Do Instructor and Course Evaluations in STEM Gateway Courses Predict STEM Retention?

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Importance of STEM for U.S. Economy

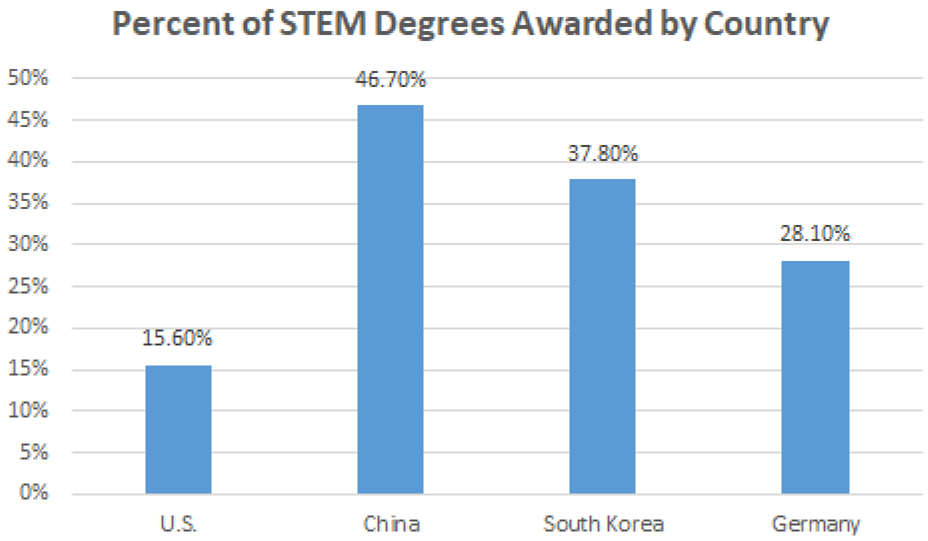
- Science, technology, engineering, and mathematics (STEM) are vital to the U.S. economy

- By 2025, 3.5 million new jobs in STEM will be created in the United States
  - These jobs will create a potential economic impact of $2.5 trillion

- Among employers, there is a perceived skills gap, as many of the technical skills required to fill STEM positions are not possessed by applicants
  - It is estimated that between 2018 and 2028 more than 2 million STEM jobs will go unfilled

U.S. Competitiveness in STEM Production

- While the number of degrees awarded in the STEM fields has increased modestly over time, only 15.6% of bachelor's degrees were awarded in these fields



STEM Retention

- 28% of bachelor's degree students and 20% of associate's degree students entered a STEM field (i.e., chose a STEM major) at some point within 6 years of entering postsecondary education
- Fewer than 40% of students who plan on majoring in STEM when entering college actually graduate with a STEM degree
- Increasing STEM retention by just 10% (up from 40%) would take care of three quarters of the shortfall needed to fill STEM jobs in the U.S.

Correlates of STEM Retention

- students' demographic characteristics
- high school academic preparation
- types of first institution enrolled
- taking lighter credit loads in STEM courses in the first year
- taking less challenging math courses in the first year
- performing poorly in STEM classes relative to non-STEM classes

Importance of STEM Retention at the University of Minnesota

- UMN is the flagship university of the state of Minnesota
- Each year, 61% of the 16,000 UMN graduates enter the state's workforce
- The University operates multiple STEM Research and Outreach Centers throughout the state enhancing the quality of agricultural production, renewable energy, water quality, wildlife management and more
  - In 2017, UMN generated $1.2 billion in research impact

Addressing STEM Retention at the University of Minnesota

- Our institution has been attentive to the importance of STEM retention by focusing on individual-level interventions

- Individual interventions have been established based on alerts triggered by factors (e.g., grades on multiple assignments) from our learning management system that are very low relative to others in their classes

- These interventions have been highly effective at our institution in increasing the number of STEM graduates by approximately 100% since 2007

Potential Importance of Reforms to Instruction and Course Design

- Focusing on reforms to instruction and course design in STEM gateway courses may be critical to improving students' persistence in STEM majors for two reasons

