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General Chemistry Student Attitudes and Success with Use of Online Homework: Traditional-Responsive versus Adaptive-Responsive

Michelle Richards-Babb^{*,†}, Reagan Curtis[‡], Betsy Ratcliff[†], Abhik Roy[‡], and Taylor Mikalik[‡]

[†]C. Eugene Bennett Department of Chemistry, West Virginia University, Morgantown, West Virginia 26506, United States

[‡]Department of Learning Sciences and Human Development, West Virginia University, Morgantown, West Virginia 26506, United States

Abstract

We investigated whether use of an adaptive-responsive online homework system (OHS) that tailors homework to students' prior knowledge and periodically reassesses students to promote learning through practice retrieval has inherent advantages over traditional-responsive online homework. A quasi-experimental cohort control post-test-only design with nonequivalent groups and propensity scores with nearest neighbor matching ($n = 6,114$ pairs) was used. The adaptive system was found to increase the odds of a higher final letter grade for average, below average, and failing students. However, despite the learning advantages, students self-reported less favorable attitudes toward adaptive-responsive (3.15 of 5) relative to traditional-responsive OHS (3.31). Specific to the adaptive OHS, the following were found: (i) student attitudes were moderately and positively correlated ($r = 0.36$, $p < 0.01$) to final letter grade, (ii) most students (95%) reported engaging in remediation of incorrect responses, (iii) a majority of students (69%) reported changes in study habits, and (iv) students recognized the benefit of using adaptive OHS by ranking its assignments and explanations or review materials as two of the top three most useful course aspects contributing to perceived learning. Instructors can use our findings to inform their choice of online homework system for formative assessment of chemistry learning by weighing the benefits, disadvantages, and learning pedagogies of traditional-responsive versus adaptive-responsive systems.

Graphical abstract

*Corresponding Author: Michelle.Richards-Babb@mail.wvu.edu.

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Supporting Information

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ORCID

Michelle Richards-Babb: 0000-0002-0487-566X

Notes

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■ INTRODUCTION

Active student participation in out-of-class problem solving through completion of homework coupled with self-directed study is linked to success in chemistry coursework.¹ Instructors of large enrollment ($N > 100$) chemistry courses have struggled with (i) the desire to assign homework for a grade and (ii) the time available for grading and providing timely written feedback. Administrative (e.g., computerized grading) and pedagogical (e.g., instant feedback) advantages of online homework systems (OHSs) have made their use commonplace in large enrollment chemistry courses. As OHSs have evolved in sophistication, student perceptions toward OHSs have shifted to become largely positive with the average student viewing OHSs as a valuable learning tool.^{2–7} However, prompt, detailed feedback and tutorial prompts are essential to students' perceptions of OHSs as effective.^{2,8–10} The more response-specific the feedback is, the more time students invest working within the OHS.^{2,11} Response-specific feedback occurs when the reason for a student's incorrect response is detected by the OHS and feedback is targeted to address that mistake. In a stoichiometry problem, for example, the system may detect that the student used an incorrect mole-to-mole ratio and provide a corresponding hint or explanation. A student who answered the same problem incorrectly, but for a different reason (e.g., incorrect molar masses), would receive different targeted feedback. Inclusion of response-specific feedback is now the industry standard for OHSs.

Eichler and Peebles differentiated “traditional-responsive” from “adaptive-responsive” OHSs.¹² “Traditional-responsive” systems (e.g., MasteringChemistry¹³ and Sapling Learning¹⁴) provide response-specific feedback that is customized and emphasizes correcting mistakes. Importantly, all students using traditional-responsive OHS complete the same sets of problems in the same order, regardless of their current content mastery. Traditional-responsive OHSs, when used for delivery of chemistry content, have demonstrated enhanced student performance in exam scores,^{2,15} course grades,^{16,17} course success rates (percent of students earning letter grades of A, B, or C),^{3,16,18} and retention.^{3,19}

An “adaptive-responsive” OHS also provides response-specific feedback, but continuously adapts learning activities and assessment items to individual students according to the student’s current content mastery.¹² Thus, students have some control of the pace at which they learn, although all students must demonstrate content mastery by an instructor defined deadline.

