Technology Ecosystem for Orchestrating Dynamic Transitions between Individual and Collaborative AI-tutored Problem Solving

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Abstract. It might be highly effective if students could transition *dynamically* between individual and collaborative learning activities, but how could teachers manage such complex classroom scenarios? Although recent work in AIED has focused on teacher tools, little is known about how to orchestrate dynamic transitions between individual and collaborative learning. We created a novel technology ecosystem that supports these dynamic transitions. The ecosystem integrates a novel teacher orchestration tool that provides monitoring support and pairing suggestions with two AI-based tutoring systems that support individual and collaborative learning, respectively. We tested the feasibility of this ecosystem in a classroom study with 5 teachers and 199 students over 22 class sessions. We found that the teachers were able to manage the dynamic transitions and valued them. The study contributes a new technology ecosystem for dynamically transitioning between individual and collaborative learning, plus insight into the orchestration functionality that makes these transitions feasible.

Keywords: Classroom Orchestration, Dynamic Transitions, Differentiated Learning, Collaborative Learning

1 Introduction

Combining individual and collaborative activities is very common in educational practice (e.g., Think-Pair-Share [4]). Such combinations can be more effective than learning solely in one mode [6]. An exciting vision for the smart classroom of the future is to *dynamically* combine collaborative and individual learning [1]. In dynamic transitions, students switch between collaborative and individual learning when the need arises (e.g., when a student is no longer progressing productively in one mode of learning). Such transitions are not pre-planned, but can happen opportunistically in order to address students' in-the-moment needs. Dynamic transitions hold potential to be maximally responsive to the fact that students learn at their own pace and may achieve more personalized learning for students than pre-planned transitions [7]. For example, teachers may team up students to work together if one of them is struggling and can use a partner's help. However, orchestrating dynamic transitions in classrooms is a major challenge for teachers [7], as it involves not only understanding students' in-the-moment needs, but also managing the transitions in real time while attending to the ongoing class activities.

Prior research has produced many tools that support teachers in orchestrating complex learning scenarios (e.g., [2]). These tools have, however, typically been designed with the assumption that a class of students progresses through instructional activities in a relatively synchronized manner [5]. Furthermore, existing orchestration tools generally focus on enhancing teacher *awareness* by providing teachers with real-time analytics [5]. Few provide intelligent support for teachers' in-the-moment, dynamic *decision-making* [8], with some exceptions (e.g., [9]). Providing intelligent support to teachers when orchestrating highly-differentiated, self-paced classrooms remains a challenging research problem [7], with little prior work in this area. Our own prior study explored the potential of supporting dynamic transitions between individual and collaborative learning in the classroom [1]. We found a need for sharing control over these transitions between students, teachers and AI systems. The study was a technology probe "Wizard of Oz" study, where a researcher mimicked part of the orchestration functionality. In the current study, we test a fully functioning system, without a wizard.

Specifically, we created a technology ecosystem (Fig. 1) that supports teachers in orchestrating students' dynamic transitions between individual and collaborative learning, both supported by intelligent tutoring software (ITS). We conducted an exploratory classroom study with 5 teachers and 199 middle-school students to gain insight into the feasibility of dynamically transitioning between individual and collaborative learning. The work extends prior work in orchestration technologies with AI support by implementing an orchestration tool that allows teachers to manage dynamic transitions between individual and collaborative learning and demonstrating that the combination of awareness support and AI-based pairing suggestions can feasibly support these dynamic transitions.

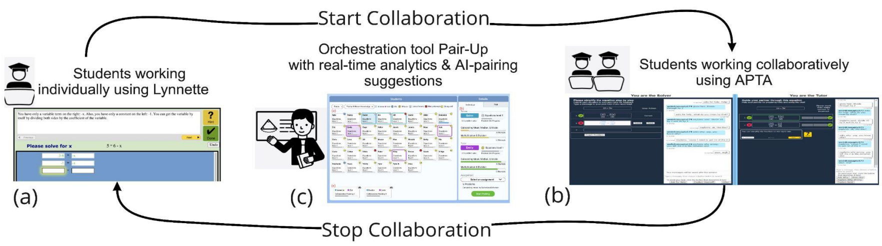

Fig. 1. Technology ecosystem for supporting dynamic transitions, including individual tutor (a), collaborative tutor (b) and the orchestration tool (c)

2 Technology Ecosystem for Dynamic Transitions

The technology ecosystem consists of two tutoring software which respectively support students' individual and collaborative learning, and a teacher-facing orchestration tool.

