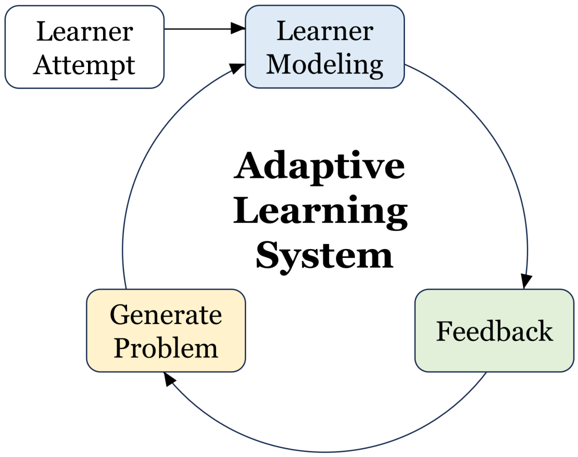


A third grader is learning to add fractions. Given the problem 1/3 + 1/4, they answer 2/7, an incorrect response. An effective human tutor would respond to this mistake by praising the student's intuition of adding the numerator and denominator while choosing future problems that focus on adding unlike denominators. If the student were using a computerized intelligent tutoring system (ITS), however, they may only receive a statement that their response was incorrect and a brief explanation of the solution before moving on to the next problem in a set collection. This approach may leave the student disheartened and less confident in their math abilities. Technologies such as ITS can revolutionize education by providing a learning experience personalized to each individual, but are currently limited by fixed curricula and an incomplete view of the learner. The next generation of personalized learning technology needs to iteratively adapt feedback and instruction to the learner throughout the learning process (see figure and headers emphasized by corresponding colors). To work towards this goal, **I use non-invasive methods to assess learners and provide multimodal, automated feedback to enhance learning.**

My work has been published and presented at top-tier international conferences in human-computer interaction and educational technology, with my top publication receiving more than 60 citations. My research has also been recognized and funded through the U.S. Army Research Laboratory Journeyman Fellowship. My ongoing work has consistently involved undergraduate and masters students; planned future projects have the potential to attract students from diverse backgrounds and cross-department faculty collaborators. I thrive in an interdisciplinary research environment, where I draw upon the strengths of my collaborators and build systems that are useful to learners in the real world. My past work has focused on modeling learners and automatically generating feedback.

## 1 Past Work: Learner Modeling

The most important element of any personalized learning environment is understanding the internal state of the learner. Most work focuses on assessing what a learner knows through their performance on selected assessment items. We are increasingly discovering the impact emotions also have in the learning process, such as influencing engagement and retention. My work scales up multi-dimensional models of a learner ability in a way that protects their privacy.

### 1.1 Modeling Learner Affect

Beyond knowledge and skills, learner emotions heavily influence their learning. For example, if a learner is bored or frustrated, they are not going to carefully lay out their goals and make a plan to accomplish them. If they feel supported by their instructor's feedback, a learner may feel more motivated to continue practicing a difficult task. While there is significant work predicting emotion from physiological signals such as heart rate, skin conductance, or facial expressions, these methods are not suitable for use in educational settings due to privacy concerns and scaling the use of sensing devices. To address this, I used machine learning models to develop continuous measures of 18 nuanced affective states using non-invasive learner activity data. I identified clusters of prototypical student profiles based on typical platform use and demographic information from a dataset of over 69,000 high school students studying algebra. I compared how models trained on these clusters performed versus a general population model. The results [1] show personalized models have a small prediction advantage over the general population model, but more work is needed to determine whether these differences are meaningful in terms of learning outcomes. I discuss future themes related to learner affect in [2]. My future work will study how learner emotions change when the instructor role is filled by a computer rather than a human.

### 1.2 Modeling Learner Algebra Performance

Traditional assessment is summative, evaluating the learner's knowledge and abilities at the end of a comprehensive unit. This is not useful for adaptive learning systems, since we need to assess the learner and provide feedback before developing the next item in the curriculum. To address this problem, I have developed automated formative assessment in order to give feedback throughout the learning process.

In [3], I developed machine learning models to predict performance on formative algebra quizzes based on aggregated click-stream data, which required curating a dataset of over 210,000 quizzes with preceding activity counts. In collaboration with researchers from the University of Florida, I compared a machine learning approach with modern psychometric methods (Item Response Theory). The results show (1) machine learning methods better predict performance on quizzes and (2) the most predictive behavioral indicators of performance were reviewing incorrect questions on a previous quiz and interacting with the discussion board. Unsurprisingly, this aligns with theory supporting interactive (versus passive) learning strategies. These findings can inform which activities to include in an adaptive learning system.

### 1.3 Modeling Learner Performance in Cyber-Physical Systems

Assessing a student's latent knowledge in the classroom is a challenging task; an incorrect answer on an exam may indicate the student hasn't mastered the target concept, made an error in a previous step, or accidentally circled the wrong item. These challenges are further exacerbated in real world tasks such as teleoperating a drone, where errors can come from misunderstanding the controls or from poor planning for the task. Furthermore, assessing the "right answer" becomes more difficult. My current work focuses on learner modeling in complex psychomotor tasks. In one project, I am developing learner behavior models in a driving context. Using concepts from robotic path planning, I define a *risk field* over the environment, encoding risk associated with navigating to that location; for example, *obstacles to avoid* carry a high risk while *remaining in the center of the lane* carries low risk. I model a learner's decisions as mostly rational; that is, they are more likely to navigate within lower-risk areas. The results show that we can produce realistic driver behaviors with this framework [4], and even predict collisions by modeling situational awareness [5]. In another project [6], I define skill in a teleoperation task relative to a set of logical task specifications. A learner's ability is then modeled as their adherence to the task specifications. This preliminary work leads to interesting future research questions, such as how to break down a learner's performance to diagnose specific areas of improvement. Instead of practicing and failing one maneuver over and over and becoming frustrated, how can a learning system adapt and provide targeted practice?

