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An Assessment of the Effect of Collaborative Groups on Students' Problem-Solving Strategies and Abilities

Melanie M. Cooper*, Charles T. Cox, Jr., Minory Nammouz, and Edward Case
Department of Chemistry, Clemson University, Clemson, SC 29634-9703; **cmelani@clemson.edu*

Ronald Stevens
UCLA Interactive MultiMedia Exercises Project, Culver City, CA 90230

This paper reports the use of tools to probe the effectiveness of using small-group interaction to improve problem solving. We find that most students' problem-solving strategies and abilities can be improved by working in short-term, collaborative groups without any other intervention. This is true even for students who have stabilized on a problem-solving strategy and who have stabilized at a problem-solving ability level. Furthermore, we find that even though most students improve by a factor of about 10% in student ability, there are two exceptions: Female students who are classified as pre-formal on a test of logical thinking improve by almost 20% when paired with concrete students; however if two students at the concrete level are paired together no improvement is seen.

It has been said that problem solving is the ultimate goal of education *(1),* and certainly this is true in any chemistry course *(2).* To be sure, most instructors value this skill and try to instill the ability to solve problems in their students. However, the term "problem solving" means different things to different audiences, from algorithmic problems to complex, open-ended problems that do not have one particular solution. A number of attempts have been made to define problem solving, including "any goal-directed sequence of cognitive operations" *(3),* and many now agree with the general definition: "what you do when you don't know what to do" *(4).*

Problem solving can be closely allied to critical thinking *(5),* that other goal of most science courses, in that it involves the application of knowledge to unfamiliar situations. Problem solving also requires the solver to analyze the situation and make decisions about how to proceed, which critical thinking helps.

A number of information processing models for problem solving have been developed *(6–8)* and attempts made to develop uniform theories of problem solving *(9).* However, many of these studies involve knowledge-lean, closed problems *(2)* that do not require any specific content knowledge to solve, and that have a specific path to the answer. The truth is that many types of problems exist and there is not one model that will be effective for all categories *(10).* For example, in teaching science we are ultimately concerned with knowledge-rich problems requiring scientific content knowledge. Studies on problem solving in chemistry have typically revolved around development of strategies derived from research on closed-ended problems, usually pinpointing areas of difficulty that students encounter in specific subject types, such as stoichiometry or equilibrium. A number of studies where students are given strategies or heuristics allowing them resolve word problems in order to produce a numerical answer by application of an algorithm *(11–13).* In fact, in many courses, students are never presented with any other type of problem. Thus for large numbers of students, particularly in introductory science courses, problem solving has become synonymous with numerical manipulations to reach a specific answer using an algorithm learned by rote.

Open-ended problem solving that requires students to use data to make inferences, or to use critical thinking skills, is much more difficult to incorporate into introductory (and even higher level) courses; it is even more difficult to assess, particularly when large numbers of students are involved. Traditional assessment methods, such as examinations and quizzes—including both short answer and multiple choice—give very little insight into the problem-solving process itself. If a student does not have a successful problem-solving strategy, these methods may not allow either the student or the instructor to see where the difficulty lies, or to find ways to improve. While other investigation methods such as think-aloud protocols and videotaped problem-solving sessions *(14)* give a more nuanced picture of the problem-solving process *(15–17),* these techniques are time consuming, expensive, and require specific expertise to analyze. These methods are certainly not applicable for the formative assessment of large numbers of students, and while they give a snapshot of a student's problem-solving ability at the time of observation, it is even more difficult to monitor students' development of problem-solving expertise over an extended period.

The upshot of all this previous research is that while we know a great deal about the problem-solving process in an abstract environment, we do not in fact have much insight into how students solve many types of scientific problems. Since we lack this information about how students approach problems and how students achieve competence, it is not easy to address the difficulties that students encounter as they develop problem-solving abilities. Indeed, while instructors value problem-solving skills highly, it is often the case that the only explicit instruction that many students are exposed to is the modeling of the skill as the instructor solves problems for students.

