Personalized Learning Experiences with AI: An Overview for Decision-Makers and Practitioners

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Abstract

This article provides an overview of technology-mediated personalized learning and the role of AI for higher education decision-makers, administrators, and practitioners. We review the historical foundations of AI and personalized learning, the key components of modern personalized learning systems, and the impact of emerging generative AI technologies. We conclude with a discussion of the role of higher education in shaping the future of AI-driven personalized learning.

Keywords: personalized learning, adaptive learning, AI and personalized learning, large language models in education, intelligent tutoring systems, personalized learning in higher education

1 Introduction

Personalized learning is an instructional approach that aims to customize learning for each student's strengths, needs, skills, and interests to achieve academic goals. This instructional approach stands in contrast to the "one-size-fits all" model of traditional classrooms. Personalized learning begins with the recognition that each learner has different individual characteristics such as prior knowledge, prior experience, attitudes, motivations, needs and preferences, but also that achieving each learning outcome requires different learning processes. AI enabled personalized learning systems use the affordances of the technology to deliver learning experiences that are customized in accordance with the individual learner characteristics and with the learning processing requirements of each learning outcome. They aim to efficiently and effectively support students to achieve academic goals.

This article provides an overview of technology-mediated personalized learning and the role of AI for higher education decision-makers, administrators, and practitioners. We review the historical foundations of AI and personalized learning, the key functional components of modern personalized learning systems, and the impact of emerging generative AI technologies on personalized learning. We conclude with a discussion of the role of higher education in shaping the future of AI-driven personalized learning.

2 Foundations of AI and Personalized Learning in Higher Education

Modern ideas of using AI to personalize instruction date back to two foundational ideas in the 1950s. Mathematician, Alan Turing, developed the "imitation game" (Turing, 1950), commonly referred to as the Turing Test, that explored the concept of machine intelligence and the ability of machines to emulate human behavior. Psychologist B.F. Skinner developed a "teaching machine" (Skinner, 1958) that broke complex tasks into simpler steps, allowed students to work through exercises at their own pace, assessed their mastery of the step, and provided immediate feedback and encouragement along the way. Taken together, Turing's imitation game and Skinner's teaching machine combine the potential of AI to emulate human behavior with using technology and theories of learning to understand and adapt to human needs. These two conceptual threads foundational to personalized learning were developed, integrated, and extended, over time as both theories of human learning and the capabilities of the technology advanced.

Herbert Simon along with his long-time collaborator, computer scientist Allan Newell, created one of the first AI programs, the Logic Theorist, that could solve general logic problems (Simon, 1957). Their work in the 1960s, and 1970s on decision-making and problem-solving led to the development of models that illustrate how people learn by interacting with their environments and using information strategically. Simon proposed that learning occurs when individuals engage in problem decomposition, breaking down complex tasks into manageable parts. He was an early proponent of using computer programs to simulate and support human problem-solving.

Lev Vygotsky's theory of the Zone of Proximal Development (ZPD) (Vygotsky, 1978) posited that the ZPD represents the gap between what a learner can do independently and what they can achieve with scaffolding or guidance from a more knowledgeable other. Together Simon's and Vygotsky's work provided theoretical frameworks for designing educational tools that assess a learner's current capabilities and offer tasks just beyond their current capability along with appropriate support to help them progress. Vygotsky's work emphasized the social and cultural aspects of learning and Simon's work suggested that technology should facilitate a type of structured cognitive engagement that was highly aligned with the ZPD concept of providing tailored assistance. Early attempts were made in the 1960s and 1970s to develop intelligent computer-assisted learning (ICAL) and computer based tutoring systems that were grounded in these ideas; however, during the 1980s, research and development of intelligent tutoring became more pronounced.

Benjamin Bloom's research showed that one-on-one tutoring resulted in the average student performing 2 standard deviations above the average of the control class (Bloom, 1984). What came to be known as the "2-sigma problem" raised the challenge of how educational systems can effectively scale the benefits of individualized instruction to a larger number of students. A significant development in the 80s was the Cognitive Tutor developed by John Anderson and colleagues at Carnegie Mellon University (Anderson et al., 1995). The Cognitive Tutor employed principles from cognitive psychology to provide personalized interactions like a good human tutor: selecting tasks that are appropriate to the learner's current knowledge, providing hints and feedback when needed and keeping a low profile when the student is progressing.

