# **Development of Scenario-based Mentor Lessons**

An Iterative Design Process for Training at Scale

Danielle R. Chine Carnegie Mellon University Pittsburgh, PA, USA dchine@andrew.cmu.edu Pallavi Chhabra Carnegie Mellon University Pittsburgh, PA, USA pallavic@andrew.cmu.edu Adetunji Adeniran Carnegie Mellon University Pittsburgh, PA, USA adetunja@andrew.cmu.edu

Shivang Gupta Carnegie Mellon University Pittsburgh, PA, USA shivangg@andrew.cmu.edu

Kenneth R. Koedinger Carnegie Mellon University Pittsburgh, PA, USA kk1u@andrew.cmu.edu

# **ABSTRACT**

In this demonstration, we showcase the recent advancement of scenario-based tutor training with a focus to scale by applying the learn-by-doing approach to teaching strategies to provide sociomotivational support. These short (~15 min.) self-paced lessons use the predict-observe-explain inquiry method to develop mentor capacity in bolstering student motivation (i.e., fostering growth mindset). These custom training modules are being created to provide supplemental mentor support within the Personalized Learning<sup>2</sup> system, an app which combines human tutoring and student math software to improve mentoring efficiency by connecting mentors to personalized resources, such as scenariobased mentor lessons, based on individual needs. Enhancing mentor training will aid in better quality mentoring at low cost. Mentor training is most effective when scenario-based practice provides trainees with response-specific feedback. To achieve feedback at scale, we illustrate an iterative design effort toward creating selected-response tasks that maintain some of the authenticity benefits of constructed-response. These scenario-based mentor lessons will be used by national level mentoring organizations as part of our efforts to scale.

# **CCS CONCEPTS**

• Applied Computing~Education • Human-Computer Interaction

# **KEYWORDS**

Learning engineering, learning sciences, human-computer interaction, scenario-based learning, mentor learning



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# 1 The Personalized Learning<sup>2</sup> Approach

The Personalized Learning<sup>2</sup> (PL<sup>2</sup>) system combines research-driven mentor training with AI-powered software that is designed to improve mentoring efficiency by connecting mentors to personalized resources with a click of a button. PL2 addresses the opportunity gap among marginalized students by syncing with students' existing math learning software and providing mentors with personalized recommendations based on mentor input and feedback and each student's math effort and progress goals. First introduced by Schaldenbrand et al. [3] the PL2 system consists of one web app each for both students and mentors. Students use math software that passes data to PL2 which is used in synergy with mentor-made post-session reflections customizing student effort and progress goals. The system takes in all of these data streams and suggests resources to identify and provide solutions to address the specific challenges each student faces. The resource library is organized by mentor competency with specific strategies mentors can recommend for students or use themselves. In addition, the PL2 team is developing scenario-based lessons which will be housed in a mentor library to improve mentor efficiency.

For effective mentoring at scale, mentors must be prepared and supported by receiving quality training and consistent coaching [2]. Quality training involves having mentors practice mentoring while receiving feedback, a research-driven strategy to increase learning [5]. We have implemented scenario-based activities to provide such practice. Within such activities, having students construct openended responses is more authentic, but providing feedback at scale is difficult (i.e., hard to collect sufficient data to train AI for automated scoring). On the other hand, selected-response questions make it easier to scale automated feedback but may not work as

well, especially when the incorrect response options are not well designed. In that case, mentors may select the correct response because the incorrect options are obviously wrong. Instead, when incorrect response options reflect genuine misconceptions of novice mentors, they become more effective as practice (and assessment). This demo focuses on a cyclic design approach (modeled from [4]) to create quality mentor lessons at scale.

# 2 Scenario-based Mentor Training

PL<sup>2</sup> is partnering with national level organizations to scale up the number of users using the existing PL2 platform. In working with partners to create personalized training, they expressed mentor needs in the area of teaching strategies for supporting student's selfefficacy and motivation. The most successful mentoring organizations attend to both student's academic and socioemotional needs allowing for relationship building and active feedback [2]. There are two goals: 1) to develop and evaluate needed support for mentor concepts supporting student self-efficacy and 2) to demonstrate and refine an interactive design process by evaluating mentor learning gains. The latter goal has mentors responding to a training scenario (i.e., a student struggling to stay motivated) by asking them to predict how to best respond and explain their prediction, followed by observing the given research recommendation, explaining the reasoning behind what they observed, and finally receiving feedback. Mentors repeat this iterative learning process with a different scenario as a postassessment to determine the transfer of learning and, ultimately, the mentor's learning gain (Figure 1).

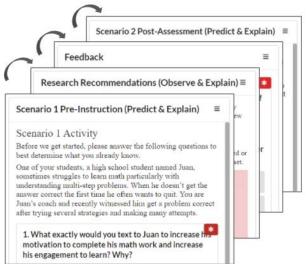


Figure 1. "Supporting a Growth Mindset" lesson a sking a mentor to predict how to best respond to a given scenario in a constructed-response question.

Both selected- and constructed-response question types are used in the predict-observe-explain iterative model. The preliminary pilot mentor responses to the constructed-response questions are used to develop optimized, more effective selected-response options for both less-desired and more-desired responses (modeled from [4]). For example, the selected-response options shown in Figure 2 were optimized from previous pilot constructed-response answers to Question 1 shown in Figure 1. The refinement of selected-response options to better reflect mentor understanding (and misunderstanding) improves the validity of measuring mentor learning on the use of strategies to attend to student self-efficacy and motivation.

The use of authentic selected-response options fosters a deeper level of learning, focuses on the "learn by doing" approach, and can provide situational and simulated experience to beginning mentors without sacrificing quality often found when scaling using selected-response questions. We determine mentor learning by comparing the quality of responses during the training scenario (preinstruction) versus the transfer scenario (post-instruction). The preferred use of selected-responses instead of constructed-responses using both live feedback and guided practice aims to maintain quality upon scaling with our nationwide partnering organizations.

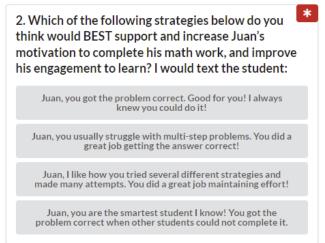


Figure 2. Selected-response question during pre-instruction requiring a mentor to predict how to best respond to the scenario. More authentic response options were created from pilot mentor constructed-response data (See Question 1 in Figure 1.)

Analysis of earlier lessons has shown some evidence of mentor learning in pre-post prediction with substantial improvement in pre-post mentor explanation ability. This evidence supports our hypothesis that short, scenario-based lessons can have a positive impact on mentor learning of how to attend to student self-efficacy [1]. We plan on using this same framework for the creation of subsequent lessons (i.e., using motivation strategies) with the goal of lessons being housed in the PL<sup>2</sup> resource library for use by our nationwide mentoring organization partners.

<sup>&</sup>lt;sup>1</sup> Link to "Supporting a Growth Mindset" module using Teacher Moments, a digital clinical simulation platform for teacher training from the MIT Teaching Systems Lab, found here: https://teachermoments.mit.edu/cohort/04f3a0e726

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