Predicting Student Performance In a Collaborative Learning Environment

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ABSTRACT
Student models for adaptive systems may not model collaborative learning optimally. Past research has either focused on modeling individual learning or for collaboration, has focused on group dynamics or group processes without predicting learning. In the current paper, we adjust the Additive Factors Model (AFM), a standard logistic regression model for modeling individual learning, often used in conjunction with knowledge component models and tutor log data. The extended model predicts performance of students solving problems collaboratively with an ITS. Specifically, we address the open questions: Does adding collaborative features to a standard AFM provide a better fit than the standard AFM? Also, does the impact of these features change based on the nature of the knowledge (conceptual v. procedural) that is being acquired? In our extended AFM models, we include a variable indicating if students are working individually or in pairs. Also, for students working collaboratively, we model both the influence on learning of being helped by a partner and helping a partner. For each model, we analyzed conceptual and procedural datasets separately. We found that both collaborative features (being helped and helping) improve the model fit. In addition, the impact of these features differs between the collaborative and procedural datasets, suggesting collaboration may affect procedural and collaborative learning differently. By adding collaborative learning features into an existing regression model for individual learning over a series of skill opportunities, we gain a better understanding of the impact that working with a partner has on student learning, when working with a step-based collaborative ITS. This work also provides an improved model to better predict when students have reached mastery while collaborating.

Keywords
knowledge tracing, collaborative learning, educational data mining, Additive Factors Model

1. INTRODUCTION
The modeling of student knowledge has been shown to be an important aspect of Intelligent Tutoring Systems (ITSs) technology. A variety of modeling approaches have been used to model student knowledge and have often been used to support individualized learning [2, 3, 15, 25]. Models can provide an accurate prediction of learning and also provide insights into how people learn. However, these types of models typically account for students who work individually with an ITS; they do not account for situations in which students learn collaboratively in dyads or small groups, supported by ITS technology. Yet collaboration cannot be ignored since it has been shown to be beneficial for student learning [6, 19] and there may be relative strengths for collaborative and individual learning [11]. Students who work collaboratively may have different learning rates than when working individually; this effect may be caused from being helped by a partner or helping a partner. A key question is, therefore: How can modeling techniques used for individual learning be adapted so they help provide predictions and insights into collaborative learning, in addition to individual learning? Specifically, how can these models be adapted to account for the fact that the collaborating partners may influence each other's learning? What insight can models provide regarding this influence? In our ITS, students work either collaboratively or individually on the problem sets. We extend the Additive Factors Model (AFM) [2, 15] by including features that are unique to collaboration, in an attempt to better model both individual and collaborative learning.

Much of the research on learning prediction has focused on modeling individual learning such as through Bayesian Knowledge Tracing [3], AFM [2, 15], and Knowledge Decomposition Model [25]. These models accurately predict student performance and can advance our understanding of how students learn. Previous research has adapted these types of models to better predict and understand individual learning, such as by treating correct and incorrect attempts differently [15] or by including the transfer that may happen between similar skills [25]. For our work, we are using a version of the AFM. The AFM has frequently been used to assess and predict individual student performance. The AFM is a generalized logistic mixed model [1]. It is widely used to fit learning curves and to analyze and improve student learning [1]. To adapt the AFM to account for aspects of collaborative learning, we can apply the same types of principles that have been applied to increase our understanding of individual learning and apply them to collaborative learning. For example, individual models can account for the transfer of learning from previous similar opportunities [25]; the same method can be applied to collaborating students having an opportunity to learn from watching their partner solve steps.

Prior research within collaborative learning has focused on analyzing collaborative processes to better understand learning and social influence [5, 20]. Within this area, there are multiple approaches for better understanding the collaborative processes.

