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The Effect of McGraw-Hill Connect Online Assessment on Students' Academic Performance in a Mechanics of Materials Course*

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Online student assessments have gained popularity in the engineering education community in the past few years. McGraw-Hill Education (MGHE) Connect has been used extensively in higher education for online assessments. However, its efficacy in engineering education needs to be investigated. This study investigates the effect of using McGraw-Hill Education (MGHE) Connect online platforms on students' academic performance in a Mechanics of Materials (MoM) course. Evaluations from twelve sections (n = 367) were collected using past years' data, where conventional paper and pencil homework were adopted as a control group with MGHE Connect-based online homework intervention for synchronous and face-to-face MoM courses as the treatment group. The study examined the effects of MGHE Connect on homework score, cumulative score, grade and pass rate. Variations due to semesters, instructors, delivery type, and modality are analyzed using a mixed model to find the effect of the intervention. Moreover, this study assessed students' perceptions of the platform and its setup. The study findings showed 'immediate feedback' and 'multiple attempts' as the two major strengths, while the 'lack of access to the step-by-step solutions' and 'need to redo' as major weaknesses. There is a difference in homework grades, with the treatment group's median being higher; however, the study found no evidence to support the claim that MGHE Connect improved students' performance and grade. Students revealed that their satisfaction was significantly influenced by the setup preference of Connect. These outcomes provide insight into how homework should be set up to improve student satisfaction while maintaining academic performance.

Keywords: engineering education; McGraw-Hill Education Connect; synchronous; performance; assessment tools

1. Introduction

The sudden eruption of a global pandemic [1] introduced enormous changes in higher education. Universities had to switch to virtual learning and this shift appears to be widely accepted for the near future. While different disciplines vary in their degree of ease in adapting quickly to a new mode of teaching, faculty must be innovative in using available technology to successfully switch to remote (virtual) teaching, while keeping or increasing the efficiency of conveying the content of their courses. Many online books and digital learning environments have appeared over the last ten years and have recently gained momentum due to the pandemic.

Homework is an important part of student learning and plays a significant role in engineering undergraduate student learning. It is positively associated with students' achievement [2, 3]. A synthesis of 15 studies [4] found that homework, especially assignments that were graded or commented on, had a significantly positive impact on student learning. A meta-analysis [5, 6] concluded that there is a positive correlation between homework and academic achievement.

In terms of delivery medium, homework can be assigned as paper-based (traditional) or web-based (online). While paper-based homework offers an opportunity for complex detailed feedback, web-based homework offers limited but immediate feedback on numerical answers. Immediate feedback has been shown to increase student engagement and learning [7, 8], an important aspect of online homework. In addition, some earlier studies found online homework leads to better student performance than traditional homework while others find there is no difference [9, 10]. Magalhães et al. [11] presented an extensive literature review of the advantages and disadvantages of online homework. They concluded that as many as half of the reviewed studies reported neutral results; no differences were found between online and traditional homework about students' performance. Evidence of online homework enhanced benefits for students is, at best, scattered. Cooke and Al Faruque [12] studied the effect of the Pearson Mastering Engineering and reported mixed results. The use of traditional hand-

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written homework, frequent assessment via quizzes, or the Pearson Mastering Engineering software for formative assessment did not have a significant impact on students' performance on exams [13, 14]. Recent studies [15] applied a blended learning model that combined traditional lectures and e-learning platforms. This learning model allows instructors to take advantage of online education with traditional face-to-face teaching and thus enhance student learning [16–19]. González, Giuliano and Pérez [19] studied the effect of computer-assisted assessment in a probability course taught to engineering students and supplied evidence that using the platform improves students' scores. This work shows that using the e-status platform in Probability & Statistics was effective in improving the academic performance of engineering students. McGraw-Hill Education (MGHE) is one of the digital learning platforms and online services which is being used extensively in higher education for online assessment to enhance students' performance. MGHE partnered with faculty members across disciplines at a diverse set of institutions to develop case studies that demonstrate Connect's effectiveness [20]. Disciplines included accounting, anthropology, biology, business, chemistry, among others; however, the engineering discipline was not represented in the study. The performance data used in this effectiveness study were based on case studies conducted by twenty different instructors from institutions of higher education. These instructors measured the effect of Connect on a set of performance indicators for student performance and instructor efficiencies using measurable metrics. While there has been a great deal of research done in collaboration with MGHE, there is little independent peer-reviewed study on the efficacy of MGHE Connect, and the results have been mixed [21, 22]. In addition, there is not much study being conducted on the effectiveness of MGHE Connect on engineering courses such as Mechanics of Materials (MoM). This study aims to investigate the effectiveness of MGHE Connect (online homework) on student performance in a synchronous online and face-to-face MoM course. The study evaluates the effects of MGHE Connect, if any, on students' course letter grades, pass rate, homework score, and cumulative score. The study's key findings will advance our understanding of how the integration and configuration of the MGHE Connect online platform will affect student performance and satisfaction in engineering education.

2. Course Description and Structure

This paper offers a comparison of students' overall performance in a Mechanics of Materials course (MoM) taught at a US University. The three-credit hour course is taught in a combined lecture/lab environment during spring and summer semesters. In the spring semester, the course meets twice per week for a total of four and one-half contact hours, over 15 weeks (about 3 and a half months). In the summer semester, the course meets three times per week for a total of nine contact hours, over six weeks. The course is typically taken by engineering students in their second year of study. Even though the course has been taught by five different instructors over the past six years, it is like a team-taught course. The instructors use the same textbook and syllabus, assign the same homework, collaborate on writing quizzes and exams, and use common grading rubrics. The course instruction closely follows the Excellence in Civil Engineering Education (ExCEEd) Teaching Model [23] with the use of common board notes among the instructors. Since the course is taught in the combined lecture/lab format, there is ample time and opportunity for active, hands-on learning during the class period. Students spend a good portion of class time working in groups to solve problems under the supervision of the instructor.

