AIED 05 WORKSHOP 6

Amsterdam, 18-22 July, 2005

Representing and Analyzing Collaborative Interactions: What works? When does it work? To what extent?

AIED 05 WORKSHOP

Amsterdam

12th International Conference on Artificial Intelligence in Education, Amsterdam, the Netherlands

Extending an Online Individual ScientificProblem-Solving Environment to Support and Mediate Collaborative Learning

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Abstract: Students sometimes develop unproductive problem solving approaches that can persist for months if not detected and addressed. Previous work has shown that such impasses can be detected through probabilistic modelling of students' strategic approaches. Unproductive approaches might be avoided and/or modulated for some students by placing them in collaborative groups of 2-4 students. Although the specific collaborative activities responsible for these strategic changes are unclear, often such group interactions result in effective problem solving. We developed a web-based synchronous collaborative environment into which online problem solving activities can easily be embedded, allowing an analysis of not only the problem-solving process, but also the collaborative activities and events as teams perform simulations. A structured collaborative interface allows segmentation of the collaborative learning event log, facilitating the establishment of linkages between the collaborative interactions and the problem solving efficiency and effectiveness. In this paper, we present our preliminary analysis explaining how this structured collaborative environment may improve the performance of individuals, and how collaborative learning might be assessed by comparing the models of students' strategic approaches to their interaction.

1. Introduction

Documenting students' problem solving performance and progress in real-world simulation environments is difficult given the complexity of the tasks. A recurring challenge for instructors is determining which students are applying the knowledge gained in introductory courses to think critically, and which ones require interventional supports. We have been addressing this challenge by constructing online problem solving systems, and layered analytical machine learning tools, collectively called IMMEX, that support the development, implementation and analysis of online problem solving [1], [2]. The singleuser version has been widely used in science classes across middle and high schools, universities, and medical schools and has logged over 400,000 scientific student problem solving episodes over the past 3 years.

From these logged problem-solving datasets, we have developed performance and progress models of student problem solving using artificial neural network clustering and Hidden Markov Modeling [3]. These analyses have enabled us to identify when students develop and stabilize with unproductive problem solving approaches. Because these strategies sometimes appear and persist for months, there is a need to provide feedback and/or interventions that might encourage students to alter their problem solving approaches [4], [5].

Collaborative learning is one potential interventional approach, as studies have shown that groups may learn faster, make fewer errors, recall better and make better decisions than individuals working on their own [6]. When we initially observed students in small collaborative groups, we noted that fewer students stabilized with inefficient and ineffective strategies [7]; however, problem solving was not effective for all student groupings. These results suggested that the group composition or interactions may contain important and as of yet unknown variables influencing strategic performance and progress. We began documenting such collaborative events and components by designing an online collaborative software environment into which the IMMEX problem solving simulations could be embedded, and through which the student interactions could be tracked and modeled [8].

The study described in this paper validates the design of the IMMEX Collaborative interface and shows that, at the problem solving level, the group actions, approaches and outcomes share similarities with those that occur in face-to-face groups. The preliminary results suggest this may be a useful approach for linking collaborative interaction analysis with problem solving outcomes. In the next section, we provide an overview of the IMMEX Collaborative environment and describe our research theses. We then discuss the preliminary experimental results and put forward some hypothesis for further work.

2. The Problem Solving Environment

In designing IMMEX Collaborative, we 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. We also felt that it would be important to construct a structured environment that realistically reflected the nature of the problem solving. For this we drew on 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 problems [9]. The final requirement 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.

The IMMEX Collaborative client interface (Figure 1) 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 horizontal frame along the bottom shows a graphical representation of the service and synchronization facilities, which are used to manage the flow of actions in the collaborative space. The mouse image moves over the name of 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. The client runs in a browser, and is managed through Java applets that communicate with the IMMEX Collaboration Server. The Collaboration Server is an HTTP server acting as a proxy, that filters, edits, and synchronizes the IMMEX HTML pages through JavaScript, and sends them to the clients.