Personalized learning systems developed in the 1990s integrated more advanced artificial intelligence techniques to engage users in dialogue, providing real-time feedback and fostering deeper learning. These early intelligent tutoring systems typically relied on a set of explicitly defined rules and heuristics written by educators and domain experts. The rules dictated how the system would respond to specific student inputs and interactions. The systems typically were designed for a single domain and had a fixed scope because expanding the number of rules led to complexity and maintenance challenges. These early systems were quite labor intensive to build because each new topic or concept required manual input from educators and domain experts.

The Open Learning Initiative (OLI), established at Carnegie Mellon University in 2002 was one of the first open educational resource (OER) initiatives to systematically integrate research from learning science into the design of courseware. By collecting data on student interactions within online courses, OLI utilized knowledge modeling algorithms to analyze student performance data, identifying patterns that informed course design and pedagogical strategies (Walsh, 2010). The initiative partnered with various educational institutions to implement and study its courses, generating insights that informed both OLI's practices and broader educational initiatives. By sharing findings and collaborating with other researchers and educators, OLI created a community-based research model for how AI and adaptive learning could be effectively integrated into higher education learning experiences. OLI also demonstrated that learning could be accelerated (Lovett et al., 2008).

As the capabilities of the technology advanced, rule-based systems have been augmented or replaced by systems that utilize machine learning to learn patterns and relationships from large datasets. Rather than relying on explicitly programmed instructions, these systems can make predictions and decisions based on data. Using algorithms to model data, they analyze student performance over time, recognize patterns, tailor content and feedback in real time, and offer targeted remediation or advanced challenges. Using natural language processing (NLP) techniques, some systems also engage in interactive conversations with students that support exploration of topics in a non-linear manner.

3 AI and Functional Elements of Personalized Learning in the 21st Century

As theories and technologies advanced, the conceptualization and implementation of personalized learning systems have also advanced. Ideas of how to best use AI to support personalization has varied significantly among researchers, instructional designers, government agencies, policymakers, educational institutions, and the EdTech industry (Bernacki et al., 2021). Systems that personalize learning may include any combination of the following six categories of functional elements: (1) Pacing, (2) Learner Modeling, (3) Adaptive Learning Pathways, (4) Task Feedback and Hints, (5) Interactive Instructional Dialogue, and (6) Insight Provision.

The amount of computational sophistication required to implement these functions varies depending on the function, the intended level of personalization, and the degree of machine vs human control. Some functions, like self-regulated pacing, may not require any algorithmic sophistication. Other functions, such as system-regulated adaptive learning pathways, can be implemented along a continuum of algorithmic sophistication. This can be implemented using simple, instructor-provided rules such as "skip this module for learners who scored 90% on the diagnostic quiz," or it can use more sophisticated machine learning algorithms trained on data. Both approaches incur trade-offs. Simpler methods are more human interpretable and require less or no training data. Data-driven methods allow more nuanced analyses and can find complex patterns in learning and improve over time as more learner data accrue.

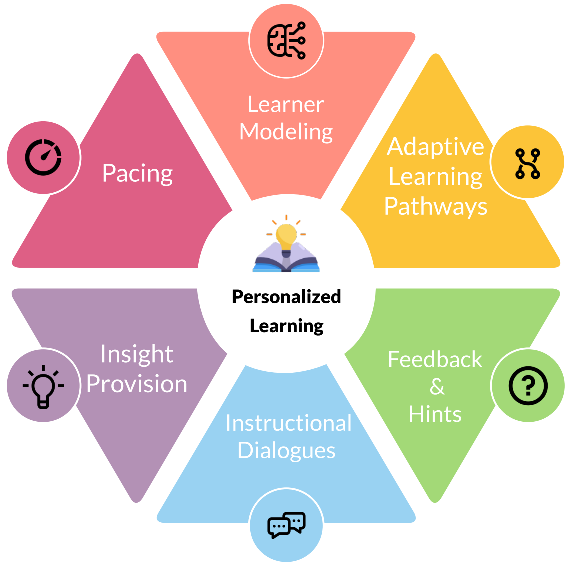

Figure 1: Six functional elements of technology-mediated personalized learning

3.1 Personalized Pacing

Pacing refers to the speed and rhythm at which learners progress through the content of a learning experience. Unlike the traditional mode of learning in which learners move through materials at a fixed pace, personalized pacing allows learners to progress at a pace customized to their needs, interests, and levels of proficiency.

