Developing a Framework for Integrating Prior Problem Solving and Knowledge Sharing Histories of a Group to Predict Future Group Performance

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Abstract

Using a combination of machine learning probabilistic tools, we have shown that some chemistry students fail to develop productive problem solving strategies through practice alone and will require interventions to continue making strategic progress. One particularly useful form of intervention was face-to-face collaborative learning which increased the overall solution rate of the problem solving while also improving the strategies used. However, the collaborative intervention was not effective for all groups making complicated.

To better model the effects of group composition we have developed a synchronous and symmetrical collaborative extension to the online IMMEX problem solving environment. This online collaborative environment appeared an accurate representation of the face-to-face collaboration episode in that both groupings showed similar gains in the problem solution frequency as well as in the differential use of particular strategies. We also noticed that some groups, like some individuals, rapidly developed and persisted with unproductive approaches highlighting the importance of identifying, and perhaps re-assembling such groups for subsequent problem solving. To support such decisions, we describe a causal model approach for integrating the performance and knowledge sharing histories of a group to help predict which groups should remain together.

1. Introduction

Collaboration has the potential to improve individual learning, increase task efficiency and accuracy, and enhance students' problem solving, while also contributing toward advances in educational research [1-3]. Although it is not always the case, groups sometimes even outperform the best individual in the group by encouraging the students to generate new ideas that they probably would not have come up with alone [4]. These studies suggest that the ability of a group may somehow transcend the abilities of its individual collaborators.

However, collaboration is a complex process where the knowledge contributions of each individual are often guided by the social aspects of communication events. Each group member brings a unique pool of knowledge grounded in his or her individual experiences, and the combination of these experiences, and the group members' personalities and behaviors will determine how the collaboration proceeds, and whether or not the group members will effectively learn from and with each other [5-7]. As such, the mere presence of group talk does not guarantee performance or learning gains, and not all groups make progress in these settings making it important to help decide which groups are productive and should remain together, and which groups are not making progress as a team [8,9]. The goal of being able to predictably assemble effective groups is therefore complicated in that the efforts must include both a performance model that documents the cognitive events influencing the completion of the task, as well as a model of the knowledge sharing contributions of the students in the group.

To better understand the contributions of knowledge sharing to the effectiveness of group problem solving it would therefore be useful to begin with a system where detailed models of individual performance exist which can then be contrasted with group performance, either in face-to-face or online environments. As a first step in this model building process we have developed an integrated, extensible and scalable online environment that models how strategies are constructed, modified and retained as students learn to solve real-world problems in science [10,11]. Our approach consists of a set of online machine learning tools that provide progressively refined measures of the problem solving process, many of them in real time [12]. First, item response theory estimates of problem solving ability are continually refined as students solve a series of simulations. Then, in parallel, self-organizing artificial neural network (ANN) analysis models students' strategies using the actions chosen to solve the problems as the classifying inputs. These strategy maps detail key qualitative and quantitative differences across the spectrum of problem solving approaches. Lastly, strategic learning trajectories are developed across sequences of performances by Hidden Markov Modeling (HMM) which stochastically describes problem solving progress with regard to different strategic and performance stages in the learning process.

Using this layered analytical approach our performance models show that students quickly adopt preferential problem solving approaches, and continue to use these approaches up to three months later when presented with similar problems. The availability of such individual performance models provides a well documented platform upon which to study the changes in these models that are induced by collaboration.

In this manuscript we first review the strategic and performance differences between students working individually and those engaged in face-to-face collaborative problem solving and document the expected performance gains in such collaborative settings. Then, we describe how we have extended this individual online problem solving environment to an online synchronous and symmetrical environment that allows groups of two or more students to simultaneously work on an IMMEX problem solving simulation. Using the machine learning modeling tools, we next describe the process of validating this system as an accurate representation of the face-to face collaboration event. Lastly, we present a Bayesian network approach for integrating both the performance history of a group as well as the prior conversational history of the group to help decidewhether or not a group should remain together for future problem solving.