Eichler and Peebles characterized the Assessment and Learning in Knowledge Spaces (ALEKS)²⁰ OHS for chemistry as “adaptive-responsive”.¹² The ALEKS system uses Knowledge Space Theory (KST) to individualize a student’s learning activities. Specifics of KST and its application to chemistry problem solving have been presented elsewhere (e.g., refs ²¹ and ²²). In ALEKS, each student’s current knowledge-space is continuously monitored and updated on the basis of the student’s performance on periodic assessments. Instead of assigning a static set of questions and problems, the instructor sets specific content objectives for students. The ALEKS system then creates an individualized set of learning activities as a “critical learning pathway” for the student to achieve the objectives. Thus, the learning environment is individually tailored to the student’s ALEKS-determined zone of proximal development, a crucial determinant of meaningful learning.^{23–25} When an instructor-scheduled assessment detects that a student forgot a specific content objective, it must be relearned before the student can progress to more advanced material. In a nonadaptive system, all students complete the same set of problems regardless of their skill set and knowledge base. This practice can be punitive for well-prepared students.⁸ Meanwhile, students with poor prior knowledge do not have their learning directed in a way that allows them to remediate efficiently.

In ALEKS, periodic assessments occur throughout the semester so students demonstrate continued content mastery, reinforcing recently learned chemistry concepts. This exploits the well-known benefits of practice retrieval on learning and long-term knowledge retention.^{26–28} The premise of practice retrieval is that encoding of information is strengthened through the act of retrieval. The focus is on accessing and using knowledge, and assessments identify specific content areas where a student needs additional practice. Practice is required until mastery is demonstrated via repeated successful problem completion. Most students do not effectively practice this type of self-assessing on their own,²⁶ so the adaptive functionality of ALEKS confers an additional learning benefit that is absent from nonadaptive, traditional OHSs.

Eichler and Peebles found that general chemistry students who consistently used ALEKS had final exam averages 5 points higher than students who used a traditional-responsive OHS (MasteringChemistry).¹² In addition, the average student spent more time (5–6 times more) working within the adaptive system than within the traditional system. Thus, the ALEKS adaptive OHS has two built-in, interdependent pedagogical benefits to aid student learning relative to traditional systems. In ALEKS, (i) homework is tailored to students’ prior knowledge and (ii) periodic reassessments guide students to engage in practice retrieval.

Students’ attitudes and motivation toward learning are moderately predictive of achievement.^{29–32} Several studies have shown that the affective domain plays a role in student success in

general chemistry.^{33,34} Cukrowska, Staskun, and Schoeman studied the attitudes of medical students enrolled in first year chemistry.³⁵ In each of five categories (e.g., perception of chemistry, difficulty in study of chemistry, approaches to work), positive correlations between attitudes and passing grades were observed. Furthermore, no student who passed with distinction had negative attitudes, and those with positive attitudes outnumbered those with neutral attitudes.³⁵ Papanastasiou and Zembylas observed that positive science attitudes were associated with improved science performance, and this association was directional or one-way in its effect.³⁶ Thus, though Eichler and Peeple's study¹² indicated that adaptive-responsive OHS may improve student learning more than traditional-responsive OHS, this result may be confounded by student attitudes (positive or negative) toward the OHS itself.

Demographically, some studies have shown that gender affects student success^{37,38} while others have defined it narrowly to certain types of courses, especially those related to STEM fields.^{39,40} Other variables such as financial capacity,^{41,42} previous academic performance,^{37,43} and, while debated, standardized test scores have also been found to predict student performance and are still used in admission requirements.^{44,45}

We sought to inform practitioners (i.e., general chemistry instructors responsible for devising learning activities and choosing formative assessment tools) of the relative advantages and disadvantages of adaptive-responsive online homework as compared to traditional-responsive online homework. The work described here is in some respects a replication of Eichler and Peeple's (particularly with respect to the first evaluation question).

¹² Our evaluation was structured to address the following questions:

1. What greater success in General Chemistry I, if any, is shown by students using adaptive-responsive versus traditional-responsive OHS?
2. What differences exist, if any, in student attitudes toward traditional-responsive versus adaptive-responsive OHS?
3. How do students respond when faced with an incorrect answer in adaptive-responsive OHS?
4. How does an adaptive-responsive OHS impact student study habits?
5. Where do students rank an adaptive-responsive OHS relative to other course aspects in terms of perceived learning in the course?