IMMEX problems require students to frame problems from descriptive scenarios, judge what information is relevant, plan a search strategy, gather information, and eventually reach a decision that demonstrates understanding. One problem set researched extensively is *Hazmat*, which provides evidence of students' ability to conduct qualitative chemical analyses. A multimedia presentation is shown to the students, explaining that an earthquake caused a chemical spill in the stockroom and their challenge is to identify the unknown chemical by gathering information using a 22 item menu containing a Library of terms, a Stockroom Inventory, and a number of different Physical or Chemical Tests (e.g. litmus test, precipitate test). This problem set contains 38 cases that can be performed in class, assigned as homework, or used as quizzes. As students perform multiple cases that vary in difficulty, student ability can be estimated by Item Response Theory analysis by relating characteristics of items and individuals to the probability of solving a given case.

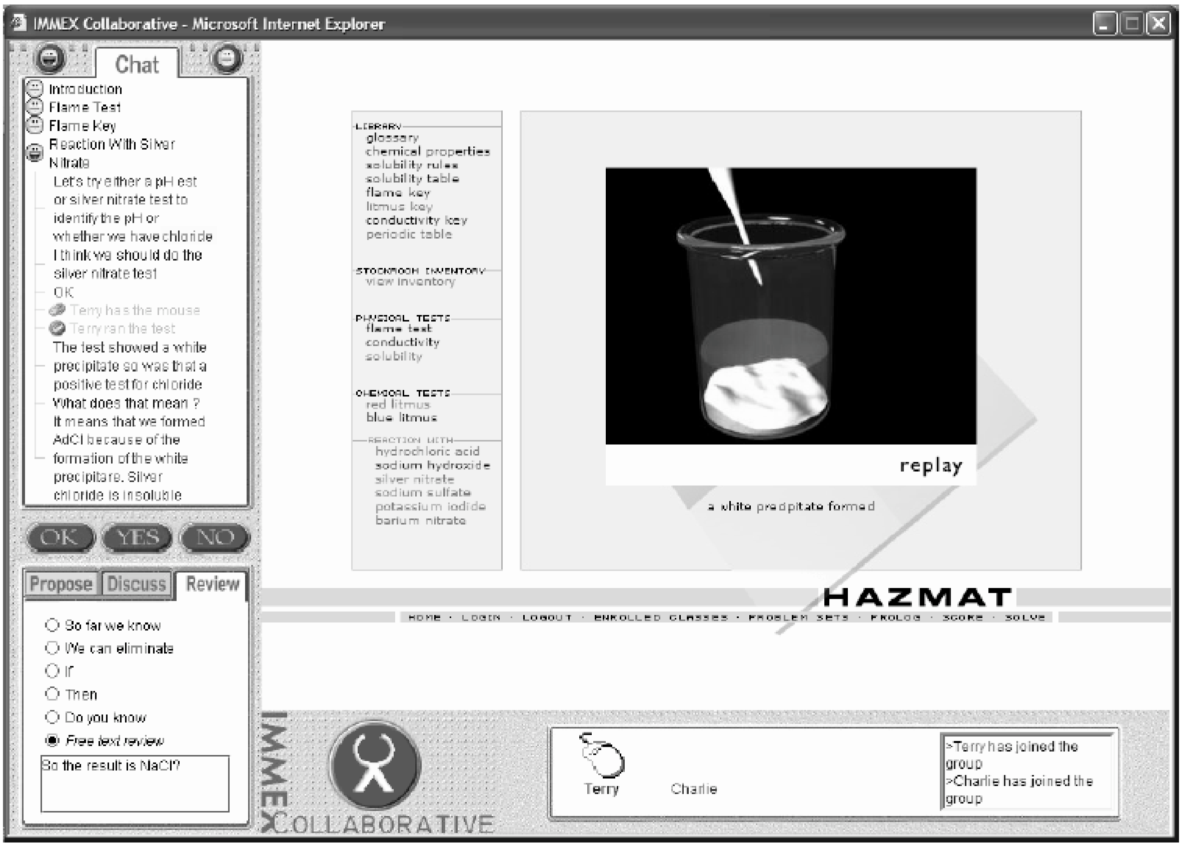

Figure 1. The main frame shows the IMMEX problem solving environment embedded within the *IMMEX Collaborative* environment which allows groups of students to use chat, sentence openers (far left) and shared mouse control (bottom) to solve problems.

