variables:

- First spoken language
- parents' education
- number of books in the household
- gender

The first language attribute describes the language the user has learned first at home (mother tongue) and is an indicator for migration background. Spelling skills and children's literacy as a whole have been found to be linked to migration background and level of education of parents (Carroll et al. 2019; Lee and Burkam 2007; Steinlen and Piske 2013). In households where German is not the first language, children tend to have poor results examining language skills (Steinlen and Piske 2013). We split the data by students whose first language was German and all other languages.

Regarding the question about the parents' education background in the survey, the users could answer 0, 1 and 2. In our study we distinguish between users with at least one parent with a high school diploma and parents without a high school diploma and thus grouped the answers of 1 and 2.

The third variable is the number of books in the household, which is often part of questionnaires measuring cultural capital (Noble and Davies 2009) and hereby used as an indicator for home literacy environment (HLE). Several studies linked the HLE to children's literacy skills (Carroll et al. 2019;



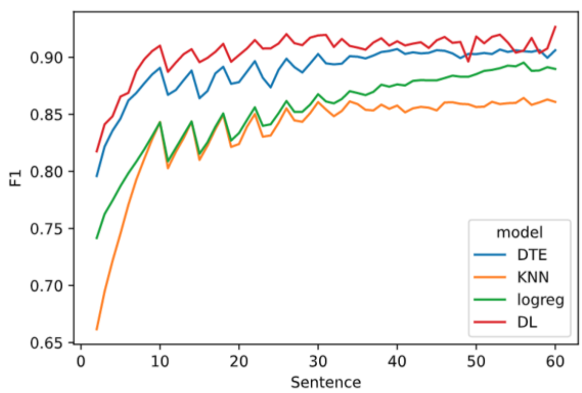


Figure 2: Accuracy and F1-Score per Sentence and Model (DTE=Decision Tree Classifier, KNN=k-Nearest Neighbor, logreg=Logistic Regression, DL=Deep Learning).

Griffin and Morrison 1997; Sénéchal and LeFevre 2002). For the number of books in the household, four answers were possible in the survey: less than ten books, more than 10 and less than 50 books, more than 50 and less than 100, more than 100. We split the user in two groups, one having less than 10 books in their household and the other having more than 100. In this attribute, we deliberately consider only the edge cases, as we have seen that the differences are otherwise too small and number of books in the household is only estimated by the students.

The last attribute describes the user's gender, which can be male or female. This variable is not obtained by the survey, but during the registration process. Moreover, the attribute is part of the training data as well, while the other three attributes are not.

After splitting the user groups according to the variables as described above, we join them with the learning process data of the respective users. To have temporal predictions, we build matrices for each sentence position. This results in 60 matrices containing the information for the current sentence and all previous ones. A matrix can thus be defined as $x_i^{previous}$, where i describes the sentence position. We then predict the early exit of the sessions with the three pretrained models, the decision tree classifier, the deep learning model, and the k-nearest neighbour model. As these are temporal dropout prediction models, we have 60 predictors for each session and each model.

To evaluate model performance, we use the metrics Predictive Parity (PP), Equal Opportunity (EO), Predictive Equality (PE) and Slicing Analysis (SA), which are described in section 2. It should be noted that PP and SA are interpreted differently than EO and PE. As PP and EO rely on precision and AUC positive results are best. EO and PE, on the other hand, rely on FPR and FNR and therefore negative results are best. To be able to compare results, we specifiy the directions of how the fairness measures are calculated so that in all cases, a positive outcome is to the benefit of the advantaged group, a negative outcome to the benefit of the protected group.