Self-paced personalized learning experiences allow learners to decide how to pace their own learning. Self-pacing allows learners to spend more time on topics they find challenging or that particularly spark their interests and spend less time in areas that are easy or uninteresting. Supporting learners to self-pace gives them a sense of control over their own learning, which can evoke positive achievement-related emotions that lead to better engagement and improved learning outcomes (Pekrun & Perry, 2014). However, without appropriate information and guidance matched to the skills of the learner, self-paced learning may not result in robust learning improvements. Not all learners have the meta-cognitive skills to allocate their time effectively, identify areas for improvement, and take steps to make those improvements. Insufficiently guided self-placed learning places too much burden on the learners to make critical decisions about their learning. Then only the learners who already possess strong self-regulated learning and meta-cognitive skills benefit from using the system (Reich, 2020).

For certain types of learning processes, having a learning system manage the pace of learning in accordance with principles from the science of learning can result in better learning outcomes. For example, when the learning objective is to memorize facts such as vocabulary, historical events, or scientific facts; or to build fluency in when and how to accurately apply rules, such as geometry rules or scientific formulas, personalized tools can manage pacing in accordance with the principles of “spacing” and “testing” (Koedinger et al., 2012). The spacing principle suggests that spreading practice over longer intervals, such as several days, solidifies long-term retention more than cramming in a short time frame (Cepeda et al., 2006). The testing principle suggests that practicing recall through activities like quizzes or self-testing is more effective for strengthening memory than repeatedly reviewing the material (Roediger III & Karpicke, 2006). These principles guide the AI in some language learning software and flashcard apps to find an optimal timing and scheduling of learning activities to promote robust retention and recall.

3.2 Learner Modeling for Personalization

Learner modeling is a crucial component in many AI-driven personalized learning systems. Personalized learning systems compile extensive information about how learners interact with the platform, such as quiz and assignment performance, time spent on learning activities, click and navigation patterns, and patterns found in responses to tasks. These data are analyzed using a variety of statistical inference and machine learning methods to derive key insights about the unique learning process of each learner, which are then used by other components of the personalized learning system to make instructional adjustments.

Insights are obtained using two main types of learner models: *knowledge models* and *affect models*. While knowledge models focus on capturing and predicting the evolving knowledge state of each learner such as their level of proficiency, misconceptions, and patterns of learning, affect models address emotional, motivational, and attitudinal factors that influence how learners engage with learning.

3.2.1 Knowledge Models

Knowledge models serve as the computational backbone that represents the current state of knowledge and skills of individual learners, patterns of their learning, and their thought processes. These models leverage learning data such as learners' responses to assessment items, intermediate problem-solving steps, number of problem-solving attempts, time spent on learning activities, and usage of system features such as help-seeking, hint display, and access to explanatory text or videos.

Skill-Centric Modeling Many knowledge models assume that learning materials and assessment items are tagged with skill labels or "knowledge components" that describe the unit of actionable knowledge and skills (Koedinger et al., 2012). A course author determines the knowledge components and associates the knowledge components with specific learning activities during the design phase of a course and further refines and restructures as the course develops.

As learners work through a series of assessment items, skill-centric knowledge models analyze the skill labels associated with each item and learner responses to trace the development of the target knowledge and skills over time, a process called "knowledge tracing" (Corbett & Anderson, 1994). Models such as Bayesian Knowledge Tracing (Corbett & Anderson, 1994) provide a binary estimate of mastery, mastered or not mastered. Other approaches can estimate dynamic changes in learner proficiency of a knowledge component on a continuous spectrum, for instance, based on Item Response Theory (Kim et al., 2023; Khajah et al., 2014). Mastery or proficiency predictions can then be used by the learning system to make learning adaptations such as sequencing tasks or providing personalized feedback.