An analysis of the face-to-face interaction between pairs of students learning with the IMMEX environment showed that their discourse often followed a predictable pattern. First, they tended to discuss which chemical or physical test to run next (the *proposal* 3 *episode*); second the students ran the test (the *event*); and third, the students discussed the results of the test (the *discussion episode*). A set of sentence openers for each episode was then developed based our manual analysis, and taking into account earlier work on effective peer dialogue [10]. Table 1 lists these eighteen openers, also located in the three tabbed panel on the lower-left hand corner of the interface (see Figure 1).

Table 1. The eighteen sentence openers are distributed across three problem solving phases: propose, discuss, and review. Each represents a different cognitive process related to the problem solving phase.

Propose	Discuss	Review
1. Let's try…	7. The test showed …	13. So far we know …
2. Why …?	8. What does that mean … ?	14. We can eliminate …
3. We should …	9. Can you explain … ?	15. If …
4. What do you think …?	10. It means …	16. Then …
5. Because …	11. Do you think …?	17. Do you know …?
6. I think (*Free text proposal*)	12. I think (*Free text discussion*)	18. I think (*Free text review*)

The sentence openers are simple enough for users to find and select those that are most appropriate, but we also allow for the use of free text by providing the opener “I think” in each of the three proposal, discussion, and review categories. IMMEX Collaborative manages the conversation through the use of topic threads (based on the context). These topic threads attempt to structure the student discussions to reflect the structure of their decision processes in selecting and explaining the results of the various physical and chemical tests. The topic threads are also used to automatically segment the sub-dialogues into episodes. Conversations that are segmented at different levels of granularity may be useful in the future for modeling structured collaborative interactions (for example, using quantitative indices, Hidden Markov Modeling [10] and neural networks [12]). In this way, the IMMEX Collaborative environment supports learners through the various phases of problem solving, facilitating an extended, in-depth, on-topic discussion, and providing a coherent view of the argument [11].

The structured interaction model is obtained by segmenting the chat log according to the flow of conversational contributions and students' actions. Every proposal segment ends with an EventType = *TestItem* (e.g. *View Inventory*), and may or may not be followed by a segment in which the students discuss the results of the test. If a discussion phase begins after a test is ordered, it will continue until another proposal opener (Stems 1 through 6) is used to propose a new test (see Table 2). In other words, discussion and subsequent proposal episodes always follow events in which students order tests. Special episodes for review can occur at any point of the chat and are identified from the third range of stems. The three "quick" buttons ("OK", "Yes", and "No") can be used to indicate agreement. Their type is inferred from the episodes to which they belong.

We have defined several quantitative indices that could be useful indicators for understanding the coherency of problem solving in this environment: *episodic alignment, episodic balance and dynamic structure*. Episodic alignment measures the linkage of the proposal/test/discussion segments with regard to each other as they occur repeatedly during the problem solving event. IMMEX verbal protocols [9] suggest that discussions should contain linked aligned sequences of proposals, tests and discussion. Episodic balance refers to the ratio of contributions in the proposal segments to those in the discussion segments of each episode. Many proposals without consensus may indicate a less effective teamwork. Dynamic structure is a coarse-grained coherency measure from a problem solving perspective: more proposals would be expected during the early framing stages of problem solving, and as the students converge upon a solution, we should see proportionally more discussion. 4

Table 2. Proposal segments (grey) begin when someone proposes a new test, and end when the test is ordered

Time	User	Sentence Opener	Text	Event Type	
2:21	Charlie	6	Let's view the inventory	Chat	PROPOSAL
2:22	Terry	3	We should click on the view the inventory sheet to see the message	Chat	PROPOSAL
2:22	Charlie	6	Do you want to spend these points?	Chat	PROPOSAL
2:23	Terry	20	Yes	Chat	PROPOSAL
2:23	**Charlie**	**0**	**View Inventory**	**Test Item**	
2:25	Terry	7	The test showed we have a sodium cation so we have carbonate, chloride, hydroxide, nitrate, or sulfate anions.	Chat	DISCUSSION
2:25	Charlie	19	OK	Chat	DISCUSSION
2:26	Terry	7	Let's try either a pH test or silver nitrate test to identify the pH or whether we have a chloride.	Chat	

In our analysis we also examine the symmetry of the contributions from the different individuals in the group [13] assuming that more 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.

