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Assessing the Effect of Web-Based Learning Tools on Student Understanding of Stoichiometry Using Knowledge Space Theory

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Chemistry as a field of science is inherently representational at the macroscopic, molecular, symbolic, and graphical level. Chemists use these representations to describe chemical phenomena and to convey their understanding of chemical concepts and processes. Consequently, learning chemistry requires the ability to integrate these different representations, as well as to visualize, conceptualize, and solve problems. Several research studies have documented the difficulties students have in recognizing and translating these different representations to mean what chemists intend *(1–8).* Many students have trouble making logical connections among the different representations and integrating them with underlying chemical concepts and principles *(9, 10).* Kozma and Russell *(10)* attribute this lack of understanding on the student's part to inconsistent and incomplete mental models that are often based on unconnected surface features of the various representations. These difficulties influence the success of students in general chemistry and their attitudes towards the science.

In a previous study, we described how knowledge space theory (KST) was used to develop an instrument to assess entering chemistry students' ability to make connections among the molecular, symbolic, and graphical representations of chemical phenomena, as well as to conceptualize, visualize, and solve numerical problems *(9).* We chose stoichiometry as the content area because it had aspects that we wanted to examine, as well as aspects that particularly present difficulties for students at the beginning level. A KST analysis of student responses to a test designed to follow conceptual development was used to define students' *knowledge structure* (mental constructs of how information within a given domain of knowledge is organized) and their *critical learning pathways* (cognitive organization or thinking patterns) *(11–14).*

The results revealed that the overall thinking patterns of students were from symbolic representations, to numerical problem solving, to visualization. *The acquisition of visualization skills came later in the students' knowledge structure.* Students had difficulties visualizing at a molecular or particulate level and making connections among the different representations. Gabel attributes these difficulties to one of three possible causes. First, instruction may have simply emphasized "the symbolic level and problem solving at the expense of the phenomena at the particle level" *(11).* Second, even if instruction had occurred at all three levels, "insufficient connections [were] made between the three levels and the information remain[ed] compartmentalized in the long-term memories of [the] students" *(11).* Third, even if instruction had occurred at all three levels and the relationships were emphasized, "the phenomena considered were not related to the student's everyday life" *(11).* Our results strongly suggested the need for teaching approaches that paid more attention to guiding students towards making the logical connections between the different representations (and the underlying meaning associated with specific features) and showing how they functioned to support the solution of problems.

The research we report here extends our earlier work by examining how students' cognitive organization or thinking patterns changed during the learning process for the concept of stoichiometry. Our comparative evaluation study explicitly examines whether an implementation of a Web-based instructional software program called Mastering Chemistry Web (MCWeb) that emphasized the various relationships while presenting them concurrently could change learning outcomes in courses with very large enrollments. We are particularly interested in assessing the impact of MCWeb on students' understanding, on how they gain and retain skills important for learning chemistry, and on their attitudes. We also examine whether using Web-based instructional tools with molecular-level visualizations could affect the construction of conceptual knowledge to assist students to understand chemical concepts and phenomena in more expert-like ways. Using the same test to track students' understanding of the concept makes it possible to assess changes in students' conceptual knowledge during the learning process.

An obvious advantage of Web-based software materials is the ability to concurrently present multiple representations to visualize chemical phenomena. The materials can provide logical links between various representations to aid students' understanding. Students can be given exercises and exploratory activities that require them to convert one form of representation to another, to reflect on the underlying meaning of the representation, and to see how representations function to support the solution of quantitative problems. Web-based learning environments can also foster process skills, facilitate guided problem solving, and model expert problem-solving strategies. Appropriately designed software materials can help students build mental links to strengthen their logical framework of conceptual understanding and to achieve mastery-level understanding of chemical concepts.

Several researchers have studied the effects of computer-based environments on student learning and have shown it to be effective in facilitating conceptual understanding and mastery of both content and process *(15–18).* However, student difficulties do arise, particularly, in rich environments where the knowledge base was not directly apparent to the students and had to be inferred *(19).* Learning environments that required active construction of knowledge through exploratory activities were more effective than expository instruction *(20).* Excessive use of unassisted or unguided exploratory activities could impede learning, since learning through discovery in a computer environment generally provides greater gains for high ability students and greater losses for low ability students *(21).*

Study Design

Our study compared two sections of students in a year-long general chemistry course for first-year undergraduates at the University of California at Irvine (UCI), a large, public, research institution. The study was conducted during the 2000–2001 academic year in the first quarter when stoichiometry was covered as part of the regular curriculum (the academic year at UCI is made up of three quarters of 10 weeks each, and the year-long general chemistry sequence is Chem 1A, 1B, and 1C). The students enrolled in the course were predominantly science and engineering majors and nearly all had one or more years of chemistry in high school.

Table1. Student Sample Demographic Characteristics

Characteristics	Demographics (%)	
	MCWeb (*n* =248)	Non-MCWeb (*n* =176)
Year in School:		
Freshman	83.6	92.6
Sophomore	10.2	5.1
Junior	4.5	1.7
Senior	1.6	0.6
Course Repeats	4.5	4.0
Gender:		
Male	47.1	61.0
Female	52.9	39.0
Majors:		
Arts	0.4	1.1
Biological Science	31.7	46.9
Engineering[a]	18.3	7.8
Humanities	4.0	5.0
Information and Computer Science	2.0	0.6
Physical Science[b]	9.9	3.9
Social Ecology	12.7	13.4
Social Science	16.7	14.0
Undeclared	4.4	7.3

[a]Includes biomedical, chemical, civil, environmental, electrical, computer, mechanical and aerospace engineering; [b]Includes chemistry, physics, mathematics and earth system science.

In the experimental design of the comparison study, two sections of students in Chem 1A were paired and taught by the same instructor. One section used the Web-based instructional software as homework (MCWeb group) while the other section used end-of-chapter problems from the textbook as homework (non-MCWeb group, control). The students in the paired sections were similar in terms of chemistry and mathematics achievement as assessed by a UCI placement test.[1] Both sections followed the conventional lecture–discussion format and the content was typical of conventional beginning general chemistry courses in the U.S. During the course, a concerted effort was made by the instructor to incorporate visual molecular representations and conceptual ideas in the lectures and exams. Students enrolled in their section of choice based on the time the class was offered and were unaware of the differences in homework during the enrollment process. A total of 248 students enrolled in the MCWeb section and 176 students enrolled in the non-MCWeb section. The demographic characteristics of the student sample in each section are summarized in Table 1.

At the beginning of the quarter, those students using MCWeb were provided with a schedule of topics along with the due dates for the MCWeb assignments. They were free to use the program at their convenience and could seek help from their instructor or teaching assistant if they had difficulties. In addition, they were able to do the assignments as many times as they wished with the understanding that only the highest score would count for a grade. For a typical assignment such as Introduction to Stoichiometry, which consisted of 10 problems, there was an average of 4.5 attempts per student with each student spending approximately 100–300 seconds on each problem.