■ METHODS

Participants

Participants were students enrolled in General Chemistry I at our institution from spring 2007 to spring 2015, excluding summer. This included 8456 students using traditional-responsive OHS (spring 2007–spring 2011) and 8557 students using adaptive-responsive OHS (fall 2011–spring 2015).

A survey examining student attitudes toward online home-work was administered the last week of fall 2007 (traditional-responsive cohort) and the last week of fall 2011 (adaptive-responsive cohort). Of the 1310 students enrolled in fall 2007, the survey was administered

to 456 students with 311 students completing the survey (68% response rate). Survey responses for the traditional-responsive cohort were available only at the item level. Of the 1339 students enrolled in fall 2011, 1100 completed the course and 962 students completed the survey (87% response rate). The survey administered to the adaptive-responsive cohort contained an additional course aspect ranking item. A total of 843 students provided ranking responses appropriate for analysis (77% response rate). Survey responses for the adaptive-responsive cohort were available at the item and student level. A priori power analysis found that each group needed only 33 subjects to gain 80% power to detect a medium-sized effect when using a statistical significance criterion of $p < 0.05$.

Measures

The student attitude survey is included as Supporting Information; psychometric adequacy has been described elsewhere.^{18,46} This survey included 36 Likert-type statements, 4 demographic questions, 4 free-response questions, and one ranking item. Overall attitudes were calculated by obtaining the mean across 26 of the Likert-type items as described previously.⁴⁶ Overall attitude scores range from 1 to 5, with higher scores representing more positive attitudes. For the present sample, Cronbach's α was 0.92, indicating strong internal consistency.

Students in the adaptive-responsive cohort (fall 2011) ranked nine course aspects (e.g., online homework, text, weekly lectures) from most useful (ranking = 1) to least useful (ranking = 9) in terms of supporting their perceived learning. Percentages for each course aspect were obtained by summing the number of 1, 2, or 3 rankings and dividing by the total number of rankings received by the course aspect (as described in ref ⁴⁶).

Our institutional registrar provided student-level demo-graphic information, class rank, residency status, SAT and ACT scores, and final letter grades for each student enrolled in General Chemistry I spring 2007 to spring 2015.

Design

A quasi-experimental cohort control post-test-only design with nonequivalent control groups was used (see Figure 1) where there was an assumption of overlapping group membership.⁴⁷ Using the MatchIt package⁴⁸ in the statistical software environment R,⁴⁹ propensity scores with nearest neighbor matching were employed to reduce unexplained variance.⁵⁰ A traditional-responsive OHS (e.g., WileyPLUS,⁵¹ then Mastering Chemistry¹³) was used spring 2007 to spring 2011 (i.e., traditional-responsive cohort). An adaptive-responsive OHS (ALEKS)²⁰ was used fall 2011 to spring 2015 (i.e., adaptive-responsive cohort). All students completed weekly online homework assignments.

This research was reviewed and approved by our Institutional Review Board (Protocol No. 1510898085). Limitations include the following:

- Results may not generalize beyond our institution
- Survey findings do not represent attitudes of students who withdrew from the course prior to survey administration

- End-of-course attitudes may differ from those obtained postcourse (weeks or months later)
- Different instructors taught the course over the time period in question (2007–2015), though our permanent instructional team routinely teaches most, if not all, of the General Chemistry I courses
- Individual instructors and the instructional team together made slight alterations to the course

However, the General Chemistry I course at our institution is coordinated across years, sections, and instructors to ensure that each student has a similar learning experience. Common syllabi are used; final numerical grades are calculated using the same algorithm (e.g., four exams, 40%; laboratory, 25%; final exam, 25%; online homework, 10%), and all students take a common final exam. In addition, every four years the departmental final exam is replaced by the 2005 First Term ACS Standardized General Chemistry Exam to assess the long-term continuity of General Chemistry I content, coverage, and depth. Thus, the most substantive course changes were use of traditional-responsive OHS beginning spring 2007 and shift from traditional-responsive to adaptive-responsive OHS fall 2011.