### 1.4 Modeling Classroom Discourse

A final pair of studies [7, 8] consider the teacher as a learner. We provide formative feedback to teachers learning effective classroom dialog strategies as a supplement to formal professional development workshops. I developed an automated pipeline to provide English Language Arts teachers feedback on key dialog strategies associated with student learning [9, 10]. The pipeline takes self-recorded audio from the classroom, transcribes it using speech recognition, applies machine learning models to identify discourse strategies, and provides visual feedback in a mobile application. I compared a traditional open-vocabulary approach (n-grams) with a deep transfer learning approach (BERT) and showed that deep learning methods may not always be the most accurate choice, particularly when the dataset is small or the learner wants an interpretable model of their performance.

## 2 Ongoing Work: Formative Learner Feedback

My current work moves away from modeling to focus on developing effective interventions for learners. Feedback gives the learner an accurate picture of their current abilities and can increase their motivation. Designing the content and delivery of feedback in adaptive learning systems is an open question. In [8], we discuss design considerations for feedback to teachers to improve their classroom discourse, such as levels of granularity. These levels included indications of which specific utterances contained desired dialog strategies, an overall percentage of utterances that contained each strategy, and a qualitative rating of strategy prevalence in the recorded audio. The results show that deep learning methods provide more accurate feedback along all levels of granularity. My current work, in collaboration with an undergraduate student, investigates how the tone and context of feedback matters. We are comparing basic rule-based text responses with feedback from large language models, which may provide more detailed and friendlier feedback. Future research needs to address how to integrate learners into the automated tutoring process so they feel empowered in their learning.

## 3 Research Agenda: Closing the Loop

Personalized learning has the potential to scale up, reaching a diverse set of learners and addressing critical skills for the future of work. For example, as robots and autonomous systems continue to develop, humans will need to rapidly learn how to work on new tasks and interact in new ways. My future work will focus on the user-facing side of adaptive learning systems by refining feedback on human-robot interaction tasks, paired with a largely unexplored area of generating new problems based on a learner's current skill level. Using established pedagogical principles, I will **design adaptive training systems for the future workplace.** I describe some potential projects below.

### 3.1 Multimodal Feedback on Psychomotor Tasks

Psychomotor tasks often have several (possibly competing) performance objectives, making it difficult to give precise feedback for improvement. I propose one line of research comparing various feedback modalities and granularities for multiobjective tasks. Designing feedback for complex domains is exciting because information can be conveyed in a variety of modalities: visual overlays, auditory alerts, and controller haptics. This project will draw upon concepts from gamification and serious play while incorporating pedagogical theories of feedback [11]. Equally important to the accuracy of automated feedback is how learners perceive and leverage their feedback; we will use affect models and user studies to understand the learner engagement with various modalities of feedback.

### 3.2 Procedural Generation of Training Scenes

A core component of a tutoring system is selecting practice items for the learner based on their skill level. Building off my work in assessment, I plan to develop theory-informed algorithms that adapt to a learner's demonstrated ability. One example is operationalizing deliberate practice [12], which focuses on refining performance through feedback and focused repetition. Given the learner's current skill, we can procedurally generate a training task composed of skills that the learner performed poorly on. I plan to implement this using commercial virtual reality headsets to simulate flying a drone outdoors in a realistic inspection task.

### 3.3 Broader Research Interests

Complementary to my core research goals, I want to empower nonexperts to understand, interact with, and develop their own autonomous systems. A well-known barrier to public adoption of cutting-edge technologies is that they are often a black box – casual users do not understand the limits of these technologies or how to fit them to their needs. I plan to develop interfaces for iterative development and prototyping as well as creating tools to go from natural language directions to formal task specifications.

## 4 Research and Mentoring Philosophy

My research is inherently interdisciplinary, integrating theories and methods across seemingly disparate disciplines. This allows me to collaborate with and draw from the strengths of an amazing array of other scholars covering education, sociology, formal methods, and mechanical engineering. I additionally publish and present my work in a variety of venues, exposing my work to different audiences. While informed by theory, my work is primarily use-inspired; I conduct basic research with an eye towards practice. My goal is to take established theory and test its applicability in novel domains. I plan to fund this work through venues such as the NSF CAREER award, the NSF Science of Learning and Augmented Intelligence program, and agencies such as NASA which have an interest in practical training.

My approach to mentoring is the same as working with any collaborator – students are part of the research team and should be involved in all stages of the project. This includes ideation, implementation, evaluation, and writing. As I discuss more in my teaching statement, I help students become independent researchers by scaffolding research tasks and empowering them to ask their own questions. I do not believe in gatekeeping in any form; students of all backgrounds have unique perspectives and can contribute creative solutions. My mentees have contributed to many of the projects discussed here. I am currently working with two undergraduates to assess skill for drone pilots and provide contextual feedback with large language models. My work with a masters student resulted in a **best paper nomination** at the Learning Analytics and Knowledge conference. I am excited to continue this work in the future.

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