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Can I have More Problems to Practice? Part 2. Student Success Related to Auto-graded, End-of-chapter YouTube Problems in a Material and Energy Balances Course

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Abstract

Interactive textbooks and online homework can uncover trends about student engagement and study practices. Here, auto-graded and randomized problems provided big data related to students' proficiency in a chemical engineering course on material and energy balances. Previously, aggregating hundreds of problems from a fully interactive online textbook, Material and Energy Balances zyBook, found a median 94% correct. For two recent cohorts, new, summative, end-of-chapter auto-graded problems were assigned. While summative problems written by an expert author were examined in the 2021 ASEE proceedings, this contribution will focus on summative problems derived from student-written problems that reverse engineer actions in YouTube videos. Previous research found that student-written "YouTube problems" were equally rigorous and required similar problem-solving skills to expert-written textbook problems when examining hand-written solutions. Now, auto-graded YouTube problems within the zyBook are investigated for the first time. Students were required to complete a fraction of the total summative YouTube problems before each of three midterm exams. For a single cohort of ~80 students, responses to ~20,000 online homework problems were analyzed. Research questions included: 1. Do students correctly solve more YouTube problems than required?, 2. Does completing more YouTube problems correlate with higher exam scores?, 3. Do formative and summative auto-graded problems correlate differently with final course grades?, and 4. How does solving end-of-chapter YouTube problems compare to end-of-chapter textbook problems with respect to final course grades? First, a median fraction correct of 100% for required YouTube problems was found for all three midterm exams, which generally shows persistence as auto-graded problems have unlimited attempts before the due date. Students scoring above the median midterm exam score correctly completed statistically significantly more YouTube problems. Correctly completing more YouTube problems positively correlated with midterm exam grades for all three exams. Almost no difference between cohorts was observed when correlating final course grades with correctly completing end-of-chapter textbook or YouTube problems. Thus, student-written YouTube problems appear equivalent to expert-written homework problems in terms of student success.

Introduction

Digital devices surround people in many parts of the world, and these devices generate big data through passive sensing as well as active interaction. In higher education, online, remote, and hybrid settings situate faculty and students in environments where clicks, page views, video watch times, etc. may be recorded. Here, the digital platform is interactive textbooks with integrated online homework, which are becoming common in engineering courses, e.g., [1-4].

Bringing active learning to textbooks has created a myriad of big data from clicks of participation to re-viewing of animations or other interactive elements [5]. Since fully interactive textbooks require regular learner participation, evidence has started to accumulate showing both high student engagement and improved academic success [1, 3, 4, 6, 7]. For example, traditional textbooks used in higher education generally garner reading rates between 20 and 50% [8-11]; However, interactive textbooks have shown median reading rates as high as 99% [4, 12, 13].

Engineering students are required to engage with numerous digital platforms as part of their coursework from email to learning management systems to specialized simulation and design tools. The focus of this contribution are digital tools generally called online homework. While online homework in math and the sciences has been used for many years, more engineering courses are also adopting online homework systems [14-23]. One advantage of online homework is auto-grading, which can provide a significant time savings for faculty and teaching assistants. Generally, online homework applies a number of best practices of learning, including immediate feedback to the learner and scaffolding problems from easier to more difficult [24-28]. Also, by allowing multiple attempts and having changing numbers and content with each attempt allows students to learn through perseverance, which aligns well with developing a growth mindset [29-31].

The online homework in this contribution is for a course in Mass and Energy Balances, which is commonly the first core chemical engineering course. This course focuses on developing engineering problem solving skills that are expanded upon in later chemical engineering courses. The engineering education literature include many contributions related to teaching this course, such as [3, 32-34], but details related to the course concepts are secondary to the analysis presented here.

While online homework can involve both formative and summative problems, this research primarily focused on summative, end-of-chapter problems called YouTube problems, which will be introduced in the next section. As the title implies, this new contribution expands upon a 2021 ASEE Conference proceeding [35], which will be referenced throughout. Summarizing our previous contribution: Additional, end-of-chapter auto-graded homework problems were assigned by requiring a fraction of the available problems before each of three midterm exams. Findings included high completion (94 to 104% median correct), 29 to 52% of the cohort completing more than the required problems, and positive linear correlations between fraction of correctly completed end-of-chapter problems and midterm exam grades. Here, several research questions are explored, including: Are the high completion and over-completion reproduced with a second cohort? and How do more visual YouTube problems compare to traditional textbook problems in terms of completion and other metrics?