Latent Representation Modeling In recent years, advanced machine learning algorithms have introduced new ways to represent student knowledge states without relying on explicit skill labels. Rather than estimating a learner's proficiency across a predefined set of skills, advanced AI models are trained on large amounts of data to produce machine interpretable representations of the learner's state and the attributes of assessment items (Piech, Bassen, et al., 2015). Although these representations lack the human interpretability of proficiency estimates from explicit skill-centric models, they often capture more subtle patterns in learning behaviors and item features. This can be useful when predicting future performance on new assessments or when performing other relevant tasks such as grouping students with comparable patterns and uncovering latent relationships among assessment items (Piech, Bassen, et al., 2015).

3.2.2 Learner Affect Models

Learners experience a series of dynamically changing affective states as they interact with a learning environment, and different affective states can impact learning in different ways (Baker et al., 2010). Some personalized learning systems track the learners' affective states, such as confusion, frustration, boredom, engagement, surprise, and delight (D'Mello & Graesser, 2012). Methods for detecting affective states can be categorized into sensor-free and sensor-based methods. Sensor-free methods analyze learner interaction patterns within the system, including conversational turns, response data, interaction timing and duration, and performance on assessment items (D'mello et al., 2008; Ocumpaugh et al., 2014; Gobert et al., 2015). Sensor-based methods track physical changes such as facial expressions, body movement, and eye gaze (Whitehill et al., 2014; Mota & Picard, 2003; Bixler & D'Mello, 2016). Both categories of detection algorithms are trained using supervised learning, which requires human-labeled examples of affective states.

3.3 Personalizing Learning Pathways

In traditional learning environments, learners are typically expected to complete the same set of lessons and learning activities in the order prescribed by the designer of the learning environment. By contrast, several personalized learning environments dynamically assign the next learning activity based on learner characteristics and the cognitive requirements of the activity (VanLehn, 2006).

Selection of learner-specific content relies on the assessment of the learners' current knowledge state. Cognitive Tutor (Anderson et al., 1995; Ritter et al., 2007) uses learner models (see Section 3.2) to estimate the learner's mastery of each skill in a lesson and continues to present activities targeting skills the learner has not yet mastered. Once mastery of all skills in that lesson is achieved, the learner is moved on to the next lesson. The ALEKS learning system (McGraw Hill, 2021) continuously assesses whether learners have retained or forgotten each of the topics relevant to the course. DeepTutor (Rus et al., 2013), a dialogue-based intelligent tutor in the AutoTutor (Graesser et al., 1999) family, dynamically selects the next task based on the learner's current understanding of each concept and in accordance with "learning progressions." Learning progressions are structured paths of knowledge states that lead to mastery. An experiment on Newtonian physics training with DeepTutor demonstrated that dynamic task selection led to significantly greater learning gains compared to a fixed learning sequence approach (Rus et al., 2014).

More recent algorithms directly optimize the selection and sequencing of learning activities based on observed learning improvements. For example, (Bassen et al., 2020) developed a reinforcement learning (RL) algorithm that is trained to dynamically and efficiently assign a sequence of learning activities based on feedback about their impact on the post-test performance. Reinforcement learning is a type of machine learning in which an AI agent learns to make decisions by interacting with an environment, receiving rewards or penalties based on the quality of its actions. The goal of RL is to optimize the AI agent's decision making process to maximize cumulative rewards over time through trial and error. (Bassen et al., 2020) uses a reward system that encourages higher post-test scores and penalizes assignment sequences that are too long. The study found that the resulting assignment algorithm, on average, improved learning gains while simultaneously reducing the number of activities needed to produce those gains compared to the way an expert instructor sequenced the same set of activities.

3.4 Personalizing Task Feedback and Hints

Personalizing learning pathways customize learning at the level of selecting and sequencing courses, modules, lessons, tasks and activities. In contrast, the focus of personalizing task feedback and hints is to give dynamic, stepwise guidance during a learner's engagement with a single task with the goal of enhancing learning outcomes.

Personalizing feedback and hints is especially useful for tasks that are completed over multiple steps. For instance, a task in an introductory statistics course might display a set of measurements and ask the learner to determine whether their mean differs from μ with 95% significance. Steps taken to solve this task could include identifying that the correct statistical test to use is the Z-test, calculating the Z-score, and running the test with $\alpha = 0.05$ significance. Most of these tasks permit more than one "correct" approach for completing the task, such as using the formula for a confidence interval instead of a statistical test. The goal of personalizing feedback and hints is to provide timely and dynamic support as learners move through steps in solving the task.

