Computer-Supported Human Mentoring for Personalized and Equitable Math Learning

Chapter · June 2021

DOI: 10.1007/978-3-030-78270-2_55

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Computer-Supported Human Mentoring for Personalized and Equitable Math Learning

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Abstract. Computer tutor data indicate that more learning opportunities yield greater achievement, but also confirm there are gaps in the number and quality of opportunities marginalized students receive that technology alone does not address. Personalized learning with mentors can close this gap in opportunities but is expensive to implement. We introduce a free, web-based application, Personalized Learning^2 (PL^2), designed to improve mentoring efficiency by connecting mentors to intervention and instructional resources. Preliminary findings indicated that PL^2's categorization of students based on math learning software data enabled mentors to focus their efforts, and that mentors found PL^2 resources to positively expand how they taught and mentored.

Keywords: Personalized learning · Mentor augmentation · Motivational resources · Design-based research

1 Introduction

More than 60 years after the Supreme Court's ruling to desegregate schools, American K-12 education remains marred by strikingly inequitable access, opportunities, and learning outcomes across racial groups and income classes. These gaps are especially big in mathematics and they perpetuate inequalities across generations [11]. While these are long-standing problems, researchers have struggled to identify effective solutions. Research undertaken in public schools in high-poverty neighborhoods provides grounds for hope. A large randomized control trial demonstrated that one year of intensive, personalized human tutoring could significantly increase math achievement for minoritized students in high-poverty neighborhoods [2]. Unfortunately, these gains came at a substantial resource cost; with a tutor providing instruction to just two students per class period, the extra costs of nearly $4,000 per student are not feasible in many districts.

AIEd technologies can lower the cost of personalized tutoring and increase student achievement [9,10], but they are not sufficient. An increase in learning

I. Roll et al. (Eds.): AIED 2021, LNAI 12749, pp. 308–313, 2021.
https://doi.org/10.1007/978-3-030-78270-2_55

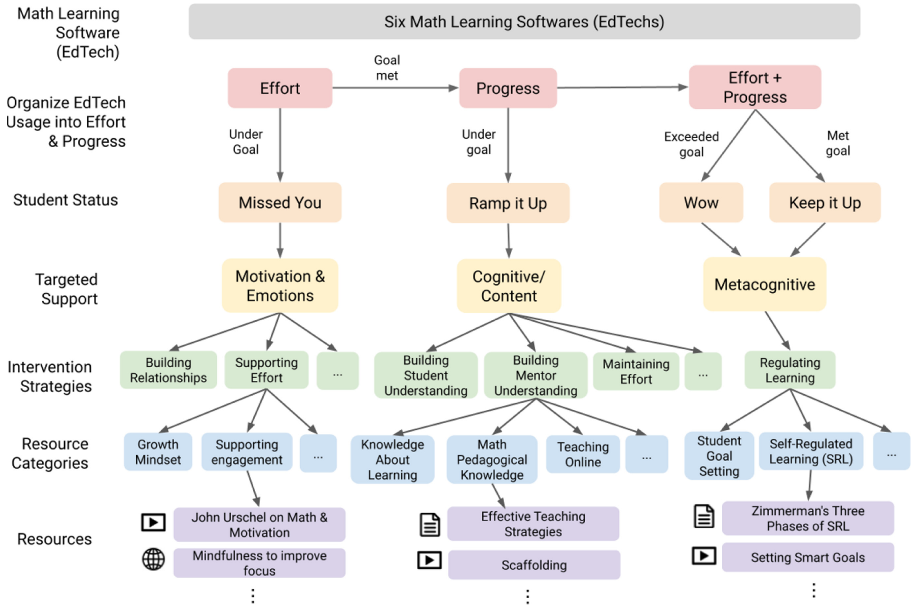

Fig. 1. PL^2 connects EdTech products to mentor and student assisting resources via a system of categorization of student data and resources based on intervention strategies.

opportunities, such as time spent making progress in math tutoring software, leads to an increase in achievement; however, marginalized students experience fewer of these opportunities for learning [5]. Many interventions aim to reduce opportunity gaps in math by addressing non-content related learner variables [1,4]. The conditions of each student and the extent to which their learning is affected is diverse [7,8,13], suggesting that there is no one-size-fits-all solution to the problem. Personalized learning, which is tailored to the social, material, and organizational needs of each child [14], may be the ideal solution, but it is not practical in terms of cost and availability of human resources for every child in the U.S. to receive one-on-one attention from a human tutor [3].

We introduce the Personalized Learning^2 (PL^2) application[1] which is designed to improve mentoring efficiency by recommending instructional resources curated from the Internet to mentors based on their students' usage of educational technology (EdTech) software. Figure 1 depicts how PL^2 connects EdTech data to resources, integrating smoothly into a mentor's workflow. PL^2 provides tools for easily navigating these resources and matching them to students' and mentors' needs. Since PL^2's initial deployment in Summer 2019, 148

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

mentors have used the system with a total of 814 students. PL^2 currently pulls data from six different EdTechs and has organized and made available to users more than 100 resources.