The protected groups are male (gender), other than German (first language), no high school diploma (parental education), less than 10 books (books in the household). PP and SA are calculated by

$$= \mathit{not\,protected} - \mathit{protected} \tag{7}$$

EO and PE, on the other hand are calculated the opposite way

$$= \mathit{protected} - \mathit{not\,protected} \tag{8}$$

It cannot be expected that there are no differences in model quality between groups, so it is important to define thresholds that delineate from fair to unfair. Different thresholds were defined in previous studies, such as 0,04 for equal opportunity by (Chouldechova 2017), 0,05 for predictive parity, and 0,02 for slicing analysis by (Riazy and Simbeck 2019) and 0.01 as well as 0.03 for slicing analysis by (Gardner et al. 2019). We set the thresholds to $Ths_{low} = |0{,}03|$ (lower threshold) and $Ths_{high} = |0{,}05|$ (higher threshold).

As a temporal dropout prediction model calculates predictors for each of the up to 60 sentences, we as well have 60 results per model and fairness measure. To be able to interpret the results more easily, we calculate the mean for each ten sentences, leading to six results per model and fairness measure.

4 RESULTS

In the following, we will present the results regarding the model fairness for first language vs. second language learners, users with high/low parental education, users with high/low number of books in the household, and gender. The attribute first language (Table 1) is fair according to the metrics predictive parity, equal opportunity, and slicing analysis. All three measures remain below the threshold of $Ths_{low} = |0{,}03|$ and $Ths_{high} = |0{,}05|$ for each model. Predictive equality, however, shows values lower -0,03, and for the decision tree and KNN model even lower -0,05. As the protected group is defined as users, whose first language is not German, the model quality is slightly better for learners with German as a 2nd language, as fewer false-positive dropout predictions are found for them.

Parents' education (Table 2) is similar regarding predictive parity and equal opportunity, as they remain below the threshold. Predictive equality and slicing analysis, on the other hand, show disparities above the thresholds of 0,05 in the last ten sentences. As the protected group is defined as users with parents without a high school diploma, the model quality is slightly higher for users with at least one parent with higher education, fewer false positives are encountered for them. Moreover, in the deep learning model, inequalities are starting earlier, already as of the 20th sentence.

Table 1: Results of the metrics Predictive Parity (PP), Equal Opportunity (EO), Predictive Equality (PE), and Slicing Analysis (SA) for the attribute first language. Models: DL=Deep Learning , DTE=Decision Tree Classifier, KNN=k-Nearest Neighbor.

	EO			PE			PP			SA		
model	DL	DTE	KNN	DL	DTE	KNN	DL	DTE	KNN	DL	DTE	KNN
Sentence												
2 to 9	-0,032	-0,028	-0,028	-0,042	-0,041	-0,041	0,010	0,013	0,013	0,002	-0,007	-0,007
10 to 19	-0,024	-0,025	-0,025	-0,050	-0,058	-0,058	0,004	0,003	0,003	-0,001	-0,017	-0,017
20 to 29	-0,024	-0,026	-0,026	-0,034	-0,057	-0,057	0,006	0,005	0,005	0,003	-0,016	-0,016
30 to 39	-0,022	-0,016	-0,016	-0,036	-0,030	-0,030	0,007	0,009	0,009	0,007	-0,007	-0,007
40 to 49	-0,019	-0,014	-0,014	-0,044	-0,046	-0,046	0,008	0,008	0,008	0,004	-0,016	-0,016
50 to 60	-0,016	-0,014	-0,014	-0,019	-0,041	-0,046	0,014	0,014	0,014	0,006	-0,013	-0,016

Table 2: Results of the metrics Predictive Parity (PP), Equal Opportunity (EO), Predictive Equality (PE), and Slicing Analysis (SA) for the attribute parents education. Models: DL=Deep Learning , DTE=Decision Tree Classifier, KNN=k-Nearest Neighbor.