All instructors require attendance, take roll, and for students with excessive unexcused absences, there is a grade reduction outlined in the syllabus. The prerequisites for the course are Engineering Mechanics (Statics & Dynamics) and Computational Tools for Engineers (Excel and MATLAB). Students are expected to be proficient in these areas. Grades are based on a weighted average of two exams (20% each), a final exam (25%), five quizzes (7.5 %), three labs (15%), one design project (5%), and homework (7.5%). Some instructors have adjusted this grading scheme without affecting learning and institutional policy. Students must earn a minimum grade of C in the course to move on to follow-up courses that require Mechanics of Materials as a prerequisite.

3. Material and Methods

This study investigates the effect of using MGHE Connect on students' academic performance in one of the core courses in Engineering – MoM Course. The participants were 367 students drawn from 12 MoM sections from a small engineering college at a US University. All students had already taken two or more semesters of classes at the university level and used computers for web searching and study support (e.g., searching and accessing educational resources).

This study used MCGH's Connect MoM as an experimental treatment. The study employs a two-group experimental design procedure to test the

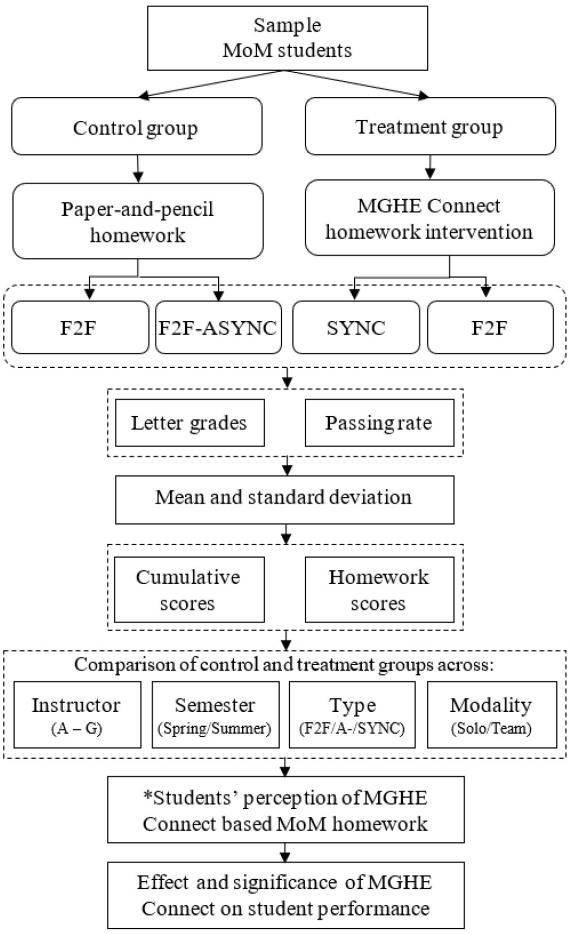

Fig. 1. Experimental procedure (Face-to-face = F2F; Face-to-Face & Asynchronous = F2F-ASYNC; Synchronous = SYNC, * NVivo software is used to analyze students' perception of MGHE Connect based MoM online homework)

efficacy of the MGHE Connect compared to the conventional paper-based homework. Fig. 1 illustrates the experimental procedure.

Students in the control group took part in a conventional paper-and-pencil homework implementation, while students in the treatment group participated in the MGHE Connect homework intervention. The online homework program used the same end-of-chapter textbook questions previously assigned to the control group. A list of all the sections considered in this study, with the corresponding number of students, mode of teaching, and type of homework is shown in Table 1.

The study used Microsoft Excel/R statistical language [24] and NVivo by QSR International [25] for quantitative and qualitative statistical analyses, respectively. Descriptive statistics such as means, medians, standard deviations, statistical visualization graphs are used to present and compare effects. When comparing two independent samples such as letter grades where the outcome is not normally distributed, and the samples are small, only non-parametric tests are appropriate [26]. For two sample comparisons (Control vs. Treatment) a t-test is not reasonable due to the presence of outliers. Moreover, the subsamples do not follow a normal distribution thereby violating assumptions. Therefore, a Mann-Whitney test (a distribution free test) [27] is employed in the following sections having statistical analysis.

In this paper, three major factors are considered to investigate the effect of using MGHE Connect on students' academic performance. These include course delivery type, modality, and instructor. The measurement of students' academic performance was assessed using the course letter grade, the cumulative and homework scores, pass rate, and letter grades. Table 1 and 2 show the counts for student participants based on these three factors.

4. Data Analysis and Results

Many universities have considered online platforms a critical part of their education strategy [28]; thus, numerous studies have employed different methods to decide the effectiveness of online educational

Table 1. MoM course sections with student count, course type of delivery and homework type

Semester	Year	Number of students	Instructional Type	Homework
Spring	2016	26	F2F	Paper-and-pencil
	2017	25	F2F	Paper-and-pencil
	2018	30	F2F	Paper-and-pencil
	2019	42	F2F	Paper-and-pencil
	2020	37	F2F-ASYNC*	Paper-and-pencil
	2021	36	SYNC	MGHE Connect
	2022	23	F2F	MGHE Connect
Summer	2017	32	F2F	Paper-and-pencil
	2018	54	F2F	Paper-and-pencil
	2019	32	F2F	Paper-and-pencil
	2020	15	SYNC	Paper-and-pencil
	2021	15	F2F	MGHE Connect

* The type of delivery for MoM course was shifted to asynchronous on March 16, 2020, because of the COVID-19 pandemic.

Table 2. Counts of students for the corresponding instructor

Instructor	**A**	**B**	**C**	**D**	**E**	**F**	**G**
Count	161	46	23	47	23	42	25

Table 3. Course grade scale

Grade	**A**	**B+**	**B**	**B–**	**C+**	**C**	**C–**	**D**	**F**
Total Score	100–90	89.99–86.67	86.66–83.34	83.33–80.00	79.99–76.67	76.66–73.34	73.33–70.00	69.99–65.00	<65

platforms [20, 29–31]. In this study, the effectiveness of MGHE Connect is measured according to its impact on a selected set of outcomes: student letter grades, passing rate, cumulative scores, and homework scores.