Those receiving assignments from the textbook were provided with a schedule of topics along with weekly homework problems from the textbook and their due dates. All homework was collected and manually graded and returned within a week for feedback. However, the amount of time spent or the methods employed in completing the homework were not monitored. In both sections, homework assignments constituted one of the requisites for the course and counted for 12% of the final course grade. The problems in the MCWeb and non-MCWeb assignments were different but both related directly to lectures and textbook. The course covered these topics: components of matter, stoichiometry, major classes of chemical reactions, gases and kinetic molecular theory, thermochemistry, quantum theory and atomic structure, and electron configurations and chemical periodicity. Silberberg's text *(22)* was used as the textbook with coverage of portions from chapters 2–8.

Student achievement was assessed using in-class examinations, pretests, and posttests. During the quarter common midterm and final exams were given to the two classes. The exams were jointly graded by teaching assistants for grading consistency across both sections. The exam items were developed by the course instructor (one of the authors) to assess understanding. Test items included a range of questions that were essay and problem-based, not multiple choice. Two test items, constructed around the concept of stoichiometry and limiting reagents, were placed in a midterm exam and analyzed in more detail. The pre–post KST instrument used for the study was developed by the research group (UCI faculty and students) and was based on the concept of stoichiometry (see appendix in ref *9*). The instrument contained eight items reflecting a hierarchical order of difficulty as determined by experts on the assumption that students' understanding of the visual and symbolic aspects of individual molecules was important for their understanding of the visual, symbolic, and graphical aspects of chemical reactivity, which in turn was important for conceptualizing and solving quantitative problems involving limiting reagents. The numerical ordering of the eight questions are random and do not correspond to the hierarchical order; see ref *9* for a fuller description of the instrument and approach. The test was administered as a 25-minute pretest during the first week of instruction before the topic was formally introduced in class. It was then administered again as a 25-minute posttest during the last week of the quarter. The questions or answers were never explicitly discussed with the students. Finally, an attitudinal survey was given at the end of the quarter to assess students' attitudes towards the courses. A copy of the full survey is provided as Supplemental Material.[W]

Web-Based Learning Tool

The MCWeb software was developed by Patrick Wegner (California State University, Fullerton) as part of Molecular Science, one of five National Science Foundation systemic initiatives for the reform of chemical education. It is organized on client–server principles and can be accessed by faculty and students at any time and any place using standard Web browsers. The server side of the system is supported by three databases: a database of learning materials; a database of assessment units; and a database for learning analysis. The database of learning materials contains animations, tutorials, and guided instructional activities that can be scheduled in a course. The database of assessment units provides individualized automated student assessment, and the database for learning analysis collects and analyzes student performance data, generating reports for the student or instructor. The assessment units are divided into ~60 units much like the topics of most general chemistry textbooks. Each unit comprises of several question templates that contain variables that support the continuous generation of question sets. Since each student has a unique set of questions, the actual questions differ every time the student goes through a unit. Students can repeat units multiple times and their scores and the average time spent on each question are recorded. Records of individual scores or class reports can be automatically generated and easily downloaded to an electronic spreadsheet. For a fuller description of MCWeb see these Web sites: *http://titanium.fullerton.edu/mcweb/about/mcweb_overv.htm; http://mc.nacs.uci.edu/mcweb/mcwebinfo.cfm* (accessed Apr 2005).

MCWeb software allows students to practice problems that emphasize the development of molecular-level conceptualization and visualization, analytical reasoning, proportional reasoning, as well as to learn to recognize and relate different representations in chemistry. As shown in Figure 1, MCWeb utilizes a computer window in a standardized screen design to present a question connecting a molecular-level visualization of the particulate nature of matter to the corresponding symbolic expression. The two examples in Figure 1 require students to explicitly link a representation of matter with atoms, ions, or molecules (depicted as circles of various colors) to its chemical formula. In order to answer these questions students would need to be able to distinguish solids, liquids, gases, ionic compounds, covalent compounds, metallic compounds, chemical formulas, combining ratios of elements in covalent compounds, and combining ratios of ions in ionic compounds in terms of the particulate view of matter. Student answers (formulas, equations, numbers, etc.) are typed into the answer box in the notational formats ordinarily used by chemists (subscripts, superscripts, scientific notations, etc.). The answers are then captured for every student and a score summary is provided at the completion of the unit. The Chem Help button at the bottom of the window displays a new window with specific tutorials associated with that unit. The Instruction button provides instructions on entering answers and the Unit Menu button returns students to the unit menu.

Directly linking molecular-level visualizations of chemical reactions to the corresponding symbolic expressions can facilitate students' understanding. Again, using circles to represent atoms, students are asked to write a balanced equation based on a visual representation of a reactant mixture and a

A

B

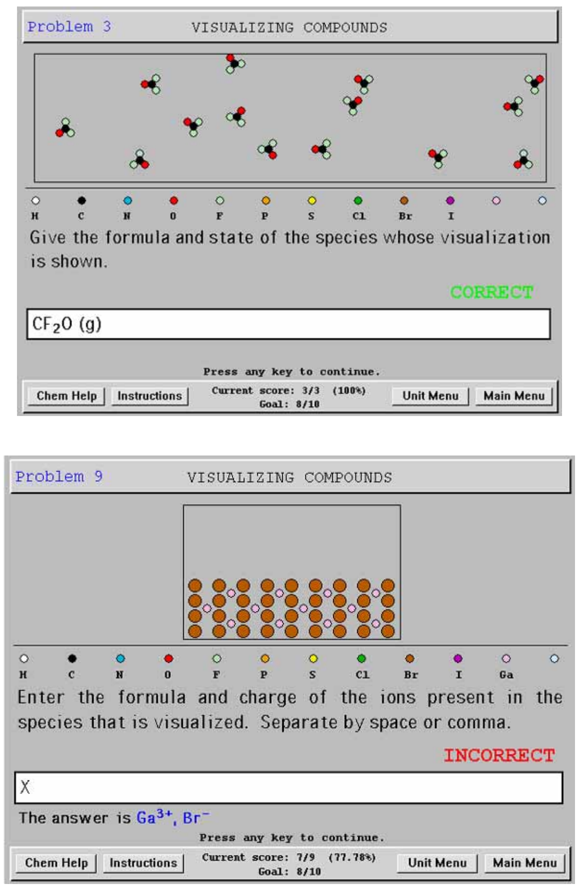


Figure 1. Sample screens from the MCWeb program unit on visualizing compounds. A: Students are asked to express a compound as a formula, indicating that compound's state of matter, given the visual representation. B: Students must indicate the charge of the ions in this visual representation. Students explicitly link a visual representation of matter (the program depicts atoms, ions, and molecules as circles of various colors) with corresponding symbolic expression.

