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Based on Personalized Content: Addressing Homogenization in AI-Supported Learning Through the Smart Mistake Solver

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Abstract. The adoption of artificial intelligence allows for an advancement in personalized learning, since the development of diverse types of learning materials and content may not succeed in always developing highly personalized experience. This article will explore personalized learning in relation to the homogeneity of a course program design based on an example of the Smart Mistake Solver program, an artificial intelligence learning assistance tool, which detects and corrects students' mistakes while dealing with math problems. The process of error detection, student model created with the help of Bayesian Knowledge Tracing (BKT) and development of personalized content are crucial aspects of the artificial intelligence support in learning. The conceptual analysis of Smart Mistake Solver demonstrates the limitations of artificial intelligence in enhancing personalized learning, which are conditioned by the necessity to use a list of predestined errors and measurable performance metrics. In conclusion, it was found that meaningful personalization should occur with respect to the specific needs of each learner within a learning experience along with distinction of learning materials; these cannot be fully met in all cases with the help of artificial intelligence.

Keywords: Personalized learning, Educational homogenization, Artificial intelligence in education

1. Introduction

Recently, digital technologies have been rapidly developing, leading to traditional technology education methods becoming obsolete. The COVID-19 pandemic has hastened the use of the digital teaching environment among educational institutions. Therefore, it has contributed to the use of instructional technology in education as well as demonstrating the variety of requirements of different learners. In conventional learning settings, learners have the opportunity to learn from their mistakes as the teacher can inspect the entire class, make inquiries, and directly communicate with them. However, this is not always possible in larger digital-learning facilities, as the learning body/source generally retreats into a standard set of either curriculum development or review.

One of the new methodologies that attempts to solve this dilemma is personalized learning. This model believes it is necessary to adapt how instruction is being provided to each and every learner's preferences/information needs. A personalized learning system must essentially involve engagement

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in customized information delivery, but it should also understand various characteristics among students in real-time and make changes accordingly.

The invention and advancement of artificial intelligence have opened up more ways of employing personalized learning. An example of an intelligent tutoring system (ITS) could contain a student model along with knowledge tracing in order to analyse the knowledge status of any single learner in order to change the instruction parameters such that he/she is motivated and engaged throughout the learning process [1-3]. Use of generative AI technology entails the assumption that the ITS can deliver an explanation, hints, or practice exercises based on the student's individual learning style and patterns [4]. The current analysis of intelligent tutoring systems (ITSs) shows that educational technology is capable of holding more interactional and adaptive learning processes [3, 4]. The utilization of this new technology allows the educational system to take into account not only whether the student has the right answer, but also the types of mistakes made or learning dysfunctional behaviours that signal to the instructor that more attention is needed in that area [5].

2. Literature review

However, different content that an AI produces does not imply successful personalization [6]. To effectively personalize learning using AI, the first step must be to understand student learning and determine which differences among students must be addressed [1, 3]. This is usually accomplished by leveraging typical learning models, types of learning errors, types of knowledge, and other theories of pedagogy [3, 7]. To elaborate, two students might arrive at a similar wrong answer to the same question because of a gap in their knowledge about the topic, a math error, or simply inability to stay focused. Therefore, if the AI learning system decides to classify both students in the same way, and apply the same rules to facilitate learning for both students, it may fail to recognize that these students require different types of educational support. Even if there are different prompts and feedback provided for each student, as well as different content developed through the AI, the approaches to support and understanding characterizing particular students within their learning do not change, because the AI learning system assumes the same conditions to interpret behaviors of all students.

Because of that, as one examines the outputs of any AI system, it would seem to the student as though the system had been personalized to him or her and adapted to each different learner. However, there is a concern about the process of the categorization of students based on the standardization of the categorization method and delivery method that has been utilized. In this paper, the term homogenization will be explained as the process of categorizing different students into the whole set of existing categories without accounting for differences in their educational needs and making the same generalizations based on certain educational experiences. Despite extensive investigation into the application of AI and various adaptive technologies, little attention has been paid to the implications of learning system development towards producing uniformity in educational experiences.