2.1 Support for Students' Individual and Collaborative Learning

A standard ITS,, Lynnette (Fig 1, a), offers support for *individual* learning of basic equation solving. Lynnette provides step-by-step guidance, in the form of adaptive hints, correctness feedback, and error specific messages, and has been proven to improve students' equation-solving skills in several classroom studies (e.g., [3]).

The Adaptive Peer Tutoring Assistant, APTA (Fig 1, b), extends Lynnette's functionality to support *collaborative learning,* specifically, reciprocal tutoring. When using APTA, two students respectively take the role of "solver" and "tutor" . The "solver" solves the math problem and can seek help from their partner. The "tutor" helps the "solver" through step by step evaluation and feedback via chat window. APTA supports the student in the "tutor" role with both math advice and advice on how to tutor. Classroom studies with an earlier version of APTA demonstrated that adaptive support (in the form of system-generated chat messages) can improve the quality of help peer tutors give and improve their domain learning, compared to the parallel non-adaptive condition [10]. APTA is a reimplementation of the earlier version and covers the same equation solving skills as in Lynnette.

2.2 Orchestration Tool for Dynamic Transitions (Pair-Up)

Orchestration of the dynamic transitions is through a tool (Pair-Up) that synergistically leverages strengths of teachers and AI (Fig. 2). The design of the tool is informed by previous user research on teacher preferences [12], log data simulation [11], and co-design sessions with teachers [13]. Pair-Up has two key features: real-time analytics of students' learning status, and the option of AI-suggested pairing partners for teachers to decide. It helps teachers make judgments about which students might benefit from transitioning from one mode of learning (individual or collaborative) to the other and (in the case of transitioning from individual to collaborative learning), who might be good partners to team up and what they should work on collaboratively. The teacher has the final say over all pairing decisions.

Real-time Analytics of Students Learning Status. Our previous user research found that teachers would like to be able to view student progress in an easily glanceable way, when orchestrating the dynamic transitions [13]. Pair-Up indicates students' recent learning behaviors such as idling, misusing the software, making lots of errors, making many attempts, and doing well through icons attached to individual student cards [3]. Additionally, in both individual and collaborative modes, teachers can see the number of math problems that student(s) completed in a progress bar in the student(s) card. To further assist in monitoring, teachers can sort students alphabetically, based on the number of math problems solved (least to most or most to least), or based on the learning status indicators.

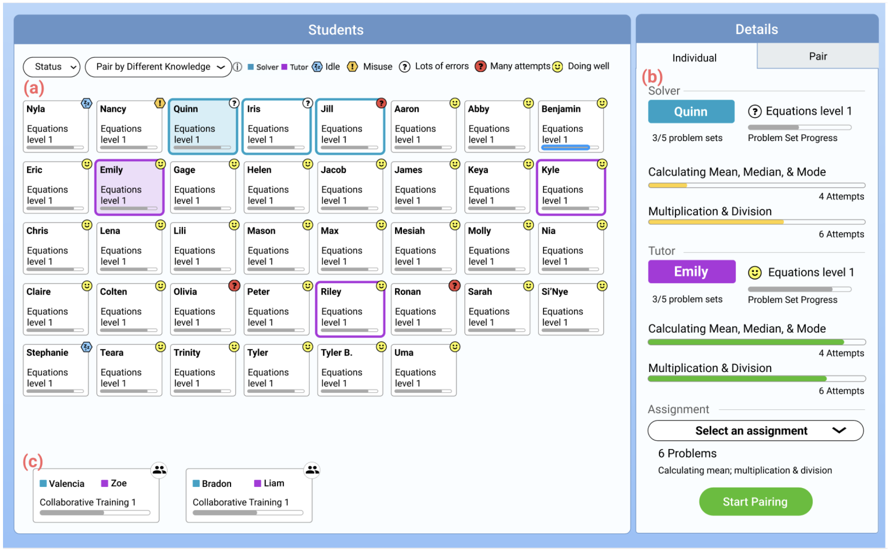

Fig. 2. The teacher-facing orchestration tool *Pair-Up*: (a) cards of students working individually, including system-suggested "solvers" (teal) and "tutor" (purple); (b) panel where the teacher can evaluate a potential match between two students by comparing their skill before deciding whether to team them up; in this panel the teacher also selects the math content for collaboration; (c) collaborating students pairs

