Scenario-based Training and On-the-Job Support for Equitable Mentoring

Danielle R. Chine[0000-0001-8196-3252], Pallavi Chhabra, Adetunji Adeniran, Joseph Kopko, Cindy Tipper, Shivang Gupta, Kenneth R. Koedinger

Carnegie Mellon University, Pittsburgh PA , USA
dchine@andrew.cmu.com

Abstract. Personalized Learning^2 (PL^2) is a mentor professional development platform designed to improve efficiency and workplace training through scenario-based instruction and personalized support. Combining research-driven mentor training with artificial intelligence (AI)-powered software, PL^2 connects mentors, often under-trained tutors, to personalized resources with the click of a button. These curated resources cover a range of topics from social-emotional learning and math content to culturally responsive teaching practices. PL^2 is addressing the opportunity gap among marginalized students by recommending specific instructional supports and social-emotional resources based on student's individual math performance and effort. This work in progress showcases our recent development of the PL^2 approach to mentoring in three ways. First, we highlight the key functions of the PL^2 system. Second, we present recent research results determining the most effective competencies for successful mentorship. Last, in response to partner feedback on which mentor competencies are most needed, we detail the development of asynchronous, scenario-based lessons, housed within the PL^2 platform for on-demand training. The use of human-computer teaming for on-the-job support offers a lower cost option for deliberate practice using scenario-based training to increase the impact and learning capacity of mentors in the workplace.

Keywords: Tutor training, mentor training, scenario-based, equitable mentoring, adult learning, workplace training.

1 Introduction

The demand for experienced quality mentors or tutors in public education and afterschool organizations is at an all-time high [8]. Due to the repercussions of the COVID-19 pandemic on the educational system, schools and organizations are struggling to recruit not only licensed teachers, but experienced and qualified mentors [8]. Historically marginalized students (i.e., Black, Hispanic, students experiencing poverty, first generation college students) are at the greatest risk of not meeting annual growth gains compared to their peers [7, 10]. In fact, students in high-poverty schools or marginalized groups have been impacted the most by recent educational disruption with the biggest declines in overall performance occurring in math [10]. A possible solution to attend to the opportunity gap experienced by these under resourced student populations is individualized instruction through mentoring. Individualized instruction through mentoring has been repeatedly found to be one of the most impactful interventions on student achievement [9]. One challenge to using mentors to address the gaps of learning loss and provide additional instructional support is the lack of experienced and skilled mentors. For purposes of this work, a mentor is an unlicensed paraprofessional who provides academic support similar to a tutor along with providing social-emotional support and relationship building skills. In addition, a “mentor” is defined as a person, oftentimes with more experience, who provides support and guidance to somebody with lesser experience and is typically younger in age [6]. This work discusses a human-computer teaming platform that provides both scenario-based training and personalized resources to mentors— many of whom are unskilled or lack experience. We discuss the need for quality upfront training and continuous on-the-job professional development. Two competencies that surveyed organizations highlighted as critical for training were ‘culturally responsive teaching practices’ and ‘awareness of biases’. We created both synchronous and asynchronous scenario-based workplace training attending to these mentor competencies within a human-computer tutoring platform. Included with the scenario-based training details are preliminary research results and feedback from mentors and our partner organizations.

2 The Personalized Learning^2 Approach

Personalized Learning^2 (PL^2) is software designed to improve K-12 student learning by combining the benefits of both human mentoring and computer-based learning with EdTech tools [12][1]. By syncing with students' math learning software, mentors can easily and effectively determine areas of student's need and access personalized resources. PL^2 ensures customized mentor support via continuous, on-the-job training and resource assistance in both math content skills and social-emotional and motivational teaching. Students, particularly marginalized students, benefit as they receive personalized resources based on their individual math learning performance, gain access to social-emotional supports, and receive resources attending to equity [4].