So we have a situation where a valued skill is often not fully developed in students, even though we implicitly expect that they will become competent problem solvers by the end of the course. The most common assessments give no real insight into student strategies for problem solving, and therefore there is little feedback the instructor can give in terms of how to improve. The traditional assessments also tend to measure and reward algorithmic problem-solving skills rather than critical thinking and application of knowledge to new situations. It seems clear that if we are serious about wanting to incorporate meaningful problem solving into our courses, then we must go beyond the traditional assessments and design systems that allow us to investigate how students solve more challenging, open-ended problems that require them to use their knowledge in unfamiliar situations. Without a reliable method to probe problem-solving ability and strategy, it is difficult to assess student progress, and it is also difficult to probe the effect of interventions designed to improve student problem-solving ability.

One solution is to use technology to amass information about how a student navigates through a problem. Unfortunately most computerized assessment methods do not make use of the powerful capabilities of technology—serving instead as a convenient conduit for quizzes and tests. Course management systems such as BlackBoard do allow students free-form input for some types of questions, yet typically only the input of the answer is monitored. These systems allow for feedback—which can be tailored to whether the student chose the correct or incorrect answer—but no insight into how the student arrived at the answer is available. In addition, these types of systems also encourage algorithmic problem types. For example, if the instructor inputs a range of variables for the question, each student can be given a different problem set. However, because a given problem can only differ in the numbers used, and not the conceptual understanding required, then students rapidly learn to solve the problems by analogy. While this method is successful in the early stages of problem-solving skill development, it is clearly not a useful method if students have no model to use for their analogy, as for example when faced with problems that arise in more realistic situations. We are ultimately concerned with the development of meaningful problem-solving skills. While rote methods are a useful chunking device for large problem-solving tasks, and are one of the reasons why experts are able to solve problems more successfully than novices *(18),* many students never move from rote methods along the continuum to develop more meaningful and useful problem-solving skills.

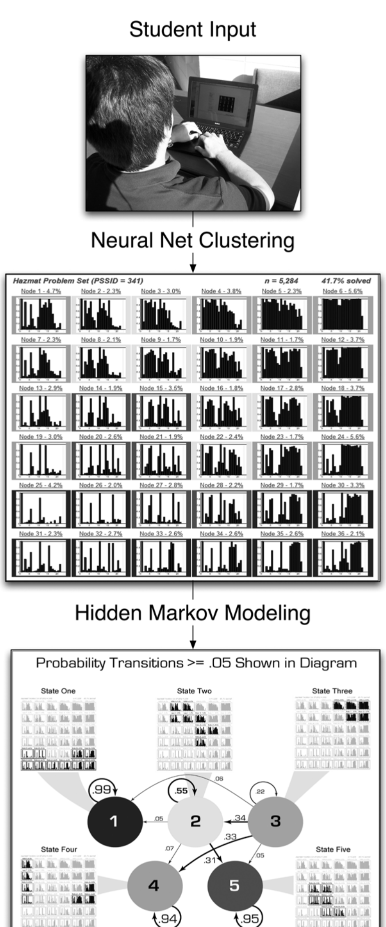

Figure 1. Sequence of data manipulation from student input to problem-solving states, via artificial neural net nodes and subsequent hidden Markov modeling. This produces five "states" that are representative of the strategy that a student uses to solve the problem.

Interactive MultiMedia Exercises Technology

In response to these difficulties Stevens et al. have developed and reported elsewhere *(19–20)* a software system (IMMEX, Interactive MultiMedia Exercises) that allows educators to track students' movement through a problem and model their progress as they perform multiple problems. With this tool we can identify students' problem-solving strategies and investigate how students' strategies change over time with repeated practice *(21).*

IMMEX assignments are typically case-based problems that pose a realistic scenario to students in such a way that they must move through the problem space to find relevant information that will help them move toward a solution. The problem used in this study, Hazmat, is a chemistry qualitative analysis problem, in which the student must identify an unknown compound based on the results of the physical and chemical tests that are requested by the student within the problem space (for a more detailed description please see the online supplement). Hazmat has 39 different cases (that is, 39 different compounds to identify), each of which may require a different strategy, or sequence of actions, based on the identity of the unknown.

