AI-based STEM education: Generating individualized exercises in mathematics

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Abstract

During the COVID-19 pandemic, the trend towards self-directed learning at universities received a strong boost. However, some students show considerable deficits regarding their self-learning competences. These become especially apparent in the first semesters, creating gaps in the students' knowledge which will not only slow down their progress in later semesters but may even lead to their dropping out of university altogether. For this reason, several approaches in the field of mathematics teaching attempt to prevent knowledge gaps from the very first week of studies, usually by employing educational instruments such as peer feedback or corrected homework. Despite these efforts, dropout rates in STEM subjects *remain high. We propose to address this problem with an instructional design based on AI algorithms which create mathematical exercises, tailoring their degree of difficulty individually to fit each student's skills and speed. Our hypothesis is that this individualized training will keep students from feeling overwhelmed and increase their motivation to study. As the exercises depend on many parameters to determine the appropriate degree of difficulty, they are adjusted iteratively, based on final or intermediate results of previously processed tasks and Learning Analytics data through Bayesian optimization.*

Keywords: AI-supported task creation, STEM Education, Personal Learning Environment, Bayes optimization (BO)

1. Introduction

Higher education has never been as accessible as today, with more and more students enrolling in university. Many of them, however, will quit within a few semesters. Despite their high standing in both economy and society, STEM subjects present an especially high dropout rate. At German (technical) universities focusing on applied sciences, about 34% of students quit without obtaining a degree. With a dropout rate of 41%, electrical engineering shows the highest turnover within the student body.[1]

But what makes all these students abandon their lessons? One of the reasons might be an insufficient number of teachers and tutors to offer individual support.[2] At the same time, several projects in the educational sciences show that first-year students often struggle with a lack of competence regarding self-directed learning.[3] Representative studies also confirm that – at least at German universities – students feel especially overwhelmed by the task of applying scientific methods to self-directed learning.[4] In addition to all this, the prerequisites for successful studies are different for each academic subject. Some fields require first-year students to be independent in their pursuit of knowledge, while others allow for a slower transition from pre-organized school life to self-organized higher education.[5] Taking into consideration how differently schools prepare students for this, so-called "directive" forms of tutoring turn out to be highly efficient, as they allow tutors to direct the learning process in accordance with the students' skill levels.[6]

Today, most German universities use digital Learning Management Systems (LMS) such as Blackboard, Moodle, ILIAS, or D2L. These systems are not only used to present content, they are also versatile management tools, allowing teachers to create exercises, organize and evaluate their classes, and communicate with students.[7] However, LMS are also criticized for perpetuating a behaviouristic approach to learning. It is still the teachers who create the curriculum, conveying only a very limited scope of the flexibility modern technology in education might allow.[8] As a unilateral approach to teaching cannot take into account heterogeneous knowledge, even well-structured seminars may lead to knowledge gaps, as students fail to keep up.

This lack of flexibility, however, also leads us to one of the possible applications of Artificial Intelligence (AI) in higher education. Deep neural networks are what makes AI indispensable for many

applications in image recognition and speech processing. For predictions based on small datasets (5–1.000 data points, typical for applications which simulate human perception), Gaussian processes (GP) are state-of-the-art.[9] Bayesian optimization (BO) is usually employed to optimize parameters when using such small datasets.[10] With an iterative process, BO captures more data, thereby allowing us to choose parameters which promise reliable predictions based on GP or suggesting further exploration to improve the robustness of the model. In higher education, GP models are already in use [11,12,13] but neither for the creation of exercises nor with BO to improve their performance.
In this paper, we address one of the most important reasons for the high dropout rate in STEM subjects: Mathematics. Using BO to adapt the difficulty of mathematical exercises to the skill level of each student, we propose an approach to differentiation which will allows for individual support, directing students with prior knowledge towards more difficult tasks while allowing students with gaps in their knowledge to practice the basics.

2. Concept

This concept has been developed as part of a design-based research project. It focuses on the creation of an AI-based tool for mathematical exercises which is meant to help students in STEM study mathematics and – in the long run – reduce the dropout rate. Our approach is both iterative and cyclical, i.e., the concept is refined by several iterations of application, each followed by a cycle of exploration, re-design and empirical evaluation.[14,15]
This paper outlines the development of a prototype and our assessment of the risks and potential of AI-based applications in higher education. First, we take a closer look at the AI architecture necessary for this project, then we focus on the students' side of the endeavour: How can an AI-based tool gain acceptance as a learning aid – and is there a risk of AI discriminating against students?