2.1 Key Features of the Personalized Learning^2 App

The PL^2 platform contains a mentor library of resources organized by competency. The PL^2 mentor resource library allows mentors to use the *Resource Assistant*, which assists mentors with finding the appropriate resource given a student's individual need (i.e., a student lacking motivation, a student struggling with a certain math skill). Mentors can view pinned resources for easy access, and also create their own resources. Mentors can also add feedback and input into the AI-driven software system using the *Make a Reflection* feature and participate in asynchronous lessons by clicking the *Lessons* tab (See Fig. 1).

[1] http://personalizedlearning2.org/index.html

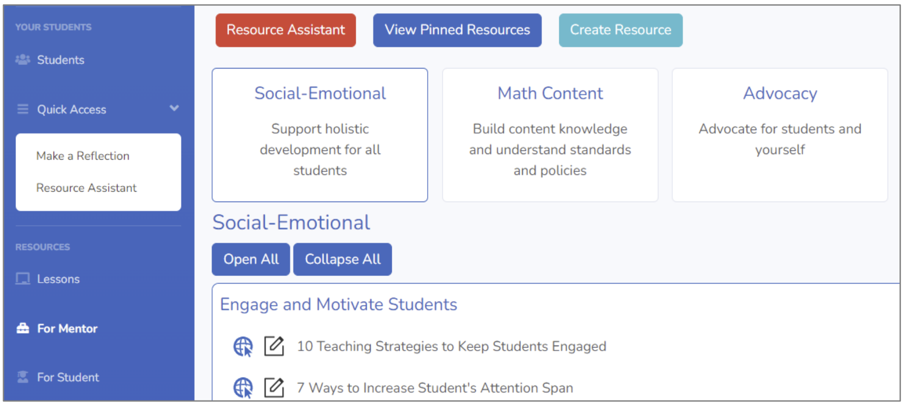


Fig. 1. The PL^2 resource library gives mentors access to the *Resource Assistant*, allows them to view pinned resources for easy access, and helps mentors to create their own resources. Mentors can also add feedback and input into the system using the *Make a Reflection* feature and participate in asynchronous lessons by clicking the *Lessons* tab.

Released three years ago, PL^2 contains both a web app for mentors and system administrators and another for students. Math learning software (e.g., ALEKS, MATHia, Dreambox) used by students is connected to the mentor platform to assist mentors with making decisions regarding recommended resources and goal setting. From the platform, mentors can see their student’s performance and customize goals by adjusting student’s effort and progress goals based on math software performance and mentor observation. Methods of measuring student effort include the number of minutes spent using the EdTech, number of topics attempted, and similar measures unique to different EdTechs. Students are assigned two effort goals within PL^2 aligned to the amount of time and number of lessons/topics attempted. Progress is determined by measuring student achievement via the number of problems correct or lessons completed demonstrating mastery development.

The status of each student (i.e., *Missed you*, *Ramp it up*, *Wow*, and *Keep it up*) is indicated by giving mentors information regarding student’s performance on both their effort and progress goals. Fig. 2 displays the status of a group of students assigned to a particular mentor. A status of *Missed you* means a student did not meet their effort goals. A status of *Ramp it up* means they met their effort goals but did not meet their progress goal. The *Keep it up* status means the student met both their effort and progress goals with students displaying a *Wow* status upon exceeding both goals.

Resources for both mentors and students are then recommended based on the student's performance toward reaching their goals and mentor feedback. Mentors give feedback by providing post session reflections via a reflection form within PL^2. The form asks non-mandatory questions regarding the mentoring session (i.e., *What’s one thing that went well?*, *What's one thing that could have gone better?*, *What do you want to remember for your next session with the student?*). The mentor is asked to choose an area(s) where a student faces challenges (i.e., social-emotional health, math, relationship building). Finally, the reflection form requires mentors to rate the session based on a five-star rating system.

