COSUMNES RIVER COLLEGE

OFFICE OF RESEARCH & EQUITY

Course Success in Asynchronous and Synchronous Online Modalities

Office of Research and Equity

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Executive Summary

Background

During the move to remote operations in Spring 2020, faculty adopted varied approaches to fully online instruction. Some instructors offered their courses with regularly scheduled online lectures (*synchronous* instruction), whereas others offered their courses with no regularly scheduled meetings (*asynchronous* instruction). The investigation described here sought to identify differences in course success as they relate to the aforementioned online modalities.

Method Overview

This investigation focused on course success rates in synchronous vs asynchronous courses. When evaluating the impact of course-level differences in success (e.g. instructional modes, format, etc.), there are numerous alternative explanations for why course success may differ from course to course (a.k.a., *confounding* factors). For example, comparing an asynchronous course in one subject to a synchronous course in another subject leaves curricular and instructional differences (unrelated to modality) as potential alternative explanations. Moreover, comparing sections of the same course (e.g. COMM 301) cannot rule out differences in instructional practice (unrelated to modality) as a confounding factor. Instructors may simply have instructional styles that explain any difference in course success.

In order to better address these potential confounds, this study focused on how success rates *changed* when an instructor switched online modalities from asynchronous to synchronous (or visa versa) for a particular course from fall 2021 into spring 2022.

Summary of Findings

1) A Bayesian statistical analysis revealed that changing to an asynchronous course had an average positive impact on course success. Holding demographic characteristics and term variables (e.g. the direction of the switch) constant, asynchronous courses had 1.22 times higher odds of success than synchronous courses (*Table 4*, page 7). For example, a course with a 63% success rate in synchronous modality would have about a 67.9% success rate with asynchronous. Only moderate certainty can be assigned to this estimate of impact. Given the data gathered for this study, there is an 87.4% chance that the average impact of switching to asynchronous format has higher success rates (*Figure 2*, page 7).
2) Although there is a modest chance that the *average* impact of switching to asynchronous is positive, there was variability in the change (*Figure 1*, page 5). This suggests that other unmeasured factors may be important to the impact of modality. Implementation factors should be considered.
3) Due to the complexity of the analysis (and the lack of technology with necessary computational power), student level characteristics were not included in the Bayesian statistical analysis. Descriptive evaluation of changes in course success rate are provided in *Table 5*. White, Asian, and Hispanic/Latinx students saw increases in course success in asynchronous formats. This was also true for students with income levels below poverty. Multi-race students exhibited a decline

in course success in asynchronous courses, but the average section level headcount for this group was very low.

Conclusions and Recommendations

This evaluation provides *tentative* evidence that instructors who switched to an asynchronous course format had higher course success on average. More thorough reflection on implementing a switch in format is required. Moreover, additional analysis should be conducted on equity gaps within asynchronous/synchronous courses.

Caveats and Limitations

As with all educational research, the evaluation described here is a pseudo-experimental design. Instructors were not randomly assigned to teach one or the other format, and students were not randomly assigned to each instructor. As such, it is impossible to completely rule out all confounding factors. For example, it is possible that instructors switched to asynchronous after reflecting on their effectiveness in either format. This would mean that the impact of asynchronous modality described here is the result of an interaction between instructional style and course format. In this case, the impact would not necessarily generalize to other instructors. Additionally, not all CACs were represented within the data. Agriculture, Food, and Natural Resources and Automotive and Design Technology did not have courses in the selected sample. Generalizability may be limited for these CACs.

Background and Methodology

Method

The present investigation sought to compare the course success of asynchronous online courses to synchronous online courses. Here *course success* is defined as the number of successful grades in a course (A, B, C, or P) divided by the total number of enrollments that received a transcript notation (including Ws and EWs). As with most educational research, an analysis comparing success in one course to success in another course is fraught with potential confounds. Two primary potential confounds relate to differences in instructional practice (that are unrelated to course modality; e.g. ability to explain difficult concepts, ways of conveying information, etc.) and curricular differences (course subject matter, assignments, etc.). For example, the simple comparison of an asynchronous online course (e.g. CRC 101) to another synchronous online course (e.g., CRCC 300) can have a myriad of confounds. The two instructors may have differing styles of communication/instruction *and* the course content could be vastly different. Any difference in course success could be attributed to the aforementioned differences and not necessarily the course modality.