	EO			PE			PP			SA		
model	DL	DTE	KNN	DL	DTE	KNN	DL	DTE	KNN	DL	DTE	KNN
Sentence												
2 to 9	-0,020	-0,022	-0,022	-0,002	-0,007	-0,007	0,002	0,002	0,002	0,009	0,008	0,008
10 to 19	-0,013	-0,022	-0,022	-0,029	-0,030	-0,030	-0,001	-0,001	-0,001	0,007	-0,004	-0,004
20 to 29	-0,005	-0,010	-0,010	0,030	0,0180	0,018	0,004	0,004	0,004	0,005	0,014	0,014
30 to 39	-0,005	-0,004	-0,004	0,047	-0,010	-0,010	0,007	0,004	0,004	0,004	-0,003	-0,003
40 to 49	-0,004	-0,005	-0,005	0,044	-0,009	-0,009	0,009	0,006	0,006	-0,007	-0,002	-0,002
50 to 60	-0,026	-0,021	-0,021	0,133	0,111	0,111	0,016	0,015	0,015	0,058	0,066	0,066

Table 3: Results of the metrics Predictive Parity (PP), Equal Opportunity (EO), Predictive Equality (PE), and Slicing Analysis (SA) for the attribute number of books in household. Models: DL=Deep Learning , DTE=Decision Tree Classifier, KNN=k-Nearest Neighbor.

	EO			PE			PP			SA		
model	DL	DTE	KNN	DL	DTE	KNN	DL	DTE	KNN	DL	DTE	KNN
Sentence												
2 to 9	-0,065	-0,051	-0,051	-0,102	-0,122	-0,122	0,011	0,010	0,010	-0,008	-0,035	-0,035
10 to 19	-0,046	-0,050	-0,050	-0,133	-0,147	-0,147	0,006	0,002	0,002	-0,005	-0,049	-0,049
20 to 29	-0,042	-0,044	-0,044	-0,079	-0,107	-0,107	0,012	0,010	0,001	-0,003	-0,032	-0,032
30 to 39	-0,034	-0,029	-0,029	-0,067	-0,103	-0,103	0,010	0,009	0,009	0,003	-0,037	-0,037
40 to 49	-0,031	-0,017	-0,017	-0,163	-0,119	-0,119	0,001	0,007	0,007	-0,041	-0,051	-0,051
50 to 60	-0,045	-0,043	-0,043	-0,213	-0,090	-0,097	0,006	0,022	0,021	-0,076	-0,024	-0,027

Table 4: Results of the metrics Predictive Parity (PP), Equal Opportunity (EO), Predictive Equality (PE), and Slicing Analysis (SA) for the attribute gender. Models: DL=Deep Learning , DTE=Decision Tree Classifier, KNN=k-Nearest Neighbor.

	EO			PE			PP			SA		
model	DL	DTE	KNN	DL	DTE	KNN	DL	DTE	KNN	DL	DTE	KNN
Sentence												
2 to 9	-0,022	-0,029	-0,029	-0,036	-0,049	-0,049	0,008	0,008	0,008	-0,001	-0,010	-0,010
10 to 19	-0,011	-0,026	-0,026	0,003	-0,018	-0,018	0,009	0,007	0,007	0,007	0,004	0,005
20 to 29	-0,009	-0,021	-0,021	0,017	-0,011	-0,011	0,009	0,007	0,007	0,007	0,005	0,005
30 to 39	-0,003	-0,009	-0,009	0,008	-0,006	-0,005	0,006	0,006	0,006	0,009	0,001	0,002
40 to 49	-0,006	-0,006	-0,005	-0,079	-0,109	-0,109	-0,001	-0,003	-0,003	-0,003	-0,052	-0,052
50 to 60	0,001	0,003	0,003	-0,149	-0,155	-0,160	-0,003	-0,003	-0,003	-0,031	-0,079	-0,081

For the number of books in the household (Table 3) we do only consider users with less than ten books and more than 100 books. Here, predictive parity shows no inequalities. Equal opportunity, predictive equality, and slicing analysis show values less than -0,03 and -0,05, which suggests the model quality is better for users with less than ten books. Specifically, for learners from households with many books, more false positives and false negatives are encountered as well as a lower value of AUC

Predictive parity and equal opportunity show again only values below the threshold for the gender attribute (Table 4). Predictive equality and slicing analysis are thus lower than -0,05 for the last 20 sentences. This means that the models are of higher quality for boys.

