Supporting, Not Solving: Human-Centered AI Systems in Education

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Abstract

Educational technologies have evolved significantly over recent decades, with AI representing the latest frontier in this progression. Current applications range from adaptive learning platforms that personalize content delivery to automated systems that provide immediate feedback. The challenge lies in developing AI educational technologies that enhance human capabilities while respecting the autonomy and agency of learners and educators. My research aims to design, implement, and evaluate human-centered AI systems in educational contexts. By prioritizing human needs and values throughout the development process, my work seeks to advance the understanding of how AI can enhance educational practices while preserving the learner's independence and the educator's role.

Keywords

HCAI, Education, Intelligent Tutoring Systems, Adaptive Learning

1. Context and Motivation

In the last decades, the advancements in Artificial Intelligence (AI) have enabled the development of Conversational Agents (CAs) (e.g., ChatGPT [1], Claude [2], Gemini [3]) that allow users to easily ask a question and obtain, in very few seconds, an answer. These CAs have been successful among learners to assist them in several tasks (e.g., writing assistant, code assistant) [4, 5].

However, while these tools increase efficiency and accessibility, over-reliance on such tools can weaken learners' critical thinking, problem-solving abilities, and overall learning experience. By delivering directly complete solutions, CAs hinder students' opportunity to work through problems independently and develop their analytical skills [6].

Human-Centered Artificial Intelligence (HCAI) [7] is a discipline whose objective is to create AI-based systems that augment and enhance human capabilities rather than substitute them [8]. This approach emphasizes the importance of maintaining human agency and control while leveraging AI's power to support and amplify human processes [9].

The application of HCAI principles in educational contexts presents both significant opportunities and challenges. In educational settings, the primary goal is not to automate tasks or provide quick answers, but to foster learning, critical thinking, and skill development. Therefore, HCAI in education can be applied to design systems to support the learning process while maintaining learner agency and promoting deep understanding.

The HCAI principles applied in the education setting are summarized in Table 1. For decades, researchers have concentrated on developing computer systems that emulate a human tutor, guiding learners through the learning process. The aim is to provide one-to-one personalized tutoring in contexts where one-to-many instructions from a single teacher is not enough (e.g., traditional classroom lectures). Intelligent Tutoring Systems (ITSs) aim to tutor learners by providing personalized feedback, automatic assessment and by answer questions, without requiring the intervention of a human teacher, improving the quality of education [10].

While significant research is dedicated to support learners, it is essential to recognize the central role of educators in the education setting. AI systems can play a valuable role in supporting teachers,

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easing their workload (e.g., expert decision making, tools for automated exercise and quizzes generation) [11, 12, 13].

Finally, the design of educational systems should be aligned with real user needs [14]. AI systems are more intuitive, acceptable and effective when students and teachers are actively considered in the design process [15].

Table 1
Overview of research themes and subthemes related to AI in education, along with conclusions from the supporting literature. The table organizes the role of intelligent systems in enhancing personalization, collaboration, and user-centered design. Table from [15].

Research Theme	**Research Subtheme**	**Supporting Literature Conclusions**
Personalized Learning	Learning Analytics Tools and Personalized Recommendation Systems	Adapt to the individual needs of students by developing intelligent tutoring systems that help them master transferable learning skills, thereby enhancing their self-directed learning abilities.
	Intelligent Systems Supporting Smart Education Development	Explore the development of intelligent systems to support personalized learning and smart education to improve the quality of education.
Teacher-Student Interaction and Collaboration	Intelligent Tutoring Systems and Expert Decision-Making Chatbots	Enhance the interaction and collaboration efficiency between teachers and students through intelligent tutoring systems and expert decision-based chatbots to improve teaching effectiveness.
	Human-Centered Smart Education Models	Emphasize the human-centric and nurturing aspects of teacher-student interactions, advocating for the retention of the core role of human teachers in education, and creating a new model of intelligent education for teacher-student interaction.
Participatory Design and User Experience	Emphasis on User Needs and Experience	The redesign of virtual assistant design and user interfaces increases the applicability and user acceptance of the technology, reflecting the principle of human-centric design.