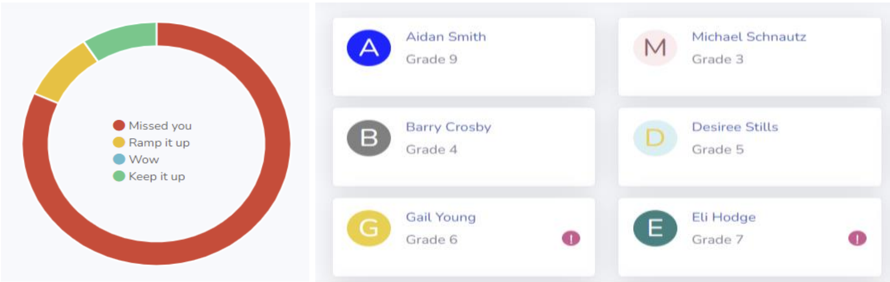


Fig. 2. The student status indicator shown on the PL^2 homepage detailing the status of students giving mentors information regarding student's performance on both their effort and progress goals. Although not all students' cards are shown due to space, from the circular graphic it is apparent the majority of students are in the *Missed you* status, meaning they have not met either of their effort goals.

Mentors can track their students' progress toward their goals and see individual and group progress in graphical form indicated by time spent using EdTech, number of problems correct, and percent accuracy with options varying based on EdTech used (See Fig. 3).

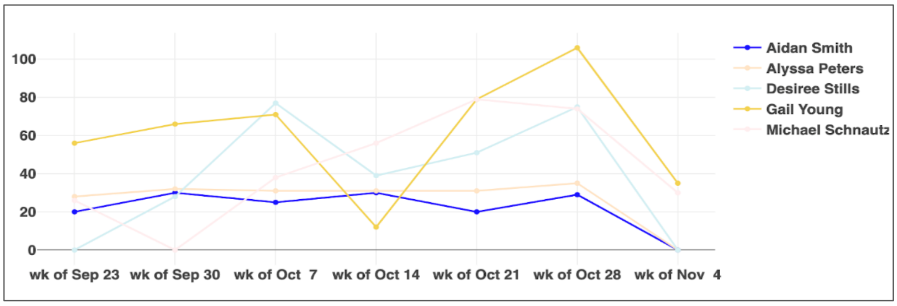


Fig. 3. A data report displaying the progress of five students assigned to a mentor within PL^2 showing the time spent using EdTech over several weeks. Mentors can use this data to identify trends and abrupt changes in student performance.

This information greatly assists mentors with seeing students' progress over longer periods of time (i.e., weeks, months). It also helps mentors identify trends in groups of students' progress, effort, and learning to assist mentors with personalizing the mentoring experience for students and recommending appropriate resources.

The PL^2 approach to mentoring provides support in two ways. First, through the use of human mentoring providing support in not only math content but social emotional learning, culturally responsive teaching practices, and relationship building. Students meet with mentors several days per week for one to two hours. This transcends the concept of tutoring into "high dosage" mentoring, an intervention found to produce significant growth gains among marginalized students [8]. Human mentoring occurs in conjunction with AI-driven software to recommend resources using student EdTech data and mentor input and feedback to provide AI-driven, personalized support for mentors. Second, the PL^2 approach is a platform for delivering and providing customized synchronous and asynchronous lessons to mentors based on individual need. The main purpose of this present work is to showcase the topics and methods of creating these scenario-based lessons.

Preliminary work on the use of the PL^2 approach to improve student learning in math was conducted through the Ready to Learn (RTL) program [4]. RTL is an after-school math intervention program designed to reach marginalized students. In partnership with the University of Pittsburgh's Center for Urban Education, RTL focuses on educational equity by providing mentor on-the-job training in the areas of mentor bias awareness and providing culturally relevant teaching practices. Preliminary data found students (~80% Black) grew by an average of 6.8 scale points on the NWEA Measure of Academic Progress (MAP) test compared to a 3.6-point improvement by matched students not in the program. This impressive growth from 2019 to 2020 is higher than typical one year growth in MAP scores (~5.5 points), despite pandemic-related challenges [4]. Further research is needed to determine the impact of using the PL^2 approach of using low-cost mentoring in synergy with computer-based tutoring. In addition, more research needs to be conducted on the influence of mentor on-the-job training and scenario-based lessons and the subsequent impact on student learning.

