Work in Progress: Rigorously Assessing the Anecdotal Evidence of Increased Student Persistence in an Active, Blended, and Collaborative Mechanical Engineering Environment

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WIP: Rigorously Assessing the Anecdotal Evidence of Increased Student Persistence in an Active, Blended, and Collaborative Mechanical Engineering Environment

Background

This work in progress describes an ongoing study of an active, blended, and collaborative (ABC) course environment used in a core mechanical engineering course. The development of this comprehensive course environment, designated *Freeform*, has built on the growing body of literature citing active learning[1], blended structures[2], and collaborative engagement[3] as positive influences on college and university science, technology, engineering, and math (STEM) outcomes. For the last six years, Basic Mechanics II (informally known as Dynamics), the core mechanical engineering course at Purdue University that focuses on dynamics and mechanical vibrations, has utilized in-class activities, highly watched problem-solving videos, and a collaborative blog space to realize an ABC environment.

Research Questions and Hypothesis

One key metric of course success, the rate of students who earn a D, F, or withdraw (DFW) from the course, has experienced near-constant improvements since *Freeform* and its ABC structures were introduced. This improvement has not yet been empirically assessed, though the decrease in the DFW rate is important because student persistence (defined as students' continuance to the next stage towards completion of their program) is a key challenge for many core engineering courses. In this study, the authors utilize rigorous cross-sectional regression methods to determine whether this drop in DFW rates can be directly attributed to increased implementation of ABC features. More specifically, we ask the following two research questions:

1. Is there significant improvement in the DFW rate after controlling for other key student characteristics likely to predict their success in Dynamics?
2. Is this DFW rate improvement most closely related to the gradual improvement in the *Freeform* environment or instructor characteristics as (s)he implements the course environment?

The authors hypothesize that the likelihood of DFW would drop in each year following the inception of *Freeform* as the new environment is institutionalized as the standard for ME 274 and as instructors add and enhance the ABC components of *Freeform* (RQ2). Moreover, as any given instructor becomes comfortable with the environment and more confident and strategic about their implementation of the course, the likelihood of student success would also increase. However, over the same time period for Dynamics at Purdue, each subsequent student cohort came in with higher levels of performance on proxy measures for prior knowledge. The authors, therefore, also test the hypothesis that there are other explanations for the variation in DFW rate besides mechanisms related to *Freeform*, such as prior performance (RQ1).

Research Design and Methods

We built a logistic regression model to predict individual-level DFW and determine whether the anecdotal drops in DFW that we observed can be attributed to the expansion of the ABC environment. More specifically, we predicted the likelihood of DFW based on the students' prior knowledge (e.g., grade in the prerequisite course), key demographics (gender), the semester and year they took Dynamics, their instructor, and their major.

Our analytic approach modeled the binary nature of our outcome of interest—likelihood of DFW for an individual student. To deal with this binary outcome, we constructed a logistic prediction for DFW probability based on three sets of factors:

$$P(Y = DFW \mid X = x) = \frac{e^{\beta_0+\beta_1 ENV+\beta_2 ACAD+\beta_3 DEMOG}}{1+e^{\beta_0+\beta_1 ENV+\beta_2 ACAD+\beta_3 DEMOG}},$$

where:

ENV is a vector of *Freeform* environment variables, including whether the instructor was involved in the development of *Freeform* and the year since the initial pilot,

ACAD is a vector of individual student academic factors, including major and grade in the prerequisite statics course,

DEMOG is a vector of individual student demographic factors, including race/ethnicity, international status, and gender.

Our dataset comprised 631 variables from student transcript files over the seven years since *Freeform* was first implemented. Our sampling frame included all students who enrolled in Dynamics *(N = 3601)*. Because of the high variability of the "off-term" student body, we focused on the students who took the "on-term" version of Dynamics each spring *(N = 2360, 7 spring semesters of data)*. Missing data were estimated via multiple imputation ($m = 5$), and the reported logistic regression coefficients and standard errors were estimated by combining the estimates found across the five imputed data sets[4, 5].

We estimated a standard logistic function (a regression of the log-odds ratio) and tested for year fixed effects to determine whether odds ratios for DFW consistently and significantly decreased over time ($H_0 : \beta_{ENV\text{-}year} = 0, H_A : \beta_{ENV\text{-}year} < 0$). We also tested for instructor effects, in particular for differences between instructors with different experience levels and philosophies. Initially, we estimated a fixed effect for each instructor. However, each instructor did not teach every semester. We, therefore, aggregated instructors into two groups to test for differences between the instructors who were involved in the design and development of *Freeform* and more independent instructors who implemented *Freeform* ($H_0 : \beta_{ENV\text{-}instr\text{-}dev} = 0, H_A : \beta_{ENV\text{-}instr\text{-}dev} \neq 0$). We added an interactive term (product of the instructor_developer dummy variable and the year variable) to determine if the effect of *Freeform* maturation and improvement over time (i.e., the year variable) on student success rates in ME 274 is moderated by having a *Freeform* developer as an instructor.