Materials and Methods

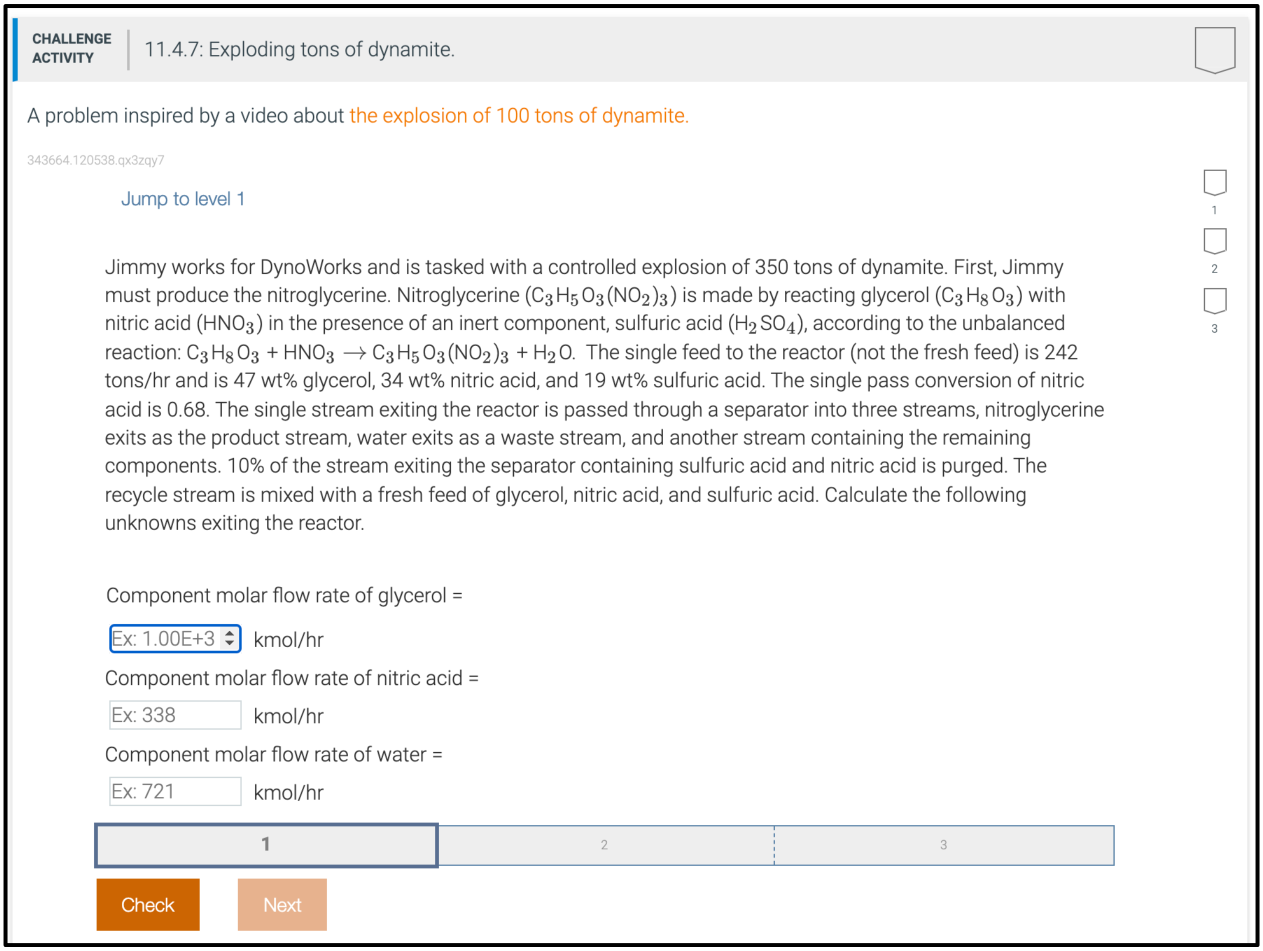
Material and Energy Balances zyBook, a fully interactive textbook with content that follows other textbooks for the course, has been used for a chemical engineering course for 6 years [36]. With over 80 sections, 140 animations, and 1300 interactions (usually via clicks), the content can be used within any HTML5 compliant web browser. The version used by the 2021 cohort included over 700 online homework problems, or challenge activities. Specifically, the first 7 chapters will be studied. Challenge activities account for 5% of a students' final course grade and are scored as correct or incorrect independent of the number of attempts. A forgiveness factor of 15 problems adjusted students' final grades, but this correction was not included in fraction correct (%) presented here. The 2021 cohort was taught online synchronously at a public university, while the 2020 cohort received half of a semester in person and half as a synchronous online course.