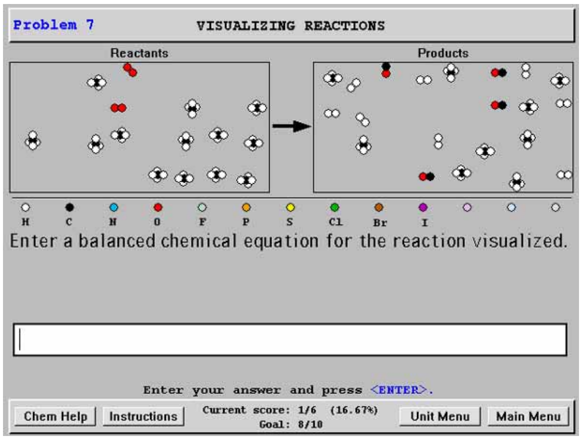


Figure 2. Sample screen from the MCWeb program unit on visualizing reactions. The question requires students to explicitly link a visual representation of a reaction using circles of various colors to represent atoms and molecules of reactants and products to a chemical equation.

A

B

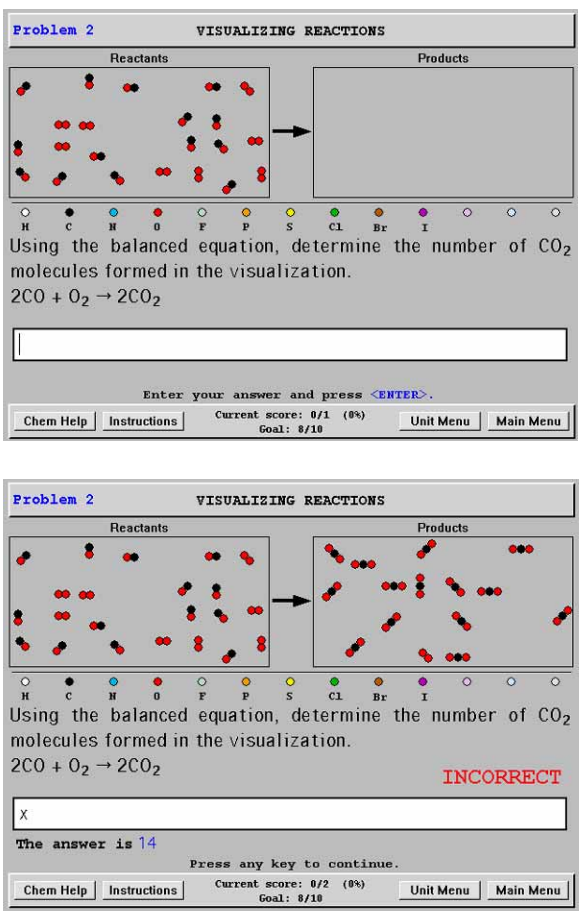


Figure 3. Sample screens from the MCWeb unit on visualizing reactions with questions that require students to link symbolic, molecular, and quantitative perspectives of stoichiometry. A: Given a visual representation of a reactant mixture and the balanced chemical equation students are asked to determine the number of molecules of product that would be formed. B: After the answer is provided, the answer is scored and the correct answer with a visual representation of the product mixture is presented.

product mixture (Figure 2). To answer this question students need to distinguish chemical formulas, chemical equations, stoichiometric ratios, and limiting reagents. Combining these representations to include numerical methods to extract quantitative information can help students progressively move to more sophisticated mental models. Figure 3 shows an example of a question linking symbolic, molecular, and quantitative perspectives of stoichiometry. The screen shown in Figure 3A provides a visual representation of a reactant mixture and the balanced chemical equation students use to determine the number of molecules of product that would be formed. After the student provides an answer, the correct answer and a visual representation of the product mixture are presented to the student, as shown in Figure 3B. Figure 4 shows an example of a question where one reactant is present in limited supply and requires numerical problem solving to extract quantitative information on the reactant that limits product formation and the reactant that is left over. All of these multiple representations help students translate information expressed in one form of representation to another and to make explicit connections to construct a logical framework of conceptual understanding.

Results and Discussion

Several comparative assessments revealed significantly better performances by the students in the MCWeb class while others showed no significant differences. We found that in no case did the students in the non-MCWeb class outperform those in the MCWeb class. The details of our results are described below. First, we describe comparative performance data for the two intact classes on midterm and final examinations, and on two test items on stoichiometry and limiting reagents that were placed in a midterm examination. Second, we describe the results of an analysis of a pre–post KST instrument that assessed changes in students' thinking patterns during the course.

In-Class Examinations

Data for the performance of students in the MCWeb class compared with the non-MCWeb class are summarized in Table 2. A locally developed 40-item placement test that as-

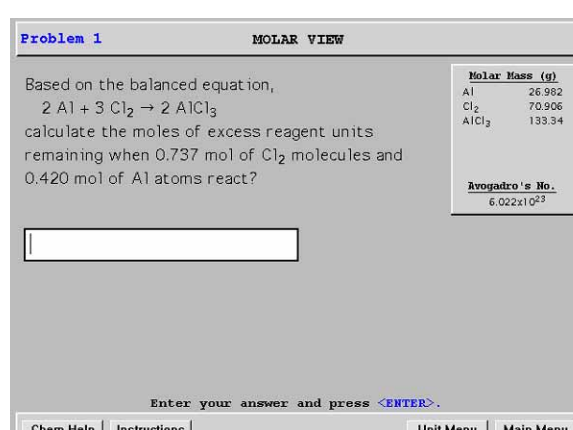


Figure 4. Sample screen from the MCWeb program unit introducing stoichiometry. To answer the question students must extract quantitative information on the reactant that limits product formation and the reactant that is left over and then calculate using that information.

sesses student's preparation for general chemistry was given to all students prior to enrollment in Chem 1A.[1] Based on an analysis of variance (ANOVA) on this placement test, there were no significant differences in the background chemistry and mathematics achievements of the students entering both classes. Using Levene's test for equality of variances for the two groups yielded a significance level of 0.68, indicating that the two samples came from populations with the same variances (a significance level $\geq$ 0.05 assumes equal variances). We performed an ANOVA on the data from the midterm and final exams to reveal the differences between the MCWeb and non-MCWeb classes. As shown in Table 2, there were statistically significant differences on the averages of student performance between MCWeb and non-MCWeb. Students in the MCWeb group outperformed their counterparts in the non-MCWeb group on paired exams in two of the three exams (midterm 2 and the final exam). On the other exam, no statistically significant difference was found between the two sections (midterm exam 1). Because the first midterm exam was held during the first few weeks of class, perhaps it was too soon to see whether there were effects on student performance from MCWeb use.