Many schools and out of school time organizations, such as the Boys and Girls Club and AmeriCorps, have partnered with PL^2 with over 150 mentors using the app. Due to the COVID-19 pandemic, both students and mentors have lower baseline knowledge and the gap for marginalized students has further increased [10]. Virtual mentoring is being used more often with mentors needing support especially related to using technology. EdTech usage has increased leading to the need for a singular data collection platform with one early PL^2 success of being able to pull in data from multiple types of software. Another challenge is the recent decrease in both quality and quantity of available mentors. With PL^2's mentoring organizations using a variety of implementation models (i.e., in-person, online, hybrid), particularly post-COVID, there is an increased need for development of asynchronous training that allows mentors to complete as-needed and on their own time [2].

3 Determining Competencies of Successful Mentorship

Upon discussing with our partners and feedback from mentors, there is an expressed need for mentor training in specific mentoring areas (i.e., How can mentors increase student engagement and motivation?, How can mentors gain math content knowledge?, How can mentors be more culturally responsive?). We have conducted preliminary research in examining the qualities of effective mentorship among our partners determining educational practitioners' attitudes toward different mentoring competencies in order to identify specific skills or competencies for which mentors need training most urgently [1].

3.1 SMART Supports Creation

Mentor resources in the PL^2 platform were organized by categories aligned with the appropriate mentor competencies. To determine appropriate mentor competencies, we synthesized from triangulation of competencies curated from educational wellness organizations, such as Danielson Group, CASEL, and KnowledgeWorks[2]. In addition, we received input and feedback from our PL^2 partners, which were all mentoring and tutoring organizations. We also surveyed 18 organization administrators to determine how important they felt each skill or competency was to successful mentorship [1]. A 4-point modified Likert scale was used with respondents rating each of the 14 competencies based on how important they felt the skill, ability, or behavior was for successful mentoring within their organization. The scale options for each randomized competency indicated with increasing importance were: [1] low priority, [2] medium priority, [3] high priority, [4] urgent. From these results the competencies were organized by theme, or super-competences. We call these super-competencies SMART supports (i.e., Social-emotional, Math, Advocacy, Relationships, Technology). This preliminary work was submitted in a prior paper [1], however, the results are an impetus for the creation of asynchronous and synchronous lessons which are the focus of this present work. Table 1 displays the 14 competencies organized into the schema of SMART supports, or super-competencies. *Engage and Motivate Students* received the highest rating (3.7) and *Understand Educational Policies and Norms* the lowest (2.2). The average priority rating is shown in the first parenthesis and the number of mentor-specific resources within the PL^2 app is shown in the second parenthesis indicated in italics. There is a lack of resources located in the following mentor competencies: *Demonstrate Awareness of Bias, Practice Self-Care, Manage Learning Environment, Stay Organized*.

Table 1. SMART supports illustrating the schema developed from the survey data organizing the 14 competencies into main themes. The first parenthesis indicates the average priority rating. The second number in parenthesis (indicated in italics) is the current number of mentor resources located within the PL^2 app. Notice the lack of resources within the *Advocacy* super-competency.