A more apt approach would focus on comparing asynchronous vs. synchronous course modalities for the same instructor within the same course. Typically speaking, very few instructors teach the same course within different online modalities during a given term. It is less unusual for an instructor to switch modalities from term to term. As such, the present investigation identified 25 instructor-course combinations that switched from synchronous to asynchronous modality (or visa versa) from fall 2021 into spring 2022. In order to evaluate these data, a multi-level Bayesian model was applied. Further details and model convergence data are provided in the next sections.

Analyses, averages, and standard deviations were conducted with *section level* data. For example, if an instructor taught three sections of the previously identified course combinations, a success rate was calculated in each section. Then averages and analyses were the conducted using the section level course success rates. If that same instructor taught three sections in fall of a particular course, and their course success rates were 61%, 62%, and 63%, respectively, the average course success rate for that instructor-course combination would be 62%. This is not an ideal way of analyzing these data because each success rate may reflect a different sample size of students. However, due to the required complexity of the analysis, the Research and Equity Office lacked the data processing (computer processing power) to do analyses in a timely manner[1].

Course Characteristics

Records from offerings in the Los Rios Peoplsoft database identified 25 instructor-course combinations that switched online course modality from fall 2021 into spring 2022 (from asynchronous to synchronous or visa versa). One of these identified courses had a section with a 100% success rate. This course was excluded due to the particular requirements of the aforementioned statistical analysis. The

[1] Data would ideally be analyzed with a Bayesian multi-level model that includes the success of each enrollment (or lack thereof) within each instructor-course combination. As an illustration of this computational difficulty, one particular iteration of this model took nearly 9 hours to run and did not fully converge.

remaining 24 instructor-course combinations represent 80 enrollment sections and 2362 enrollments. Instructor-course combinations and sections counts can be found in *Table 1* below. Eight instructor-course combinations switched from asynchronous to synchronous, and 16 switched from synchronous to asynchronous. Among courses that switched from asynchronous to synchronous, 15 sections were asynchronous and 13 were synchronous. This is because instructors could teach a different number of enrollment sections for a particular instructor-course combination in fall and spring. For example, an instructor may have taught one enrollment section of CRC 101 in fall (asynchronously) and two enrollment sections of the same course in spring (synchronously). Additionally, ten of the instructor-course combinations were taken from faculty who taught both online modalities in fall and spring. These faculty switched to one or the other modality in Spring entirely. For these faculty, the course data from the opposite modality in fall was excepted. This helped simplify some computational aspects of the analysis.

Table 1. Instructor-course combinations and associated section counts.

	Number of Sections		
Change Type	**Asynchronous**	**Synchronous**	**Instructor-Course Combinations**
Asynchronous to Synchronous	15	13	8
Synchronous to Asynchronous	26	26	16
Total	**41**	**39**	**24**

Table 2 below describes the Career and Academic Community (CAC) of the 24 instructor-course combinations. A third of these courses were identified within the Social and Behavioral Sciences (SBS) CAC, and none were identified for Agriculture, Food, and Natural Resources (AFNR) or Automotive, Construction, and Design Technology (ACDT). The lack of representation from the latter may have something to do with the necessity of in-person offerings for the AFNR and ACDT CACs

Table 2. Instructor-course combinations by CAC.

Course CAC	N
Agriculture, Food, and Natural Resources	0
Arts, Media, and Entertainment	5
Automotive, Construction, and Design Technology	0
Business and Computer Science	2
English and Language Studies	2
Health and Human Services	4
Science, Mathematics, and Engineering	3
Social and Behavioral Sciences	8
Total	**24**

Table 3 presents data on average section level demographics amongst the synchronous and asynchronous courses selected for the study. On average, asynchronous sections had higher representation of Female, Low Income, and Asian students. Given the potential differences in

composition of online course modalities, demographics in *Table 3* were entered as control variables for all formal statistical analyses.