The total number of challenge activities problems analyzed for the two cohorts multiplied the number of students completing the course by the number of required problems. Overall, 49,000 and 33,000 problems were investigated for the 2020 and 2021 cohorts, respectively. However, the main focus is on problems pertaining to Chapters 1 to 7 for only the 2021 cohort, which accounts for ~20,000 problems.

For the 2020 and 2021 cohorts, end-of-chapter problems were assigned to give students additional practice before each of the three midterm exams. Students received full credit for correctly completing a percentage of the available problems. Generally, students were given one week to complete the problems before each of the midterm exams. Midterms were taken in weeks 4, 10, and 14, while the final exam was administered in week 16.

YouTube problems are student-written problems that reverse engineer actions from a YouTube video [37, 38]. YouTube problems that were edited and coded into challenge activities were authored over many previous years. First, a link is provided to a video in the challenge activity (Figure 1); these videos are publicly available, but not always necessary, for solving the problem. Under the link is a problem statement, usually about one paragraph, and numerical answer boxes and/or multiple-choice drop downs. If a student enters one or more incorrect answers, the full solution is shown. During a subsequent attempt, the numbers and concepts change randomly with up to thousands of variations for each problem.

End-of-chapter YouTube problems require multiple concepts from the chapter, or even preceding chapters, with many steps to solve. Thus, YouTube problems may be referred to as summative problems. Conversely, in-section challenge activities are located within most sections with 3 to 6 scaffolded problems. A total of 278 in-section problems were required prior to the third midterm exam, which will be compared to the 39 required, end-of-chapter YouTube problems. Students have an unlimited number of attempts; both before getting a problems correct the first time as well as after subsequent attempts used for practice. Previous publications provide examples of other challenge activities [3, 39].


CHALLENGE ACTIVITY | 11.4.7: Exploding tons of dynamite.

A problem inspired by a video about the explosion of 100 tons of dynamite.

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Jump to level 1

Jimmy works for DynoWorks and is tasked with a controlled explosion of 350 tons of dynamite. First, Jimmy must produce the nitroglycerine. Nitroglycerine ($C_3H_5O_3(NO_2)_3$) is made by reacting glycerol ($C_3H_8O_3$) with nitric acid (HNO_3) in the presence of an inert component, sulfuric acid (H_2SO_4), according to the unbalanced reaction: $C_3H_8O_3 + HNO_3 \longrightarrow C_3H_5O_3(NO_2)_3 + H_2O$. The single feed to the reactor (not the fresh feed) is 242 tons/hr and is 47 wt% glycerol, 34 wt% nitric acid, and 19 wt% sulfuric acid. The single pass conversion of nitric acid is 0.68. The single stream exiting the reactor is passed through a separator into three streams, nitroglycerine exits as the product stream, water exits as a waste stream, and another stream containing the remaining components. 10% of the stream exiting the separator containing sulfuric acid and nitric acid is purged. The recycle stream is mixed with a fresh feed of glycerol, nitric acid, and sulfuric acid. Calculate the following unknowns exiting the reactor.

Component molar flow rate of glycerol =

Ex: 1.00E+3 kmol/hr

Component molar flow rate of nitric acid =

Ex: 338 kmol/hr

Component molar flow rate of water =

Ex: 721 kmol/hr

1 2 3

Check Next

Figure 1. Screenshot from Material and Energy zyBook of a YouTube problem related to a reacting system.

Table 1. Number of students and end-of-chapter YouTube problems required and available before each midterm exam.

	Exam 1	Exam 2	Exam 3	Final
Students (#)	77	68	64	63
Required problems (#)	13	15	11	-
Available problems (#)	39	49	43	-

The number of required end-of-chapter YouTube problems for each exam varied from 26-33% of the available problems (Table 1). Therefore, fraction correct may be presented as a percent of either required or available problems. From the beginning to the end of the semester, 18% of students withdrew from the course, which was 7% higher than the previous year. The largest decrease in students was from Exam 1 to 2.