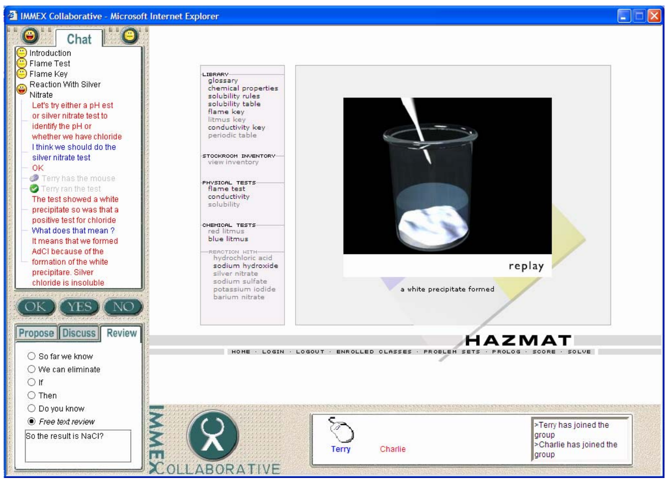

Figure 1. The main frame shows the IMMEX problem solving environment embedded within the IMMEX Collaborative system which allows groups of students to use chat, sentence openers (far left) and shared mouse control (bottom) to solve problems.

2. The IMMEX Problem Solving Environment

Our problem-solving system is called IMMEX (Interactive Multi-Media Exercises) which follows the hypothetical-deductive learning model of scientific inquiry [13] and the cognitive model of scientific discovery as dual search [14]. In these simulations students need to frame a problem from a descriptive scenario, judge what information is relevant, plan a search strategy, gather information, and eventually reach a decision that demonstrates understanding. One, of several, problem sets researched extensively is *Hazmat*, which provides evidence of students' ability to conduct qualitative chemical analyses [10,12]. *Hazmat* contains a problem solving library of 38 cases, each of which begins with a multimedia presentation that is shown to the students. This explains that an earthquake caused a chemical spill in the stockroom and their task is to identify the unknown chemical by gathering information using a 22 item menu containing a Library of terms, a Stockroom Inventory, and different Physical or Chemical Tests (e.g. a precipitate test as shown in Figure 1). When a student selects an item, that event is logged into the performance data stream.

3. Modeling the Performance Strategies of Students Working Individually and in Groups

A combination of artificial neural network analysis and hidden Markov modeling is then applied to this data stream to identify the most common student strategies and to model how these strategies change with time and experience. As students navigate the problem spaces, the IMMEX database collects timestamps of each student selection. The most common student approaches (i.e. strategies) for solving *Hazmat* are identified with competitive, self-organizing artificial neural networks [15-17] using these time stamped actions as the input data. The result is a topological ordering of the neural network nodes according to the structure of the data where geometric distance becomes a metaphor for strategic similarity. Often we use a 36-node neural network and the details are visualized by histograms showing the frequency of items selected for student performances classified at that node (Figure 2 A). Strategies so defined consist of actions that are represented in all performances at that node (i.e. with a frequency of 1 such as items 1 and 11) as well as actions that are present in only a portion of the performances, and therefore with a frequency of less than 1. .

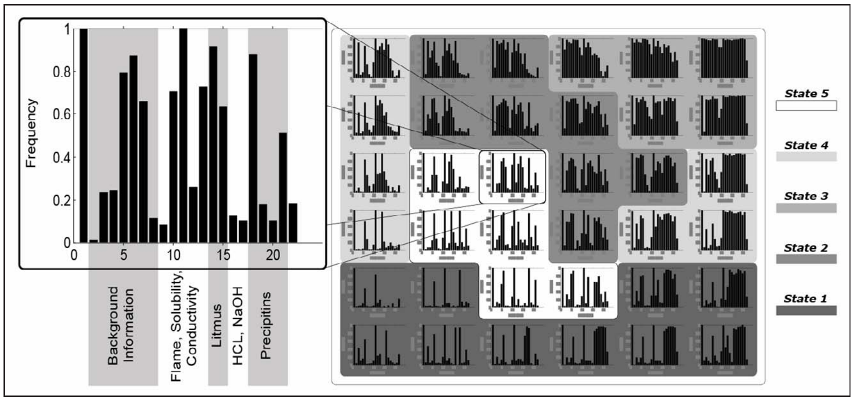

Figure 2. Sample Neural Network Nodal Analysis. a.) The selection frequency of each action (identified by the labels) is plotted for the performances at node 15, and helps characterize the performances clustered at this node and for relating them to performances at neighboring nodes. **b.)** This figure shows the item selection frequencies for all 36 nodes, and maps them to different HMM states.