Analysis

Student proportion correct on the 2005 First Term ACS Standardized General Chemistry Exam was compared fall 2007 to fall 2011 using a *z*-test of proportions. Student letter grades for all students spring 2007 to spring 2015 (excluding summers) in General Chemistry I were analyzed as the outcome variable in ordinal logistic regression using homework type as a dichotomous predictor variable. To reduce unexplained variance, propensity scores with nearest neighbor matching were used with earned class rank as a proxy for student performance (freshman, sophomore, junior, senior), self-reported gender identification (male, female), residency status as a measure of financial capacity as defined by the participating institution (resident, students paying in-state tuition; nonresident, students paying out-of-state tuition), and ACT composite scores as covariates. This condensed the overall sample to 12,228 participants, 6,114 matched pairs distributed evenly between traditional-responsive and adaptive-responsive cohorts.

Attitudinal results were quantified as described above with item-level means and standard deviations used for independent sample *t*-test comparisons. Though parametric *t*-test methods are most appropriate for interval and ratio scales of measurement, Romano et al.⁵² and Norman⁵³ demonstrated that these methods are “robust” (i.e., give correct results despite violating one or more assumptions) for use in evaluating group differences for discrete ordinal data.

For the adaptive-responsive cohort, open-ended responses to two free-response questions were analyzed using the NVIVO qualitative data analysis software following a symbolic interactionist approach.⁵⁴

1. “After incorrectly answering an ALEKS online homework question, what did you do?”

2. “Has use of the ALEKS online homework changed your chemistry study habits?”

The symbolic interactionist approach focused our coding first on manifest content to categorize responses and then through iterative second cycle coding focused on deeper, latent content in an attempt to understand communicative intent of student responses. All data was coded by two raters, and all discrepancies were discussed until consensus was reached. The coding system that emerged from patterns found in the narrative data is presented in Table 1.

In addition to qualitative coding and analysis of coded text, mixed methodological data transformation was used to quantify codes and examine relations among axial code categories (e.g., Are differences in valence related to differences in engagement or study change?). For this mixed methodological quantitative analysis of transformed qualitative data, engagement was dichotomized by combining passive engagement with no productive engagement, which was then compared to active engagement. Similarly, study change was dichotomized by combining explicit and implicit study change, which was compared to no study change. χ -square tests of independence were used to determine the strength of relationship between engagement, valence, and study change.

■ RESULTS AND DISCUSSION

Student Performance on ACS Final and General Chemistry I Grades

The 2005 First Term ACS Standardized General Chemistry Exam was administered as the final exam in fall 2007 (traditional-responsive) and fall 2011 (adaptive-responsive). We compared final exam scores between these two groups, recognizing the limitation that these are nonrandom samples of each cohort. Students who used the adaptive-responsive OHS ($M = 65.9\%$ correct; $SD = 17.2$; $n = 1007$) scored higher on the ACS final exam than those who used traditional-responsive OHS ($M = 60.1\%$ correct; $SD = 16.1$; $n = 1002$), and this difference was significant ($z = 2.69$, $p < 0.01$) with a small effect size $d = 0.35$.

Using the package `mlogit`⁵⁵ in R,⁴⁹ a choice was made to utilize a multinomial logistic regression to model the relation-ship between the two content delivery methods and final letter grade. There are five assumptions that must be met: (i) the errors are independent and distributed in the same manner, (ii) the sample has developed from external factors, (iii) the taste variation is known and systematic, (iv) there is a lack of serial correlation within the error terms, and (v) proportional substitution patterns exist between alternatives.⁵⁶ The first was verified with an a priori Gumbel extreme value distribution while the second is clear because students self-select into courses. While choice-making behavior is an artifact of individual histories, within each of the course settings there was a shared experience that was defined by rules and expectations defined in the syllabus implying that while there were differences in student decisions and actions, they were limited in scope and countable and thus nonrandom, satisfying the next two conditions. Finally, the last requirement is a direct consequence of the independence axiom and is assumed by the multinomial logit model.

The final letter grade of A was chosen as a baseline to show which subgroups (e.g., male students with C final letter grade) showed predicted improvement within the adaptive-response environment relative to a comparative group (e.g., male students with A). Relative risk ratios, a ratio of two probabilities that serves as a measure of effect size, were used to allow easier interpretation of outcomes existing as exponentiated logit coefficients.