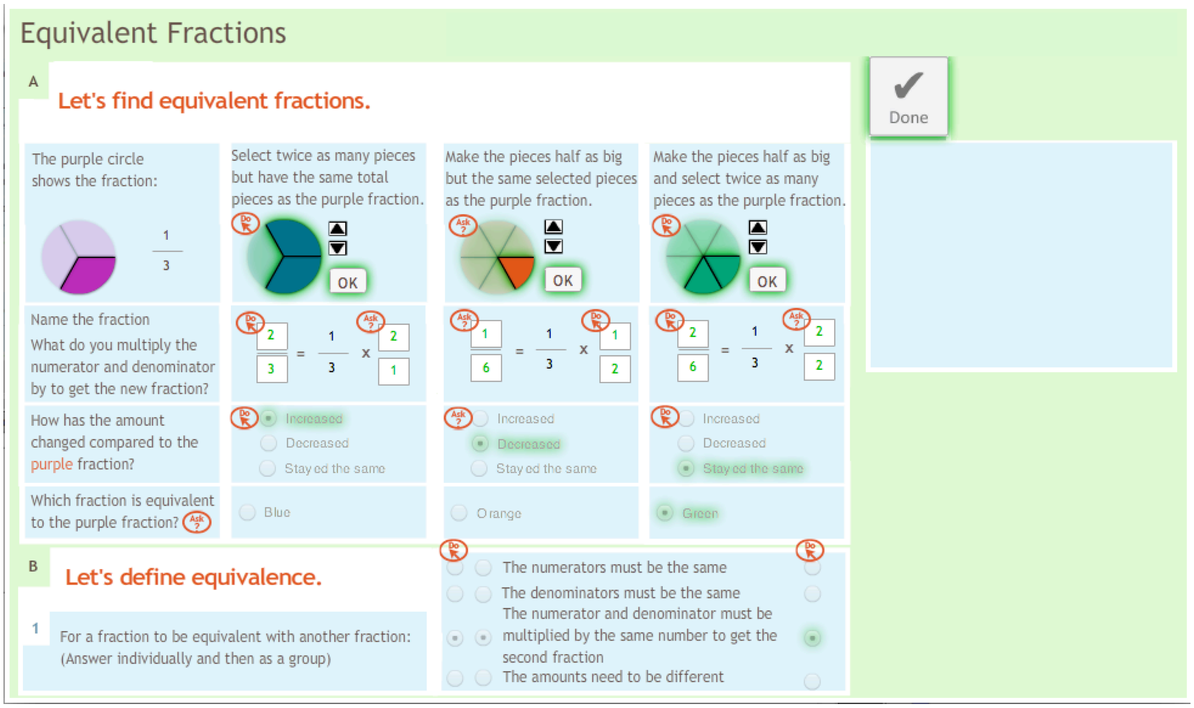

Figure 1. An example of a conceptual problem showing the different steps assigned to the partners in the collaborative condition based on the "Do" and "Ask" icons.

Some research aims to detect and classify collaboration skills, such as social deliberation skills and collaborative networks [21, 24]. Other research looks at the change in communication and processes that happen over time [10, 18]. Research has also focused on group dynamics and how we can recognize and intervene with groups that are not collaborating well [8, 9, 16]. Another aspect of collaboration that has been studied is asynchronous work that occurs on discussion boards and how this can influence learning and retention [22, 23]. Although this research is broad in the types of research questions that are addressed and covers many aspects of collaboration, much of the work does not attempt to predict student performance as students collaboratively solve problems. Such predictions could support student learning, for example by informing problem choices for dyads to help students where they are struggling. There has been previous work that has studied predicting performance by predicting posttest scores based on pair actions and found student interactions are predictive of the posttest score [17]; however, this work focuses on environments where the actions of collaborating students within a dyad or group cannot be distinguished (i.e., it is not known who took the action). In collaborative environments, in which the actions of the students within a collaborating group can be distinguished (e.g., a collaborative ITS), including collaborative features in models that have typically been used to predict individual performance may support a better understanding of the collaborative learning process and the ability to predict performance when students are collaborating. Previous work has attempted to address this issue by predicting performance of students based on their speech with an intelligent agent and found semantic match scores as a key predictor of later test performance [12]. Our work adds to this body of literature by investigating the prediction based on student actions within a system and how students will later do on similar items. The analysis of the student actions may provide different insights into the collaborative processes.

Extending the AFM with collaborative features enables us to study how collaboration might influence learning. Prior research with collaborative learning has shown that within mathematics, collaborative learning may better help students acquire conceptual knowledge, whereas individual learning activities may be more conducive to learning procedural knowledge [11]. Since our data set, obtained with a fractions tutor that supports collaborative learning, described below, includes both conceptual and procedural activities [13], we can study whether and how collaboration affects learning differently for these types of activities. By separately fitting models capturing collaborative and individual learning to data from procedurally versus conceptually oriented problems, we may be able to add to the understanding of how the different aspects of collaborative learning may have different strengths for different types of knowledge.