3. Performance Models and Analysis of Collaborative Events

The first experiment involved eight freshman university chemistry students working in pairs at a distance through the IMMEX collaborative environment. Each group performed four randomly presented cases of *Hazmat,* which varied in difficulty. Fifteen problem solving sessions were logged and analyzed for both the collaboration events (Table 3).

Table 3 lists the average percentages and total numbers (in the boxes) of chat interactions (proposals, discussion and review), actions (ordered items and background information) and mouse control (handling rate) for each individual and group. The chat percentages are to be interpreted referring to the averages of total number of groups' contributions as the mouse control's percentages relate to the rates of total ordered and background's items selected by each members. Even where the work was not shared (e.g. low mouse transfer rate), all of the chats included near equal participation of individuals proposing, discussing and reviewing. Analysis of the values in the table shows the following:

• Group 1 selected more tests and spent less time reviewing than the other groups.
• Group 2 chatted the most, and had the greatest percentage of proposals, but ran the fewest tests. This group was one-sided in that they never passed the mouse, indicating that one individual may have dominated the problem solving session.
• Group 3 chatted little, but its members shared their workload better than the other groups.
• Group 4 spent a lot of time reviewing information, and shared problem solving responsibilities as evidenced by the passing of the mouse

Table 3. Communication, test ordering, and mouse control actions (data averages)

	Chat				Item		Mouse
	Propose	Discuss	Review	Total	Ordered	Background	Control
User 1	22%	27%	8%	57%	9	9	78%
User 2	20%	20%	4%	43%	2	1	22%
Group 1	**41%**	**47%**	**12%**	***35***	**11**	**10**	***21***
User 3	32%	17%	7%	57%	6	5	100%
User 4	24%	13%	7%	43%	0	0	0%
Group 2	**56%**	**30%**	**14%**	***50***	**6**	**5**	***11***
User 5	25%	17%	7%	49%	5	6	64%
User 6	23%	19%	9%	51%	3	3	36%
Group 3	**48%**	**36%**	**17%**	***20***	**8**	**9**	***17***
User 7	15%	16%	14%	49%	3	3	53%
User 8	16%	23%	16%	55%	5	7	47%
Group 4	**31%**	**39%**	**30%**	***33***	**8**	**10**	***18***

We also studied the coherency of collaborative events using our interaction models. In general, groups' conversations were episodically balanced and aligned: the number of subdialogues (pairs of episodes) was proportional to the number of problem solving events, reflecting the fact that the members usually make some hypotheses and *proposals* before ordering tests or background information, and then they *discuss* the results obtained. The data showed that these episodes were paired together. Moreover we found that there is a strength coherency between the trends of the interactions and the problem solving framing stages (dynamic structure). As expected, more proposals occur 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. The interaction analysis gives us some information about the students' interaction, but it does not tell us much about the effectiveness of the group learning, and how the interaction models match with more or less efficient problem solving approaches.

To follow students' performance and progress, we have automated layered analytic models of how strategies are constructed, modified and retained as students learn to solve online problems like *Hazmat*. These strategies are modeled first by self-organizing artificial neural network analysis, using the tests that students choose to solve the problems as the classifying inputs. This generates a 6 x 6 matrix of strategies detailing the qualitative and quantitative differences among problem solving approaches. In Figure 2 the highlighted boxes in each neural network map indicate which strategies are most frequently associated with each state. Then, progress models are developed across sequences of performances (defined by the neural network nodal classifications) by HMMs, which stochastically describe problem solving progress with regard to different strategic stages in the learning 6 process. These analytic layers operate as background processes and can generate performance measures in real-time (see [3] for more detail).