Social-Emotional	**M**ath Content	**A**dvocacy	**R**elationships	**T**echnology Tools
Engage and Motivate Students (3.7)*(32)*	Demonstrate Content Understanding (3.4)*(19)*	Demonstrate Awareness of Biases (3.5)*(0)*	Build Relationships with Students (3.5)*(7)*	Use Technology Effectively (3.0)*(17)*
Foster Independent Learning (3.5)*(3)*	Understand Educational Policies and Norms (2.2)*(5)*	Use Culturally Responsive Teaching Practices (3.4)*(9)*	Personalize Learning (3.4)*(4)*	Stay Organized (2.7)*(0)*
Apply Social-Emotional Learning Practices (3.3)*(12)*		Practice Self-Care (2.9)*(0)*	Communicate with Caregivers (2.5)*(10)*	
Manage Learning Environment (3.1)*(0)*				

This novel method of categorizing mentor competencies into SMART supports calls attention to the *Advocacy* super-competency with *Demonstrating Awareness of Bias* and *Practice Self-Care* containing zero resources. *Demonstrate Awareness of Bias* had one of the highest ratings (3.4) according to PL^2 partners and the need for more resources related to *Use of Culturally Responsive Teaching Practices*, which had a high

2 https://danielsongroup.org/, https://casel.org/, https://knowledgeworks.org/

priority average rating of 3.5 and 3.4, respectively. The dedication of PL^2 to attending to equity and the expressed need from our PL^2 partners for training and resources related to these competencies sparked creation of lessons within the PL^2 app [1].

4 Scenario-based Training

The PL^2 mentor platform contains mentor-specific resources, student EdTech data, and scenario-based training organized by mentor SMART supports. Deliberate practice of scenario-based learning mimicking workplace fundamentals (i.e., mentors working with students) are at the forefront of mentor support. Scenario-based training has shown to be an impactful method of achieving learning gains by providing simulated experience and deliberate practice in a safe environment [13]. Deliberate practice is difficult and requires mentors to persevere in the learning process. Fortunately, focused and deliberate practice can yield substantial rewards— large growth gains [5].

Within the PL^2 platform we offer both synchronous and asynchronous lessons. Synchronous lessons are presented live to mentors as interactive presentations containing live links and videos housed within *Lessons*. Currently, upfront lessons provided include: *Strategies for Effective Tutoring & How PL^2 Supports Them*, *Student Engagement & Motivation Strategies Using PL^2*, *Introduction to Teaching Math and Gaining Math Support*, and *Using Culturally Responsive Teaching Practices*. From the feedback received from PL^2 partners we are expanding our synchronous lessons offered and are currently creating on-the-job, in-person lessons related to demonstrating an awareness of bias and strategies for fostering independent learning. Asynchronous lessons are currently being added with a focus on areas indicated as high priority according to our partners surveyed and feedback showing expressed areas of need (i.e., *Demonstrate Awareness of Bias*, *Build Relationships with Students*, *Engage and Motivate Students*). This work focuses on the development and structure of mentor asynchronous training modules.

4.1 Asynchronous Scenario-based Training

Asynchronous scenario-based lessons have been created for continuous, on-the-job support that mentors can complete on their own time and at their own pace. Some asynchronous lessons already created include: *Supporting a Growth Mindset, How to Present the Lesson to Students: Framing Task Difficulty, Using Intrinsic and Extrinsic Motivation Strategies* [3]. Recent plans upon receiving survey feedback from partners include creating more asynchronous lessons related to the following competencies: *Demonstrate Awareness of Bias* and *Manage the Learning Environment*. A segment from part of an asynchronous, scenario-based training titled *Reacting to Errors*, instructing a mentor on how to best respond to a student making errors while being cognizant of student self-efficacy is shown in Figs. 4-6. This module uses an introductory training scenario, walking a mentor through predicting and explaining the best mentor response. Then they observe the research-based recommendation and explain their thoughts of applying the research-driven recommended strategy. Finally, as a post-assessment and to provide further formative instruction, the mentor completes the cycle again with a transfer scenario to determine their ability to apply their learning from the initial training scenario. The constructed-response question in Fig. 4 asks mentors to predict or choose how they would approach the student in recognizing his mistake while attending to his self-efficacy. This lesson aligns with the competency of *Engage and Motivate Students* within the *Social-Emotional* SMART support.