Figure 2 B is a composite ANN nodal map that shows the topology of performances generated during the self-organizing training process. Each of the 36 matrix graphs represents one ANN node where similar student's problem solving performances have become competitively clustered. As the neural network was trained with vectors representing selected student actions, it is not surprising that a topology developed based on the quantity of items. For instance, the upper right of the map (nodes 6, 12) represents strategies where a large number of tests were ordered, whereas the lower left contains strategies where few tests were ordered. Once ANN's are trained and the strategies represented by each node defined, new performances can be tested on the trained neural network and the node (strategy) that best matches the new performance can be identified and reported.

On their own, artificial neural network analyses provide point-in-time snapshots of students' problem solving. Any particular strategy, however, may have a different meaning at a different point in a learning trajectory. More complete models of student learning should also account for the changes of student's strategies with practice. Our approach here is to have students perform multiple cases in the 38-case Hazmat problem set, and classify each performance with the trained ANN. Predictive models of student learning trajectories are then developed from sequences of these strategies with HMM [18,19].

The outputs of this modeling process are shown in Figure 3 where each of the 1,790 students solved 7 *Hazmat* cases. One level (stacked bar charts) is derived from HMM and shows strategic profiles for each of the 7 sequential performances. For this modeling we postulated 5 hidden states that students may pass through as they become experienced Hazmat problem solvers. On the first case, when students are framing the problem space, the two most frequent states were States 1 and 3. Moving up an analytical layer from HMM states to ANN nodal strategies (the 6 x 6 histogram matrices) shows that State 3 represents strategies where students ordered all tests, and

State 1 where there was limited test selection. Consistent with the state transitions in the upper right of Figure 3, with experience students transited from State 3 (and to some extent State 1), through State 2 and into States 4 and 5, the more effective states. By the fifth performance the State distributions stabilized after which time students without intervention tended not to switch their strategies, even when they were ineffective.

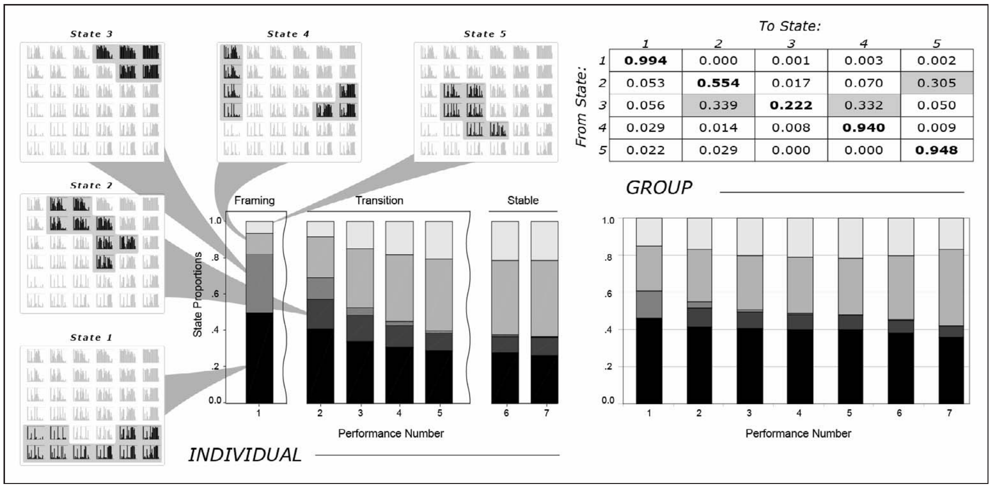

Figure 3. Modeling Individual and Group Learning Trajectories. This figure illustrates the strategic changes as individual students or groups of students gain experience in Hazmat problem solving. Each stacked bar shows the distribution of HMM states for the students (N=1,790) after a series (1-7) of performances. These states are also mapped back to the 6 x 6 matrices which represent 36 different strategy groups identified by self organizing ANN. The highlighted boxes in each neural network map indicate which strategies are most frequently associated with each state. From the values showing high cyclic probabilities along the diagonal of the HMM transition matrix (upper right), States 1, 4, and 5 appear stable, suggesting once adopted, they are continually used. In contrast, students adopting State 2 and 3 strategies are more likely to adopt other strategies (gray boxes).