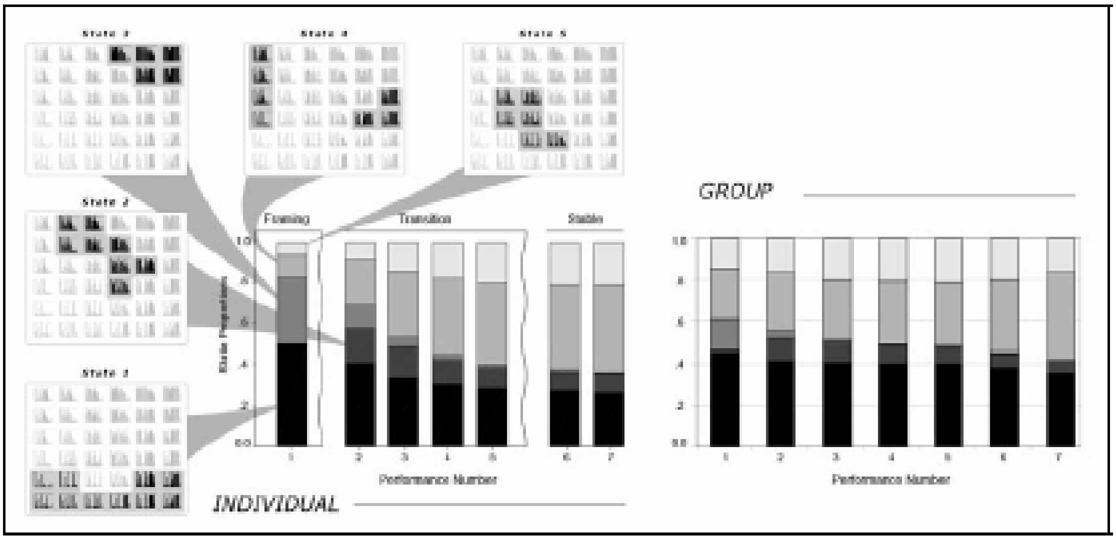

Figure 2. The learning trajectories for individuals (A) and groups (B) suggest that once students adopt a strategy in stable state (1-4-5), they are likely to continue to use them. In contrast, students adopting State 2 and 3 strategies are less likely to persist with those approaches and more likely to adopt other strategies.

An example of student strategy development is shown in Figure 2A, illustrating the distribution of HMM state usage as students solved 7 different *Hazmat* cases. On the first case, when students are framing the problem space, the two most frequent states represent either a limited number of test selections (State 1), or an extensive number of test selections (State 3). As students develop experience, they transit through states, as shown by the state transitions in Figure 2A. Students transit from State 3 (and to some extent State 1), pass through State 2 and into States 4 and 5. By the fifth performance the distribution of approaches appears to have stabilized, showing that without intervention, individuals learning alone generally tend not to switch their strategies, even when their strategies were ineffective.

Also shown in this figure is a similar learning trajectory for 5452 Hazmat performances which were collected from students who worked collaboratively in face-to-face groups of 2 or 3. Consistent with the literature [6] [10], having students work in collaborative groups significantly increased their solution frequency. More importantly, ANN and HMM modeling of these performances showed (Figure 2B) that the collaborative learners stabilized their strategies more rapidly than individuals, used fewer of the transitional States 2 and 3 and more State 1 strategies (limited and/or guessing approaches). This suggests that the group's interaction helped students see multiple perspectives and reconcile different viewpoints, events that seem to be associated with the transitional states. The collaboration may have replaced the explicit need for actions that are required to overcome impasses, naturally resulting in more efficient problem solving.