4.1 The Effect of MGHE Connect on Student Letter Grades

Student letter grade provides relative performance, knowledge, and growth of the student. Even though it is less informative about a student's skill performance and/or subject knowledge, it cannot be disregarded. Therefore, it is essential to examine the correlation between the use of MGHE Connect and final course grades to determine if there is a positive or negative effect. The standard course grading scale used in the MoM course is shown in Table 3.

In this study, the effect of MGHE Connect on a student's letter grade depicted in Fig. 2 shows how grades are distributed in each group (treatment and control). Students must earn at least a C grade to pass the MoM course. Fig. 2 shows higher proportions of 'pass' grades (A, B, C+ and C) and lower proportions of 'fail' grades (C–, D, and F). The MoM classrooms using MGHE Connect earned a more favorable course grade distribution, with an average increase of 7.4 % more students earning A's and B's when compared to classrooms not using Connect. To make reasonable judgments about whether this relationship is statistically significant, detailed comparisons between control and treatment groups are performed. A Fisher Test [26] is performed to determine if differences in distribution of letter grades between control and treatment are significant. The differences were statistically significant (p-value = 0.0229) and it is expected (Fig. 2). Proportion tests are used to assess the effect on individual passing grades. The test concluded significant differences for the grade 'A' (p-value = 0.0416).

4.2 The Effect of MGHE Connect on Student Passing Rate

The progressing/pass rates in treatment and control groups are shown in Fig. 3. The rate is also referred to as progressing rates as students cannot progress to the next core course without passing the MoM course. The progressing rate of the treatment group (96.2%) was significantly higher than the progressing rate of the control group (84.0%). The treatment group is higher in the progressing rate by 12.2% compared to the control group. This comparison showed a positive effect of the treatment on the passing rate. However, the impact of such intervention would be clearer once the statistical significance is tested. In this study, individual student work such as the total exam and homework

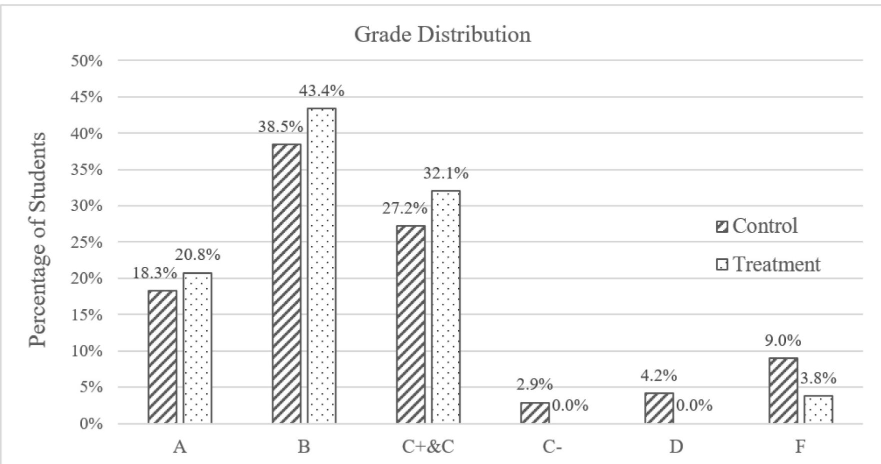

Fig. 2. Overall Letter Grade Distribution in Treatment and Control Groups.

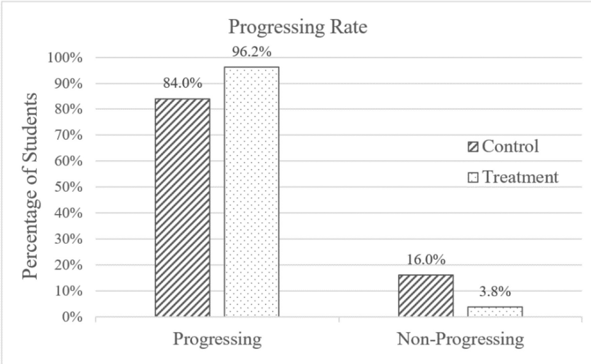

Fig. 3. The Progressing (at least C Grade) Rates of Treatment and Control Groups.

scores are used as a common criterion of measurement and discussed in the next sub-section.

4.3 The Effect of MGHE Connect on Student Cumulative Scores

Cumulative scores from the two cases (Control and Treatment) are compared to determine the effect of treatment. Cumulative scores are computed using the grading criteria adopted by each instructor in a particular course for required assignments. The cumulative scores measure the net effect of all assignments including the homework. The specific effect of homework assignments will be analyzed in Section 5.

From Fig. 4, student cumulative scores are approximately the same in both groups. A mixed effects model [32] is used with modality, type, semester, and instructor as random factors (effects). A mixed model fits a fixed effect (group: control vs. treatment) and the differences due to the random factors fitted as random effects. Small variations estimated for the random factors show that they do not influence the fixed effect meant to assess the difference between control and treatment effects. Any effect that cannot be explained by these fixed and random factors is accounted for in the residuals. Model estimates for standard deviations

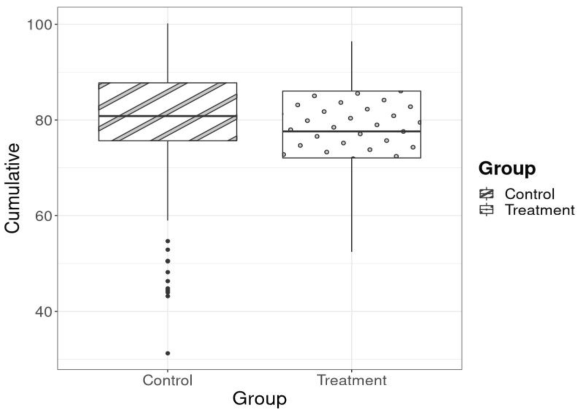

Fig. 4. Comparison of cumulative scores between the two groups.

showed that there is no variation in student cumulative scores based on instructors.

The control and treatment groups took three exams, quizzes, homework, and design projects over the course of a semester. While some instructors changed the assignments without affecting assessments and learning outcomes, the estimated deviations for the instructor factor are insignificant and the cumulative score is analyzed using Semester (Spring/Summer), Modality (Solo/Team) and Type (F2F/F2F-ASYNC/SYNC) as they show variability based on estimated deviations.