A statistical correlation using a Pearson product correlation coefficient (r^2) showed that there was a significant relationship between the success of students on the final examination and their performance on homework. The results revealed that the students' average homework scores significantly correlated with the scores on the final examination for both MCWeb students and non-MCWeb students. The r^2 value for the MCWeb group was 0.68; for the non-MCWeb group it was 0.69 (the correlation was significant at the 0.01 level). Pearson's correlation coefficient represents the degree of the association between the two variables; a correlation value of ~0.7 is generally accepted as indicating a high degree of correlation and suggests that there is a significant relationship between the two variables.

The results on the two-item stoichiometry and limiting reagent tests are summarized in Table 3. Of the two test items, one was constructed as a conceptual question that required students to invoke underlying concepts using diagrams with circles to represent atoms (test item A, Figure 5). Its solution required an understanding of both the principles of stoichiometry and limiting reagents and was not solvable by means of algorithmic manipulations. The other was constructed as a multistep quantitative problem-solving question that required finding numerical solutions (test item B, Figure 5). This question could be solved by means of algorithmic processes using memorized sets of mathematical manipulations. However, the multistep question does require the use of multiple algorithms. Our reasoning was that by increasing the number of algorithmic manipulations the need for an understanding of the chemistry behind the manipulations might become more apparent.

Student responses to both questions were scored in a binary fashion, as being either completely correct (1) or incorrect (0). The responses were then categorized into four possible combinations of responses for the two groups: both item A and item B correct, item A correct and item B incorrect, item A incorrect and item B correct, and both item A and item B incorrect. The frequencies in each response category are summarized in Table 3. A χ^2 analysis was used to test the significance level of the differences between performances by the students in both groups. The probability for significance was set at p = 0.05. An inspection of these data revealed that the performance on the algorithmic question (item B) was not significantly different for the two groups. However, the difference was statistically significant for the conceptual question (item A). The MCWeb students outperformed the non-MCWeb students on this question. When McNemar's

Table 2. Student Exam Average Scores

Assessment (Total Points)	MCWeb (n =248) Mean	SD	Non-MCWeb (n =176) Mean	SD	Analysis of Variance (ANOVA) F Value	p Value
UCI placement test (40; 40 items)	29.2	4.2	28.7	4.3	1.77	0.18
Midterm exam 1 (80)	55.4	15.5	54.5	13.4	0.58	0.46
Midterm exam 2 (90)	33.4	17.3	26.8	16.6	15.64	0.00[a]
Final exam (120)	71.6	22.7	67.0	21.9	4.34	0.04[a]

[a]Statistically significant at $p \leq 0.05$.

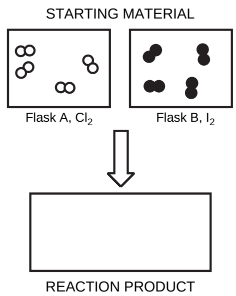
Table 3. Response Frequencies for Test Items A and B with Corresponding Significance Levels

	A Correct	B Correct	A and B Correct	A Correct B Incorrect	A Incorrect B Correct	A and B Incorrect	Significance (p) from McNemar's test[a]
MCWeb (n =248)	157	86	64	93	22	69	0.00[c]
Non-MCWeb (n =176)	81	75	34	47	41	54	0.59
Significance (p) from χ^2 test[b]	0.00[c]	0.10	0.12	0.02[c]	0.00[c]	0.52	

[a]McNemar's test was used to test the significance of the differential performance between test items A and B within each group; [b]A χ^2 analysis was used to test the significance of the differences between the MCWeb and non-MCWeb groups; [c]Statistically significant at $p \leq 0.05$.

Test Item A

Chlorine, Cl_2, and iodine, I_2, react to give ICl_3. The contents of flask A and B are mixed in a reaction flask.



1. Show the situation in the reaction flask after reaction has occurred.
2. Write a balanced reaction equation that describes this reaction.

Test Item B

Suppose you want to prepare a sample of tin(IV) iodide, SnI_4. You weigh out 0.945 g of Sn and 1.834 g of I_2. After mixing in an appropriate solvent, the distinctive color of iodine fades away signaling the completion of the reaction. The orange solid product, SnI_4, is collected on a filter. The solid has a mass of 1.935 g.

1. Which is the limiting reactant? (Note: To receive credit for this question, you must clearly show all your reasoning).
2. How many grams of the other reactant remain after the reaction is complete?
3. What is the theoretical yield of SnI_4?
4. What is the percent yield of SnI_4?

Figure 5. Paired test items for stoichiometry.

test was used to test the significance of the differential performance between test items A and B within each group, the differences were statistically significant for the MCWeb group but not significantly different for the non-MCWeb group. McNemar's test was used for this analysis (rather than a χ^2 analysis) because the same students answered both test items and the questions were not independent of each other *(23)*.

The results indicate that overall, the students in the MCWeb group were better at conceptual problem solving than the non-MCWeb students. Further, within the MCWeb group, the students were better at conceptual problem solving than numerical or algorithmic problem solving. This does not follow the trend observed by Pickering and Nurrenbern *(3)*, Sawrey *(5)* and Nakhleh *(25)*. Nurrenbern and Pickering report significant differences ($p < 0.05$) between student performances on conceptual and algorithmic questions involving limiting reagents, where the students' conceptual problem solving abilities lagged behind their algorithmic problem solving abilities. Sawrey and Nakhleh further support Nurrenbern and Pickering's findings.

As a further analysis, we examined the relationship among the numbers of students for the two groups in the four categories of possible combinations of responses—both A and B correct, A correct and B incorrect, A incorrect and B correct, and both A and B incorrect. As shown in Table 3, a χ^2 analysis of the response category with both test items correct showed that there was no statistically significant difference between the students in the MCWeb group and the non-MCWeb group. These students had high conceptual and quantitative problem-solving abilities and had a good understanding of the concept of stoichiometry and limiting reagents. Similarly, when the category with both questions incorrect was considered, no statistically significant difference between the two groups was found. These students were the ones with low conceptual and quantitative problem-solving abilities.

However, as shown in Table 3, statistically significant differences do arise in the categories with item A correct–item B incorrect and item A incorrect–item B correct. The

Table 4. Comparison of Content Knowledge in Pretests and Posttests[a]

Sample Group	Test Item Number (Values Are Percentages)							
	1	2	3	4	5	6	7	8
MCWeb Pretest (n = 113)	85	92	65	31	46	33	43	56
MCWeb Posttest (n = 113)	98	95	73	67	86	60	72	63
MCWeb Gain[b] (n = 113)	13	3	8	36	40	27	29	7
Non-MCWeb Pretest (n = 83)	88	89	64	29	39	27	39	47
Non-MCWeb Posttest (n = 83)	93	93	55	58	90	34	57	73
Non-MCWeb Gain[b] (n = 83)	5	4	-9	29	51	7	18	26

[a]Values represent the percent frequency of correct responses for each question on the KST test; [b]The gains represent the difference in percent frequency of correct responses between the pre- and posttests for each question on the KST test.

results indicate that the MCWeb group had a greater number of students with high conceptual–low quantitative problem-solving abilities and these students had a stronger understanding of the conceptual basis of stoichiometry and limiting reagents over quantitative problem solving. This was not the case for the students with low conceptual–high quantitative problem-solving abilities. The results indicate that many students from the non-MCWeb group were better quantitative problem-solvers and had a weaker understanding of the underlying concepts and principles behind their mathematical manipulations. These students were probably using algorithms in their solutions. Overall, the results suggests that while there were no statistically significant differences between the two groups in terms of the high conceptual–high quantitative problem-solving ability students and the low conceptual–low quantitative problem-solving ability students, differences did exist among students that were conceptual problem solvers or quantitative problem solvers. Students in the MCWeb group tended to be more conceptual problem solvers while students in the non-MCWeb group tended to be more algorithmic problem solvers.