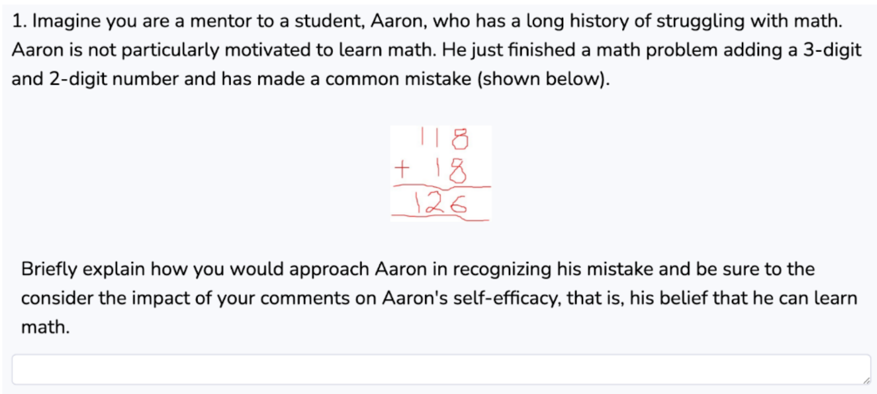
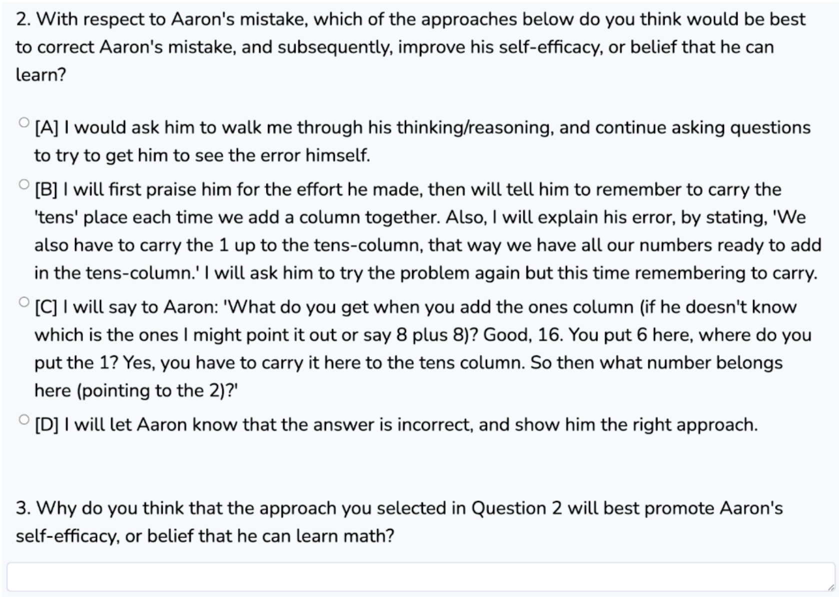


Fig. 4. A segment of the *Reacting to Errors* asynchronous lesson showcasing the initial training scenario asking mentors to predict or choose how they would respond to the given scenario while attending to the student's self-efficacy.