The other academic and demographic variables included in our logistic model (to date) are based on findings in literature regarding factors affecting college/university academic success[6, 7]. Based on the variables available in our data set, our logistic model also included cumulative (college) GPA, letter grade in Statics (a prerequisite for Dynamics), ethnicity, gender, and declared major. Declared major was included because anecdotal reports from Dynamics instructors indicated that students with majors other than Mechanical Engineering (ME) struggle with the class more than ME majors.

Descriptive Statistics and Initial Findings

We first demonstrate the aggregate trend of student success observed in spring Dynamics classes, which has motivated this ongoing study. Figure 1a shows the consistent downward trend in DFWs for the seven spring semesters of *Freeform*, a monotonic decrease except for the anomalous rise in the spring of 2015 (which will be further investigated in the future). Across the same time period, students enrolling in Dynamics recorded higher incoming SAT/ACT math scores (ρ= 0.12, p <0.001), higher cumulative college GPA (ρ= 0.06, p = 0.002), and higher Statics grades (ρ= 0.14, p <0.001) as illustrated in Figure 1b. The SAT/ACT scores were matched using 2009 concordance tables[8], and the improved performance in math scores, GPA, and Statics grades could partially explain the large drop in DFW rates[6]. Interestingly, and a note for future work, Statics has just begun to implement some aspects of the *Freeform* environment.

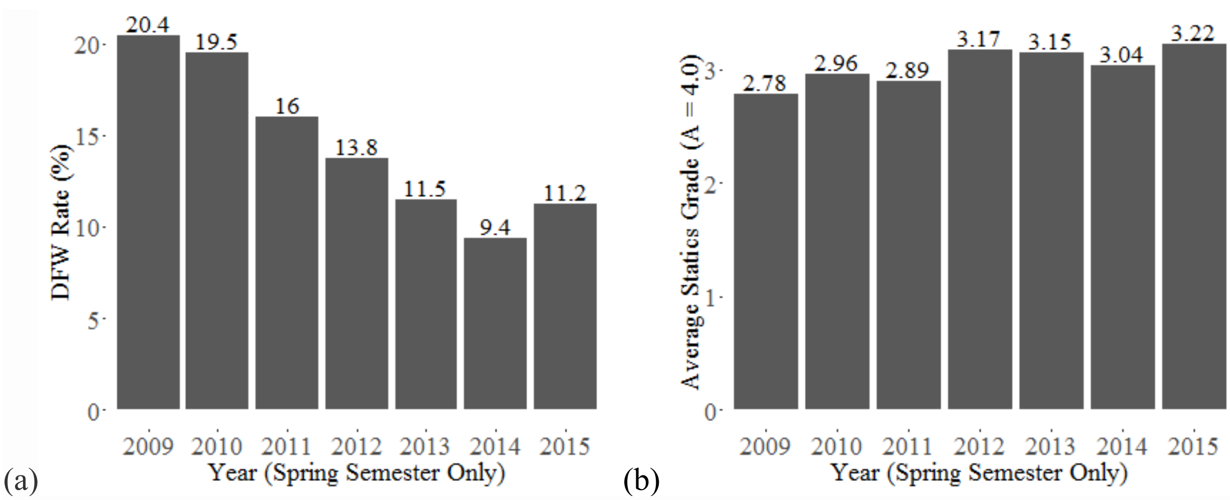

Figure 1. Since the inception of *Freeform*, (a) the DFW rate for Dynamics has decreased, and (b) Static grades have increased.

The odds ratios (ORs) as well as the p-values for the coefficient estimates of our full logistic model are listed in Table 1. The odds of DFW are defined as *the probability of DFW divided by the probability of passing* in Dynamics. Given the definition of the OR, an OR value less than 1 means a **decreased probability of failure (DFW).**

The initial results in Table 1 indicate that four variables are statistically significant at the α = 0.05 level in their influence on the odds of failure: year of enrollment, incoming GPA, major, and statics grades of C or lower (D- likely insignificant due to small sample size), and international status. Interestingly, the effect of being taught by a faculty member who developed the *Freeform* environment is not statically significant, and the interaction between instructor and year is also insignificant. In Figure 2, the predicted probabilities of DFW over each of the years since the pilot of the *Freeform* environment are shown for the two categories of instructors while holding all of the other variables equal. The 95% confidence interval bands around these predicted probabilities are also shown, which notably overlap.