4.4 Comparison of Control and Treatment Groups Across Semesters

Significance testing is performed using a Mann-Whitney test to compare scores from the two groups to determine any effect due to Semester in which the courses were taught. From Fig. 5, the cumulative score median for treatment is smaller than control in Spring. The effect is reversed in Summer.

Fig. 5 shows that there is almost no variation in median cumulative scores (and their distributions) due to semesters in the control group. However, with treatment group, the median cumulative score is higher during Summer. Comparing median cumulative scores between semesters showed significant differences. Also, the difference in medians (per Mann-Whitney test) is significant in Spring (p-value $\approx$ 0.0015) and (p-value $\approx$ 0.0426) Summer semesters. While the difference in medians is significant at a 0.05 significance level, we must be cautious in concluding significance for Summer as the p-value is close to the significance level and requires further investigation.

4.5 Comparison of Control and Treatment Groups using Course Delivery Type (Instruction)

The cumulative scores are compared based on course delivery type/instruction. F2F-ASYNC delivery was conducted only once in Spring 2020

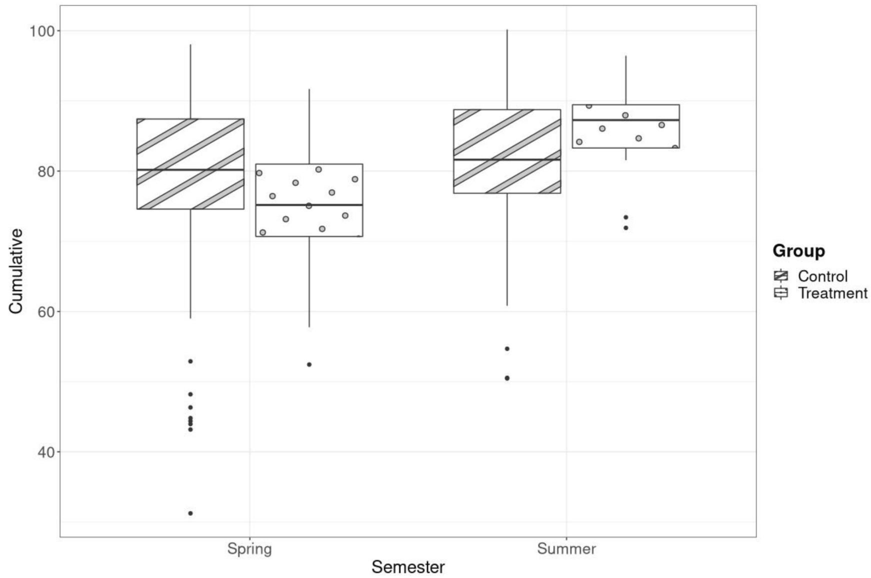

Fig. 5. Comparison of cumulative scores across semesters.

and was excluded from analyses. From Fig. 6, the control group does not show variations in the cumulative scores. However, differences can be seen in the treatment group.

The treatment group showed a greater median cumulative score in F2F and a lesser score in SYNC as seen in Fig. 6. These differences, however, are significant only in the SYNC group.

Since scores varied significantly across semesters, further testing is performed to compare the two groups within semesters. The p-values show that there is no significant difference in scores between the two groups when F2F (p-value $\approx$ 0.3022) is considered. The differences are primarily due to the SYNC delivery type (p-value $\approx$ 0.0045). This effect could partly be explained by noting the treatment group is present in Spring while the control is in Summer.

4.6 Comparison of Control and Treatment Groups using Modality

The cumulative scores based on modality (Solo/Team) are compared in this section. There are only two years, 2017 and 2019, when the course was team-taught and there is no treatment group when the course was team-taught in 2019. From Fig. 7, we see the two groups showing variations in the cumulative scores when the course was taught solo (p-value = 0.0141). Within a given semester, the significant differences are more pronounced in

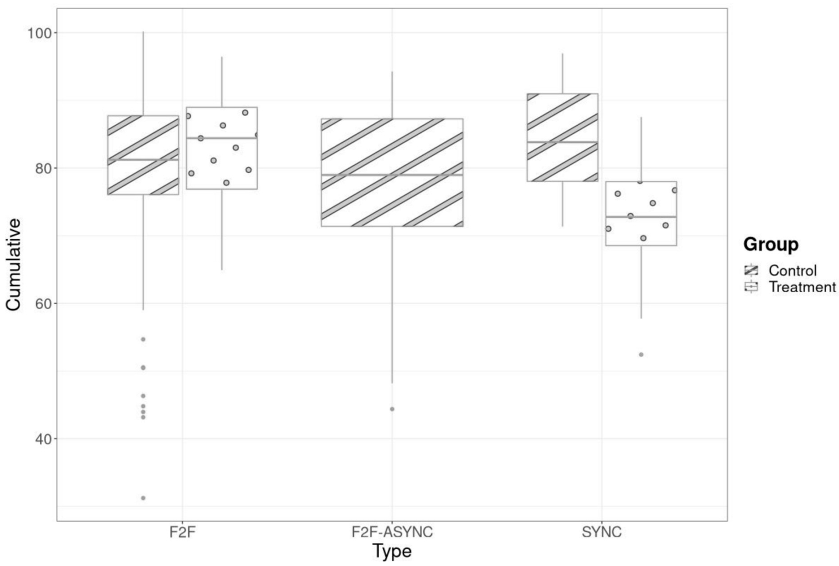

Fig. 6. Comparison of cumulative scores among different modes of instructional delivery.