Because Hazmat has over 20 different items for students to choose, and these items can be observed in any order, there are literally thousands of possible paths that students could take through the problem. Therefore, rather than trying to identify identical problem-solving strategies or paths through the problem, we use artificial neural net (ANN) software to aggregate similar performances *(21).* That is: the software recognizes similar patterns of student actions and groups them together. These clusters of similar performances appear as "nodes" in the neural net output as shown in Figure 1. Once the neural nets are trained with large numbers of student performance data, each subsequent student performance on a problem is then assigned to a particular node. A typical analysis results in up to 36 nodes or strategy clusters.

In order to simplify the output, and to include the changes in student strategy over time we then analyze sequences of student performances with hidden Markov modeling (HMM) techniques *(21).* HMMs are used to model processes and find patterns in data that emerge over time. HMMs have been used in speech recognition software, and more recently to characterize sequences in collaborative problem solving *(22)* and to analyze individual problem solving *(21).* In hidden Markov modeling we postulate a series of states that the student may pass through as they improve their problem-solving strategies. Many sequences of student strategies are modeled by the HMM software and the ultimate output provides a series of states that are linked to the ANN nodes. The complete sequence of data manipulation is given in Figure 1.

The result of all this data manipulation is that each performance by a student can be assigned to one of five problem-solving states determined by HMM that is reflective of that student's strategy choice over time. These states represent a clustering of similar nodes from the ANN analysis, and also indicate whether that state is stable over time; that is, whether a student will stay within that general strategy. The numbering of the states is an artifact of the modeling software used and does not imply any kind of hierarchy. With this tool—the IMMEX software system—we have a sensitive probe for how students choose to navigate through problems and whether that strategy changes with experience. We have previously reported the use of these techniques to track student development of problem-solving skills *(21)* and a more detailed explanation of the method is available in the materials and methods section of the online supplement.

In tandem with this strategy analysis, it is also possible to generate an estimate of student ability, by using item response theory (IRT) *(23),* which is a better gauge of student success than reporting the percent correct, since IRT allows us take the difficulty of the problem into account as well as whether the student got the problem correct. Since we have thousands of student performances on each of the 39 cases of this IMMEX problem, we are able to calculate both item difficulty for each case, and student ability—which is reported as a number between 20 and 80. By using all these data mining techniques in tandem we can generate a large pool of data on student strategies and on student abilities.

Collaborative Grouping as an Intervention

The ability to analyze student strategies and monitor the change in strategy and ability over time gives us a unique opportunity to track students' progress, and assess the effectiveness of interventions designed to improve students' problem-solving skills. This paper reports the results of experiments developed to assess the effectiveness of collaborative learning groups in improving student problem-solving strategies and students' success on problem-solving tasks.

Collaborative learning has been the subject of extensive study, and is typically classified as a less-structured form of cooperative learning *(24).* Students working in collaborative groups may work together on a short-term task, without formal roles or learning goals. In contrast, cooperative groups typically have long-term goals, students often have roles to play within the group, and the task is usually structured so that each student has a definite contribution to make.

While small group learning is a staple of the K–12 education system, and most of the early research on its effectiveness was performed in this area, the use of small-group learning in higher education is becoming increasingly prevalent. A meta-analysis *(25)* of small-group learning in science indicated that this method was generally effective in promoting higher achievement, more satisfaction, and increased persistence in STEM disciplines. Another study *(26)* of small-group learning limited to chemistry reported similar conclusions. However, most of the positive results reported refer to increased student satisfaction and persistence in the course. There are conflicting reports on the effect of collaborative groups on students' problem-solving ability. For example, in a meta-analysis of the research on teaching problem solving, Taconis reports that the structure of the groups is critical to the success of the activity, and that improvements in problem solving are dependent on using formally structured cooperative learning groups incorporating specific guidelines and feedback *(27).* Heller reports that students in a large introductory physics class were taught a structured method for solving problems, and that students who had practiced in collaborative groups performed better on tests than students who had practiced alone *(28).* Singh *(29)* also found that students who had worked in pairs on a conceptual survey of electricity and magnetism had significantly increased normalized gains on subsequent individual performances.