The main difference between feedback and hints is when and how support is given. Feedback is reactive, provided after a learner takes an action (or a series of actions) to inform them about the quality of their thoughts and actions and providing an opportunity to adjust (Schwartz et al., 2016). Hints are proactive in nature and provide just enough assistance for learners to complete a difficult task. Hints are a form of scaffolding through which learners can improve by completing harder tasks than they would alone, an instructional approach closely aligned with the concept of Zone of Proximal Development (Wass & Golding, 2014; Vygotsky, 1978).

Feedback and hints can be generated based on expert-crafted "production rules" that model the learners' decision processes (Ritter et al., 2007) or "constraints" that need to be met by a correct process (Mitrovic, 2003). While this approach has been empirically proven to be effective (Koedinger et al., 2013), it requires extensive expert labor and empirical research. This challenge has led to the development of data-driven approaches in which machines learn how to generate hints and feedback from past learner responses. This data-driven approach works particularly well with tasks that permit various problem-solving paths and for which the steps involved are relatively simple and have clear structures, such as logic proofs (Stamper et al., 2008) and programming (Price et al., 2016; Piech, Sahami, et al., 2015).

Prior to the emergence of the current more powerful generative AI models, developments in natural language processing (NLP) methods enabled the training of complex algorithms that map learner responses to the appropriate feedback and hints. These methods had the advantage of handling more open-ended and freeform student responses such as natural language texts or code written in text-based programming languages. However, they required human-labeled demonstrations of feedback and hints at a scale that quickly became impractical even for relatively simple tasks. The challenge of using these methods was not only that the model must learn the patterns within complex responses, but also that the space of possible student solutions grew prohibitively large with task complexity (Kim & Piech, 2023). Some methods bypassed the need for large, annotated datasets by programmatically emulating the problem-solving process to generate synthetic responses along with the steps that led to the responses (Wu et al., 2019), but these methods remain limited to open-ended tasks that still entail a well-structured problem-solving process at their core.

3.5 Personalizing Interactive Instructional Dialogues

Synchronous, interactive dialogues between learners and instructors are the hallmarks of human tutoring, a form of instruction that has consistently been shown to be more effective than conventional classroom teaching (Bloom, 1984; VanLehn, 2011). Several explanations exist as to why interactive tutorial discourse can enhance learning. First, through dialogues learners can be prompted to explain their reasoning so that the instructors can intervene with timely feedback and hints soon after an error is identified (Merrill et al., 1992). This helps learners recognize more easily where their understanding needs to be refined (VanLehn, 2011). Instructors can also *scaffold* (Wood et al., 1976) the learners' reasoning with varying levels of specificity by engaging in cooperative execution and prompting them to push further along their current line of thinking (M. T. Chi et al., 2001).

Researchers have long sought to replicate the benefits of human tutoring dialogues in computer-based personalized learning environments. AutoTutor is one of the earliest attempts to incorporate dialogues into personalized learning (Graesser et al., 1999). Dialogues in the AutoTutor follow a 5-step structure that was observed is dialogues of many human tutors (Graesser et al., 1995): (1) tutor presents problem, (2) learner gives an initial answer, (3) tutor gives short feedback, (4) tutor and learner collaboratively improve the answer in a multi-turn conversation, and (5) tutor follows up on learner understanding. Each turn in the dialogue is chosen from a fixed set of discourse moves based on the Expectation-Misconception Tailored (EMT) discourse framework. Using the EMT framework, AutoTutor evaluates a learner's response against a set of anticipated features of a correct response and against a set of anticipated frequent misconceptions. This approach has been shown to be more effective than conventional instruction in domains that have strong verbal foundations such as computer literacy, conceptual physics, and critical thinking (Nye et al., 2014).