In this paper, we extend the AFM to (a) distinguish the learning that may occur when working individually versus collaboratively and (b) to capture learning that may occur from observing a partner's answers to steps. We also explore (c) whether the effect of these features is different in activities designed to support learning of concepts, compared to activities designed to support learning of procedures. By modeling student knowledge when working collaboratively, we aim to develop a better understanding of collaborative and individual learning processes. An improved model would also allow us to more accurately predict student performance and has the potential to support learning more effectively within an ITS, for example through improved problem selection for collaborative learning.

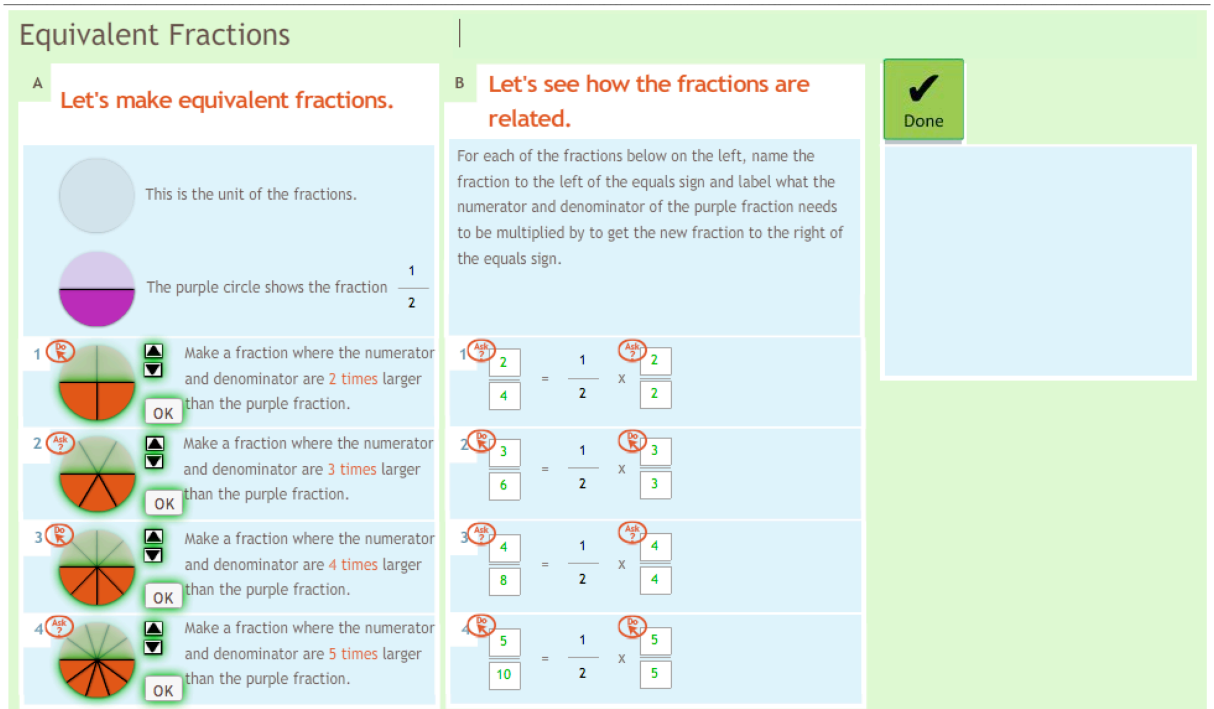

Figure 2. An example of a conceptual problem showing the different steps assigned to the partners in the collaborative condition based on the "Do" and "Ask" icons.

2. METHODS

In the following sections, we present the collaborative ITS for fractions learning that was used in our study and explain the experimental set-up that was used for data collection.