We found that students working in groups solved a higher percentage of the problems (63% for groups vs. 51% for individuals), stabilized their strategic approaches quicker, and used a more limited repertoire of strategies than did students working alone [10,20]. Some indication of why the collaborative grouping was effective comes from the different state distributions of individual and group performances (Figure 3). Group performances stabilized with nearly twice the frequency of State 1 which represents strategies where very few tests are ordered suggesting very limited, but highly effective test ordering strategies. The successful use of this approach by collaborating students, along with the decreased use of transitional States 2 and 3 may suggest that the collaboration environment allowed students to make rapid transitions to effective states rather than needing to explicitly transit through them as do many individuals. It is also interesting that students often retained and reused the strategies used during group performance when they were again asked to solve problems individually suggesting that the group intervention altered individual behavior and learning for these students (M. Cooper, personal communication).

4. Extending the IMMEX Problem Solving Environment to Include Collaboration

Having established that face to face collaboration improves the problem solving process for some students in some groups, we next wished to better understand the circumstances that allow groups to succeed. For this purpose the individual IMMEX learning environment has been extended to a collaborative one structured to provide evidence about both the goal of solving the problem, as well as the interaction and communication that occurred during the process [21-23].

In designing the IMMEX Collaborative environment (refer to Figure 1) we drew from multiple literature sources. We first felt that it should interpret actions in a shared workspace as acts of communication, as if the students were seated around a table engaging in problem solving, just as it occurs in face-to-face collaboration [24]. We next felt that it would be important to construct a structured environment that realistically reflected the nature of the problem solving task itself [25]. For this we drew from earlier verbal protocol research showing how students propose hypotheses, run physical and chemical tests, and reflect on the results of those tests in a repetitive fashion as they solve IMMEX problem [26]. These hypothesis-test-reflect segments within a performance are termed episodes.

An empirical analysis of the interaction between pairs of students learning with the IMMEX environment confirmed the existence of these episodes as their discourse often segmented into a predictable pattern where they tended first to discuss which chemical or physical test to run (the *proposal episode*); followed by running the test (the *event*); and lastly by a discussion of the results of the test (the *discussion episode*). A final design feature was that the environment needed to be structured to facilitate the automated modelling of the group interactions in a way that would accommodate the thousands of current and future IMMEX users and be amenable to similar layered analytical modelling approaches as those we have applied to problem solving itself [27].

The result was an IMMEX Collaborative client interface (Figure 1) that is divided into three portions. The main window is a shared workspace dedicated to the collaborative navigation of the IMMEX multimedia web pages. Actions taken by students in this frame are automatically reflected on the other group members' screens. The vertical frame on the left side shows the structured chat interface with a three tabbed panel.

The tabs contain sentence stems distributed across three problem solving phases: *propose, discuss,* and *review*, each of which represents a different cognitive process related to the problem solving phase. These were developed based our manual analysis, and taking into account earlier work on effective peer dialogue [27]. Those shown for Review included “So far we know..’, ‘We can eliminate…’, etc. The bottom horizontal frame shows a graphical representation of the service and synchronization facilities, and is used to manage the flow of action and control in the collaborative space. The mouse image highlights the student who has control of the workspace, as if the members were seated in front of the same monitor, passing the mouse among each other.

Our first goal within this collaborative workspace was to determine how closely the performances of students collaborating online matched with what was occurring during face to face groupings, using solution frequency, strategy usage, strategic transitions, etc., derived from the automated modelling approach described above.

For these pilot studies we collected performances from four groups of two students who performed 3-4 IMMEX cases. The preliminary results indicated that the solution frequency (68%) and time on task were similar to that of face-to-face groups, suggesting that the interface neither changed the nature of problem solving in this environment, nor interfered with the overall effectiveness of the problem solving in large ways. At the strategic level, this was further supported by greater than expected usage of HMM States 1 and 4 by the groups, also mirroring that found with face-to-face collaboration in *Hazmat* (Table 1). Finally, it is encouraging that the solved index (i.e. 2 points for solving on the first try, 1 point for the second try, and 0 points for missing the case) of State 1, 4 and 5 performances was 17/20, whereas was only 3/10 for State 2 and 3 performances indicating that the problem solving was also effective.