This points to an important challenge in the field of educational technology lending to the necessary questions researchers must wrestle with: How can intelligent learning systems ensure true personalization of the educational process while not creating uniformity in educational experiences?

To illustrate how the problem of the clash between individualized education and standardization might occur in practice, the example of the "Smart Mistake Solver," which is an AI-based math education program, will be given attention. In this program, a Production Model is used to classify the errors made by students, and also a Student Model with the help of Bayesian Knowledge Tracing (BKT) is utilized to keep track of the knowledge skills of learners [8]. These data are used to

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generate hints and different tasks and modify the provision of feedback based on performance level [9]. This program serves, on the one hand, as a proof of how such technology helps to personalize education since, depending on errors, different students will receive individualized assistance. On the other hand, this example raises the important question of whether the implementation of standard techniques of the categorization of errors and student characteristics can provide sufficient accuracy in reflecting the individual peculiarities of students. If methodologies used in the program are standardized, then tailor-made materials may be used, but it will not reflect the difference in how the students learn.

To solve this problem, this study suggests the use of a learner-centered approach to "meaningful personalization" in intelligent learning systems. It is necessary to distinguish between the idea of personalization being limited to the provision of information to different learners and the concept of personalization as the process of identifying and responding to student differences. This study presents four dimensions of design with respect to personalization, namely, the multidimensional representation of learners, the multilevel adaptation, the dynamic modeling of learners, and the variability of instructional responses. First, the representation of learner performance by a system should not be restricted to the characteristics of the learner's ability level (for example, accuracy, mastery level, and so forth). The second dimension connotes the concept of adaptation both in terms of the generation of content and the feedback provided to learners by means of an assortment of methods. The third dimension implies that the models of learners should be constantly updated according to their present performance and not through classification processes. Finally, the system should be able to provide different instructional solutions related to the same learner's mistakes provided the learners have different past experiences with learning. Using this framework, this study addresses the issue of designing personalized learning systems in order to prevent the development of new homogenization tendencies in education.

3. Method

In this paper, the authors take a conceptual design-based approach in order to investigate how intelligent learning systems can provide personalized learning assistance in ways which will help avoid the tendency to homogenized learning processes. This paper will be focused not on empirical studies aimed at assessing the efficiency of the application of some particular instructional intervention via the use of experiment-based data. Instead, this paper will present a conceptual framework which will focus on identifying potential design problems related to personalized learning systems based on A.I.

The first problem that this paper addresses is related to the fact that although a given personalized learning system is based on A.I. Generates different types of instructional materials for different students; this does not, in fact, mean that this particular system has implemented truly meaningful personalization of learning. Moreover, many intelligent learning systems continue to utilize learner models that were defined beforehand, error classification techniques, and different pedagogical principles. This is the reason why the same learner is given different exercises as well as feedback, however, the response given to the same learner in learning systems may be dependent on similar concepts.

To demonstrate the applicability of the proposed framework in practice, we will use the Smart Mistake Solver as our case study within the domain of educational technology. As you may know, the Smart Mistake Solver is an artificial intelligence application for mathematics education where this system learns how students make mistakes solving problems and provides assistance based not only on the specific mistake made by the student but also according to his/her learning process.

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The Smart Mistake Solver contains five interconnected functional components, all working together to introduce errors made by students in mathematics. As shown in Figure 1, these modules form a continuous learning loop in which students' subsequent performance is used to update the system and guide further adjustments.