Box plots are used to display fraction correct data, with each box representing the middle 50% of data, including the 1st quartile, median, and 3rd quartile. Mean values (usually triangles in box plots) can help clarify skewness. Effects of individual outliers, which can skew the mean, are minimized by using box plots. Hypothesis testing was performed when correlating different data sets. Conducting *t*-tests generated *p* values with statistical significance occurring when $p < 0.05$. When $n > 20$, the use of *t*-tests is justifiable even with nonnormal distributions [40].

Results and Discussion

Analyzing ~20,000 student responses to auto-graded problems will address four research questions:

1. Do students correctly solve more YouTube problems than required?
2. Does completing more YouTube problems correlate with higher exam scores?
3. Do formative and summative auto-graded problems correlate differently with final course grades?
4. How does solving YouTube problems compare to textbook problems with respect to final course grades?

<u>Do students correctly solve more YouTube problems than required?</u>

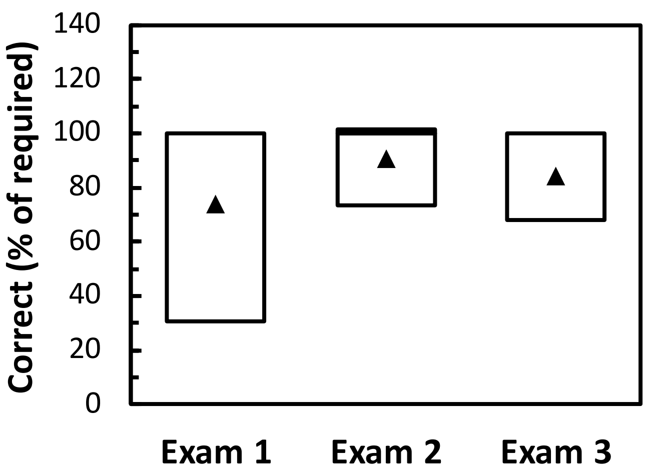


Figure 2. Fraction correct of end-of-chapter YouTube problems required before each midterm exam. Triangles represent mean.

Before all three midterm exams, students correctly solved assigned end-of-chapter YouTube problems (Figure 2). Additional auto-graded problems were available, so scores over 100% are possible. For all three exams, the median correct was 100%. The 3rd quartile was 100% for Exams 1 and 3 and 102% for Exam 2. Therefore, at least half of the cohort correctly completed at least the required number of problems, which is a positive finding. The largest spread between the 1st and 3rd quartile correct was observed for Exam 1 when a 1st quartile correct of 31% was found. Performing ANOVA analysis resulted in statistical similarity for all three exams ($F(3, 208) = 2.15$, $p = 0.12$).

Comparing the 2020 to the 2021 cohort, the fraction of problems answered correctly on Exam 1 was higher and statistically significant ($p = 0.002$) for the 2020 cohort [35]. One possible explanation was the 2020 cohort instructed in person for this part of the semester compared with the fully remote instruction in 2021. Fraction correct on problems before Exams 2 and 3 were statistically similar ($p = 0.23, 0.61$, respectively); Both cohorts only received remote instruction during this portion of the semester.

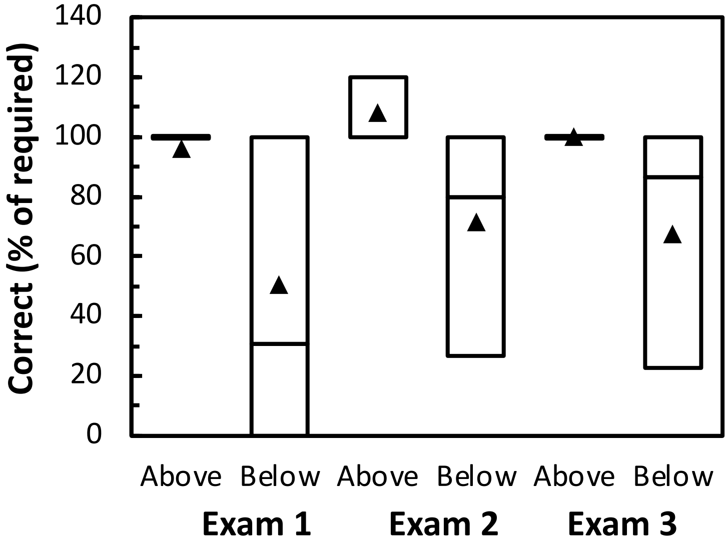


Figure 3. Fraction correct of end-of-chapter YouTube problems required versus dividing the cohort by above and below median exam scores. Triangles represent mean. p values between above and below for each exam is < 0.003.