Table 1. Solution Frequency, ANN Strategy, and HMM State for 4 Student Groups Performing Multiple Hazmat Cases. Note: 1st try/ 2nd try means solved on the first or second attempt.

	Group 1				**Group 2**			**Group3**				**Group 4**			
Solved	1st	1st	1st	1st	1st	1st	no	2nd	no	1st	no	2nd	1st	1st	no
Node	18	1	7	23	26	33	33	16	16	2	16	20	27	21	11
State	4	4	4	4	1	1	1	2	2	2	2	5	5	5	3

Perhaps the most unexpected finding from this pilot study was that most groups rapidly developed a rapport resulting in the negotiation of a strategy that was repeatedly used across tasks (see repeating State information in Table 1). To our knowledge this is not a well documented phenomenon, although, given our findings regarding strategy stabilization by individuals, perhaps not overly surprising. We have recently confirmed this finding with an additional 19 group performances on a second chemistry problem set. While the above results are based on only a limited number of groups and performances they suggest that the problem solving process occurring during the online collaboration is not overtly different from that in face-to-face groups and that it may be possible to integrate our problem solving performance models with similar models of the collaboration components to monitor and improve the effectiveness of group problem solving.

5. Developing a Decision Network Framework for Modeling Group Effectiveness

Investigators are increasingly incorporating intelligent analysis and facilitation capabilities into collaborative distance learning environments to better understand the nature and importance of knowledge sharing components in the collaboration activity. [27-29]. In doing so, the dialog is generally broken into segments of differing granularity prior to analysis through the use of quantitative indices [30], HMM [27] or neural networks [31]. In our analysis scheme, we first separate the collaborative event into two components, a performance model which relates to the goal of solving the problem, and a conversational or conversational structure that models the group dynamics during the problem solving episode [28].

If the online collaboration is a valid reflection of problem solving then the prior problem solving histories of the participants should influence, and be correlated with these quantitative indices, i.e. two effective individual problem solvers should show good collaborative problem solving structure, and two ineffective problem solvers should show poor problem solving structure. Instances where the problem solving histories and the collaborative problem solving outcomes are not correlated will be highlighted as unexpected (Table 2) as they would suggest that either a communication breakdown or the contribution of other variables to the knowledge sharing component has influenced the outcome. These examples will be particularly important for studying the relative contributions of problem solving and knowledge sharing in group performance.

Table 2. Example Outcomes from Collaborative Pairings. This table shows the possible collaborative outcomes from pairing students with different problem solving abilities and unknown conversational structures. Results like lines 2 and 4 would not be expected based on problem solving models alone, and therefore may be particularly revealing regarding the conversational structures associated with the collaboration outcomes.

STUDENT 1			STUDENT 2			GROUP OUTCOME	
Problem Solving	Conversational Structure	+	Problem Solving	Conversational Structure	=	Problem Solving	Conversational Structure
Efficient	?		Efficient	?		Efficient	Expected
Efficient	?		Efficient	?		Inefficient	Unusual
Inefficient	?		Inefficient	?		Inefficient	Expected
Inefficient	?		Inefficient	?		Efficient	Unusual

To begin to relate collaborative events with strategic and performance outcomes, we will investigate low performing groups and focus on trying to reliably decide whether the group is failing to progress; Group # 3 in Table 1 may be an example of such a group. The simplest hypothesis here is that one of the two partners is the primary cause for an unproductive group [32]. This may or may not be true but will serve as a good starting point for understanding collaborative breakdowns. The first challenge is identifying unproductive groups and predicting which ones will not improve. Our criteria for an unproductive group is one *that is failing to solve problems using an inefficient strategy(s), and as a group, is not engaging in or progressing towards effective collaboration'*. This definition represents a worst-case scenario but helps define various intermediate conditions between success and failure.

From our previous modeling of individual problem solving performances, the literature on collaborative learning, and our pilot studies, it would appear that there would be a high level of uncertainty in modeling either the prior performance or knowledge sharing histories and particularly in combining the two models. Yet it is also likely that dependencies will exist, suggesting that probabilistic causal models may be a useful approach towards development of predictive models for improving the effectiveness of collaborative interventions.