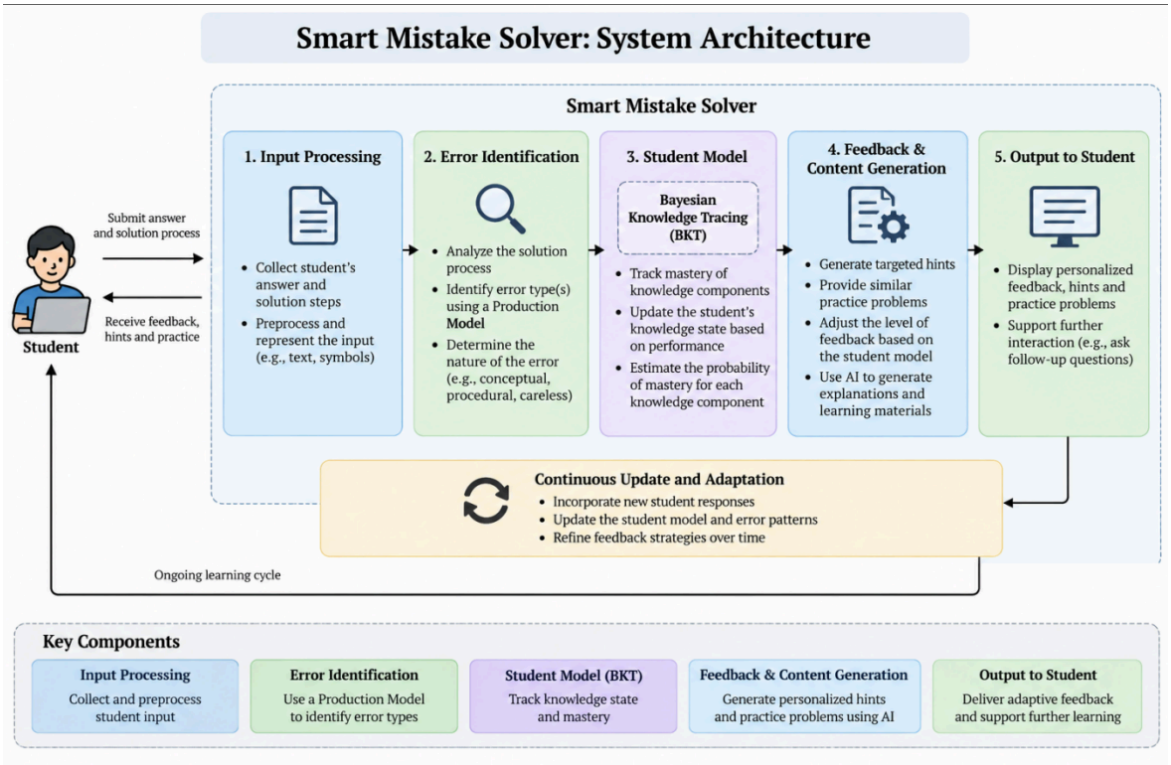

Figure 1. Smart Mistake Solver system architecture (picture credit: original)

As shown in Figure 1, Smart Mistake Solver consists of a number of interacting functional modules: Input Processing, Error Identification, Student Model, Feedback and Content Generation, and Output to Student. These modules work together to identify common errors in students' mathematical problem solving and track each student's learning progress, so that the system can give personalized support to the students.

The "Input Processing" module captures answers and problems; the "Error Identification" module uses the production model to analyze students' problem-solving process (e.g.), to identify error types and patterns, conceptual errors, procedural errors, and computational mistakes). It allows the system to identify what stage of problem-solving the student has problems with.

The "Student Model" records the level of mastery of different knowledge points. Bayesian Knowledge Tracing (BKT) methods are used for estimating and updating the individual level of knowledge point mastery in the original version of the model [8].

Combining the error information produced by the Error Identification module with both learning levels stored by the Student Model, this information becomes an input for the Feedback and Content Generation module. It produces hints, similar problems to be solved, and personalized feedback depending on the learning state and new performance of the student.

The last module, Output to Student, provides feedback (e.g., hints and explanations). According to the process of continuous update and adaptation (Figure 1), the performance is used to update the knowledge in the Student Model and error information.

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In this paper, the Smart Mistake Solver was not presented as a ready system having conducted large-scale empirical validation. The framework demonstrates that the Smart Mistake Solver design features can provide insights into the implementation of intelligent learning systems.

By studying this example, it is possible to empirically analyze personalized design features that were integrated into the Smart Mistake Solver application. Some examples of self-initiated feedback based on error types are presented in the application.

One of the major purposes of this case study is the identification of potential limitations of conditions existing at present when using predefined error types. In this respect, Smart Mistake Solver can become information for creating more dynamic systems.