When separating the cohorts by the median exam score, further analysis of the summative, end-of-chapter YouTube problems were performed (Figure 3). Statistically significant differences in fraction correct on YouTube problems for students above and below the median exam score were found ($p < 0.003$). Of students scoring above the median exam score, the median (and 3rd quartile) fraction correct on end-of-chapter problems was 100%, while those scoring below the median exam score resulted in median fraction correct of 31, 80, and 86%, respectively. The 1st quartile for Exam 1 was 0%, meaning at least a quarter of students scoring below the exam average did not correctly complete a single, summative YouTube problem. Similar statistically significant differences were observed for the 2020 cohort [35].

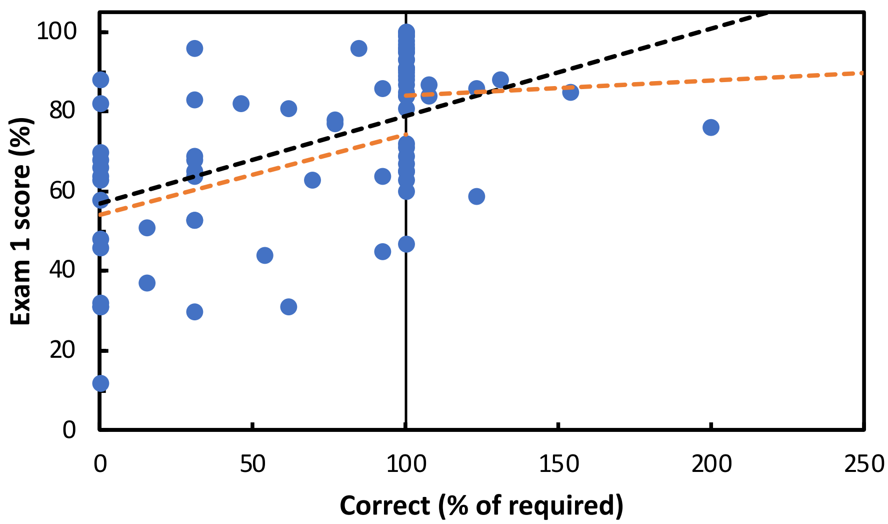
Table 2. Percent of students above or below 100% correct of required problems.

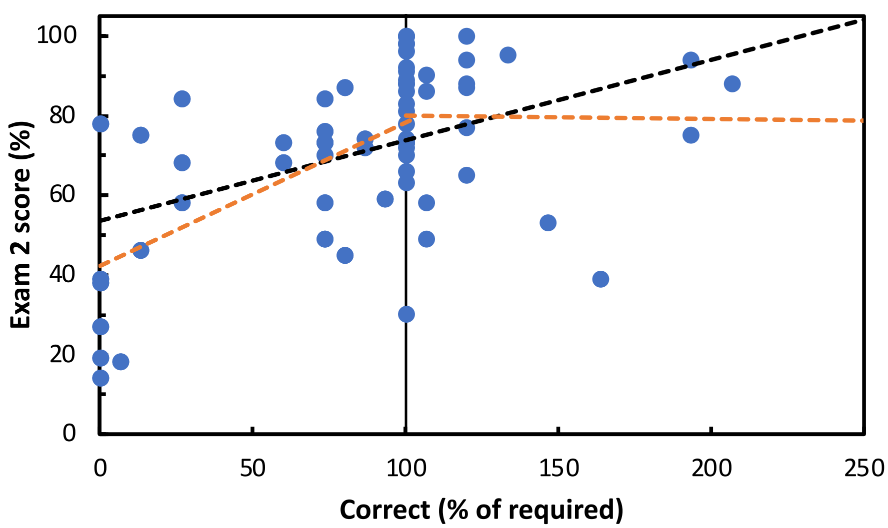
Students (%)	Exam 1	Exam 2	Exam 3
>100	10	25	14
=100	43	37	55
<100	29	39	22
0	18	9	9

Although the number of students taking each exam decreased throughout the semester, higher fractions of students correctly completed at or above the required number of YouTube problems for Exams 2 and 3 compared to Exam 1 (Table 2). Exam 3 resulted in the largest percentage of students completing 100% or more of the required problems (69%) followed by Exam 2 (62%) and Exam 1 (53%). While not examined on the individual student level, student withdrawing from the course were most likely not completing 100% or more of the required YouTube problems. Exam 1 resulted in the largest percentage of students not completing any of the required problems correctly at 18%, which shows a lack of engagement more than a lack of ability or preparation.