Bayesian belief and decision network technologies are useful when there is a need to reason probabilistically about possible outcomes of a combination / series of events to resolve the inherent uncertainty in the process. The variables and associated links of the belief network we propose are shown in Figure 4. The goal of this network is to use a Group Quality measure to help decide whether the group should continue together or not. Parents of Group Quality include Group Effectiveness, which relates to if the problem was solved and with what type of strategy, and Group Predictability which relates to the interaction of individuals within the group. Given the rapid stabilization of groups around particular strategies an additional parent Prior Group Quality includes information about the prior performance of the group.

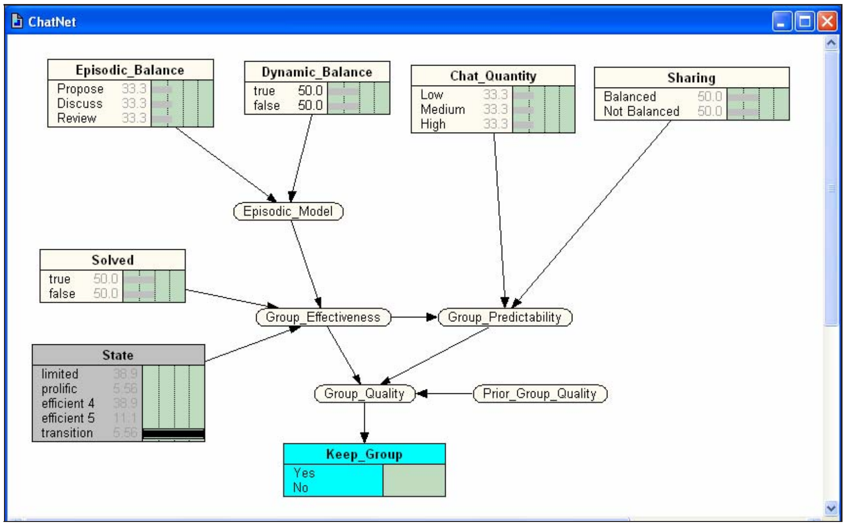

Figure 4. Proposed Causal Model for the Effectiveness of Collaborative Problem Solving .

Group Effectiveness is shown as a descendent of two performance measures (IRT and/or solved, and Strategic State information described earlier), as well as measures of the collaborative event that relate to the problem solving performance. These are Episodic Balance and Dynamic Balance. From the problem solving perspective, the suggestion for such indices comes from prior verbal protocol analysis described earlier [26], while from the collaborative learning perspective the indices draw on the ideas of shared representation of the workspace [33] and the contributions of independent ideas from collaborators (i.e. co-construction) [34]. Episodic balance is the ratio of chat segments chosen from the Propose, Discuss and Review sections of the Collaborative Interface. Many proposals without consensus about what test to order may indicate a less effective teamwork and/or problem solving structure. Dynamic Balance is a finer grained and more dynamic measure of Episodic Balance that suggests the degree of convergence on a solution. Early during a problem solving event the students would be expected to engage in more hypotheses generation and testing, whereas once evidence is obtained and hypotheses are refined, there should be more discussion leading to closure (Lawson, 1995). In preliminary studies we have, in fact, found more proposals occurring during the early framing stages of problem solving (88% cases) and, as the students converged upon a solution, there was proportionally more discussion (69% cases). In 94% of the chat logs, the amount of discussion increased (from 25% to 64%) in the second half of the performances, as the proposal rates decreased [23].

The Group Predictability metric attempts to capture the idea that most groups start out as traditional groups where members agree to work together, but are not necessarily highly motivated to do so [9]. Some groups however will evolve into highly effective teams whose performance may surpass that of the individuals. We feel that groups that are engaged in a rich and balanced discussion are more likely to continue to do so in the future than groups that do not possess these characteristics. We will initially estimate the predictability of the group through two metrics. The first is the quantity of chat communication, which is similar to the density of activity index described by Avouris et al, [30]. The second metric relates to the overall balance of the chat and the symmetry or sharing of responsibility [29]. A more balanced and symmetrical collaboration should include near equal participation by individuals in the proposal and discussion sessions, near-equal responsibility of test ordering (as evidenced by mouse sharing), and symmetry across the framing and closure sections of the problem solving session.

Using the above indicators, we anticipate that the most effective collaborations would be those that are symmetrical, episodically aligned and balanced, and dynamically well structured. While these measures will initially be reported / used across the entire problem solving event, alignment and balance can also be modelled at episode levels to provide a finer level of analysis if needed.

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