My dissertation work aims to exploit AI methods to enhance both student and teacher work. The objective is to support the student learning process, analyzing existing approaches' opportunities and limitations, and develop, test and evaluate new techniques and tools to support both students and teachers in the learning journey.

2. Background and Related Works

An increasing number of scholars are exploring how to support learners in different subjects. Several works have tried to identify the best learning path to master a given math concept employing a Reinforcement Learning (RL) algorithm. Liu et al. [16] have developed a system that takes into consideration both which concepts the learner has already mastered and their releationship with several other concepts yet to be mastered to identify the sequence of exercises to suggest to the learner. Li et al. [17] have exploited a Hierarchical RL algorithm to re-adapt the sequence of exercises based on the learner's actual knowledge and the goal to achieve. More recent works exploit Large Language Models (LLMs) to co-create stories with the learner to learn math language using voice interaction [18] and visual representation of the scenes [19].

In other works, LLMs are used to provide timely feedback and answer to learners' questions. Kazemitabaar et al. [20] developed CodeAid, an LLM-based assistant designed to support programming students without revealing full solutions but providing help, pseudo-code, and code explanations.

Hou et al. have developed CodeTailor [21] which creates Pearson puzzles by employing an LLM. This system provides personalized help to students while encouraging the cognitive engagements.

Choi et al. [22] conducted a design workshop with educational experts and educators on the potential usage of LLMs to transform a monologue lecture script into pedagogically meaningful dialogue. Subsequently, they developed VIVID, a LLM-based system that allows co-creation of pedagogical dialogues. ReadingQuizMaker [12] supports educators to easily create high-quality multiple choices and open-ended questions by employing a (Natural Language Processing) NLP-based process starting from a text.

These works illustrate how, when intentionally implemented, AI can be leveraged to develop systems that can engage learners in mastering concepts and support educators to enhance their teaching processes.

My objective is to study these approaches and explore how to effectively integrate AI into educational systems to support meaningful learning, foster critical thinking, and enhance both student and teacher experiences.

3. Research Objective

The overall objective of my research is to explore how AI can both support **learners** to reach their learning goals and give **teachers** practical support. This research will be conducted aiming to answer the following research questions:

- **RQ1**: How to design AI-based systems to effectively support student and teachers in everyday learning activities?
  - **RQ1.1**: What kind of interaction between learners and AI promote engagement, reflection, and active participation without hindering skills' development?
  - **RQ1.2** How can AI-based systems be designed to empower teachers?
- **RQ2**: What key features and best practices can be identified in these systems to inform the design of AI-based educational tools?

4. Research Approach

This research will proceed through three phases to design educational AI-based systems that support learners and teachers, while keeping them central to the process. To answer the research questions outlined in Section 3, I plan to:

1. Asses the current status of AI-based learning. I am conducting a review of the existing literature to analyze the strenghts and the limitations of the current approaches, with particular attention to how they can help both students and teachers (RQ1).
2. Design, implement, and evaluate AI-based systems that can empower teachers (RQ1.2) and support learners (RQ1.1). To this end, it is essential to preserve their role and agency throughout the whole process.
3. Guideline derivation. Starting from the designed systems, I will extract the guidelines for the design of a HCAI educational system that can be used to augment and enhance both educators and learners' capabilities, while increasing engagement and pleasure to learn (RQ2).

5. Contributions to Date

During my first year, I reviewed the literature to build the foundation steps to develop a system that can help students in their learning journey.

Existing math ITSs often employ RL algorithms to suggest sequences of exercises based on the learner's ability to correctly and **completely** solve previous exercises. However, these systems are not able to capture when the student struggles to solve a specific intermediate step. This limitation is due