Controlling for covariates used in propensity score matching, a full model for each final letter grade with A as a comparative baseline was found to be predicted by

$$\begin{aligned}\beta_0 + \beta_1 + \beta_2 + \beta_3 + \beta_4 + \varepsilon &= A \\ \beta_0 - 0.002\beta_1 + 0.088\beta_2 - 0.047\beta_3 - 0.177\beta_4 + \varepsilon &= B \\ \beta_0 + 0.192\beta_1 + 0.293\beta_2 - 0.499\beta_3 - 0.319\beta_4 + \varepsilon &= C \\ \beta_0 + 0.494\beta_1 + 0.507\beta_2 - 0.449\beta_3 - 0.319\beta_4 + \varepsilon &= D \\ \beta_0 + 0.242\beta_1 + 0.753\beta_2 - 0.447\beta_3 - 0.393\beta_4 + \varepsilon &= F\end{aligned}$$

where β_1 is the current student class rank, β_2 is the gender identification, β_3 is the student residency status, and β_4 is the student ACT score.

One should note that, due to the statistical framework of the multinomial logit model and selection of A as baseline, we were only able to measure changes from all other letter grades in comparison to the letter grade of A. This focused us on probabilistic improvements for students using an adaptive-response versus traditional-responsive OHS. Findings revealed no significant overall effect of OHS across all letter grades, but the adaptive-responsive versus traditional-responsive OHS had significant success indicators among specific letter grades in two of the three demographic categories as well as ACT score and OHS type (see Table 2).

Using significant results in Table 2, certain subgroups were likely to improve using the adaptive-responsive OHS. Risk ratios below 1.0 should be interpreted as the likelihood, keeping all other variables constant, that a student will stay in that category as opposed to increasing one letter grade. For example, if we observe a matched student with traditional-responsive OHS who earned a D in the course, he or she was 0.216 times more likely to stay in the same category. Thus, he or she has a 78.4% better chance of improving using the adaptive-responsive system. Similar directional outcomes delineated by affected subgroups are described in Table 3.

Attitudes: Likert-Type Survey Responses

Average overall attitude toward online homework (calculated from responses to 26 Likert-type survey items) was generally positive at 3.31 ($n = 311$) for the traditional online homework sample. For the adaptive online homework sample, the overall attitude score was less positive at 3.15 ($SD = 0.68$, $n = 843$). While we had frequency distributions, we did not have student-level data for overall attitude from the traditional-responsive cohort thus precluding inferential statistical comparison.

However, seven individual Likert-type survey items provided information on students' attitudes toward the two OHS types. The mean and standard deviations for students who used each OHS type and who responded to these items are presented in Table 4. For all

seven survey items, students expressed more positive attitudes toward the traditional versus the adaptive OHS with students expressing significantly more positive attitudes for six of the seven survey items.

Attitudinal data for the adaptive sample was available at the student level. As a result, attitudes toward adaptive online homework by final grade could be examined. Between overall attitude toward adaptive homework and final numeric grade, we found a moderate and statistically significant positive Pearson correlation ($r = 0.36$, $p < 0.01$, $n = 843$). Furthermore, there were significant differences in average overall attitude by final letter grade earned. For this analysis, categorical final letter grades (A, B, C, D, and F) were converted to numeric data (4, 3, 2, 1, and 0, respectively). The distribution box plot shown in Figure 2 visually depicts the general trend of final letter grade earned and overall attitude toward adaptive OHS. Students who were more positive toward adaptive online homework earned higher letter grades, a result similar to that found by Papanastasiou and Zembylas³⁶ who provided evidence for the one-way directionality of this result (e.g., better attitudes result in higher grades).

Attitudes: Open-Ended Survey Responses

As displayed in Table 1, open-ended survey responses were qualitatively coded into one of three categories on each of three axial coding dimensions: Engagement, Valence, and Study Change. Table 5 displays the number of coded instances by subcategory within Valence and Engagement. In total, there were 878 responses for this question. In terms of Valence, the majority were neutral (778), with no implication of emotional content. Eighty (80) coded responses had negative valence reflecting frustration and irritation, such as, *"First, I swore out my computer because now I would have to do 3 extra problems for 1 mistake, then I would hit explain"*. Twenty (20) responses reflected positive Valence, such as, *"I usually clicked on the explain button. It was very useful in being able to understand the problem"*.