When distinguishing between the different machine learning models, we see few differences. Most of the time, either all three values are above the threshold or they are not.

5 CONCLUSION AND OUTLOOK

In our study, we evaluated an in-session dropout prediction model regarding fairness for four different variables which are known to have impact on children's literacy skills. We explored the following research questions:

RQ1: How fair are in-session dropout prediction models considering different fairness measures?

RQ2: What is the potential for discrimination for different demographic groups?

RQ3: How do different ML implementations of prediction models differ with respect to their discrimination potential?

The results with regards to research questions 1 and 2 are mixed. The fairness measure of predictive parity never exceeds the threshold. This means, that the probability for a predicted early termination to truly terminate the session early is equal for protected and unprotected groups. The same holds true for equal opportunity, except for the HLE attribute. The probability of session termination which was incorrectly predicted to be a successful session is higher for users with more than 100 books in the household. If the model outcome leads to interventions, these users would not get the intervention they need, as the model would predict them to successfully finish the session. In contrast, predictive equality is above the threshold for all attributes. This means that a successfully finished session is incorrectly predicted as an early termination. In an educational setting, this leads to interventions for users who would not need them. Depending on the intervention, this can hinder users to achieve high levels of learning, for example, if tasks are adjusted based on the prediction. Slicing Analysis is as well often above the threshold.

The results have shown that the fairness of a model is assessed differently by various definitions. It is a matter of context which definitions should be used, and which are more important than others. In an educational setting, users who don't receive help and interventions although they need it, are as poor as users who do not reach high levels of learning although they would be able to accomplish it.

With regards to research question 3, we see that different implementations do not make much difference in evaluation in terms of fairness.

However, interesting correlations emerge in the temporal analysis. The longer the session, the more data about the user is available, the better the accuracy, but at the same time, the fairness decreases. This may indicate that the additional data in longer sessions can be used to improve the prediction, but at the same time may also have a discriminatory influence. This results in a trade off between accuracy and fairness. This is particularly evident for the variables parental education background and gender.

Another interesting finding is that discrimination is higher for variables that are not balanced (such as number of books in the household). The attribute gender, on the other hand, is fairly well balanced and also has the lowest disparities.

Overall, our work shows that in-session prediction models can be discriminatory. However, this is largely dependent on three factors: on the one hand, different metrics produce different results; on the other hand, different demographic subgroups can be found in user groups, which can be affected by discrimination to different degrees; at the same time, training data (in our case, sentence numbers) have an influence and fairness decreases with higher model accuracy. In our study, ML implementation did not affect the fairness of the model.

Our study comes with several limitations which need to be considered in further interpretations. First, the survey for three of four attributes is conducted voluntarily among users. This results in a selection bias, as we only investigate data of users who were willing and motivated enough to answer the survey. Secondly, the variable gender was part of the model's training process while the other attributes were not. Last, the attributes parental education and number of books in the household are grouped in two, although more than two answers were possible in the survey.

Our research has shown that temporal dropout prediction, even in in-session scenarios, is at risk to discriminate different groups. We see three factors that affect the fairness of the model: 1) different fairness metrics, 2) demographic groups, 3) different training data. We therefore suggest always evaluating predictive models using several measures and placing the results into context. Furthermore, our analysis has shown, that it is important not only to evaluate discrimination with regard to gender or migration background but to extend the examination to variables that are known to have an impact on the educational path, such as parental education or HLE. Further research should consider ways to address the disparities through pre-, in-, or post-process methods.

Our work looks at the evaluation of an online platform specifically for teaching German. Nevertheless, our research can be transferred to other subjects. Especially platforms that are used in a school context are used in particular for assigning homework, like Orthografietrainer.net. However, transferring MOOC dropout predictions is not possible and the use of our approach is recommended.

Again, it is important to look at multiple measures, as improving one definition of fairness can lead to a worsening of another.

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