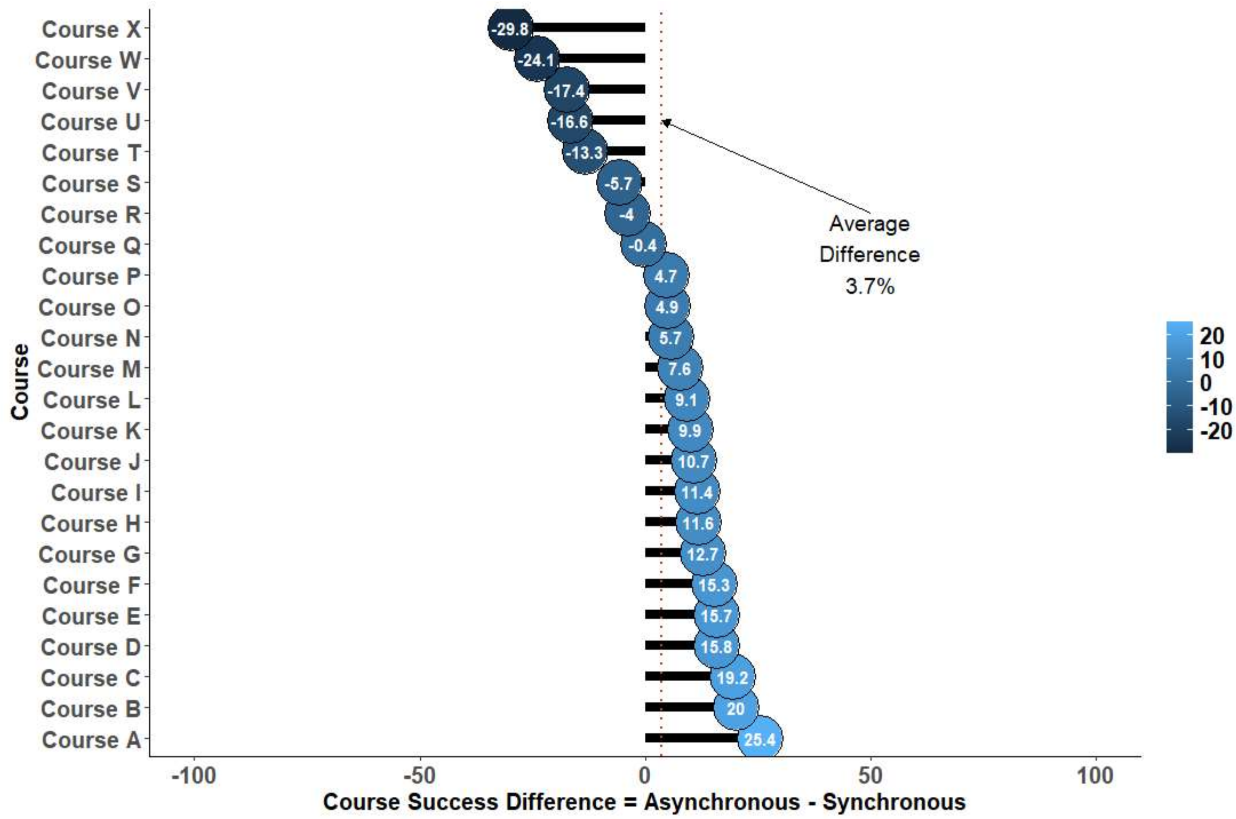
Table 3. Average Demographic Characteristics of Asynchronous vs. Synchronous Courses - Standard Deviation in Parentheses