2.1 Individual and Collaborative Fraction Tutors

In the study that produced the data set that we analyze in the current work, students worked with an ITS that targeted equivalent fractions knowledge either working individually or with a partner. We developed two parallel versions of a fractions tutor, one with embedded collaboration scripts and one for individual learning. We created all tutor versions using the Cognitive Tutor Authoring Tools (CTAT), which we extended so it supports the authoring of tutors with embedded (static) collaboration scripts that are tied to the problem state [14]. Both the individual and the collaborative tutor versions had procedural and conceptual problem sets. Figure 1 shows an example of a conceptual problem, which shows the student different relationships between the numerators and denominators and that only the one where the amount stays the same shows an equivalent fraction. On the other had, Figure 2 shows an example of a procedural problem where the student makes equivalent fractions by multiplying the numerator and denominator by the same number. The individual ITS provides standard ITS support (step-level guidance for problem solving, with correctness feedback, next-step hints, and error-specific feedback messages) while the collaborative ITS also has embedded collaborative scripts. The students working collaboratively did so through a synchronous, networked collaboration. That is, collaborating students sat at their own computer and had a shared (though differentiated) view of the problem state. They could discuss the activity through audio by using Skype.

The collaboration was supported through proven collaboration scripts such as the use of roles, cognitive group awareness, and unique information, embedded in the interactions with the ITS. First, the embedded collaboration scripts defined roles that distribute the activities between the students and provide guidance to the students about what they should be doing to interact with their partner and help to scaffold this interaction. A second collaborative support feature we used in the collaborative problem sets is cognitive group awareness. Cognitive group awareness means that group members have information about other group members' knowledge, information, or opinions and has been shown to be effective for the collaboration process [7]. The last collaborative support feature is the use of unique information to create a sense of individual accountability. Individual accountability means that each group member takes responsibility for the group reaching its goal [19]. All of these collaboration features, as implemented, assigned different problem steps to each student within a collaborating dyad. The "Do" and "Ask" icons shown in Figures 1 and 2 indicate which student was responsible for solving a given step and which student had the role of supporting the other student; on the screen of the collaborating partner, the "Do" and "Ask" icons would be flipped. Therefore, problem steps divide into a student's own steps and that student's partner's steps. This distinction is important because, we will see, our extended AFMs treat these steps differently.

Our ITS is uncommon in that it was developed to support both collaborative and individual learning. This means that our data logs contain both records of individual and collaborative sessions, with a common set of features that is typical of ITS log data. (The data from the collaborative sessions were captured as separate streams from each student, where a partner's actions are not associated with a student's id.) Although the collaborative tutor had three different types of support for collaboration, each scaffolding the interactions between the students in different ways, each of these support type led to the same pattern of information in the log data. For every step in a tutor problem, one student was responsible for answering the step and the other student's role was to monitor and help; therefore, the steps in the log data can be assigned to one partner or the other. Although not all collaboration environments allow for the distinction between student actions within a group, many environments can record this data and would then have similar log data to what we have, possibly even when student roles are not as clearly defined and supported.

2.2 Data Source

Our data is a set of collaborative and individual data that had been collected from a study [13] in which 4th and 5th grade students engaged in a problem-solving activity with the ITS for fractions learning described above. The experiment was a pull-out design, in which the students left their normal instruction during the school day to participate in the study. The data set comprises 84 students. Each teacher paired the students participating in the study based on students who would work well together and had similar math abilities. These pairs were then randomly assigned to one of four conditions: collaborative conceptual, collaborative procedural, individual conceptual, and individual procedural. Twice as many students were assigned to the collaborative conditions as to the individual conditions, so that the number of dyads in the collaborative conditions equaled the number of individual students in the individual conditions. Each student or dyad worked with the tutor for 45 minutes in a lab setting at their school during the school day.

We analyzed all tutor problems in terms of the underlying knowledge components (KCs) related to fraction equivalence. For the four conditions, the KCs were the same between the individual and collaborative conditions, but there was no overlap in the KCs between the conceptual and procedural items, as conceptual and procedural KCs were modeled separately.

3. MODELS

In this section we review the standard AFM and then present the models we made by adding collaborative features to this model.

3.1 Additive Factors Model

We first present the standard AFM, because this model is the basis on which all of our other models are built. The AFM [2] shows that the log-odds that a given student correctly solves a given step in a problem are a function of three parameters capturing, respectively, the given student's proficiency, the ease of the given knowledge component (KC, the skill the student is learning), and the learning rate. It assumes that the learning rate differs by KC but, for any given KC, is equal for all students. It further assumes that students differ in their general proficiency but in a way that affects all KCs and KC opportunities equally.