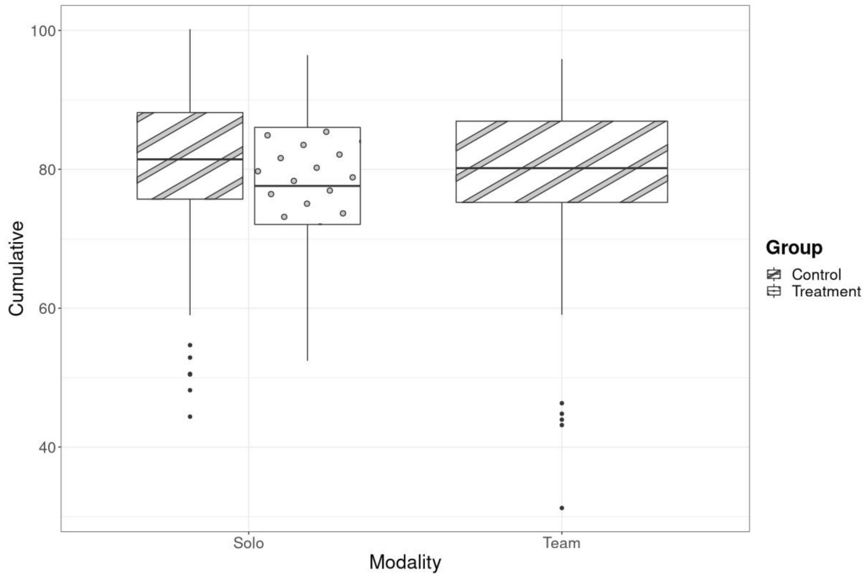

Fig. 7. Comparison of cumulative scores based on modality.

spring semester when compared to summer semester.

4.7 Comparing Cumulative Scores Before and After the Pandemic

The COVID-19 pandemic increased the prevalence of online teaching and learning due to mandatory shutdowns across the globe [1]. There were significant challenges, at least in the beginning with most institutions, in accommodating teaching in a virtual environment. We were curious about the effect of the pandemic on student performance. To that end, we analyzed the data by examining pre/post pandemic observations (cumulative scores). Treatment groups were not present prior to 2020. In terms of effect due to semester, there were no significant differences pre/post pandemic. However, there was a marked difference in cumulative scores between the two groups (control and treatment) especially in summer semester.

The cumulative scores are slightly higher in the summer semester when compared to spring; however, the differences are not statistically significant. After the pandemic, the differences in summer are significant. It should be noted that the summer semesters had an extra credit component of 2.5 points and 4.5 points in 2018 and 2021 (treatment). This could explain the observed significance. It is more likely that this effect will be absent when the scores are adjusted for the extra credit.

5. The Effect of MGHE Connect on Student Homework Scores

The control and treatment group took exams, homework, quizzes, and design projects over the course of a semester with some exceptions where quizzes/projects or both were removed. Course review showed that the instructor policies on whether to opt in for quizzes/projects or both did not change learning outcomes and aligned with institutional policy. The two groups are identical in every respect with the exception that the treatment group used MGHE Connect-based homework. Homework scores for the two groups (Control and Treatment) are compared to determine variability in the treatment effect due to homework assignments. There are two semesters (Summer 2018 and Summer 2021) where extra credit of 2.5 points and 4.5 points were given respectively. Since extra credit was used in two semesters, the homework scores for those were adjusted and standardized as shown in Fig. 8.

A mixed effects model is used with modality, delivery type, semester, and instructor as random effects like the earlier analyses with cumulative scores. The estimated variability due to the random effects on homework scores is shown in Table 4.

The treatment score for homework is higher than the control in Spring semester as seen in Fig. 8 (A, B). Thus, the standard deviations are computed for both scores with extra credit (not adjusted) and without extra credit (adjusted). Table 4 shows the standard deviations estimated for several factors influencing homework scores. These values are greater than those estimated for the overall cumulative scores. This is reasonable as the assessed treatment effect corresponds directly to homework scores. Instructors from different semesters used the treatment. These semesters had different modalities as well as delivery types. Hypothesis testing demon-

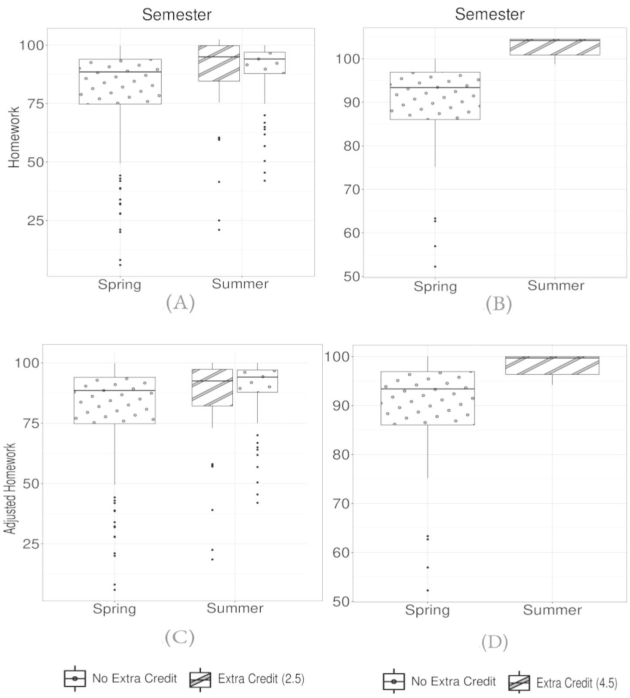

Fig. 8. Comparison of homework scores between the two groups. Scores were adjusted by 2.5 points and 4.5 points as one of the instructors offered extra credit for motivational purposes. The distribution of the adjusted homework scores (C, D) remains unchanged when compared to its counterparts (A, B). However, the extra credit will shift the scores upward as noted in (A) and (B).

strates that these deviations are statistically significant.

Differences are seen between the two groups as shown in Fig. 8. The sample size for the treatment group in summer (2021, with 4.5 points extra credit) is small (n = 16) resulting in a noticeably less variant box plot.

To provide a detailed comparison between these groups, the homework grade is further analyzed based on the three factors: semester, course delivery type, and modality.

5.1 Comparison of Control and Treatment Groups across Semesters

A Mann-Whitney test comparing homework scores between semesters showed significant differences (p-value < 0.0001) based on the observed data. The scores vary significantly across semesters between the two groups and treatment scores are higher than the control group. It can be noted that extra credit was offered in the treatment group during summer semesters. These effects also contribute to the observed differences in the homework scores as seen in Table 5. Mean and median of control and treatment groups across semesters.