Turning to Engagement, the majority of coded responses were passive (482). These students responded that they *"hit the explanation button"*, but did not actively seek any additional learning support. Responses coded as actively engaged (347) indicated attempting to find answers through additional resources. For instance, *"I usually tried to reference notes. If that failed I used Wikipedia"*. Active Engagement responses also included asking friends and use of the textbook. Very few students (49) gave responses that were unproductive, such as, *"Tried to figure it out, if I couldn't then I guessed or gave up"*.

Table 6 displays the number of coded instances by subcategory within Valence and Study Change. In total, there were 862 responses for this question. For Valence, the majority of coded responses were neutral (542), such as, *"I study the same amount"*. Negative Valence responses (188) reflected frustration, such as, *"Yes, in a bad way. I study way more and seem to not understand much from the system. It spread it out because it is extremely time consuming, and I wouldn't have enough time to do it on the day the assignment was due"*. Positive valence responses (132) often noted perceived benefits from ALEKS, such as, *"Yes it helped me a lot to do chem problems on a regular basis as well as point out my weaknesses. I study more and more often"*.

In terms of Study Change, most students state Explicit change in their study habits (467). There were 133 responses coded as Implicit Study Change, where students stated that they did not change but their answer implied change, such as, “*No, less, just days before the test*”. Lastly, 262 participants unequivocally indicated that there was no study change. Mixed methodological data transformation was used as described in the Analysis section above, and a χ -square test of independence revealed significant interdependence between Valence and both Engagement and Study Change [$\chi^2(2) = 66.97, p < 0.05$ and $\chi^2(2) = 7.81, p < 0.01$, respectively]. Interestingly, active engagement and positive study change were related to less positive valence. However, examination of responses indicated that some negative valence responses may be positive from an instructor perspective, such as this response to the Study Change question presented previously: “*Yes, in a bad way. I study way more and seem to not understand much from the system. It spread it out because it is extremely time consuming and I wouldn't have enough time to do it on the day the assignment was due.*”

Course Aspect Rankings

Aggregate course aspect rankings assigned by General Chemistry I students in each section in the fall 2011 adaptive cohort are shown in Figure 3. Similar trends emerge across all seven sections taught by five instructors. Students in 6 of 7 sections, and for all sections combined, perceived weekly instructor-run lectures as the most useful course aspect (83.5% overall). Students ranked adaptive homework explanations or review materials and online assignments as the next two most useful course aspects (65.7% and 57.3% overall, respectively), followed by back tests and exams (49.3% overall).

■ CONCLUSIONS

We believe that online homework improved our students' mastery of chemistry content through low stakes formative assessment giving prompt, response-specific feedback targeted at student self-remediation of incorrect responses. Herein, we investigated whether use of an adaptive-responsive OHS (ALEKS) that tailored homework to students' prior knowledge and periodically reassessed students to promote learning through practice retrieval had inherent advantages over traditional-responsive OHS. Consistent with Eichler and Peeples's research,¹² we found that students who used an adaptive-responsive OHS earned significantly higher final exam scores (5.8% higher on average) than students who used traditional-responsive OHS. While the predictive impact of OHS type on final course grades for all students was not significant, adaptive-responsive OHS was significantly more effective for average, below average, and failing students, especially those with an earned letter grade of D.

Similar to previous studies, students' overall attitudes toward both OHS types were generally positive.^{2–7,18,19} However, students reported more favorable views of traditional online homework relative to adaptive online homework (3.31 versus 3.15). Students who were more positive toward adaptive OHS earned higher final letter grades ($r = 0.357, p < 0.05$), consistent with research on attitudes and motivation as moderately predictive of achievement.^{29–32} Though we have no evidence for the directionality of this relationship,

Papanastasiou and Zemblayas have previously provided evidence of one-way directionality.³⁶