The AFM is a generalized mixed model. p_{ij} is the probability that student i gets step j right, θ_i is the random effect representing the proficiency of the student i. The fixed effect portion of the model includes β_k (the ease of KC k), γ_k (the learning rate of this KC), and N_{ik} (the prior learning opportunities the student had to apply KC k). The Q_{kj} term represents if an item the student encounters (i.e., a step in a tutor problem) uses KC k.

$$\ln\frac{p_{ij}}{1-p_{ij}} = \theta_i + \sum_k \beta_k Q_{kj} + \sum_k Q_{kj}(\gamma_k N_{ik}) \tag{1}$$

The standard AFM presented in Formula 1 is based on individual learning parameters of the opportunities that the individual has had with the KC. For the individual learning condition, these are all steps the student encountered in which the given KC applies. When this model is applied to the collaborative learning condition, on the other hand, these are the steps with the given KC that the given student is responsible for solving. This model however does not take into account that the learning rate for students may be different when working in a group compared to individually or that the students may learn from watching their partner solve problems.

3.2 Additive Factors Model with Condition

To investigate the difference in learning rates that may occur when students work individually, as compared to working in pairs, we added a feature to the original AFM that changes the slope based on condition (individual v. collaborative). Similar to the assumption that students learn at different rates from correct and incorrect answers in Pavlik, Cen, and Koedinger's Performance Factors Analysis, PFA [15], students may learn different amounts (per opportunity) when they are working individually versus collaboratively. In the collaborative condition, students are talking with their partner (through Skype) while solving steps that have been assigned to them. Having a partner may have an influence on their learning, even on steps that they (and not their partner) are responsible for solving. A student may get more learning out of a step they solved because of fruitful discussion with the partner, but could conceivably also learn less than when solving the step alone, with tutor help only, for example if the partner simply tells them the answer and the student does not reflect on the answer. In Formula 2, we capture the influence that the presence of a partner has on the student's own opportunities. A term c is added to represent the condition that the student is in at a given step. This allows the learning rate of a KC, γ_{kc}, to vary depending on the condition, so as to capture a difference in the learning that occurs between individual and collaborative work, on the student's own steps

$$\ln\frac{p_{ij}}{1-p_{ij}} = \theta_i + \sum_k \beta_k Q_{kj} + \sum_k Q_{kj}(\gamma_{kc} N_{ikc}) \tag{2}$$

By adding the condition parameter to the model, we can capture any differences in learning rates that may occur between working individually and within a group.

3.3 Additive Factors Model with Partner Opportunities

Within collaborative learning, there is an opportunity for students to learn from their partner's actions. Recall that when students work collaboratively in our tutoring system, the students are assigned to different roles for any given step (either solve it or help the partner solve it). Therefore, steps in tutor problems classify as the student's own steps or the partner's steps. On the partner's steps the student is watching and possibly providing advice, feedback, and explanations, which may create a learning opportunity for that student, even though he or she is not solving this step. Thus, we need to model the learning that occurs not only

Table 1. Prediction accuracy for the individual and collaborative procedural dataset across all models. The asterisks indicates the model with the best performance for that criterion.

Procedural Models	Log Likelihood	RMSE	AIC	Parameters
Standard AFM	-2010.34	0.4738	4080.69	30
AFM with Condition	-1983.39	0.4717	4056.77*	45
AFM with Partner Opportunities	-1984.59	0.4712	4059.17	45
AFM with Condition and Partner Opportunities	-1972.97*	0.4674*	4065.94	60

on a student's own opportunities (as modeled in Formulas 1 and 2) but also on their partner's opportunities. Learning on partner opportunities may be analogous to the learning decomposition that happens as students learn reading and their learning of a certain word benefits from seeing words with identical stems [25]. Although the student is not interacting directly with the tutor, there may still be learning. We assume that the learning that occurs when watching and/or helping a partner is possibly different from that which occurs when *doing* steps. We therefore added a new fixed parameter that takes into account the learning that could happen on a partner's opportunities. In the model seen in Formula 3, $\rho_k N_{lk}$ represents the learning (with its own learning rate) from a partner's opportunities on KC k (N_{lk}).

$$\ln \frac{p_{ij}}{1-p_{ij}} = \theta_i + \sum_k \beta_k Q_{kj} + \sum_k Q_{kj}(\gamma_k N_{ik}) + \sum_k Q_{kj}(\rho_k N_{lk}) \qquad (3)$$

By adding the learning from partner's opportunities to the model, we can capture how students learn from their partner's opportunities, when their role is to observe and provide help and advice. This provides insights into the importance of helping a partner's work. The model also may provide better predictions of student performance when working in a collaborative condition where the student's actions can be differentiated.