5.2 Comparison by Course Delivery Type (Instruction)

The adjusted homework scores are analyzed based on the delivery type (F2F, F2F-ASYNC and SYNC). F2F-ASYNC was conducted only once in Spring 2020, and it did not have any treatment groups. Fig. 9 shows the comparison of control and treatment groups for the different delivery types.

The treatment group scores are higher in F2F group and lower in the SYNC group compared to

Table 4. Standard deviations of random effects in homework scores

Effect	Standard deviation (Not Adjusted)	Standard Deviation (Adjusted*)
Instructor	2.73	3.21
Semester (Spring/Summer)	2.45	2.21
Type (F2F/F2F-ASYNC/SYNC)	1.57	1.86
Modality (Solo/Team)	5.54	4.27
Residual (Unexplained)	17.06	17.02

* Extra credit points were excluded from the adjusted scores.

Table 5. Mean and median of control and treatment groups across semesters. Significance testing on medians using Mann-Whitney test on homework scores

Semester	Group	Mean	Median	Wilcoxon p-value
Spring	**Control**	80.5	88.6	0.0001
	Treatment	90.2	93.4	
Summer	**Control**	88.8 (87.8)*	94.5 (94.0)*	< 0.0001
	Treatment	103.0 (98.3)*	104.0 (99.7)*	

* Values in the parenthesis are mean and median after adjusting for extra credit.

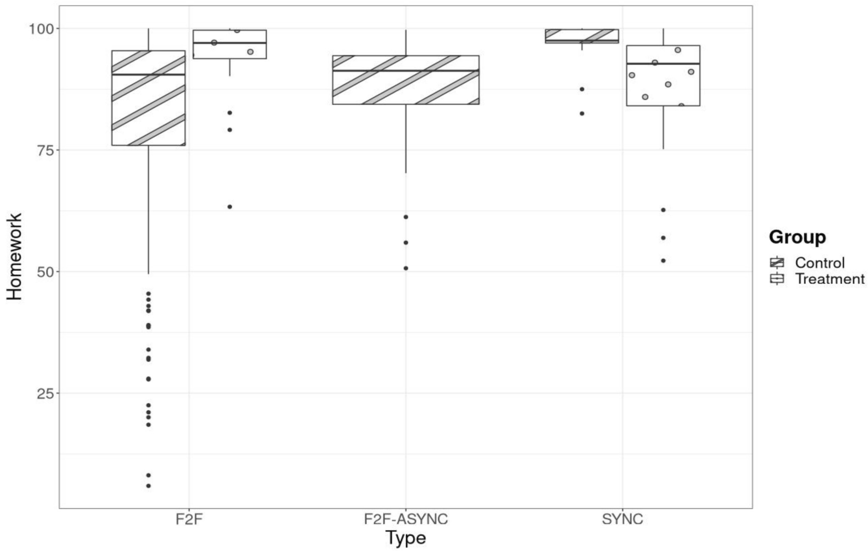

Fig. 9. Comparison of homework scores among different modes of instructional delivery.

Table 6. Mean and median of control and treatment groups among instruction delivery modes

Type	Group	Mean	Median	Wilcoxon p-value
F2F	**Control**	83.1 (82.5)*	90.8 (90.5)*	< 0.0001
	Treatment	96.8 (95)*	98.8 (97.0)*	
F2F-ASYNC	**Control**	87.1 (87.1)*	91.3 (91.3)*	
SYNC	**Control**	95.2 (96.5)*	97.5 (97.5)*	< 0.0001
	Treatment	88.4 (88.4)*	92.7 (92.7)*	

* Values in the parenthesis are mean and median after adjusting for extra credit.

the control group. Table 6 summarizes the mean and median for the groups across semesters. A Mann-Whitney test comparing homework scores between different course delivery types showed significant differences (p-value < 0.0001) based on the observed data.

Comparison for SYNC semesters has not been made as it was conducted only for the treatment group in Spring and for Control group in Summer. A Mann-Whitney test comparing homework scores of course delivery types for F2F across semesters showed significant differences in F2F type (p-value < 0.005) for both Spring as well as summer semesters.

Table 7. Mann-Whitney results comparing homework scores for semesters and type of instructional delivery

Type	Semester	Wilcoxon p-value
F2F	**Spring**	< 0.0001
	Summer	< 0.0001
SYNC	**Spring**	Treatment group in Spring and Control group in Summer
	Summer	

5.3 Comparison by Modality

The modality (Solo/Team) showed differences in homework scores (p-value = 0.00044 with extra credit and p-value = 0.00042 without extra credit). It can be seen from Fig. 10 that the treatment scores are higher than control in the Solo group. The Team group did not have any observations in the treatment group therefore excluded from the analysis.

The differences between the control and treatment group in the solo modality are statistically significant irrespective of the semester.

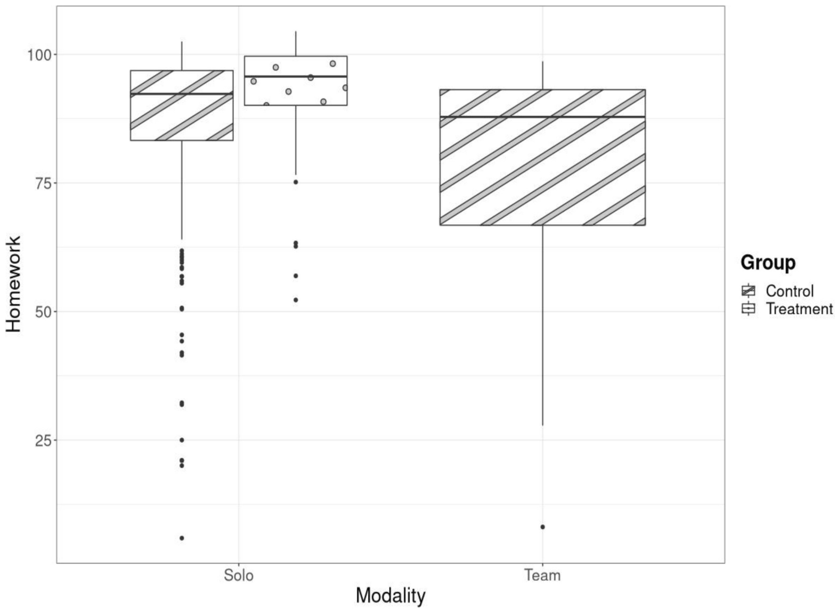

Fig. 10. Comparison of homework scores based on modality.