Qualitative student responses revealed dislike of adaptive periodic assessments, despite known benefits of practice retrieval on long-term retention of content.^{26–28} Most students reported engaging in passive (55%, $n = 878$) or active (40%, $n = 878$) remediation (e.g., hit explain button, referred to class notes or textbook, asked a friend) after incorrectly answering a question in adaptive-responsive OHS. A majority of students also reported explicit (54%, $n = 862$) or implicit (15%, $n = 862$) changes to study habits with adaptive-responsive OHS, similar to previous work on traditional-responsive OHS where 68% reported improved study habits.¹⁸ In terms of attitudinal valence toward the adaptive-responsive OHS, most students were positive or neutral when engaged in remediation (91%, $n = 878$) and when considering changes in study habits (78%, $n = 862$). Weekly instructor-run lectures and adaptive OHS were ranked as the first and second most useful course aspects for students' perceived learning. Similar rankings for traditional online homework in organic chemistry I coursework were obtained previously.⁴⁶

General chemistry instructors can use our findings to determine whether benefits (e.g., positive impacts of the system for average, below average, and failing students) of using an adaptive OHS outweigh its disadvantages (e.g., less positive attitudes) relative to traditional OHS. In addition, learning is difficult and takes time and effort students may not wish to devote to it unless forced. This is exemplified by our finding that, with use of adaptive OHS (which students spend more time working within relative to traditional OHS),¹² our students' active engagement (i.e., using resources to find answers) and positive study change (e.g., study more, spread out study) were related to less positive valence. From an instructor perspective, active engagement and good study habits are important attributes that promote learning despite students' apparent displeasure at devoting time to learning.

We make the following best practice recommendations for instructors who choose adaptive OHS based upon our findings as well as instructional experiences teaching general chemistry at a major research university for 15+ years. First, for multisection, multi-instructor, large enrollment courses, coordination of online homework in terms of system used and parity of weekly assignments (i.e., depth of coverage and objectives due) are critical to promoting a positive student learning experience with any online homework resource. Second, instructors should (i) minimize periodic assessments to one every other week, or 1 to 2 or 1–2 between each exam (as suggested during ALEKS training), (ii) set weekly deadlines for content objectives within the OHS that are coordinated with lecture to encourage regular study of course material throughout the academic semester,⁵⁷ and (iii) not schedule assessments immediately before scheduled exams when students are focused on self-directed study, which research has shown to be a requirement for learning.¹ Lastly, it is important for instructors to discuss with students learning pedagogy and evidence for why adaptive OHS that (i) tailors homework to students' prior knowledge^{23–25} and (ii) engages students in self-testing or practice retrieval^{26–28} may aid them in their learning and long-term retention of general chemistry concepts.

Supplementary Material

Refer to Web version on PubMed Central for supplementary material.

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Figure 1.

Research design: quasi-experimental cohort control post-test-only design with nonrandom propensity score matched (NR PSM) groups where X_1 and X_2 are traditional-responsive and adaptive-responsive homework, respectively, with corresponding final letter grades given by O_1 and O_2 .

Figure 2. Distribution box plot (minimum, first quartile, median, third quartile, and maximum) of overall attitude toward adaptive online homework categorized by final letter grade.

Figure 3.

Top three ranked most useful course aspects in terms of perceived student learning in the lecture portion of the General Chemistry I course. Rankings based on an end-of-course survey with a ranking scale: 1 = most useful; 2 = next most useful; etc. (Note: The Chemistry Learning Center (CLC) was open and available for free, drop-in tutoring on M, T, and W evenings.)

Table 1

Coding System Applied to Free-Response Survey Items

Category	Code	Code Definition
Engagement ^a	Active Engagement	Response reflects that participant used multiple resources to find the correct answer
	Passive Engagement	Response reflects that participant only used the explanation button
	No Productive Engagement	Response reflects that participant gave up, guessed, etc.
Valence ^a	Positive Valence	Participant response indicates positive attitude toward ALEKS or indicated the methods used were helpful or more helpful than others
	Neutral Valence	Participant response was neither positive nor negative
	Negative Valence	Participant response indicated irritation or frustration
Study Change ^b	Explicit Study Changes	Participant claims a clear study change
	Implicit Study Changes	Participant claims no study change, but extended response indicates a study change of some sort
	No Study Change	Participant claims there was no study change and response does not indicate otherwise

^aResponses to this question: "After incorrectly answering an ALEKS online homework question, what did you do?"

^bResponses to this question: "Has use of the ALEKS online homework changed your chemistry study habits?"