Many existing instructional dialogue systems share similar architectures in that they have a dialogue template, a pre-defined set of dialogue moves such as hints, collaborative refinement, and question answering, and an algorithm that decides the system's next action (Graesser et al., 1999; VanLehn et al., 2002; Ventura et al., 2018). The decision about the next move relies on natural language processing (NLP) to extract relevant features in the learner's responses. These features include the contents of the response, the learner's cognitive-affective states, the difficulty of the problem steps, and past dialogue states (M. Chi et al., 2011). The decision-making algorithm can be manually designed or learned through trial and error to maximize long-term learning gains (M. Chi et al., 2011).

Current dialogue systems, however, are far from achieving the ideals of good human tutoring. Systems developed prior to the recent development of powerful generative AI technology have a limited range of instructional strategies and rely on rigid dialogue structures that restrict the learners' ability to engage more freely (Graesser et al., 2001; Jurenka et al., 2024). While the turns in instructional dialogues can be automated to some extent, the details — such as domain-specific feedback, hints, and varying levels of scaffolding — require laborious manual crafting.

While dialogue-based intelligent tutors are often assumed to enhance learning, more dialogue does not always lead to better learning gains (VanLehn et al., 2007; Evens & Michael, 2006). Early studies found that computerized tutors with dialogue did not consistently outperform less interactive tutors that provided stepwise feedback and hints (VanLehn, 2011). One possible explanation is that these dialogue systems employed suboptimal dialogue strategies. Supporting this idea, (M. Chi et al., 2014) demonstrated that improving dialogue strategies can lead to increased learning gains.

3.6 Personalizing Insight Provision

A valuable yet sometimes overlooked aspect of the data collection and modeling used in personalized learning systems is the ability to provide actionable insights to personalize learning to a wide range of stakeholders in the broader learning ecosystem - instructors, learning designers, administrators, and learning science researchers.

The richness of the data that personalized learning systems collect about student use and learning provides an unprecedented opportunity for keeping instructors in tune with the many aspects of their students' learning. AI enabled learning systems can support a new level of effectiveness and efficiency for blended-mode instruction. The AI analyzes and models the data that are automatically collected from the students' interactions with the system and communicates key information on the class's learning and progress to guide an instructor's ability to personalize instruction (Thille & Smith, 2011).

AI can also be used to create early warning systems and suggest interventions for student retention from the data collected from traditional course management systems. Unlike the level of intervention that those systems suggest, personalized learning systems can present instructors with a measurement of learning for each objective and suggest interventions. Because they collect and model finer grained learning data, appropriately designed and instrumented AI personalized systems can provide more detailed information, such as the class's learning of sub-objectives, the learning of individual students, and the types of tasks students struggle with the most. The data collected from all the students in a class enable instructors to make immediate adjustments to their teaching. The data collected across multiple classes provide information to adjust the course design. The effectiveness of these systems in supporting instructors to personalize learning has been limited by their inability to communicate insights in ways that are easily interpretable and actionable.

4 Using Generative AI to Personalize Learning Experiences

The rapid development of large generative AI models and accounts of their powerful reasoning capabilities might give the impression that perhaps there is a single AI system that possesses all the functional elements described above and acts as a fully functional personalized learning system. However, as of the writing of this article in February 2025, no such silver-bullet AI exists to handle all personalization decisions, and we expect this to remain the case for the foreseeable future.

Generative AI models are a category of AI models designed to produce new, original data that resembles the training data they were exposed to, as suggested by the term "generative." Modern generative AI models that are the subjects of recent attention are primarily trained on massive datasets collected from the web. Large language models (LLMs) such as ChatGPT, Gemini, and Claude are a subset of generative AI models that are trained to generate text. Although contemporary LLMs are trained through multi-stage development pipelines that typically involve more than just training to generate text based on the statistical co-occurrence patterns in training data[1], most of the training effort is still spent on learning to generate tokens in the massive training data, a step called "pre-training." This nature of LLM training makes LLMs very useful for performing sophisticated tasks that are like many language generation or instruction following tasks found on the web (McCoy et al., 2023), such as text summarization, factual question answering, logical reasoning, programming, and essay and creative writing (Chang et al., 2024). Making learning personalization decisions that will produce better learning outcomes, however, is not a language generation task that aligns with the types of tasks commonly found on the web.