The analysis of MGHE Connect's effects on students' homework grades revealed that the treatment group outperformed the control group in F2F interactions. A Mann-Whitney test comparing the homework grades for different F2F course delivery methods across semesters revealed that there were significant variations in the F2F method for both the spring and summer semesters. Additionally, the Sole group's treatment scores are greater than those of the control group.

6. Student's Perception of MGHE Connect based MoM Online Homework

This study conducted a survey on the strengths and weakness of MGHE Connect to measure students' perceptions of and satisfaction with the platform and its setup. After Spring 2021 and 2022, students in the treatment group were asked to participate in a survey to ascertain their perceptions of the MGHE Connect. The survey involved two open-ended

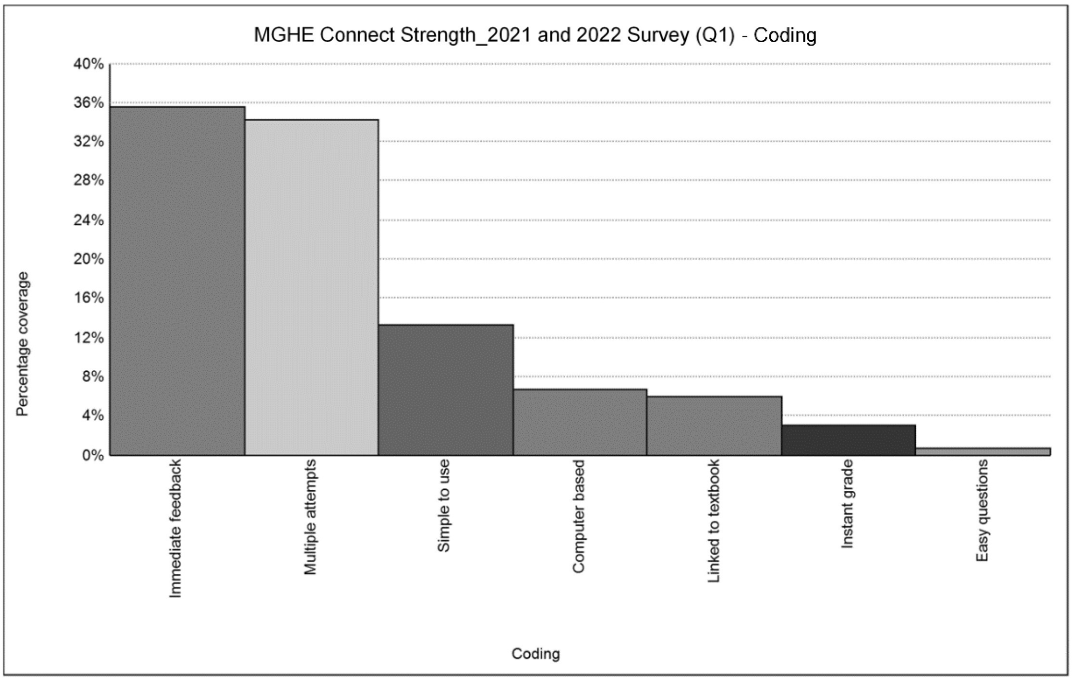

Fig. 11. The frequency of the responses on the strength of MGHE Connect based MoM online homework.

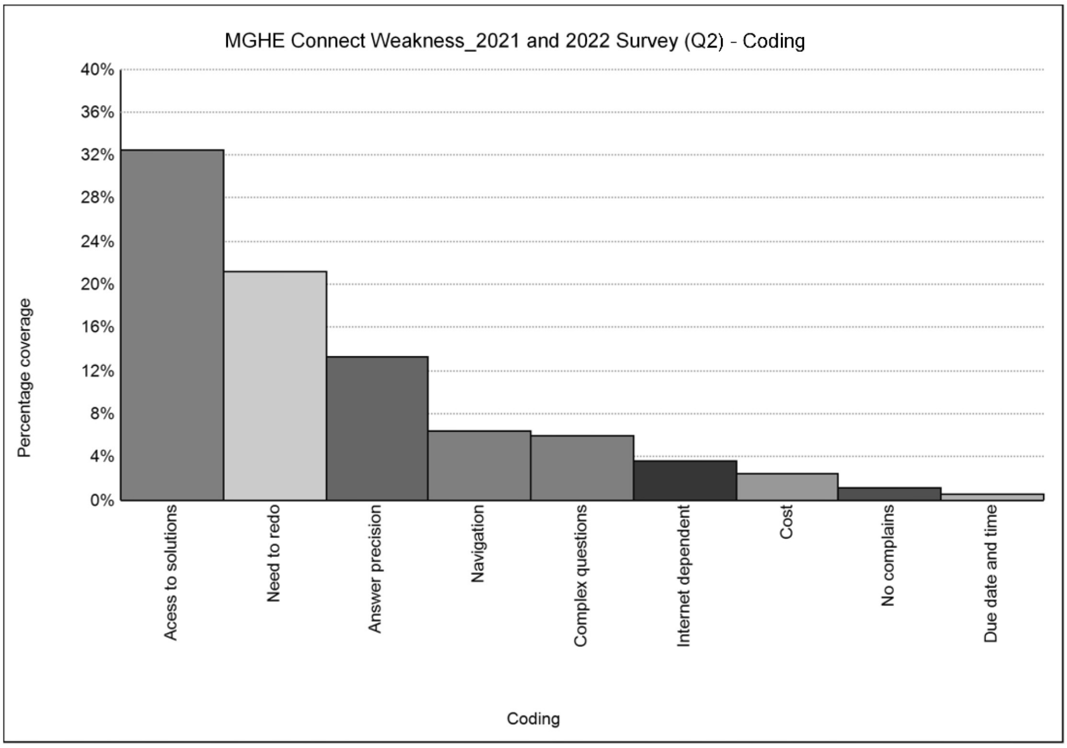

Fig. 12. The frequency of the responses on the weaknesses of MGHE Connect based MoM online homework.

questions. These includes: Q1–What did you like best about McGraw-Hill Connect (on-line homework)? and Q2–What did you like the least about McGraw-Hill Connect (on-line homework)? In Spring 2021 and 2022, a total of 45 students participated in the survey. This survey was not mandatory, and students were not rewarded/penalized for completing/not completing it. The software NVivo12 Plus © by QSR International [25] was used to code the survey response and calculate the frequency of codes. Figs. 11 and 12 show NVivo results on the strengths and weaknesses of MGHE Connect based MoM online homework respectively.