4. Result

By conducting an analysis of artificial intelligence-supported personalized learning approaches together with the "Smart Mistake Solver," this paper has shown that while AI may help to provide differentiated instruction to a small degree based on student performance, the differences in outputs from different systems do not automatically lead to real personalized learning.

Smart Mistake Solver shows how powerful AI can be in its potential application to a personalized learning approach. Instead of helping the user one-on-one as conventional systems do, merely judging the user's input to provide feedback that is either "right" or "wrong," Smart Mistake Solver takes it further by determining this precisely through specific analyses of the nature of the errors committed by students.

However, it is clear that Smart Mistake Solver and conventional systems could potentially provide comparable results, but this does not necessarily imply that the users are receiving learning materials tailored to precisely meet the needs of each individual one. This is because AI systems make use of certain, specific categorizations of errors, methods in which they approach learners, and a predefined set of rules to analyze the actions of learners.

This issue could be seen in the application of the implementation of the Smart Mistake Solver learning system. For instance, students could have performed the same mathematical errors; however, the causes behind the errors could be different. For one's problem, the problem could be grounded on a lack of understanding of what he was trying to achieve; for the other one, it could be simply an error caused by being careless of the calculation.

In conclusion, it could be asserted that when it is said that AI can enhance the differentiation of learning instruction material, it does not necessarily mean that the variability of the content automatically contributes to the creation of a personalized learning.

5. Discussion

Related to the findings of the analysis presented in this paper, it can be concluded that personalization of learning with the aid of AI is not simply the provision of distinct learning materials to diverse learners. Even though AI tools can produce various hints, practice problems, and feedback according to learners' errors, performance, and demonstrated knowledge, the output would still be based on some existing classifications of learners, such as those created and utilized in the personalized learning systems [3, 7]. Consequently, merely different content would not constitute the necessary basis for the deep understanding of differences among learners.

This finding has further implications for the development of educational technology. Designers of personalized learning systems should go beyond the number of various pieces of information that can be generated by the system and concentrate on the reasoning behind showing this particular

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information to a learner. That is, research on the use of AI in education shows that it is hard to represent the uniqueness of learning experiences of each learner in terms of computations, while the use of intelligent tutoring systems suggests that there are other ways to assess the relevant differences between the learners [7, 8]. Thus, real personalization implies not only the diversity of content but also the perception of learning behavior and assessment of the needs of the learners. If the system relies on fixed classifications of errors and uses some predefined rules, learners might get the same support even if they have different needs.

This argument also applies to the "Smart Mistake Solver" tool. The future development of such an AI tool could put more emphasis on the reasons causing the mistakes of learners instead of focusing on the type of error. If it is hard to find the reason for the error, the human approach could serve as an alternative way for receiving feedback and updating AI-based conclusions [10]. For instance, teachers could analyze specific issues where the learning behavior can demonstrate different needs of the learners while they perform similarly.

Moreover, this analysis has its limitations. It is based mainly on the conceptual analysis of design cases, but there is no evidence received from the performance of the students based on this design as to whether it enhances personalized learning outcomes. Further research could apply actual user tests or real data to confirm the effectiveness of different approaches to learner learning analysis and possible solutions for preventing the tendency for homogenization within personalized learning.

6. Conclusion

In this paper, the author investigates the relationship between AI-enabled personalized learning and the inclination towards conformism, using the design case of the "Smart Mistake Solver", which illustrates the importance of distinguishing the generation of multiple materials from the idea of personalization. The case shows how effective personalization of learning materials consists of the ability of the AI system to detect the fundamental needs of students and to accommodate them correctly.

The main contribution of this paper is represented by the proposition of the learner-centered approach, which suggests that to understand students properly, it is necessary to see beyond their observable errors or academic scores. The Smart Mistake Solver is a perfect example illustrating how to develop learning support materials by taking the underlying causes of students' errors into account.

There is a lot of scope for further research in terms of assessing these design ideas through the analysis of authentic learning data and user testing, and determining whether the achievement of personalized learning can be facilitated by the incorporation of more sophisticated learner profiling procedures and involvement of teachers.

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