Nonetheless, strategically using generative AI can potentially mitigate some of the limitations noted above in existing systems. For example, LLMs offer promising directions for scaling feedback and hints to a wide variety of task domains without requiring large amounts of human labeled training data. While some studies have highlighted issues with LLM-generated feedback, such as inaccuracies and unsolicited information (Jia et al., 2024) and difficulties in recognizing unfamiliar student errors (McNichols et al., 2024), other studies demonstrated that out-of-the-box LLMs can generate coherent, fluent, and accurate feedback for specific tasks. These include problem-solving in conceptual physics (Wan & Chen, 2024), open-ended middle school math (Baral et al., 2024), data science project reports (Dai et al., 2023), and programming assignments (Wan & Chen, 2024).

Despite such potential, there are several challenges that still remain to be addressed for LLM-generated feedback to be reliable (Stamper et al., 2024). LLM generated feedback and hints lack the instructional design that goes into expert-crafted feedback and hints, such as when they should be triggered and how specific they should be. Existing personalized learning systems make these decisions based on a learner's estimated knowledge states and on principles that have been repeatedly proven by evidence. Moreover, rigorous studies remain to be carried out to measure the impact of LLM feedback and hints on learning outcomes.

In addition to potentially scaling feedback and hints, advancements in generative AI provide new opportunities for improving upon the limitations noted above in current approaches to personalizing interactive instructional dialogues. LearnLM (Jurenka et al., 2024) is a recent effort to further train an existing large language model on a large corpus of human tutor dialogues and synthetic datasets to derive a generative AI tutor that can engage in freeform dialogue. These studies are still at their nascent stages, but preliminary results demonstrate promising potentials for improving the instructional capacities of LLMs (Jurenka et al., 2024) and we expect more studies to test the short- and long-term learning outcomes of generative AI tutors as they evolve.

The potential of generative AI for better personalized instructional dialogue reaches far beyond simply replicating the behaviors of typical human tutors. Systematic analyses of human tutoring processes show that both expert and novice tutors rarely implement sophisticated, evidence-based tutoring strategies (Graesser et al., 1995, 2009, 2012; VanLehn, 2011; Pearson et al., 1995). (Graesser et al., 2012) notes that this is where computerized personalized learning systems can improve upon human instruction by performing more accurate student modeling and systematically implementing a wider range of instructional strategies. While the rigid dialogue-based tutoring systems prior to the development of generative AI had not fulfilled this hope, we remain optimistic that the information processing and instruction-following capabilities of recent LLMs (Ouyang et al., 2022) paired with datasets that demonstrate effective instructional strategies can make progress towards this goal.

[1] Examples of additional training steps include, among others, fine-tuning for instruction following (Wei et al., 2021) and training to align outputs with human preferences and task requirements through feedback from humans (Bai et al., 2022; Ouyang et al., 2022) or machine verifiers (Jaech et al., 2024).

5 The Role of Higher Education in Advancing AI-Driven Personalized Learning

While the research and experimentation with AI to support personalization is ongoing, faculty and administrators can play two critical roles in shaping the future of AI-powered personalized learning. The first role is to guide the use of current technology to support student learning. Instructors can encourage students to use AI as learning support rather than performance support, advising students not to use AI to replace effort on core learning tasks or to mask their struggles in developing core skills. Support for students should include explicitly identifying the target knowledge and skills of the curriculum, encouraging students to reflect on why the skills have value, and demonstrating how the core learning tasks are designed to support students to develop the valued knowledge and skills (Valcea et al., 2024)

The second role is to collaborate in research and experimentation that advances the technology and the science of human learning. A significant challenge in advancing AI for personalized learning is the lack of datasets that link various instructional strategies to learning outcomes across diverse contexts. Understanding the impact of instructional strategies on learning outcomes requires massive amounts of data that adequately capture the learners and contextual variables over time. Such an undertaking to create the learning environments and data systems is not small or inexpensive and will require the cooperation of many institutions and faculty. Administrators should encourage and support faculty experimentation and research in the various uses of AI to personalize student learning.

The role of colleges and universities now is to lead the process of improving post secondary education through thoughtful, sustained, and iteratively improved application of AI and the science of learning to the design, implementation, evaluation, and ongoing improvement of personalized learning environments. In leading this effort, institutions of higher education have the distinct advantage of having the faculty who possess the domain expertise, the expertise in engaging in research, and the passion not only for their own fields of study but also for their students' learning.

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