Even though a number of proven, successful projects have been developed to improve teaching and learning by incorporating some group or teamwork *(30–32)*—for example, Peer-Lead Team Learning (PLTL) and Process-Oriented Guided Inquiry (POGIL)—little evidence currently exists for wide-scale adoption of small-group learning in higher education science courses. This discrepancy between the evaluated, positive experience of some and the general practice of many may be because the evidence for the effectiveness for small-group learning is not persuasive, or because it has not been disseminated widely enough, or simply because of inertia or disinterest on the part of instructors.

We present in this report evidence that most students working in collaborative groups on case-based problems, can improve their problem-solving strategy and their ability (indicated by IRT analysis), and that the improvement persists when the student returns to working alone. Furthermore we show that some students benefit more from working in groups than others, and that factors affecting group learning effectiveness are gender and logical thinking ability.

Previous Work

We have previously reported *(21)* that students who solve several cases of an IMMEX problem stabilize on a particular strategy after about five performances. That is, after a period of framing the question and exploration of the problem space, a student will settle on a strategy, which may or may not be productive. In our work we have found that a typical student will not improve in problem-solving ability (at least while we are monitoring their activity) after they have completed about five problems. We have also found that students who work in groups tend to stabilize more rapidly on a strategy than individuals, and the trajectories to stabilization are different. Groups of students also showed improved success rates in this experiment, improving from 55% correct for individuals to 65% success for groups *(33).*

These preliminary results offer a tantalizing insight, suggesting that collaborative groups might be effective in promoting more successful problem solving. However, an important question remains: do the improvements in the problem-solving success rate and strategy choice persist after collaborative grouping? A common criticism of group work is that some students do not contribute or benefit from the collaboration and "hitchhike" on the work of other students. In fact, previous reports indicate *(27, 34)* that the structure of the groups is critical to the success of the activity, and that improvements in problem solving are dependent on using formally structured, cooperative learning groups that incorporate specific guidelines and feedback for students.

We therefore chose to answer two questions, ones that might provide more details about the applicability of group work in an informal collaborative setting:

- What is the effect of collaborative grouping on students who have previously stabilized on a strategy for that problem?
- Does the nature of the group affect the effectiveness of collaborative grouping?

This research was performed with 713 students enrolled in the first semester of a general chemistry course for science and engineering majors. All students had signed informed consent forms giving permission for their data to be used in this analysis.

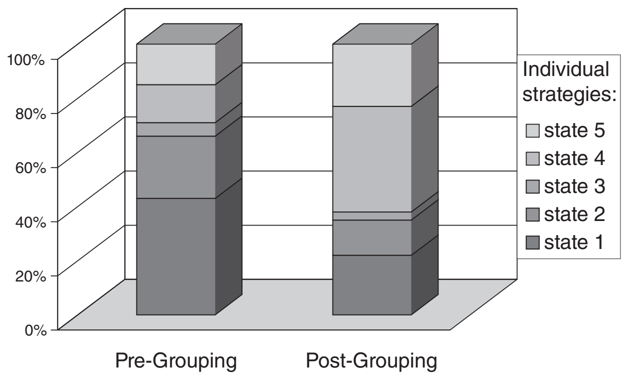

Figure 2. Strategies used by individuals who have stabilized on a strategy, before and after grouping. The strategies are significantly different ($\chi^2 = 228$, $p < 0.001$). The five states (1–5) are the outputs from the hidden Markov modeling, and are discussed in more detail in the online supplement.