The percentage of students above 100% was similar across exams when comparing across cohorts [35]. The percent of students at or above 100% was 53, 62, and 69% for 2021 and 59, 49, and 64% for 2020. Overall, having unlimited attempts and being able to work with teaching assistants or the professor during office hours led to between about half and two-thirds of students being successful in solving all of the required summative problems.

Does completing more YouTube problems correlate with higher exam scores?





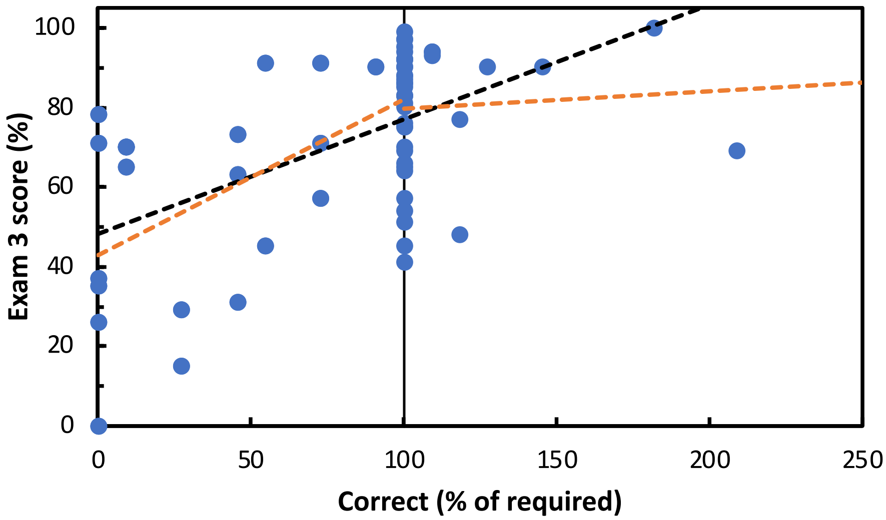


Figure 4. Exam score as a function of fraction correct on required YouTube problems. Black lines are a linear fit to all data. Orange lines represent linear fits above or below 100% correct of required problems.

Table 3. Slopes (m) and Pearson coefficients (R) for above and below 100% of required end-of-chapter YouTube problems correctly completed for each midterm exams.

	Full cohort		**<100%**		**≥100%**	
	m	R	m	R	m	R
Exam 1	0.22	0.55	0.20	0.31	0.04	0.10
Exam 2	0.20	0.49	0.36	0.58	-0.01	0.02
Exam 3	0.29	0.55	0.39	0.45	0.04	0.06

For all three midterm exams, correctly completing end-of-chapter challenge activities exhibited a positive, linear correlation with exam grades (black dashed lines in Figure 4). These correlations were quantified by slopes and Pearson coefficients (Table 3). Pearson coefficients on the order of 0.5 confirm that a linear correlation fits the data reasonably well. Exam 3 resulted in the largest slope, while Exam 2 resulted a slightly smaller slope than Exam 1. While having positive slopes in all three cases when examining all students is an encouraging result, correlation does not imply causation. Examining the data more closely, exam scores appear to level off after 100% correct of required problems.

Below 100% correct, Exam 3 resulted in the largest slope (0.39) followed by Exam 2 and Exam 1. A few outliers, who scored high exam scores (>70%) after completing few required problems (<30%), are noted. For greater than or equal to 100% of required, linear fits resulted in relatively small slopes between -0.01 to 0.04. The slope for Exam 2 was slightly negative, which is partially due to an outlier who correctly completed 287% of required problems and scored 84% on the exam. Since at exactly 100% correct of required corresponded to a range of exam scores, low Pearson coefficients were observed and indicated a poor linear correlation. Overall, between 74 and 86% of students who correctly complete more problems than required scored in the A or B range on the midterm exams. Similarly, the y-intercept of the greater than or equal to 100%

correlations for all three exams was ~80%, which is a B grade. Correlations for both overall and above/below 100% of required exhibited similar qualitative trends for a previous cohort [35].