3.4 Additive Factors Model with Condition and Partner Opportunities

The final model combines the collaborative features of the previous two. This model takes into account both the differences in learning rates that may occur for a student's own opportunities between individual and collaborative learning (captured in Formula 2) and also includes the learning that may occur by observing a partner's opportunities while working collaboratively (captured in Formula 3). Please note that the c (condition term) was not included in the partner's opportunities, because students who work individually do not have any partner opportunities to observe, making the partner opportunities always be 0 for students working individually.

$$\ln \frac{p_{ij}}{1-p_{ij}} = \theta_i + \sum_k \beta_k Q_{kj} + \sum_k Q_{kj}(\gamma_{kc} N_{ikc}) + \sum_k Q_{kj}(\rho_k N_{lk}) \qquad (4)$$

This model combines the collaborative features of the previous two models to capture how these two ways of possibly benefitting from collaboration might balance.

4. RESULTS

For our analysis of the models, we evaluated the data from the procedurally-oriented tutor problems and the conceptually-oriented tutor problems separately to be able to see if the collaborative features that were added to the model have different effects for these two types of knowledge. Because students were assigned to either work on procedurally or conceptually oriented problems, there was no overlap in the students in the two datasets. Additionally, there was no overlap in the KCs in the datasets since any given KC captured either procedural or conceptual knowledge. With neither an overlap in students nor KCs between the datasets, the datasets can be analyzed separately, so as to analyze how collaboration (versus individual learning) might influence the learning of conceptual and procedural knowledge differently.

We measured the prediction accuracy of all of the models across the two data groups using the log likelihood, the root mean squared error on the training set (RMSE), and the Akaike information criterion (AIC). The log likelihood and RMSE provide a measure of fit not taking into account the complexity of the model. The AIC takes into account the complexity of the model when determining the fit of the model; it imposes a penalty based on the number of parameters. All of the models were run through a LIBLINEAR library in C [4]. Although in a standard AFM, the learning rate is restricted to be greater than or equal to zero, this restriction was not enforced in our models.

4.1 Procedurally-Oriented Problems

On the procedural dataset (see Table 1), the more complex models (i.e., the models that capture the influence of working with a partner in the ways discussed above) have a better fit in terms of log likelihood and RMSE, compared to the standard AFM. When comparing the models based on the AIC, all of the models that model aspects of collaborative learning have an improved AIC over the standard AFM. The AFM with Condition has the best AIC fit. Since the parameters are the same for the AFM with Condition and the AFM with Partner Opportunities, yet the former has a lower AIC, the condition the students are working in may be a better predictor of performance than having additional opportunities to observe a partner solving a step. Put differently, on procedural problems, having partner help when solving a step may influence learning more than helping a partner solve a step. It should be noted, however, that the difference in AIC between the two models is very small. The AIC for the model that combines the two collaborative features (AFM with Condition and

Table 2. Prediction accuracy for the individual and collaborative conceptual dataset across all models. The asterisks indicates the model with the best performance for that criterion.

Conceptual Models	Log Likelihood	RMSE	AIC	Parameters
Standard AFM	-1383.81	0.4815	2843.61	38
AFM with Condition	-1362.72	0.4804	2839.44	57
AFM with Partner Opportunities	-1359.67	0.4815	2833.33*	57
AFM with Condition and Partner Opportunities	-1344.50*	0.4772*	2841.01	76

Partner Opportunities) is higher, even though the log likelihood and RMSE are lower, indicating that the complexity of the model out-weighs the added gains.

4.2 Conceptually-Oriented Problems

For the models that were run on the conceptual dataset (see Table 2), the more complex models (i.e., those modeling how collaboration might influence learning) again have a better fit in terms of log likelihood and RMSE. As with the procedural dataset, these results indicate the importance of both the condition the students are working in (i.e., influence of partner help on the student's own opportunities) and of the partner opportunities (i.e., influence of helping a partner). When comparing the models based on the AIC, all of the models with collaborative features have an improved AIC over the standard AFM, and the AFM with Partner Opportunity has the best fit. Unlike with the procedural dataset, on conceptual problems, being able to observe a partner solving a step has more of an impact on predicted performance than condition.