Demographic Characteristic	Fully Online - Asynchronous	Fully Online - Synchronous	Overall
% Hispanic/Latinx	28.1% (8.9)	27.8% (9.6)	28% (9.2)
% Black/African American	7.2% (4.3)	9.6% (10)	8.4% (7.7)
% White	21.1% (9.8)	20.3% (9.6)	20.7% (9.7)
% API	34.3% (12.3)	31.1% (13.9)	32.7% (13.1)
% Female	57.2% (15.1)	48.9% (16.6)	53.2% (16.3)
% Low Income	50.9% (8.6)	47% (11.5)	49% (10.2)
Number of Sections	**41**	**39**	**80**

Findings and Analysis

The change in average course success rate (asynchronous minus synchronous) for each of the instructor-course combinations is depicted in *Figure 1* below. Most instructor course combinations exhibited higher course success rates for asynchronous courses. This equates to an *increase* in success for instructors switching to asynchronous courses from synchronous, and a *decrease* in success for instructors switching from synchronous to asynchronous.

Figure 1. Change in average course success rate for each instructor course combination.



Nevertheless, there is notable variability in the change in course success. A formal statistical model is required to determine how *certain* we should be changing to an asynchronous course results in a higher course success rate on average. A Bayesian statistical analysis can help determine the likelihood/probability that asynchronous courses have higher success rates given the data.

Model Specification

The data gathered for this investigation are "nested" in structure. That is, multiple enrollment sections (either synchronous or asynchronous) are nested within each instructor-course combination. This is similar to *repeated measures* designs where a participant will be assessed multiple times during a study (assessments are clustered in participants). Additionally, the data analyzed here are success rates which are not necessarily normally distributed. A Bayesian generalized hierarchical linear model (GHLM) was used to analyze these data in order to estimate certainty in the higher success rates of asynchronous courses.

Given the evaluation of rate data, the model used a *beta distribution* likelihood function and a *logit* link function. All priors for model coefficients and covariances were set to be *weakly informative* – meaning they are scaled to include an acceptable range of values as implied by the data. Prior distributions for coefficients were normally distributed around zero and scaled based on the standard deviation of the outcome variable (success rate).[2] The posterior distribution was sampled using Hamiltonian Monte Carlo. The sampling was split across four MCMC chains, each with 1000 warm-up steps and 1000 samples after warm-up. Warm-up samples were not included in the analysis.

In this case, demographic variables (percent African American, percent White, percent API, percent low income, percent Hispanic/Latinx, and percent female), asynchronous vs. asynchronous, order of the switch (e.g. from asynchronous to synchronous or synchronous to asynchronous), and term (fall or spring) were entered into the Bayesian GHLM. All of the aforementioned variables, aside from order of switch, were set to vary within each course-instructor combination. Intercepts were set to vary within course-instructor as well.

The inclusion of demographics data helps to rule out explanations related to differences in composition between asynchronous and synchronous courses. Additionally, allowing the effect of asynchronous vs. synchronous to vary within instructor course combination is essential. If the effect of switching to asynchronous (or synchronous) is extremely variable across courses and instructors, then we should be less certain about the impact of course modality.

Analysis and Results

The previously described model converged with no divergent samples. ESS, R-hat, MCSE and parameter estimates can be found in *Table 4* below. R-hat values for each parameter estimate were very close to 1 – suggesting that the posterior distribution was adequately sampled. Similarly, MCSE values were small for each parameter – suggesting that stable parameter estimates were gathered. That is, they are unlikely to vary much from sample to sample. Inspection of model predictions from posterior samples suggest that the model fits the data well (see Appendix).

The mean/average value for the posterior estimate of the effect of asynchronous modality was 0.221 – which evaluates to an odds ratio of 1.24. Put more simply, switching from synchronous to asynchronous course modality increases the odds of success by a factor 1.24. For example, if an instructor had a course success rate of 63%, a switch to asynchronous would result in a course success rate of 67.9%. It should nevertheless be noted that the 95% high-density interval (HDI) – a range including the most likely values of impact of asynchronous modality – includes negative values. This suggests that there is some possibility that the average impact of switching to asynchronous is negligible or negative – even though the most likely value (the average) suggests a positive impact.