<u>Do formative and summative auto-graded problems correlate differently with final course grades?</u>

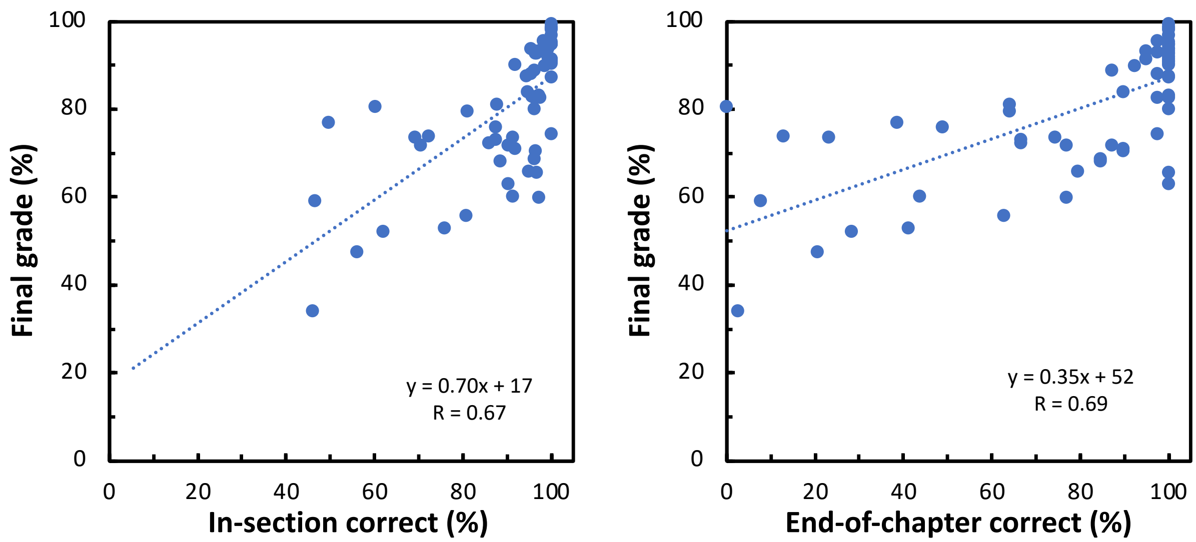


Figure 5. Final grade as a function of fraction correct of (left) in-section problems and (right) end-of-chapter YouTube problems (n=63 in both panels).

Positive linear correlations were found when comparing final grades to fraction correct of both in-section and end-of-chapter problems (Figure 5). In-section correct was aggregated from assigned problems from Chapters 1 through 7 with a maximum correct of 100%. End-of-chapter correct was aggregated from assigned problems before each of the midterm exams and capped at 100%; Students who correctly completed more problems than assigned received a score of 100% correct. Final grades were calculated with 80% of the grade coming from quizzes and exams and 20% from homework, reading participation, challenge activities, and attendance. Final grade as a function of in-section correct and end-of-chapter correct showed linear correlations with high Pearson coefficients of 0.67 and 0.69, respectively. The slope with respect to in-section correct was twice that of end-of-chapter correct. The intercepts of the linear correlations vary dramatically also. Additional context to compare these correlations is considered next.

How does solving YouTube problems compare to textbook problems with respect to final course grades?