The study findings indicated that 69.93% of the Q1 responses mentioned that 'immediate feedback' and 'multiple attempts' are the two major strengths while 53.75% of Q2 responses named the 'lack of access to the step-by-step solutions' and 'need to redo – the need to complete the whole homework to check the answer key' as major weaknesses.

While it is challenging to quantifiably measure

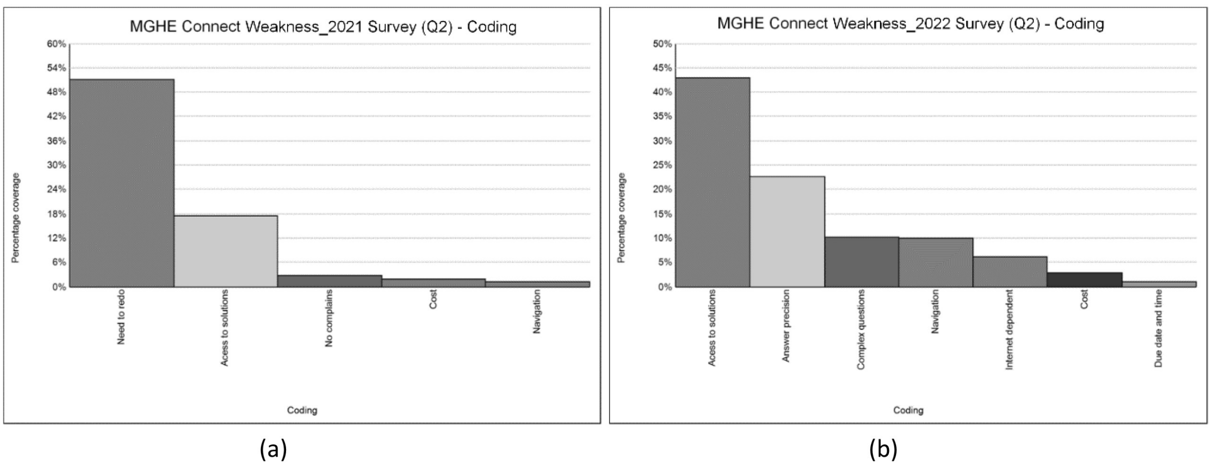

Fig. 13. The coding and frequency of the responses on the weaknesses of MGHE Connect based MoM online homework: (a) 2021 survey and (b) 2022 survey.

student satisfaction, based on the qualitative feedback from a weakness and strengths survey data, access to solution or ability to see answers right away are reported to be the major causes of student dissatisfaction. Fig. 13 shows the frequency and coding of the weaknesses mentioned in Spring 2021 and 2022 student survey.

The major weakness in Spring 2021 is that students need to complete all the homework questions to check if they made any mistake and redo their homework. However, after receiving student feedback in Spring 2021, the setup preferences for Spring 2022 were updated and students had access to answer key to redo each question on the fly. In Spring 2022, 'need to redo" was not mentioned but students identified "access to solution" (step-by-step-guide) as another weakness of the online homework assessment. Students' immediate access to both a step-by-step solution and a "homework study mode" after the online homework due date is crucial. These outcomes offer an insight into how homework should be set up to improve student satisfaction while maintaining academic performance.

7. Conclusions

This study focuses on implementing online assignments using McGraw Hill Connect as a way for increasing the mastery in a sophomore, Mechanics of Materials (MoM) course. The study used six years of data where conventional paper and pencil homework (10 course sections data) was adopted as a control group and compared with MGHE Connect-based online homework for one synchronous and one face-to-face MoM courses.

Hypotheses were tested using nonparametric Wilcoxon Rank Sum and Mann-Whitney U tests. The effect of McGraw Hill Connect online homework on the course homework scores, student letter grade, student passing grade and student cumulative score is analyzed. Comparison of homework scores incorporated different course modalities (solo/team instructors), delivery types (F2f/F2F-Async/Sync), semesters (Spring/Summer) and different instructors.

There were some significant differences between homework scores, showing higher median for the online homework, due to the multiple attempts. However, the study did not find evidence supporting the positive effect of McGraw Hill Connect on the student's overall academic performance (final letter grades).

The study conducted a Mann-Whitney U test and a two-sample t-test to examine the effects of Connect on the course letter grades, and homework and exam score, respectively. No statistically significant differences in student letter grades and total exam scores between the distinct groups were found. Although the results of exam scores for the treatment group were not statistically significantly higher than the control group, the results show that Connect-based homework in MoM classes provides students with benefits, including a greater pass rate. The result shows there are statistically significant differences in homework scores between the control and treatment groups. The progressing rate of the treatment group (96.2%) was higher than the progressing rate of the control group (84.0%). The higher homework scores contributed to an overall progressing rate. Students' immediate access to step-by-step solution and to a "homework study mode" after the homework due day are crucial. The results show that Connect-based homework could be used as an effective means of achieving one of the major goals in higher education – passing rates. The benefits of Connect on student performance documented in this study may well extend beyond MoM and into other disciplines. However, these suggestions are based on a limited data set on Connect-based intervention which is implemented only during the COVID-19 pandemic. This calls for further study to investigate whether pandemic-related school closures have changed student performance, specifically younger students, and students from families with low socioeconomic status, and whether the intervention gives a flexible choice for a student to improve their homework grades or improves student learning-knowledge. We leave this as an area for future research.

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