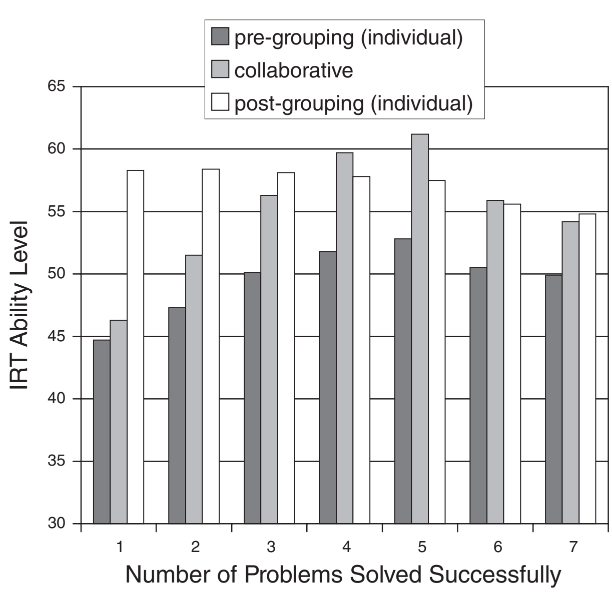

Figure 3. Comparison of student abilities (as determined by IRT levels) for pre-grouping (individual), collaborative, and post-grouping (individual) performances. The first five individual post-grouping performances are all significantly higher in ability ($p < 0.001$) than the fifth individual pre-grouping performance.

Experiments and Results

Effect of Collaborative Grouping on Students Who Have Previously Stabilized on a Strategy

As previously discussed we have shown that students stabilize on a strategy after about five performances of a problem *(21)*. Thus the question arises, "Will grouping disrupt the strategies of students who are allowed to stabilize prior to group work?" To ensure that most students had stabilized on a strategy they were required to perform five individual cases of the problem. Although in previous work students had worked in groups of three or four, in this study the students were then asked to work in assigned pairs in collaborative groups to perform five more cases of the problem. Finally each student performed five more cases individually. This individual–group–individual design allowed us to collect data and to perform comparisons of strategy, success rate, and student ability.

Figure 2 shows a comparison of students' individual strategies before and after grouping, and a cross-tabs comparison between the distribution across states for the fifth individual performance of the subjects (thus giving them time to stabilize). Their individual performances immediately after working in groups gives a χ^2 value of 228, which is greater than the critical value at a 0.001 confidence level, indicating that there is a significant difference between the distributions. Therefore, even individuals who had been given time to stabilize on a strategy adopted different strategies after solving problems in collaborative groups.

A further comparison of student performances showed that the distribution of the states used by students in groups and the final individual states were not statistically different. This indicates that the students retained the problem-solving strategies they had developed within the groups.

An analysis of the state distribution showed that, after grouping, a higher percent of students adopted more successful strategies. For example, as shown in Figure 2, more students use state 5 after grouping, which is correlated with a more efficient strategy and a higher success rate. In fact, the students' solved rate increased from 58% before treatment to 69% after treatment. As noted before, however, success rates on problems of this type can be misleading because cases of the problem are of different difficulty. If instead of success rates we use IRT to analyze student performances, this provides another metric to compare student performances before, during, and after grouping.

IRT provides us with a measure of student ability. Figure 3 compares average student ability before, during, and after collaboration by performance number (the number of problems the student has completed). Note that the pre-collaborative student ability stabilizes after performance number 4 in much the same way as the strategies do. Student ability rapidly increases during collaboration and levels out, and there is no significant difference between the abilities during and after collaboration. Note that after grouping individual student ability remains fairly constant and statistically the same as the group performance ability. It appears that we are seeing the same trends in stabilization and perturbation by using IRT analysis as we saw with HMM models; that is, student problem-solving strategies and abilities are changed and improved by working in groups, and that improvement is retained by the individual after working in a group.

Effect of Group Type on Problem-Solving Ability

In previous studies *(33)* students were randomly assigned to work in groups of two–four students. In this study students were grouped in pairs according to their scores on the GALT test (Group Assessment of Logical Thinking) *(35),* which includes questions on proportional reasoning, data inferences, and control of variables. Based on the results students were assigned to three levels corresponding to Piaget's theories of intellectual development:

> **Formal:** Students are able to do proportional reasoning, make inferences from data, control variables, and understand conservation of matter.
>
> **Pre-Formal:** Students who are pre-formal may be able to perform at a formal level on some tasks and not on others.
>
> **Concrete:** Students' thinking levels are not fully developed; for example, a concrete student is not able to reason from data, and may not be able to undertake many of the problem-solving activities found in a college general chemistry course.

Previous reports *(36)* have indicated that despite Piaget's original findings that formal thinking levels may be attained as early as 11–14 years old, up to 50% of college first-year students have not reached a fully formal thinking stage. In our study we found that 54% of the general chemistry students were formal (F), 38% pre-formal(P), and 8% concrete (C).