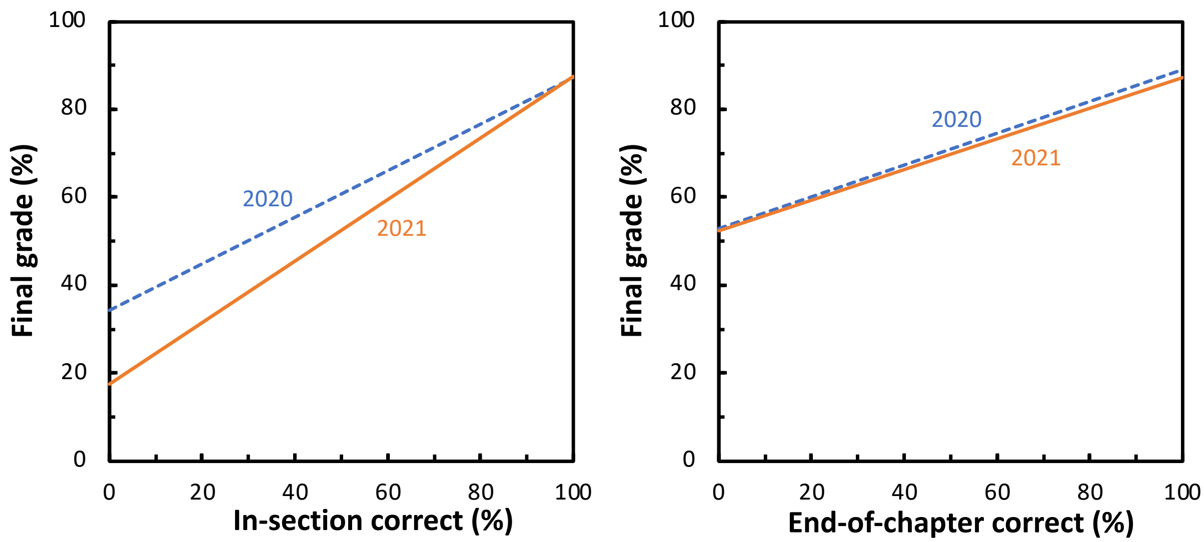


Figure 6. Final grade as a function of fraction correct of (left) in-section problems and (right) end-of-chapter problems. Both cohorts had the same in-section problems. 2020 cohort has textbook end-of chapter problems, and 2021 cohort had YouTube end-of chapter problems.

While many variables change from year to year when teaching a course, such as the modality of the course as noted earlier, comparing the 2020 and 2021 cohorts finds some valuable insights. From the 2020 cohort (Figure 6), fraction correct for in-section problems resulted in a larger positive slope when linearly correlating with final grades than end-of-chapter textbook problems (0.53 to 0.36); the intercept for end-of-chapter was larger than in-section. For both intra-cohort comparisons, relative slopes and intercepts between in-section versus end-of-chapter correct are similar.

Inter-cohort comparisons show excellent agreement for end-of-chapter problems; the linear correlations overlap for most of the range. This finding is significant since the end-of-chapter problems were completely different between the cohorts. While the 2020 cohort had expert-written textbook problems, the 2021 cohort had student-written YouTube problems. Therefore, the student-written YouTube problems appear equivalent to expert-written summative problems in terms of overall success across an entire semester. With respect to in-section problems, a steeper slope and smaller intercept were observed for 2021 compared to 2020. While students completing most of the in-section problems correct (≥80%), earned similar final grades, students completing less than 60% of the in-section problems earned lower final grades. For example, at 60% correct in-section problems, the difference in linear correlations is ~6.6%, which is more than half of a letter grade. This difference between cohorts may be related to the fully remote course in 2021 compared to 2020.

Conclusion

Reverse engineered, end-of-chapter YouTube problems within an auto-graded online homework platform were analyzed. By assigning a required number of summative problems before each midterm exam, students had the ability to choose which problems they wanted to solve. 100% median fraction correct of required problems was found for all three midterm exams. Students scoring above the median exam score correctly completed statistically significantly more YouTube problems across all three midterm exams. Summative problems completed before Exam 3 had the largest percentage of students (69%) completing 100% or more than the required number of problems.

Furthermore, correctly completing more summative YouTube problems positively correlated with midterm grades for all three exams. However, completing more than the required number of summative YouTube problems showed little correlation with exam grades, although most exam scores for these students were at least 80%. Finally, fraction correct on in-section or formative, auto-graded problems correlated much more strongly with final grades than the summative YouTube problems. Overall, auto-graded online homework problems can help develop problem solving skills through immediate feedback, multiple attempts, and other features. By applying these tenets of focused practice when solving YouTube problems shows evidence that transfer to new, timed exam problems is very plausible.

Further research into data beyond fraction correct, including attempts before correct, is warranted. In addition, continuing to investigate aggregated data sets as well as changes over cohorts and course modality could be investigated. Finally, the YouTube problems are freely available to instructors through zyBooks and should be maintained many years beyond the competition of the funded project supported by the National Science Foundation.

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Disclaimer

One of the authors may receive royalties from sales of the zyBook detailed in this paper.

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