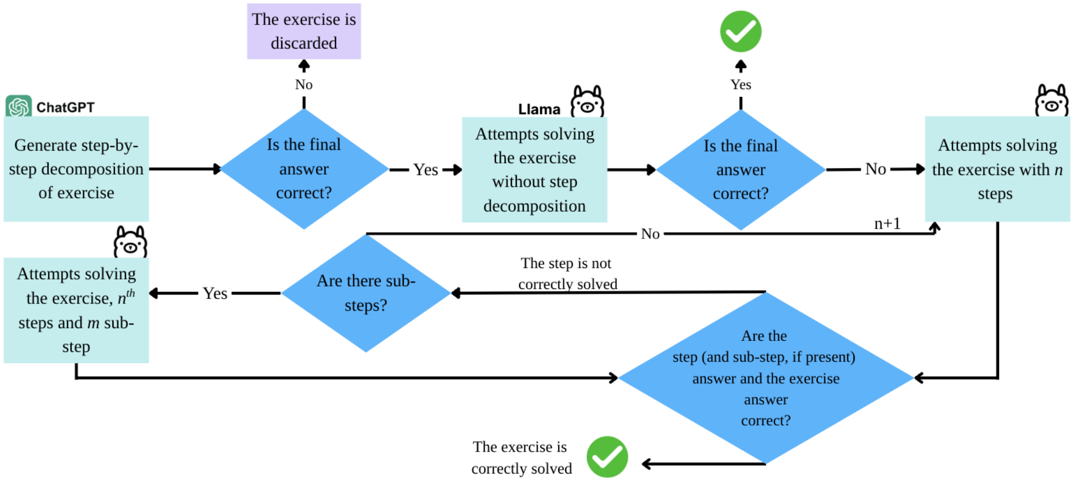

Figure 1: Overview of the approach. Step-by-step solutions are generated and their final answers are verified for correctness. A Llama model is then prompted to solve the exercise. If the answer is incorrect, the model is iteratively provided with intermediate steps and sub-steps.

to the fact that existing educational math datasets they are trained on do not include intermediate steps interactions.

To build a step-aware adaptive ITS, it is necessary to decompose exercises into detailed step-by-step solutions, thus enabling the training of a RL algorithm employing simulated student that interact with the system.

In my work, I leveraged GPT-o3-mini[1] to break-down the solution of exercises from the Junyi educational dataset [23] into intermediate steps. If the intermediate step was still too complex, additional sub-steps were generated. The step-by-step decomposition provided by GPT-o3-mini was validated by comparing the generated exercise solution with the actual one, ultimately retaining only correct decompositions. Subsequently, I analyzed whether the generated steps and sub-steps effectively guided learners toward the correct solution.

To evaluate this, I used three models of varying sizes from the Llama family [24, 25]. Each model was first asked to solve an exercise directly. If it failed, it was progressively provided with the generated intermediate steps and prompted to solve both the current step and the full exercise. If the model struggled with a specific intermediate step and sub-steps had been generated, these were also provided, and the model was asked to solve the sub-step, the corresponding step, and the complete exercise. The process is outlined in Fig.1.

Results show that the models were able to solve 42% more exercises when guided by intermediate steps, compared to when prompted to directly solve the whole exercises. These findings proved the usefulness of the generated step-by-step solutions to guide the students - in this case, simulated by models from the Llama family - toward the solution of math problems.

6. Long Term Goals

Currently, I am starting my second year of the National Ph.D. program in Artificial Intelligence at Politecnico di Torino under the supervision of professor Luigi De Russis.

During my first year, I have explored the existing literature studying how researchers have integrated AI in educational systems to support both students and teachers.

During my second year, I will continue developing the previously mentioned step-aware ITS. Additionally, I plan to design multimodal systems that enable stakeholders to interact with the technology through various input and output modes (e.g., voice, text). I also intend to conduct user testing with interested participants to evaluate the system's effectiveness and usability.

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In the third year, I aim to extract key design principles from my findings and define a set of guidelines for developing AI-based educational systems that can enhance and augment learners and educators capabilities while keeping their autonomy and agency central to the design process.

In conclusion, I expect my work to contribute to more responsible and effective uses of AI in education, enhancing student engagement, supporting teachers, and promoting systems that align with human-centered values.

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Declaration on Generative AI

During the preparation of this work, the author used ChatGPT in order to: grammar and spelling check, paraphrase and reword. After using this tool, the author reviewed and edited the content as needed and takes full responsibility for the publication's content.

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