5. DISCUSSION

AFMs are widely used models for predicting student performance. However, these models have mostly been used to predict the performance of students who are working individually. Students who are working collaboratively may go through different learning processes as they interact with other students, which currently are not accounted for in the standard AFM. In this paper, we wanted to see if adding collaborative features to AFM had an impact on the accuracy of the predicted learning performance of students in ITSs. Specifically, we investigated two mechanisms by which collaboration might influence learning. First, students might have different learning gains on steps they are responsible for solving because of the influence of a partner, such as through productive discussion or by being distracted. Second, a student might benefit from collaboration through engaging in discussion with a partner on steps that the partner is solving or by observing a partner as the partner solves the step. These two mechanisms were tested by two different ways of extending the AFM. First, we took into account the condition the student is working in (collaborative v. individual) by allowing the learning slope to vary based on condition. Second, we included the partner opportunities to capture the learning that may occur from observing/discussing a partner's answers to steps. These different learning mechanisms may differ for students who are working to acquire different types of knowledge. To take this into account, we analyzed our datasets for conceptual and procedural knowledge separately.

We first investigated if there is a difference between the learning rate of students working individually and those working collaboratively. To model the effect a partner may have on the steps that a student is responsible for solving, we added condition as a feature to the learning slope parameter. For both the procedural dataset and the conceptual dataset, the models that included condition outperformed the standard AFM based on AIC and log likelihood. Condition may be a useful predictor to include in a model for performance when students work collaboratively (or even, alternate between working collaboratively or individually) to more accurately predict performance.

To answer the question if observing and working with a partner on the partner's opportunities has an impact on learning (the second mechanism by which collaborative learning might help), we added an additional learning slope for a partner's opportunities to the standard AFM. Again, for both the procedural and conceptual datasets, the models that included the partner's opportunities outperformed the standard AFM based on AIC and log likelihood. This indicates that observing and helping a partner solve problems has an impact on a student's learning when working on either procedurally oriented problems or conceptually oriented problems. A partner's opportunity to practice a KC may be important to include in a learning model where students have the potential to work with another student.

Although the models built on the procedural and conceptual datasets cannot be compared directly, we can observe some differences in the order of the model fits that may indicate differences in the importance of different learning processes when acquiring different types of knowledge. The best model for the procedural dataset was the AFM with Condition, whereas the best fitting model for the conceptual dataset was the AFM with Partner Opportunity. These differences in the best-fitting model may indicate that collaboration might influence learning differently when learning procedural knowledge than when learning conceptual knowledge. When students are acquiring conceptual knowledge, observing a partner or helping a partner solve a step may have more of an impact than when a student is acquiring procedural knowledge.

The work makes a number of contributions to the field of EDM. It is one of the few to address how standard student modeling techniques in EDM can be applied to collaborative learning. Our modified AFM model predicts student performance as students collaboratively solve problems. The model can be applied to learning in collaborative environments in which the actions of the students within a collaborating group can be distinguished. The work extends the AFM so it can be applied to collaborative learning, capturing two different mechanisms by which collaboration might help students learn with a collaborative ITS. By applying these new models to a data set on both collaborative and individual learning, the work demonstrates that these two mechanisms might both be at work in conceptual and procedural learning, although to varying degrees. These findings contribute to enhance the understanding of the relative strengths of collaborative and individual learning.

A limitation of this dataset is that we do not have a comparison between the difficulty of the procedural and conceptual datasets. Any differences between the models for these datasets may not be due to the type of knowledge that is being acquired but may be related to where the students were in the learning process for these different types of data while learning. For future work, we are interested in using these models for student data where the students switch between working individually and collaboratively on the same sets of KCs, both conceptual and procedural. By modeling this data using the new AFMs we have created, we can better understand how the models will generalize to a more natural learning situation in the classroom. In addition, the models can be applied to situations where students come to the collaboration with different skills to see how students learn the skills from their partner. The AFMs with the added parameters provide improved models to better predict when students have reached mastery while collaborating or working individually.

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