Analysis of the Data Using Knowledge Space Theory

Student responses on 704 pre–post KST tests from the MCWeb and non-MCWeb groups were analyzed in a binary fashion as being either right (1) or wrong (0). Questions that required explanations were marked correct only if the answers were consistent with their reasoning. The percent frequencies of correct responses were analyzed and the connectivities of these responses (or student thinking patterns) were established using KST. In order to compare performances between the two groups on the pre and posttest, we focus on KST responses from a subgroup of 113 students from MCWeb and 83 students from non-MCWeb who included their student identification numbers with their responses to both the pretests and posttests. This enabled us to compare their changes in thinking patterns. The pre- and posttest performance of the MCWeb and non-MCWeb subgroups were consistent with those of the larger groups. An analysis of variance comparing the means of each subgroup (pretest–posttest for MCWeb and non-MCWeb) with the corresponding larger groups showed no statistically significant differences ($p > 0.05$).

As expected, the students' knowledge base increased during the quarter. However, the results revealed that the MCWeb group made greater gains and outperformed the non-MCWeb group at the end of the quarter. The pretest data comparing mean scores (out of 8) at the beginning of the quarter showed that there was no statistically significant difference between the two groups as determined by ANOVA ($M = 4.5$, SD = 1.8 for MCWeb and $M = 4.2$, SD = 1.8 for non-MCWeb; $F = 1.29$, $p > 0.05$). A Levene's test for equality of variances for the two groups gave a significance level of 0.69 indicating that the two samples came from populations with similar variances. This was not the case with the posttests at the end of the quarter. There was a statistically significant difference on the means of the performance between the two groups: $M = 6.1$, SD = 1.5 for MCWeb and $M = 5.5$, SD = 1.7 for non-MCWeb; $F = 6.99$, $p < 0.05$. The results are summarized in Table 4 as shown by the comparison of the percent frequency of correct responses to each item on the test.

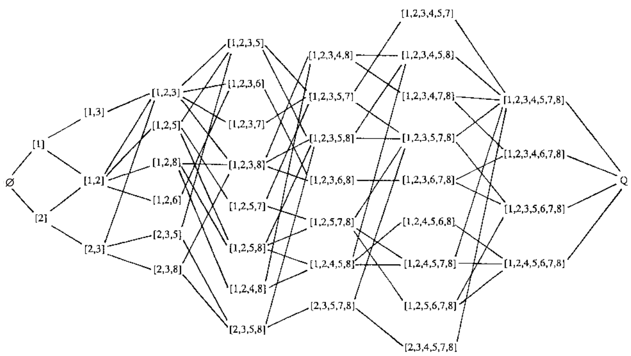


Figure 6. KST pretest knowledge structure. (See also ref 9.)

Table 4 also shows that the scores of both groups of students improved from the pretest to the posttest to a point at the end of the quarter where an acceptable mastery of the concepts was attained. The posttest data revealed that the MCWeb group outperformed those in the non-MCWeb group in six of the eight test items. A comparison of the item learning gains between the pretests and posttests for the two sections showed that the MCWeb students had made greater improvements than their counterparts on five of the eight items as seen from the differences in percent frequency of correct responses between pretests and posttests.

KST depends on collecting student data from a set of questions that reflect different levels of understanding of the material. The test must have some hierarchical ordering of the questions so that students progress in a logical fashion from fundamental concepts to more complex concepts. The set of questions answered correctly by a student is called a *response state.* For example, a student who answers questions 1, 3, and 6 correctly is in the response state [1,3,6]. Theoretically, an eight-item test can have 256 (2^8) possible response states, from the null state (∅ state) where no questions are answered correctly to the Q state where all the questions are answered correctly. Typically, about 60–100 student response states are observed. The more focused (or structured) the learning, the fewer the response states that will be observed.

From these student response states, the KST analysis identifies a subset of 10–40 response states (called *knowledge states*) that represents the *knowledge structure* of the student population as a whole. The procedure to obtain the knowledge structure is a systematic trial and error fitting using the χ^2 analysis for goodness of fit ($p = 0.05$) with the restriction that each state must have a preceding state and a succeeding state (other than ∅ and Q) in the final network. In other words, one must be able to successively progress one question at a time along each learning pathway from one state to the next, beginning from the null state (∅) and ending at the state with all questions correct (Q). The cognitive organization or connectivity of the material can then be determined. The resulting knowledge structure reveals several learning pathways that represent possible ways students learn. Finally, from the most populated knowledge states, the most probable learning pathways are identified as *critical learning pathways* that best define the class as a whole. The critical learning pathways denote how the typical student progresses through the material. Reference 9 provides a full description of the methods employed to construct the knowledge structure from the student data, as well as a fuller description of the pretest knowledge structures.

Optimization of each set of data (pretest and posttest) from both groups of students gave well-defined knowledge structures. The fits revealed that the students do use some logic or pattern of thinking in responding to the questions. If student responses were completely random then a knowledge structure cannot be constructed from the data. The fits to the pretest data for the MCWeb group and the non-MCWeb group gave identical knowledge structures with 41 knowledge states for both groups (Figure 6). The relative distributions of the percent population in the knowledge states were very similar for both groups, indicating that the base knowledge at the beginning of the quarter was very similar. This was not the case at the end of the quarter. The fits to the posttest data revealed knowledge structures with 12 knowledge states for the MCWeb group and 13 knowledge states for the non-MCWeb group. The posttest knowledge structures are summarized in Figure 7.

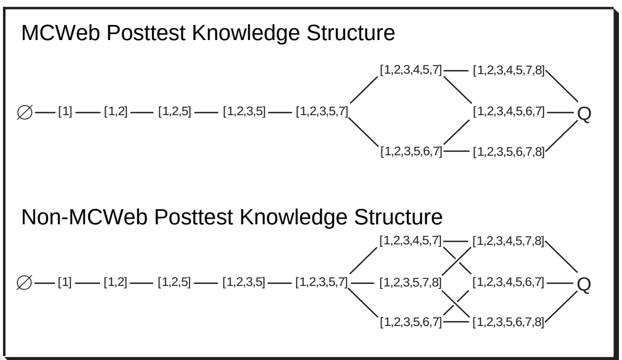


Figure 7. KST posttest knowledge structures.