AI-suggested Pairing Partners for Teachers to Decide. Previous user research found that teachers prefer to have the AI system suggest potential candidates to pair up. However, they very strongly prefer to have the final decision over all dynamic transitions [12]. They also like to be able to select an appropriate pairing algorithm (for making suggestions) based on the learning goals [13]. Based on surveying of 54 math teachers [12], teachers most commonly used two pairing strategies in collaborative activities: random pairing (so students work with new partners) and pairing students with different knowledge levels, so that students who are wheel-spinning or making slow progress [11] can work with a partner who is further along learning the particular skills at issue. Accordingly, the tool has two pairing policies: *random pair*, and *pair by different knowledge*. In the *random pair* policy, Pair-Up suggests random students in the class as solvers and tutors. In the *pair by different knowledge* policy, Pair-Up suggests students who are making slow progress on some of the knowledge components to be solvers. Once the teacher selects a solver, Pair-Up then suggests three "tutors" who are ahead of the "solvers" in the knowledge components they are struggling with.

Teachers have full agency over choosing which policy to use, as well as whether to follow system pairing suggestions or override suggestions and pair students based on their judgment. If they activate the system suggestions function, Pair-Up will suggest students take on the role of "solver" or a "tutor", by highlighting them in teal and purple outline,. The teacher however will make the final pairing decision. In addition, teachers can pair students without tool suggestions. Teachers can pair students to work collaboratively, and select an assignment (which contains three equation solving problems) they see as fit for the pair (e.g., an assignment focused on skills that the "solver" is struggling with). Based on students' progress, teachers can also choose when to unpair to stop the collaboration.

3 Feasibility Testing in Classroom

We conducted an in-person classroom study in a suburban public school near Pittsburgh, with five middle school math teachers and 199 students participants from 11 classes. One teacher teaches special education with 7 students who have an Individual Education Program (IEP). Each class participated for 2 sessions, each lasting 33-37 minutes. After a short video tutorial, students started with individual equation solving. The teachers paired up students as they wished. When students were done with the collaborative assignment or when they were unpaired by the teacher, they switched back to individual work.

We analyzed log data to study students' dynamic transitions. During the 22 class sessions, 210 collaboration episodes (defined as two students teamed up to work collaboratively on one assignment) happened, with on average of 18 episodes in each class over the duration of the study. The teachers generally were able to use the orchestration tool autonomously. Similarly, the students were able to work with tutoring softwares. Two teachers in the study teamed up all students at the same time, and three paired students up at different times as they saw fit. All participating teachers stated that they see pedagogical value in dynamic transitions. However, the special education teacher expressed that transitioning between learning activities may be challenging for her students. Still, all five teachers reported being likely to use such a technology ecosystem in their regular classrooms.

4 Conclusion

In this study, we introduced a new technology ecosystem to support dynamic transitions between individual and collaborative learning, which has not been tried before in the AIED literature, to our knowledge. We tested the feasibility of the ecosystem in 11 classrooms. The substantial number of collaboration episodes (on average 18 per class) is one piece of evidence of feasibility, showing that all teachers were able to use the orchestration tool to initiate dynamic transitions between individual and collaborative learning. All participating teachers reported being likely to use the technology ecosystem in their daily practice. Thus, the study provides insight into what orchestration tool functionality makes it feasible for teachers to manage dynamic transitions between individual and collaborative learning: a combination of (1) support for monitoring students' real-time learning progress in both individual and collaborative learning modes; (2) AI-generated pairing suggestions regarding whom to team up, with (3) full control by the teacher over pairing and unpairing decisions, Future work will further analyze students' learning process in dynamic transitions, and further improve the tools as our understanding of how to support teachers continually evolve. The ecosystem will support further research into the value of dynamic transitions, including how they affect students' learning outcomes, compared to for example pre-planned transitions. This exploratory study brings us closer to the vision of the smart classroom of the future, where the students transition dynamically between different learning modes, at moments that such transitions may be most helpful.

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