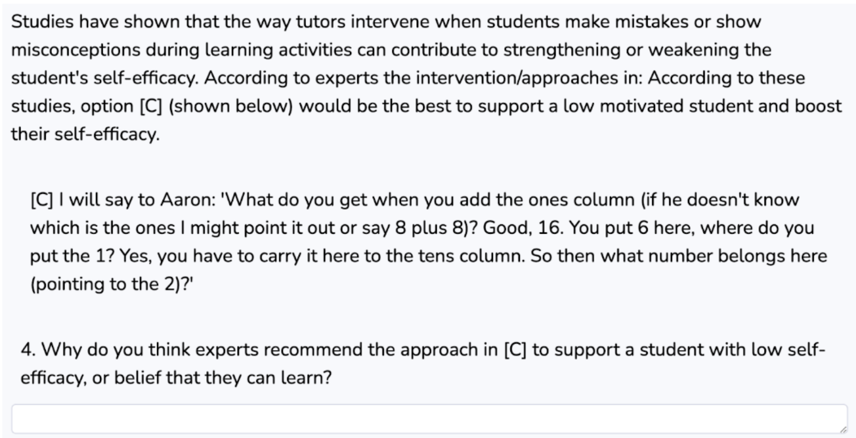


2. With respect to Aaron's mistake, which of the approaches below do you think would be best to correct Aaron's mistake, and subsequently, improve his self-efficacy, or belief that he can learn?

- [A] I would ask him to walk me through his thinking/reasoning, and continue asking questions to try to get him to see the error himself.
- [B] I will first praise him for the effort he made, then will tell him to remember to carry the 'tens' place each time we add a column together. Also, I will explain his error, by stating, 'We also have to carry the 1 up to the tens-column, that way we have all our numbers ready to add in the tens-column.' I will ask him to try the problem again but this time remembering to carry.
- [C] I will say to Aaron: 'What do you get when you add the ones column (if he doesn't know which is the ones I might point it out or say 8 plus 8)? Good, 16. You put 6 here, where do you put the 1? Yes, you have to carry it here to the tens column. So then what number belongs here (pointing to the 2)?'
- [D] I will let Aaron know that the answer is incorrect, and show him the right approach.

3. Why do you think that the approach you selected in Question 2 will best promote Aaron's self-efficacy, or belief that he can learn math?

Fig. 5. A segment of the *Reacting to Errors* lesson within the training scenario displaying the selected-response question intended for the mentor to predict or choose the best approach followed by a constructed-response question asking them to explain.



Studies have shown that the way tutors intervene when students make mistakes or show misconceptions during learning activities can contribute to strengthening or weakening the student's self-efficacy. According to experts the intervention/approaches in: According to these studies, option [C] (shown below) would be the best to support a low motivated student and boost their self-efficacy.

[C] I will say to Aaron: 'What do you get when you add the ones column (if he doesn't know which is the ones I might point it out or say 8 plus 8)? Good, 16. You put 6 here, where do you put the 1? Yes, you have to carry it here to the tens column. So then what number belongs here (pointing to the 2)?'

4. Why do you think experts recommend the approach in [C] to support a student with low self-efficacy, or belief that they can learn?

Fig. 6. A segment of the *Reacting to Errors* lesson within the training scenario revealing the research-recommended strategy for the formative training scenario. Mentors are then asked why they think the research-recommended response is suggested by experts as both a constructed-response question and then as a selected-response (not shown).

Mentors complete the training scenario which concurrently involves deliberate practice and applying the research-recommended strategy to the initial training scenario. Then as a post-assessment quantifying their learning gains, they participate in a similar transfer scenario (i.e., predict the best response, explain your response, observe the expert-recommended strategy, explain the expert-recommended strategy). The comparison of mentor performance from the initial scenario (training scenario) to the final scenario (transfer scenario) is used to determine mentor learning gains. The transfer scenario uses a similar scenario and follows the same predict-explain-observe-explain pattern of inquiry. The inquiry model (i.e., predict-explain-observe-explain) of asking mentors to respond to a given scenario and apply the research-recommended strategy for both the training and transfer scenarios has been developed to give unskilled or under-experienced mentors the situational experience needed to be successful. In addition, mentors receiving feedback, particularly corrective feedback, throughout the lesson is associated with high learning gains [15]. We are using preliminary data from the constructed-response questions to create more authentic selected-response question options. The use of pilot mentor response data from the constructed-response questions to optimize the selected-response question options is modeled from Wang et al. [14]. The creation of more authentic and "real life" mentor responses for selected-response questions from constructed-response data allows us to capture common misconceptions among mentors and use them as "less-desirable" or "incorrect" answer options. This increases not only the validity of the mentor training as an accurate assessment of mentor understanding but increases scalability through the use of selected-response question types.