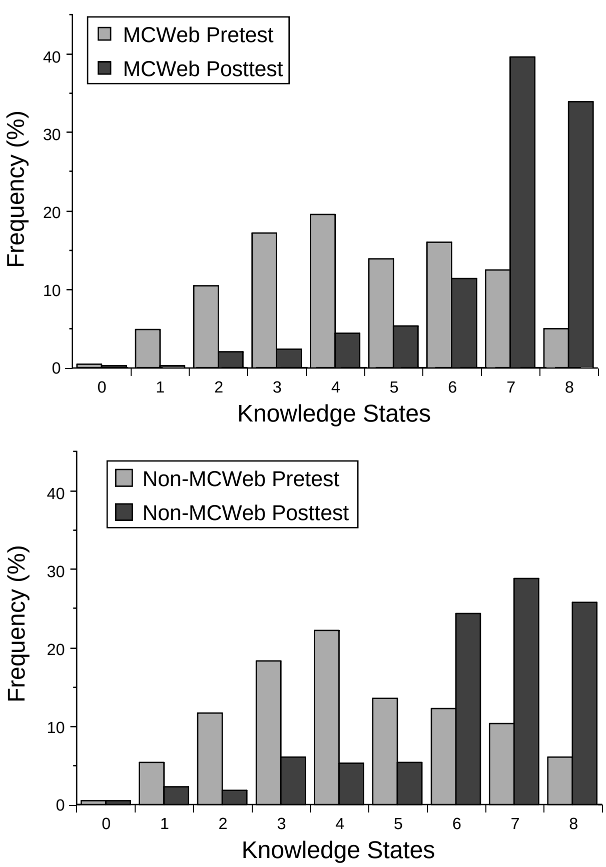


Figure 8. Comparison of the percentage of students in the knowledge states. In the histogram, 0 is the null knowledge state (∅); 1, knowledge states with only one correct answer; 2, knowledge states with two correct answers; 3, knowledge states with three correct answers, etc., to 8, the Q knowledge state (all questions correct).

An examination of the fits for the knowledge structures in Figure 7 revealed three interesting findings. First, as shown in Figure 7, the students' posttest knowledge structures showed a more focused (or structured) learning when compared to their pretest knowledge structures for both groups. However, the learning was more focused (or structured) for the MCWeb group over the non-MCWeb group as evidenced by the 12 knowledge states for the MCWeb group versus the 13 knowledge states for the non-MCWeb group.

Second, an examination of the relative distribution of the percent population in each of the knowledge states showed that while the distributions were very similar on the pretests for both groups at the beginning of the term, this was not the case at the end of the term. The posttest knowledge structures revealed that even though content knowledge had increased for both groups and a greater population of students had progressed to knowledge states further along the knowledge structure, students in the MCWeb group had made far greater strides in moving further along the knowledge structure than the non-MCWeb group. These data are summarized in the histograms shown in Figure 8. The histograms compare the percent population of students on the pretests and posttests from each group in each of the knowledge states starting from the state with no questions correct (∅) to students in knowledge states with all questions correct (Q). In the histograms, 0 represents the null knowledge state; 1 represents all the knowledge states with only one correct answer; 2 represents all the knowledge states with two correct answers; and so forth, to 8 representing the Q knowledge state (all questions correct). As seen from Figure 8, overall the MCWeb students made significant improvements relative to the control group. For example at the beginning of the term, the Q knowledge state comprised 5% of the students in the MCWeb group and 6% of the students in the non-MCWeb group. Similarly, 12% of the students in the MCWeb group and 10% of the students in the non-MCWeb group were in knowledge states with seven questions correct. At the end of the term, 34% of the students in the MCWeb group and 26% of the non-MCWeb group were in the Q state, and 40% of the students in the MCWeb group and 29% of the non-MCWeb group were in knowledge states with seven questions correct.

Third, an examination of the pretest and posttest critical learning pathways of the students in both groups showed that, overall, there were no major differences between the two groups on the pretests and there were no major differences between the two groups on the posttests. However, there were significant differences between the pretests and posttests for both groups. The critical learning pathways show the most probable order in which correct answers to questions were obtained and reveal how the majority of students see the connections between the materials on the questions (Figure 9).

In examining student critical learning pathways it is helpful to study a hypothetical expert-learning pathway, which shows a possible way that an expert's knowledge could be organized. An expert's learning pathway would include: (1) representing chemical phenomena at the molecular, symbolic, and graphical level; (2) linking, transforming, and moving fluidly among different chemical representations; and (3) transferring chemical knowledge and skills to solving problems. While a number of expert hierarchies are possible, a plausible hierarchy for the expert is depicted in Figure 9. The reasoning was that an understanding of the visual and symbolic representations of individual molecules (items 1 and 3) was important for the understanding of the visual, symbolic, and graphical representations of chemical reactivity (items 6, 2 and 8); which in turn was important for conceptualizing and calculating stoichiometric product formation in reactions (item 5). Finally, all of these elements were essential for conceptualizing and solving limiting reagent problems (items 4 and 7). In each case, the assumption was that visualization from a molecular perspective was key to the understanding of symbolic representations and in transferring that knowledge to graphical representations and numerical problem solving.

Comparison of the expert pathway with that of the student critical learning pathways reveals how experts differed from novices. The overall logical connections for the hypothetical expert in our study were from visualization, to symbolic representations, to numerical problem solving. The overall thinking patterns of the students, on the other hand, were from symbolic representations, to numerical problem solving, to visualization. As shown in Figure 9, visualization came last in the students' knowledge structure on both the pretests and posttests for both groups of students. Overall, the questions involving numerical problem solving to extract quantitative information (items 5 and 7) appeared earlier than expected from visualization or conceptual development (items 4 and 6).

Furthermore, the posttest critical learning pathways revealed that even though the MCWeb students outperformed the non-MCWeb students on the KST instrument, their overall thinking patterns remained symbolic representations, to numerical problem solving, to visualization. Thus, there was little change in the students' overall thinking patterns over the quarter. In both groups, the algorithmic quantitative questions (items 5 and 7) appeared even earlier than the visualization or conceptual questions (items 4 and 6) on the posttest student learning pathways. Novice students, as shown by numerous studies, are more likely to approach problems by searching for specific formulas or equations that could be used to manipulate the variables given in a problem, rather than reasoning conceptually in terms of core concepts or big ideas and by building mental models or representations of the problem *(24).* Our results indicate that the students in both groups were unable to make a transformation in their thinking patterns but that MCWeb was useful and successful in teaching visual and conceptual reasoning methods.