2 Method

EdTech Data. Interviews with mentors planning to use PL^2 revealed they use multiple technology products, and additional products can create fatigue and inefficiencies. To reduce this fatigue, PL^2 integrates mentors' existing softwares. PL^2 pulls data from six different EdTechs including McGraw Hill's ALEKS, Carnegie Learning's MATHia, and Imagine Learning's Imagine Math.

Data from the six EdTechs varies, creating a design challenge for presenting data consistently. All EdTechs provide a measure of how much time a student spent in the system, but not all measured completion of sub-units of curriculum, and the granularity of sub-units varied greatly. To find consistent measurements across EdTechs, we computed abstract quantities in the form of effort and progress using data from each EdTech. Effort and progress were selected for their relationship to students' motivational and cognitive obstacles, respectively. We calculated effort using time on system and curriculum sub-units completed, and progress using accuracy on the sub-units completed.

Resources. Internet resources can be helpful in addressing the opportunity gaps students face by supporting their self-efficacy [12], feelings of belonging [15], growth mindset [16], and utility value of STEM [6]. These resources are scattered across the web and therefore can be difficult to find, and mentors may not know what to search for. PL^2 was designed to help make sense of the unwieldy number of resources available on the internet by selecting, organizing, and summarizing relevant materials according to a three-tiered hierarchy: Strategy → Category → Resource (see Fig. 1). Strategies are the highest level in the structure for finding appropriate resources for an issue. For example, a mentor may see their student is not putting effort into their work and explore resources within the Supporting Effort strategy. This strategy has categories of resources including Growth Mindset and Supporting Engagement. Within each category there are existing resources (e.g., videos, links to external websites, papers, interactive activities). This structure supports varying degrees of mentor expertise to navigate through resources and allows mentors to create their own resources. Resource strategies were organized according to enabling conditions that were identified through interviews with PL^2 partners as candidate root causes for student success (see Fig. 2).

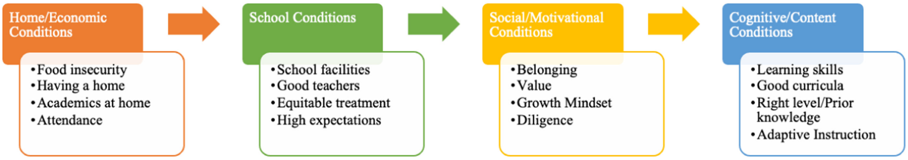

Fig. 2. Themes emerged from interviews indicating many enabling conditions that must be met for students to succeed.

Categorizing EdTech Usage. PL^2 organizes student usage into four categories called "student statuses" (See Fig. 1) that correspond to optimal intervention strategies: Missed You designates a failure to meet effort goals, indicating a motivational or emotional strategy is likely needed; Ramp It Up signifies meeting the effort goals but falling short on progress goals, indicating a potential need for a content or cognitive intervention; Wow represents students exceeding their goals, indicating that the student needs a more challenging goal; and Keep It Up is for students meeting their effort and progress goals, indicating that they are on track. As shown in Fig. 1, there is a hierarchical structure for calculating the student status, which is organized according to progression of the enabling conditions seen in Fig. 2. Motivational needs are prioritized over cognitive needs, and therefore effort is assessed prior to progress.

3 Results

The distribution of statuses in 2020 accounting for 3612 student-weeks in the EdTechs was 28.5% Missed You, 18.2% Ramp it Up, 40.2% Wow, and 13.1% Keep it Up, indicating the categorization strategy can detect variability in students' behaviors. In total, there are 58 resources designed for mentors, 40 for students, and 16 for either students or mentors that have been neatly organized into 3 methods of targeted support, 9 strategies, and 36 resource categories. Thus far, interviews with mentors using PL^2 have led to expressions of PL^2's ability to positively expand the way they teach and mentor by thinking about students in different ways, as illustrated by the following quote from a PL^2 mentor: "I like using the 'Parent Engagement' resource because that is one of the bigger problems I have in my district. It is a great resource that provides me with new/creative ideas on how to engage parents with their child's academics."

4 Conclusions and Future Work

The design of PL^2 engaged a community of mentors, teachers, and students and provided an example of design-based research that is not common in the AIEd community. PL^2 also exhibits a novel attempt at connecting multiple EdTech data streams and methods for comparing and using student data across EdTechs. Future work for the PL^2 project includes empirical studies and validating the efficacy of the application. We also plan to revise our measure of progress to include information about a student advancing through their curriculum.

Acknowledgment. This work is supported by the Chan Zuckerberg Initiative (CZI) Grant # 2018-193694. Any opinions, findings, and conclusions or recommendations expressed in this material are those of the authors and do not necessarily reflect the views of the Chan Zuckerberg Initiative.

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