5 Discussion & Conclusion

Currently, the PL^2 platform is transitioning from a primarily mentor-specific resource app to a holistic system. We are providing not only personalized resources but dual functionality as a training platform for mentors. Since initial submission of this article, we have repackaged the PL^2 platform into a system of three focused solutions. The first solution is PL^2 *Training*, which contains the resource library discussed previously and also houses asynchronous lessons for on-demand and as-needed access by mentors. At the time of press, we have created a dozen asynchronous lessons that were rated high-priority by competency and/or have few resources located within the mentor library (i.e., *Foster Independent Learning, Demonstrate Awareness of Biases, etc.*).

The second solution, PL^2 *Toolkit*, repackages student EdTech status features, goal setting, and recommended resources allowing mentors to personalize the learning experience for their students. Within the *Toolkit*, mentors can get a quick snapshot of a student's progress with data from both EdTech software and embedded tools for reflections and goal setting. Presently, we are seeking out ways of adding more AI-driven features to increase personalization of resources, such as using natural language processing to assess open-response questions for purposes of scaling with our nationwide partners.

The last focused solution in the PL^2 solution trifecta is the *Tutoring Corps*. The *Tutoring Corps* is a team of trained mentors ready to go on-demand for as-needed mentoring support for our partners. Recent changes due to ramifications of the COVID pandemic have caused a nationwide shortage of qualified teachers and mentors. PL^2 has approached this obstacle by developing a strategic plan in recruiting quality mentors. Based on a model proposed by Kraft and Falken (2021) in *A Blueprint for Scaling Tutoring and Mentoring Across Public Schools*, we designed a mentor recruitment plan targeting undergraduate college students. Recruitment of college students is often easier because of their need for volunteer hours for graduate applications, internships, and resume building. As a benefit to organizations, college students are often unable to accept compensation. In addition, aside from volunteer work, college students can receive mentoring certifications, participate in training, gain valuable experience working with children, and contribute to the community. Necessary mentor qualifications include being English speaking, possess quality reading, math, and writing skills, and have a willingness to work with children. Fortunately, many college students today come with math competence and ability to tutor up through middle school oftentimes matching in math skills to trained mentors.

We are also working on several functionality advances, such as a student-facing PL^2 version allowing students to directly access resources, monitor their own goals, and directly message mentors. The latter feature creates a method of asynchronous, as-needed communication between mentor and student to improve the efficiency and accessibility of supportive tutoring for students.

Future work consists of surveying more partners in differing mentoring roles (i.e., supervisors, mentors, coaches) to determine their perspectives regarding mentoring competencies. This will assist us with the creation of asynchronous lessons based on mentoring roles and organization types (i.e., public school, tutoring organization, support network). Moreover, research is being conducted on our asynchronous lessons by analyzing the pre- to post-instruction learning gains determined by the selected-response and constructed-response data by comparing mentor performance of training and transfer scenarios [3]. Some of the research questions we are investigating include: What differences exist among mentors' perceptions of learning and their demographics (i.e., race, gender, age) and also self-reported level of experience? Do mentors reporting a high level of experience perform better? Do mentors learn new mentoring strategies and skills from short scenario-based lessons? This last question is of particular importance with preliminary evidence supporting vast improvements in mentor learning as a function of our scenario-based mini lessons [3].

Lastly, the high cost of one-on-one coaching programs makes it hard to scale [8, 11]. The PL^2 platform is working towards enabling lower cost mentoring without sacrificing learning quality. The use of human-computer teaming for on-the-job support offers a lower cost option for deliberate practice using scenario-based training to increase the impact and learning capacity of mentors in the workplace.

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