Let's now examine the four groups' fifteen performances as they learned collaboratively. First, from Table 4A ,the solve rates on the first and second attempts combined was 68% (average of columns "1st" and "2nd" combined in Table 4A) which was very similar to the performance of face-to-face groups and significantly higher than individuals (~53%) [3]. Similarly, from Table 4B the progress states obtained by mapping of the ANN performance nodes of each group performance to the associated states derived from HMM showed enrichment for States 1 and 4, much like face-to-face group performances (refer to Figure 2B). A surprising finding was that most of the groups stabilized their approaches quite quickly as evidenced by the use of consistent strategies from case to case, even when the cases were of different difficulties and whether they 7 solved the case or not (see Table 4B). However, it appeared that the collaborative interface was flexible and allowed the groups to solve the cases in multiple ways. Group 4 was the only one that changed its stabilized strategy passing from State 5 (the more effective, see solve rates in Table 4A) to State 3 (the less effective). This is not surprising because this case, Iron III Nitrate, is the third most difficult Hazmat case and deserves more attention. It is interesting that the flexibility shown by this group enabled them to solve this case, demonstrating that chats and collaboration events are as sensitive to problem difficulty as they are when individuals perform IMMEX cases.

Table 4A: Solve rates of HMM stases.
Table 4B: Strategy trajectories: solving tries, ANN nodes and progress states

A	Not solved	1st try	2nd try
State 1	30.4%	51.7%	17.9%
State 2	35.2%	43.1%	21.7%
State 3	46.3%	32.4%	21.3%
State 4	36.1%	44.9%	19.0%
State 5	23.5%	56.5%	20.0%

B	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

Note: *1st try/ 2nd try* means solved on the first or second attempt

The next step is to document correlations between interaction models and strategic problem solving approaches. One starting point may be to use the HMM state differences we have seen between individual and face-to-face groupings. Face-to-face groups use fewer State 2 strategies; collaboration seems to help these students transit through this state faster. In the data presented here, Group 3 stabilized with State 2 strategies, and this was also revealed in the nature of the interaction. The analysis in Table 3 shows that they had fewer discussions, fewer interaction overall, and no mouse sharing. While this could happen because of an incorrect use of the tool or because of the tool itself, this group also had the lowest solution frequency and ordered the fewest number of tests suggesting a lower quality problem solving and collaboration experience overall.

4. Conclusion and Future Work

The goal of these studies was to begin validating the usefulness of a synchronous, symmetrical approach for relating the dynamics of online collaboration with the effectiveness / efficiency of concurrent problem solving. The preliminary results are encouraging in that the solution frequency, time on task, and interaction statistics were similar to what is observed in face-to-face collaboration, suggesting that the interface neither significantly changed the nature of interaction and problem solving in this environment, nor interfered with the overall problem solving. 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*.

Perhaps the most unexpected finding was that most groups rapidly develop a rapport that resulted in the negation of a strategy that was repeatedly used across previous tasks. To our knowledge this is not a well documented phenomenon although, given our results with individuals, perhaps not overly surprising . Analysis of a second chemistry problem set with 19 groups is providing similar results. The most disappointing aspect of these studies is that while the chat sessions were episodically aligned and balanced, the students did not always use the tabs and sentence stems as designed and intended, and instead often used the free-text box. While manual coding by a series of raters was possible for this small performance sample, future scale-up and automation efforts will require student training on the use of these features (perhaps in the context of formal instruction on problem-solving and critical thinking) and/or restriction of the free-form text interface.

While these results are based on only a limited number of groups and performances they suggest an approach around which to integrate the prior strategic models with models of the collaborative interaction. To establish a mapping between the nature of the collaborative event and the strategic problem solving approaches and validate other emerging hypotheses, we plan to continue gathering data and running dynamic analyses so that we might better understand how students' strategies might be improved through strategic collaborative learning situations.

Supported in part by grants from the National Science Foundation (ROLE 0231995, DUE 0126050, HRD-0429156). The authors would like to thank Dr. Melanie Cooper and Charles Cox at Clemson University, and Dr. Marcia Sprang (Placentia-Yorba Linda School District) and Tricia Um (MIT),for participating in pilot design and validation studies, and Dr. Marco Ronchetti at the University of Trento for guidance and support.

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