The posttest critical learning pathways in Figure 9 showed that at the end of the quarter typical students (in both groups) progress through the items in the following sequence: 1 → 2 → 5 → 3 → 7 → 4 → 8 → 6. The question that appeared first in the critical learning pathway was item 1, which required students to translate a visual representation of the molecular perspective of gaseous ammonia to its symbolic representation. Next came item 2, which required students to write a symbolic representation of a chemical reaction (i.e., write a balanced chemical equation for the reaction of N_2 with H_2 to provide NH_3). Then came item 5, which required numerical problem solving to extract quantitative information (stoichiometric ratios) from a balanced chemical equation. As shown in Table 4, ~90% or more of the students in both groups were able to answer these questions correctly. The next item on the pathway was item 3, which asked students to explain the information conveyed by the symbolic representations (or formulae) of substances. Item 3 was answered correctly by 73% of the MCWeb students and 55% of the non-MCWeb students. Thus, many students could balance a chemical equation (item 2) and work a quantitative problem on stoichiometric ratios (item 5), but could not interpret the significance of the subscripts in the formulae of that equation (item 3).

The next level of difficulty in the pathway came from items 7 and 4, which involved stoichiometric problems in which one reactant was in limited supply. Item 7 was a quantitative problem-solving question that required a numerical solution. It was less complex than the question in test item B in Figure 5 and could be solved by a simple algorithm. Item 4 was a molecular level visualization or conceptual question that examined the chemistry behind the manipulations

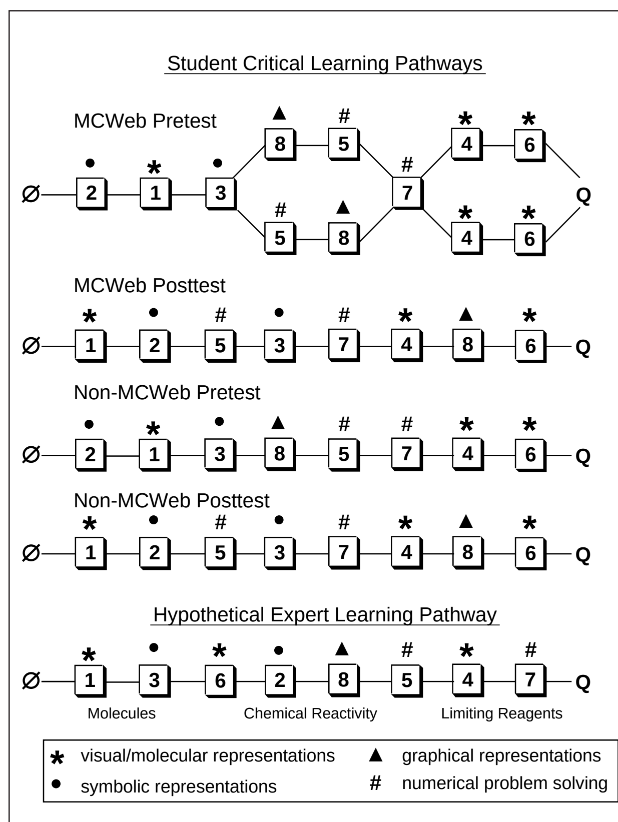


Figure 9. Comparison of student critical learning pathways. The student (novice) critical learning pathways represent the most probable sequence of response states in the knowledge structure and shows the order in which correct answers to questions were obtained. The expert learning pathway represents the hypothetical hierarchical sequencing of questions as determined by the research group. The null state, ∅, indicates no correct responses; Q is the state where all questions are correct. A copy of the test is provided in ref 9.

in item 7. Item 4 was also less complex than the corresponding question in test item A in Figure 5. As shown from the pretest data in Table 4, at the beginning of the quarter, the trend followed that observed by Pickering and Nurrenbern *(3),* Sawrey *(5),* or Nakhleh *(25).* Students' conceptual problem-solving ability tended to lag behind their algorithmic problem-solving ability. These students had a limited understanding of the chemistry behind their manipulations. This was not the case at the end of the quarter. The posttest data showed that the students' conceptual problem-solving ability *no longer* lagged behind their algorithmic problem-solving ability. A greater percentage of students in both groups were able to answer items 7 and 4 correctly. Further, the MCWeb students outperformed the non-MCWeb students on both of these test items. On question 7, 72% of the MCWeb students and 57% of the non-MCWeb students answered correctly, while 67% of the MCWeb students and 58% of the non-MCWeb students answered question 4 correctly. When McNemar's test was used to test the significance of the differential performance between items 7 and 4 *within* each group, the differences were not statistically significant for either group (p = 0.51 for MCWeb and 1.00 for non-MCWeb). Students in both groups had made gains in their conceptual understanding of the concept, but the gains made by the students in the MCWeb group were greater than their counterparts in the non-MCWeb group.

The next question, item 8, asked students to pick the graph that best represented the formation of a product when one reactant was added indefinitely to a fixed amount of the other. This question appeared later than expected from the expert pathway in both pre and posttests. Perhaps the abstract and dynamic nature of this question made it particularly difficult for students. However, as shown from the posttest data in Table 4, the non-MCWeb students (73%) performed better than the MCWeb students (63%) on this question. This result is largely unexplained because neither the MCWeb homework nor the textbook homework emphasized this aspect of stoichiometry.

Table 5. Student Responses to Sample Survey Questions

Survey Statements	Likert-Scale Ratings[a]			
	MCWeb (n =183)		Non-MCWeb (n =147)	
	Mean	SD	Mean	SD
How much did each of the following aspects of the homework help your learning?				
As a tool to force you to think by a questioning process	3.5	1.17	3.62	1.02
In improving your understanding of the material	3.48	1.19	3.58	0.99
In helping to prepare for exams	3.13	1.27	3.33	1.14
As a help to focus on areas of weakness	3.35	1.24	3.54	1.03
The amount of homework assigned each week	3.12	1.17	3.31	0.96
As a result of your work in this class, how well do you think that you now understand the concept of stoichiometry and limiting reagent?	3.92	0.97	4.01	0.91
How much has this class added to your skills in each of the following?				
Solving problems	3.54	0.96	3.53	0.95
Visualizing at a molecular level	3.57	0.93	3.52	1.07
To what extent did you make gains in any of the following as a result of what you did in this class?				
Understanding the main concepts	3.59	0.85	3.63	0.9
Ability to think through a problem	3.46	0.98	3.43	0.99
Confidence in your ability to do this field	3.16	1.13	3.04	1.22
Enthusiasm for the subject	3.09	1.22	3.03	1.24
How much of the understanding of the main concepts do you think you will remember and carry with you into other classes or aspects of your life?	3.49	0.9	3.41	0.89
How much did the textbook help your learning?	2.68	1.04	3.13	0.99

[a]The scale ranges from 1 (no help) to 5 (very much help) for question 1; for questions 2–6 the scale range is 1 (not at all) to 5 (a great deal).