Students were paired up in all possible combinations (F–F, F–P, F–C, P–P, P–C, C–C) and asked to perform the same problem-solving sequence as described above (five individual, five group, five individual).

Analysis of the HMM states used by each type of group showed that there was no significant difference in state distribution, although there was a difference when groups with and without concrete students were compared; an indication that the presence of a student in the group who was having difficulty did tend to change the group performance.

A more informative insight into group functioning was obtained using IRT analysis. When student ability pre-grouping was compared to student ability post-grouping a number of interesting trends emerged, as shown in Figure 4. For most students the average gain for students is around six units (or 10% because most students' pre-grouping ability level is between 45 to 50 IRT units), which is statistically significant at the $p < 0.001$ level. When these data are viewed by type of group and student logical thinking level, however, two sets of data are significantly different from the rest. Groups consisting of two concrete students show almost no gain in ability after working together. Clearly for these students, who are not intellectually prepared for a complex problem like Hazmat, repetition and discussion of a problem do not lead to increases in ability. However if concrete students are paired with pre-formal or formal students their gains are equal to those in all the other groups, indicating that if they are paired with a student who can explain the problem and discuss it with them, they can improve their problem-solving performance significantly.

The other significantly different result is the gain in ability for pre-formal students paired with concrete students, which is the only incidence significantly larger than the average gain. A possible explanation for this finding is that pre-formal students are forced into the role of decision maker and teacher in this type of group. Our data provide evidence that these students can become more proficient problem solvers. As shown in Table 1 the pre-formal students in a P–C group have a final ability level of 56.4, which is identical to the final level of the formal students in any group. Moreover, as shown in Table 1, the improvement in ability for formal students does not depend on the group type. It is only for pre-formal and concrete students where differences appear. Both types of students begin with the same level of ability, and both appear to benefit by around the same amount from pairing with formal or pre-formal partners. It is only the pre-formal–concrete, and the concrete–concrete student pairings that appear to produce different results. Furthermore, if these data are analyzed by the sex of the student we see that most of the gain for preformal students actually occurs

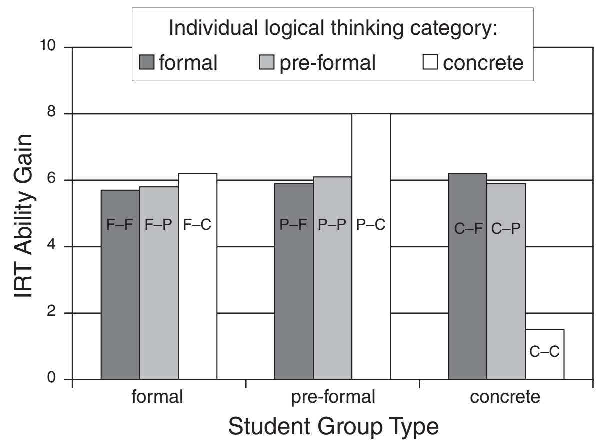

Figure 4. Gain in student ability for each logical thinking level by the type of group. On average the gain is ~6 ability units as determined by IRT, except for pre-formal students grouped with concrete students, who gain ~8 units, and for concrete students paired together who do not appear to benefit from collaboration. The gain is statistically significant for every group at the $p < 0.001$ level, except for the C–C group. Actual IRT ability values are given in Table 1.

Table 1. Students' Average Abilities Measured by IRT Values Compared with GALT Results Group Assignment

Group Type (from GALT Results)	Item Response Theory Values (Range Is 20–80)					
	F–F (*N* = X)	F–P (*N* = X)	P–P (*N* = X)	F–C (*N* = X)	P–C (*N* = X)	C–C (*N* = X)
Concrete, Pre-Grouping				46.1	46.1	46.1
Concrete, Post-Grouping				52.3	52.0	47.6
Pre-Formal, Pre-Grouping		46.4	47.6		48.4	
Pre-Formal, Post-Grouping		52.3	53.7		56.4	
Formal, Pre-Grouping	50.4	50.8		50.2		
Formal, Post-Grouping	56.1	56.6		56.5		

Note: Values are statistically significant for every group (except for the C–C group) at the $p < 0.001$ level.