Table 1. Odds ratios and p-values for coefficient estimates for full model

	Odds Ratio	**p-value**
Environment Variables of Interest		
Year (since *Freeform* pilot, spring "on-term" only)	0.87	0.021[a]
Instructor: Non-Developer of *Freeform*	Reference	
Instructor: Developer of *Freeform*	0.73	0.411
Interaction: Instructor_Developer*Year	0.94	0.460
Academic Controls		
GPA (at start of semester in which Dynamics taken)	0.075	< 0.001
Major: Mechanical Engineering	Reference	
Major: Non-Mechanical Engineering	2.06	< 0.001
Statics Grade: "D-"	0.89	0.907
Statics Grade: "D"	4.09	0.005
Statics Grade: "D+"	3.23	0.009
Statics Grade: "C-"	2.26	0.010
Statics Grade: "C"	2.30	0.001
Statics Grade: "C+"	1.27	0.356
Statics Grade: "B-"	1.09	0.769
Statics Grade: "B" (median statics grade for all students)	Reference	
Statics Grade: "B+"	0.66	0.195
Statics Grade: "A-"	0.52	0.220
Statics Grade: "A"	0.69	0.320
Demographic Controls (Self-Reported)		
Domestic Student, Ethnicity: White	Reference	
Domestic Student, Ethnicity: Asian	1.06	0.853
Domestic Student, Ethnicity: Black or African-American	1.51	0.452
Domestic Student, Ethnicity: Hispanic/Latino	1.16	0.726
Domestic Student, Ethnicity: Other	0.47	0.399
International Student	1.89	0.002
Gender: Male	Reference	
Gender: Female	0.96	0.877
(Intercept)	464.76	< 0.001

Note. The odds ratio (OR) is defined as the odds of DFW for a one unit increase in a given variable (holding all other variables constant) divided by the odds of the reference case. For categorical variables, the OR is calculated for each level of the variable (holding all other variables constant), using one level as the reference.

[a] *p*-value adjusted for a one-sided significance test

Conclusions, Implications, and Next Steps for Work in Progress

Our initial results indicate that a significant amount of the variance in DFW rates can be explained by factors besides the improvement in student preparedness (RQ1). These statistically significant explanatory factors include constructs from all three categories of variable sets: environment, academic, and demographic (RQ2). There is a significant year effect, as *Freeform* was institutionalized and improved. The effect of having an instructor who developed *Freeform* is insignificant, potentially indicating that the *Freeform* environment can be adopted and

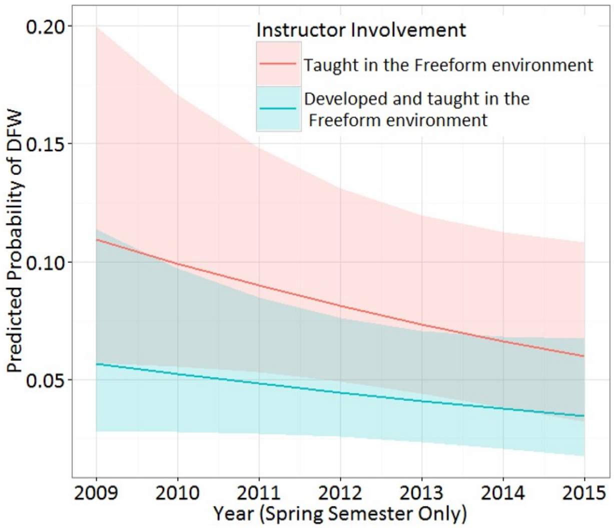

Figure 2. Predicted P(DFW | X) in years since *Freeform* pilot for different instructor groups (based on one data set with imputed missing values).

understood quickly by non-developer instructors. As prior research has suggested[6, 9], GPA is the variable with the largest effect on predicting student success (OR = 0.075, $p < 0.001$). The ORs also indicate that the students who earn a C or less in Statics, major in a degree other than ME, or are international students may need additional support structures to help them succeed in Dynamics. Ongoing work and additional information may help increase the precision of these estimates and our understanding of why the *Freeform* environment has succeeded in lowering student failure.

Next steps for this work include testing the persistence of variable effects in "off-term" semesters as well as investigating the post-Dynamics effects of engagement with this course. Further, we intend to include additional student characteristics (e.g., level of engagement with the *Freeform* components) and instructor characteristics (e.g., number of times taught in the *Freeform* environment). We anticipate results that will provide more rigorous, less biased, and efficient estimates for the individual- and class-level components that explain variance in DFW rates. These results would provide immediate implications for the next phase of our work as we prepare to assess the next on-term implementation of the course in Spring 2016. Our findings would also have long-term significance for other classes in mechanical engineering and related disciplines and for classes at other institutions that are considering implementing a comprehensive, *Freeform*-style learning environment.

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