Finally, the question that appeared last in the knowledge structure was item 6. In fact, item 6 appeared last in all four critical learning pathways in Figure 9 (pretest and posttest). This question presents students with a visual representation of a reactant mixture and a product mixture for the reaction $X + 2Y \rightarrow XY_2$ using circles to represent atoms and asks them to identify the balanced chemical equation that best represented that reaction. A significant number of students gave $3X + 8Y \rightarrow 3XY_2 + 2Y$ as the answer. We attribute this to an *alternate conception* that perhaps arises from students' intuitive or fragmented knowledge. For these students the arrow in the balanced chemical equation was nothing more than an equal sign where the number of atoms on each side of the equation had to equal each other, rather than the chemical process expressed in that equation *(26)*. Alternate conceptions have been described as conceptual ideas "that are not consistent with the consensus of the scientific community" *(27)*. It is generally agreed that alternate conceptions are persistently held by students. While many strategies have been reported in the literature to be effective in overtly confronting students' alternate conceptions, the success rates of these have been far from perfect *(28)*. As seen from Table 4, the MCWeb students made significantly better improvements over the non-MCWeb students on this question (60% versus 34%).

Student Attitudinal Surveys

Students in both groups were asked to estimate how well the homework helped them learn, how well they felt they understood the course material, how much the course activities had added to their skills, and the degree to which they had made gains in the course. A five-point attitude scale was used with each degree given a numerical value, 1–5. Thus a total numerical value could be calculated from all the responses. Table 5 shows the mean responses to several of the survey questions. Based on a t-test for equality of means there were no statistically significant differences between the two groups on the survey questions (significance, $p = 0.05$) except on the question regarding how much the textbook had helped their learning ($p = 0.0001$). The non-MCWeb students felt that the textbook had better helped their learning than the MCWeb students. In informal discussions, many MCWeb students commented that they tended to rely more on "Chem Help" in MCWeb and their lecture notes than their textbooks. They felt that the focus and the types of examples worked out in the textbook did not relate to the questions on MCWeb.

In the comment section of the survey many students commented on the strengths and weakness of their homework. Those in the MCWeb group felt that the homework had better helped their learning:

> I found that the electronic homework was a great tool for learning. It provided a weekly (at least) practice of chemistry and forced me to actually do the work. It also forced me to learn concepts until I could prove that I really understood the material (via posttest). I also like the precision in which I have to enter the answers because it encourages a more careful approach to reading/answering the questions.

> Although I wasn't too fond of the idea of electronic homework at first, I would have to say it has helped me a great deal in understanding the lesson. Even in areas I would not understand during lecture or discussion, the electronic homework in a way forced me to learn it, and I'm glad I took this class opposed to the 8:00 am [non-MCWeb] class.

> I really like the homework because it made me study more than I normally would.

> The electronic homework was essential to my understanding of the concepts reviewed in class.

A few said that they had difficulties with the MCWeb homework. They were upset that the program was "picky" and required answers to be entered in specific ways:

> The electronic homework is difficult to use because it requires exact typing.

> The program is picky at times, and it is fairly troublesome to have to input the answer "PERFECTLY".

Others did not like spending time in front of a computer screen:

> I would prefer text based or questions handed out, sitting in front of a computer for a long time is no fun.

> This was an excellent class. Even though I despise electronic homework, and would prefer to do pages of book homework, I believe the hours I put into each assignment helped me tremendously. I understand how electronic homework can force us to spend quality time with the material, but good students spend that much time on book homework anyway.

A few of the non-MCWeb students complained about the experimental design. Knowing that MCWeb students carried out Web-based homework they felt that they should be allowed to do the same:

> I think the electronic homework should be assigned to all classes (instead of textbook homework) or at least encouraged as a study aid.

> I feel I could do better with the computer based homework rather than the book homework.

Finally, some students commented that the homework was most demanding. Even though the content covered was the same as prior years, because of the required homework some students perceived the workload to be heavier:

> The homework load was a little too much. Because we have to do practice problems and the actual posttest which are kind of similar but not.

> The electronic homework should be a little easier on the grading scale. It is hard and sometimes too much time consuming on a weekly basis.

Overall, student comments were positive. They found that they had learned a great deal and had achieved more than they thought possible.

Conclusion

In summary, this study revealed that using the MCWeb software in large-scale instruction provided an overall benefit to introductory chemistry students. The study's initial goal was to examine methods of using technologies to improve student learning. In particular, we wanted to find ways to actively engage students in large-scale instruction beyond the level currently seen in our conventional lecture–recitation courses. A problem-solving activity engages students and puts them into an active role in the learning process. Students benefit from working problems on their own or in collaboration with other students and from receiving rapid formative feedback. For instructors and teaching assistants in large-scale instruction, the administration of individualized problems as in-class activities or as homework can be overwhelmingly demanding. The manual grading alone can place an enormous burden and it is almost impossible to provide rapid turnaround for effective feedback. One way to meet these demands was to use a server-based system to assign and manage individualized problems. Furthermore, since each student had a unique set of questions and the actual questions differed every time the student went through a unit, students could repeat units multiple times. For example, the MCWeb-server generated and scored over 200,000 *individualized* problems during a single quarter as opposed to the same 100 problems that were assigned from the textbook. The advantage of this approach was that students spent considerably more time on their homework focusing on mastery of the material.

We found that implementing the MCWeb software as homework improved instruction and learning outcomes in chemistry. When compared with a group of students who carried out homework from their textbooks, the students who used MCWeb performed significantly better in subsequent assessments. For example, those in the MCWeb group outperformed their counterparts in the non-MCWeb group whether measured in terms of in-class exams, conceptual versus algorithmic tests, or a KST test to assess their ability to make connections between the molecular, symbolic, and graphical representations of chemical phenomena, as well as to conceptualize, visualize, and solve numerical problems. Furthermore, the MCWeb students emerged as better conceptual problem-solvers than the non-MCWeb students. Analysis of the KST pretests and posttests showed that both groups made significant improvements in their understanding of stoichiometry and limiting reagents, but that the MCWeb group showed more improvements than the non-MCWeb group. In both cases, critical learning pathway analysis showed that the overall thinking patterns of the students were from symbolic representations, to numerical problem solving, to visualization on the pretests and posttests. Thus, visual or conceptual reasoning at a molecular level came last in the students' knowledge structures even after completing homework that emphasized the relationships between the various representations. Many students found this type of reasoning difficult and our studies reveal that MCWeb was successful in teaching these methods to introductory chemistry students. However, a single quarter of instruction was probably not adequate to change their overall thinking patterns. Previous studies have shown that a change in students' thinking patterns can be effected by explicitly making the instructors' (expert) logic pattern much more transparent to students than is commonly done by constantly repeating what seems obvious to the expert *(12, 13).*

[W]Supplemental Material

A copy of the full survey to assess students' attitudes towards the courses is provided in this issue of *JCE Online.*

Acknowledgments

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Note

1. Students at UCI are required to take a 40-item placement test on mathematics and chemistry aptitude prior to enrolling in Chem 1A. The cut-off score for enrollment in the course was 23 correct.

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