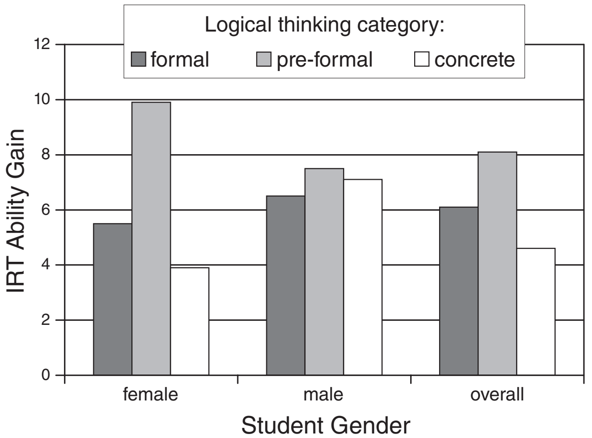

Figure 5. Gains in student ability after grouping, by gender and group type.

with the preformal female students, as illustrated in Figure 5. Female students who are classified as pre-formal show marked improvements in problem-solving ability after working in a group, although female concrete students do not seem to benefit in the same way.

Interestingly, further analyses showed that there were no differences in female achievement based on group composition. That is, all female groups had the same improvements as male–female groups. These findings are somewhat different from those reported by Webb *(37),* in which girls were found to be less successful than boys in mixed-gender, cooperative learning groups. However these earlier studies were done with pre-college students, who are a very different population than the self-selected students in a general chemistry course aimed at science and engineering majors.

Discussion

Using over 100,000 performances by 713 students on a problem, we have shown that we can improve student problem solving by having students work in collaborative groups. These improvements are retained after grouping and provide further evidence of the positive effects of having students work in groups. This finding is in contrast to the previously discussed reports *(27)* indicating that collaboration alone was not sufficient to improve problem-solving ability. In our study, however, students were not learning new material; rather they were trying to apply this material to an ever-changing situation (analysis of unknown compounds). The question remains: why does simply working collaboratively in a group in an unstructured environment appear to have such a positive effect on problem solving, and why does this effect linger in subsequent performances?

An explanation surely lies in the fact that students are forced to become more thoughtful about their actions. That is, group problem-solving promotes metacognition *(24).* Students must explain to their group why they think an action should be taken and what the result might mean for their particular problem. Rather than guessing, or choosing all items (strategies that can clearly be followed by inspection of the neural net outputs), discussion within the group seems to produce more thoughtful and effective strategies that stay with the student in subsequent attempts. For example, after grouping, many of the students who had previously stabilized on ineffective strategies shifted to a more effective strategy as shown in Figure 2, which shows the distribution of strategies before and after working in collaborative groups.

There are three potential strategies that have been proposed to explain learning during collaboration *(38):*

1. Other-directed explaining, which occurs when one peer instructs another
2. Co-construction, in which both peers either elaborate or critique each other's contributions
3. Self-explanation, listening to one peer self-explain

Self explanation has been well documented as a technique for improvement of problem-solving strategies as a student works alone *(15),* and it is thought that all three mechanisms can produce improvements in learning for groups of students. The authors report that "the pattern of communication is largely shaped by the background knowledge of the participants".

This improvement in problem-solving ability and strategy can be followed even more closely by analyzing performances using the student's logical thinking ability and gender. It seems clear that most students can benefit from collaborative group work of this type, although students who are at a concrete thinking level should not be grouped together. The students who benefit most from this type of problem-solving intervention are the female pre-formal students who are placed in a situation in which they must take on the role of leader in the group. It is probable that these students are becoming self-directed explainers. That is, they are having to explain to their partner how and why they are working through the problem in particular way. Chi et al. have previously shown that this type of interaction tends to produce the highest gains in problem-solving activities *(38).* Webb *(37)* has also reported that giving explanations is positively correlated with achievement, while receiving explanations may not result in improvements.

The most significant outcome of this research is that students retain their improved strategies and are better problem solvers when working alone after being part of a group. The inference is clear: even informal collaborative groups are a valuable tool in a teacher's arsenal that can lead to measurable improvements in student problem-solving ability in a relatively short time.

Acknowledgments

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