Table 4. Representativeness, Accuracy, and Estimates of Model Parameters

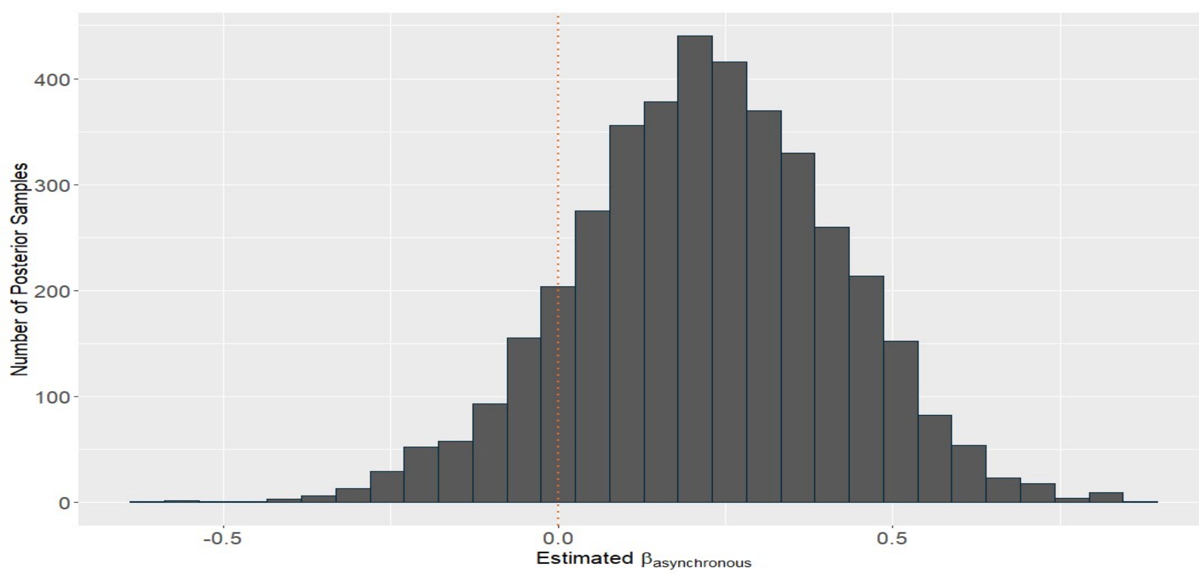
Parameter	ESS	Rhat	MCSE	Estimate	SD	95% HDI	
(Intercept)	2,334	1.000	0.022	0.426	1.071	-1.732	2.487
Term	3,438	1.001	0.003	-0.153	0.193	-0.529	0.222
Order of Switching: Synchronous to Asynchronous	2,718	1.002	0.006	0.331	0.329	-0.326	0.988
Asynchronous Modality	**3,189**	**1.000**	**0.003**	**0.221**	**0.197**	**-0.185**	**0.601**
Percent African American/Black	2,205	0.999	0.039	-1.806	1.835	-5.420	1.835

[2] Further, and more detailed description of how model priors were scaled and calculated can be found at: https://cran.r-project.org/web/packages/rstanarm/vignettes/priors.html. Goodrich B, Gabry J, Ali I, Brilleman S (2022). "rstanarm: Bayesian applied regression modeling via Stan." R package version 2.21.3, https://mc-stan.org/rstanarm/.

Percent White	2,389	1.000	0.028	-0.117	1.353	-2.790	2.618
Percent Asian	2,140	1.000	0.026	0.028	1.191	-2.304	2.391
Percent Low Income	4,636	0.999	0.013	0.266	0.914	-1.550	2.018
Percent Hispanic/Latinx	2,569	1.000	0.024	-0.891	1.241	-3.367	1.548
Percent Female	3,567	1.000	0.012	0.624	0.710	-0.775	1.995

To further examine the certainty of the estimate, the *posterior distribution* of the effect of asynchronous course modality was examined. The posterior distribution can be thought of as the range of probable values for the *average* effect of asynchronous course modality given the data gathered. This posterior can be found in *Figure 2* below. A smaller, but notable, region is below zero (below the orange dotted line) – suggesting that there is some (although small) probability that the average effect of changing to an asynchronous modality is not above zero. Further evaluation of the posterior distribution suggests that 12.6% of values are below or equal to zero. This equates to about a 12.6% chance that changing to asynchronous modality will have no or negative impact on average, compared to an 87.4% chance otherwise.