Table 2

Multinomial Logit Model: Relative Risk Ratios per Predictor and Final Letter Grade with Final Letter Grade A as Comparative Baseline

Predictor	Final Letter Grade, Risk Ratio (Standard Error) ^a			
	B	C	D	F
Gender	1.092 (0.063)	1.340 (0.066)	1.661 (0.083)	2.123 (0.076)
Class Rank	0.998 (0.050)	1.212 (0.050)	1.639 (0.056)	1.024 (0.056)
Residency Status	0.954 (0.068)	0.607 ^b (0.069)	0.639 ^b (0.085)	0.639 ^b (0.077)
ACT Score	0.838 ^b (0.010)	0.727 ^b (0.011)	0.676 ^b (0.013)	0.675 ^b (0.012)
OHS Type	0.894 (0.063)	0.548 ^b (0.065)	0.216 ^b (0.086)	0.720 ^b (0.073)

^aNot significant unless otherwise indicated.

^bSignificant result; evaluated at $p < 0.01$.

Table 3

Significant Probabilistic Success Measures for Matched Students in Traditional-Responsive and Adaptive-Responsive Online Homework Systems

Subgroup	Final Letter Grade in Traditional-Responsive System	Probabilistic Improvement When Using the Adaptive-Responsive System, %
Female	C	25.4
	F	52.9
In-State Students	C	39.3
	D	36.1
	F	36.1
ACT Score	B	16.2
	C	27.3
	D	32.4
	F	32.5
Homework Type	C	45.2
	D	78.4
	F	28.0

Table 4

Comparative Statistics for Individual Survey Items Addressing Students' Attitudes toward Online Homework for Traditional-Responsive OHS Relative to Adaptive-Responsive OHS

Survey Item	Sample Statistics: $M^a \pm SD (n)$		Significance Levels and Effect Size	
	Traditional-Responsive OHS	Adaptive-Responsive OHS	<i>t</i> -Statistic	Hedge's <i>g</i>
11. Overall, my experience with the online homework was positive.	3.5 $\pm$ 1.2 (311)	2.9 $\pm$ 1.3 (843)	5.90 ^b	0.48
12. In the future, I would be less apt to take a course that included online homework assignments.	2.4 $\pm$ 1.7 (310)	3.3 $\pm$ 1.2 (843)	7.07 ^b	0.67
13. The online homework was worth the effort.	3.7 $\pm$ 1.2 (299)	3.2 $\pm$ 1.2 (843)	4.89 ^b	0.42
14. The online homework assignments were a waste of time.	2.4 $\pm$ 1.7 (308)	2.8 $\pm$ 1.2 (843)	2.89 ^c	0.30
15. The online homework assignments were relevant to what was presented during lecture.	3.9 $\pm$ 1.1 (308)	3.6 $\pm$ 1.0 (843)	3.88 ^c	0.24
16. The online homework assignments did not further my understanding of general chemistry concepts.	2.3 $\pm$ 1.8 (308)	2.4 $\pm$ 1.1 (843)	0.83 ^d	0.08
19. The online homework helped to improve my attitude toward chemistry.	2.8 $\pm$ 1.2 (309)	2.5 $\pm$ 1.2 (843)	3.61 ^c	0.25

^aMean and standard deviation values of survey response scores based on this Likert scale: 1, strongly disagree; 2, disagree; 3, neutral (neither agree or disagree); 4, agree; and 5, strongly agree.

^bSignificant result; evaluated at $p < 0.01$.

^cSignificant result; evaluated at $p = 0.01$.

^dNot significant; $p = 0.41$.

Table 5

Comparative Student Responses to Question “After Incorrectly Answering an ALEKS Online Homework Question, What Did You Do?” Coded on Engagement and Valence Dimensions

<u>Student Responses by Engagement, <i>N</i></u>				
Valence	Not Productive	Passive	Active	Row Total
Negative	15	38	27	80
Neutral	34	426	318	778
Positive	0	18	2	20
Column Total	49	482	347	878

Table 6

Comparative Student Responses to Question “Has Use of the ALEKS Online Homework Changed Your Chemistry Study Habits?” Coded on Study Change and Valence Dimensions

<u>Student Responses by Study Change, <i>N</i></u>				
Valence	No Change	Implicit	Explicit	Row Total
Negative	41	51	96	188
Neutral	214	70	258	542
Positive	7	12	113	132
Column Total	262	133	467	862