2.1. The technology behind the tool

Mathematical exercises are easily scaled to make them more or less challenging: Change parameters such as the number of variables or types of calculation involved, and the difficulty changes accordingly. We envision to use this parameterization for an AI tool which matches exercises to students' skill levels.
First, we task the AI with predicting the probability of a student correctly solving a certain exercise. This way, teachers can use simple tasks to introduce their classes to new topics, and then increase difficulty to match individual speed and skill. The advantages of such differentiation are obvious: Working on exercises tailored to their knowledge ensures that students see constant progress and stay motivated – the risk of frustration due to overly complex tasks is dramatically reduced. At the same time, the AI creates an efficient feedback loop, automatically correcting the students' work, recognizing gaps and providing appropriate follow-up exercises. If new aspects of an exercise seem too hard for a student, the system will automatically switch to repetition.
The AI aims to provide exercises which students will correctly solve with a probability of σ. To ensure long-term success, the parameter σ must be empirically based on factors such as student motivation. For this, we suggest $\sigma \approx 80\%$ as a starting point. Motivation should always be a priority as it determines whether or not the training sessions are completed. In order to keep students engaged, the first exercises introducing them to new topics must be especially well-designed – and to do this, we need high-quality GP models to create an a-priori model from little to no datapoints.
When a student S first works on an exercise E, there is no data the model could use to predict the outcome. There is, however, data from other sources: We suggest using datapoints from other students S' who have already worked on exercise E. At the same time, we compare the performance of students S and S' by comparing their work on other types of exercise E'. This data may then be compared with the results of past semesters or even other universities – provided, of course, that the students' anonymity can be guaranteed.
In this context, Learning Analytics help us understand the data surrounding the learning process. This, in turn, helps us support the students – with prediction, intervention, recommendation, reflexion and iteration.[16] Identifying and supporting students who are at risk of dropping out[17] improves these students' odds of graduating and the overall quality of education.
Fortunately, universities provide researchers with an abundance of data which can be used to drive Learning Analytics. To name just one example: A Technical University in Germany may use the LMS ILIAS for the seminars "Mathematik 1–4". This means that around 200–250 students in Electrical Engineering and Computer Engineering use this system every year to download scripts and notes, work on exercises, and communicate through group forums.

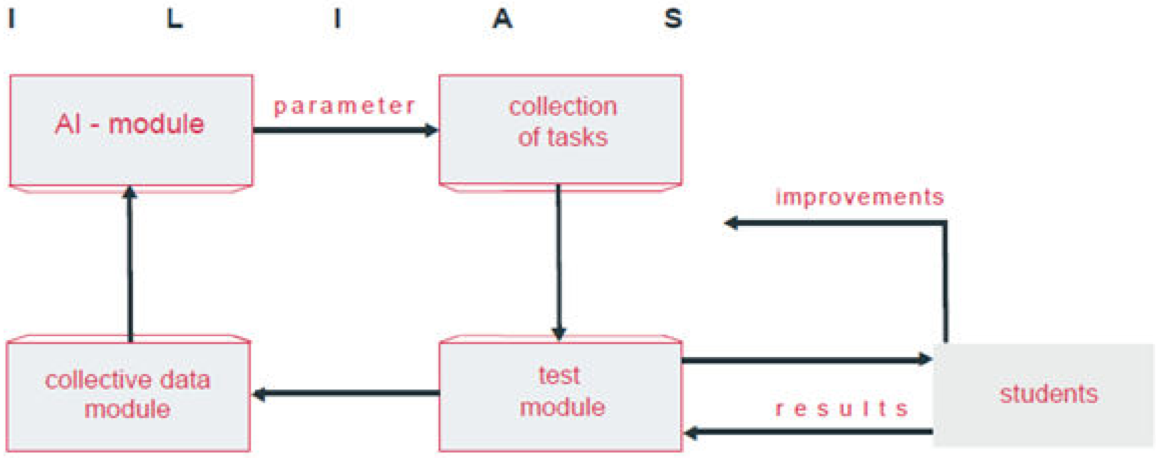

Fig. 1 Visualization of the research design

2.2. The educational concept behind the AI tool

When it comes to digital education, AI is regarded as one of the most groundbreaking technologies of our time.[18] German universities, too, are starting to integrate it into their educational concepts[19], albeit usually in the form of third party solutions such as chatbots or assistance systems. Considering the amount of sensitive user data collected by these applications, the number of on-site solutions is still surprisingly low.

Compared to international competitors, the German education system has only just begun to tap into the potential that is AI in education. Possible reasons for this slow advance are – among other things – open questions regarding ethics and data protection. Some, for example, argue that the human perspective makes education what it is today, and that it would be unethical to let machines evaluate students. Others worry about the potential for discrimination: If the machine does not need to explain why it does what it does – could its seemingly objective results not be abused to discriminate against certain people or groups? And then, from a purely legal point of view, there is also the issue of information privacy: If AI is to be integrated into higher education, the students' right to data privacy must be protected at all times.[17,20]

Furthermore, German universities have not involved their students in the debate on AI. As a study conducted by the Institute for Internet and Democracy shows, neither the students' opinions nor their acceptance play any role in the universities' current concepts for AI-based educational programs.[20] At the same time, though, it seems safe to assume that the students' opinions on AI will prove crucial for its successful application in this field.[21]

These aspects – ethics, data security and acceptance – are to be studied with our AI-based tool. We are already collecting data for the seminars "Mathematik 1–4" (Prof. Heiss, Prof. Lange-Hegermann), reviewing, among other things, student interaction with the software, polls included in our prototypes, and interviews with focus groups to gauge the students' reaction to the AI. A longitudinal study (mixed methods design) accompanies this iterative and cyclical collection of data.

3. Conclusion

With the number of students enrolling in university on the rise and with different subjects demanding very different levels of self-organization, there is an increasing demand for e-learning concepts to support students at risk of falling behind. The concept presented in this paper offers a new perspective on the application of individually tailored exercises. Our project focuses on the often dramatically different levels of skill and experience first-year students display, as they are strongly linked to the pace at which these students acquire knowledge during their first semesters at university.

By offering individual tutoring in the first semesters, we hope to decrease the dropout rate in STEM subjects and improve the overall quality of tutoring. At the same time, our project is also meant to provide new data on the possible applications of AI in higher education – which, as research on AI as an educational tool progresses, may be used to lay the empirical groundwork for the development of new models and prototypes.

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