Figure 2. Posterior distribution of the effect of asynchronous course modality.



(standard deviations in parentheses). As can be observed in the table, it is difficult to determine clear trends for demographic groups. Hispanic/Latinx, Asian, and White students saw increased course success in asynchronous courses. Multi-Race students had a decline in course success in asynchronous courses – but the average section level headcount for this group was very small. Additionally, below poverty students had increased course success in asynchronous courses. A measure of certainty cannot be assigned to these average values due to the lack of a formal statistical analysis.

Table 5 - Average Course Success Rate and Average Change in Success

Demographic	Mean (SD) - Synchronous Courses	Mean (SD) - Asynchronous Courses	Change in Success	Mean Headcount Per Section
African American	68.5% (27.2)	67.3% (37.4)	-1.2% (29.3)	2
Asian	69.4% (26.8)	75.9% (24.2)	6.4% (32.5)	9

Filipino	77.5% (29.1)	65.8% (38.6)	-11.7% (53.1)	2
Hispanic/Latinx	57.3% (24.3)	61.8% (26.9)	4.5% (27.5)	7
Multi-Race	68.7% (28.3)	54.1% (31.2)	-14.6% (24.6)	2
Pacific Islander	80% (44.7)	73.3% (43.5)	-6.7% (72.3)	<1
Unknown Race/Ethnicity	44.8% (47.4)	85.7% (37.8)	41% (46.7)	<1
White	62.3% (20.3)	66.3% (29.7)	4% (32.4)	5
Female	60.3% (23.6)	65% (24.8)	4.7% (28.7)	16
Male	68.1% (20.6)	72% (20.7)	3.9% (14.9)	11
Unknown Gender	50% (50)	70% (44.7)	20% (27.4)	1
Non-Binary Gender	100% (0)	100% (0)	0% (0)	1
Below Poverty	58.5% (20.9)	64.6% (28)	6.1% (27.4)	8
Low	61.7% (25.7)	63.2% (28.7)	1.6% (31.7)	7
Middle and Above	70.3% (19.2)	69% (20.7)	-1.3% (16.8)	10
Unknown Income	65% (27.6)	67.5% (28.6)	2.5% (35.4)	3
Total	**64.6% (16.2)**	**67.2% (20.5)**	**3.7% (14.7)**	**27.5**

Conclusions and Recommendations

This evaluation provides *tentative* and moderate evidence that changing to an asynchronous course format may result in higher course success on average. Nevertheless, more thorough reflection on implementing a switch in format is required. Moreover, additional analysis should be conducted on equity gaps within asynchronous/synchronous courses.

Caveats and Limitations

As with all educational research, the evaluation described here is a pseudo-experimental design. Instructors were not randomly assigned to teach one or the other format, and students were not randomly assigned to each instructor. As such, it is impossible to completely rule out all confounding factors. For example, it is possible that instructors switched to asynchronous after reflecting on their effectiveness in either format. This would mean that the impact of asynchronous modality described here is the result of an interaction between instructional style and course format. In this case, the impact would not necessarily generalize to other instructors. Additionally, not all CACs were represented within the data. Agriculture, Food, and Natural Resources and Automotive and Design Technology did not have courses in the selected sample. Generalizability may be limited for these CACs.

Appendices

Course success rate predictions for each of the 24 instructor course combinations can be found in the figure below. The line in the center of each box (the median) represents the model prediction for the average course success of each course. Orange dots represent the actual course success for the course.

Bayesian estimation produces a sample of a "posterior distribution". This posterior distribution represents all the likely values (and unlikely) values of a given value based on the data. The box and whiskers plots provide a sense of the range of those posterior values for each course and instructor combination – that is the values that are likely (and unlikely) given the data. Here it is clear that the most likely values (the median line) are very close to the actual course success values.