- First, prior research has demonstrated that instructional quality is positively related to STEM retention

- Second, STEM gateway courses serve as prerequisites for STEM majors
  - At UMN, we have observed disproportionately high DFWN rates in these courses, which not only reduces STEM retention, but also lowers a first year student's probability of graduating in 4 years by 20%

Study Rationale

- Our institution currently does not have a systematic or evidence-based understanding of the relationship between STEM gateway course characteristics, student evaluations of courses/instructors, and student outcomes such as retention in STEM programs
- Understanding these relationships provides an opportunity to identify potential retention interventions tied to the course and/or instructor

Study Objective

- Our objective was to evaluate the predictive relationship between instructor and course evaluations of STEM gateway courses (i.e., large, credit-bearing introductory courses that are often used as screens for STEM fields) and future student retention in STEM majors, after controlling for potentially confounding effects of student, course, and instructor characteristics

Research Questions

- To what extent are students' course and instructor evaluations predictive of student retention after controlling for individual student, instructor, and course characteristics?

- After controlling for other covariates, is student retention predicted by:
  - Student characteristics?
  - Instructor characteristics?
  - Course characteristics?

METHOD

Data

- Raw 2018/2019 data was subsetted to include only students who:
  - took more than one STEM course in the fall of 2018
  - took at least one course (in subject) fall 2019
  - were in a course with SRT response data
- In the final data set, there were 5,390 unique students,
  ...in 628 sections of 73 STEM courses
  ...with 424 unique primary course instructors.

Variables

- Student variables:
  - (somewhat limited)
  - Prior achievement
  - Courseload
- Instructor variables:
  - Race/ethnicity
  - Gender
  - Education
  - Time in job
  - Faculty status
- Course variables
  - SRT variables:
    - Mean course rating
    - Mean instructor rating
    - Workload
    - Required preparation
  - DFWN Rate
  - Enrollment total
  - Course format
  - Online/in-person

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Analysis

- The analysis could be broken down as follows:

1. Data exploration
   a. Descriptives for STEM retention
   b. Interrelationships between independent variables of interest
2. Fitting a baseline model
   a. Determining best hierarchical structure
3. Specifying a final model
   a. Entering independent variables into hierarchical structure
   b. Finding a convergent model

Model Considerations

- Hierarchical data
  - Could require Hierarchical Modeling
  - Students are nested in instructors
  - Instructors are nested in courses
  - Accounts for associations within each level

- Binary outcome
  - Retained vs. Not Retained
  - Requires logistic modeling

RESULTS

Data Exploration

STEM Retention Descriptives

- "Retained" - took and passed STEM courses fall 2018, and took at least one STEM course fall 2019.
- Of 5,390 students, 4,695 (87.11%) stayed in STEM*

Course	Sample Size	Retention Rate
CHEN: Material & Energy	127	99.2%
EE: Circuitry Lab	108	99.1%
EE: Digital System Design	107	98.1%
CSE: First Year Experience	917	97.7%

- 30 classes (41.1%) had 90% retention rate
  - Only 1 course had <50% retention rate (1.2%)
- Students who were retained took slightly more courses on average - 2.67 vs. 2.26
- ...and had slightly higher average ACT scores - 29 vs. 27

Variable Selection

- Goal: Create a model that predicts likelihood of retention for an individual based on course evaluations, while controlling for covariates

- To do this, we select for variables in the following categories:
  - Student variables
  - Instructor variables
  - Course variables

Student Characteristics

- Average student ACT score for all students was 28.55 (*SD* = 3.76)
  - The minimum ACT score was 11, and the maximum was 36
- The average student took 2.62 classes (*SD* = 0.83)
  - We set the minimum to 2 classes, in order to exclude students who are taking a STEM course to fulfill a major requirement
  - A few students took 6 courses - this is attributed to the fact that labs and discussion sections were treated as separate when both had distinct SRT data

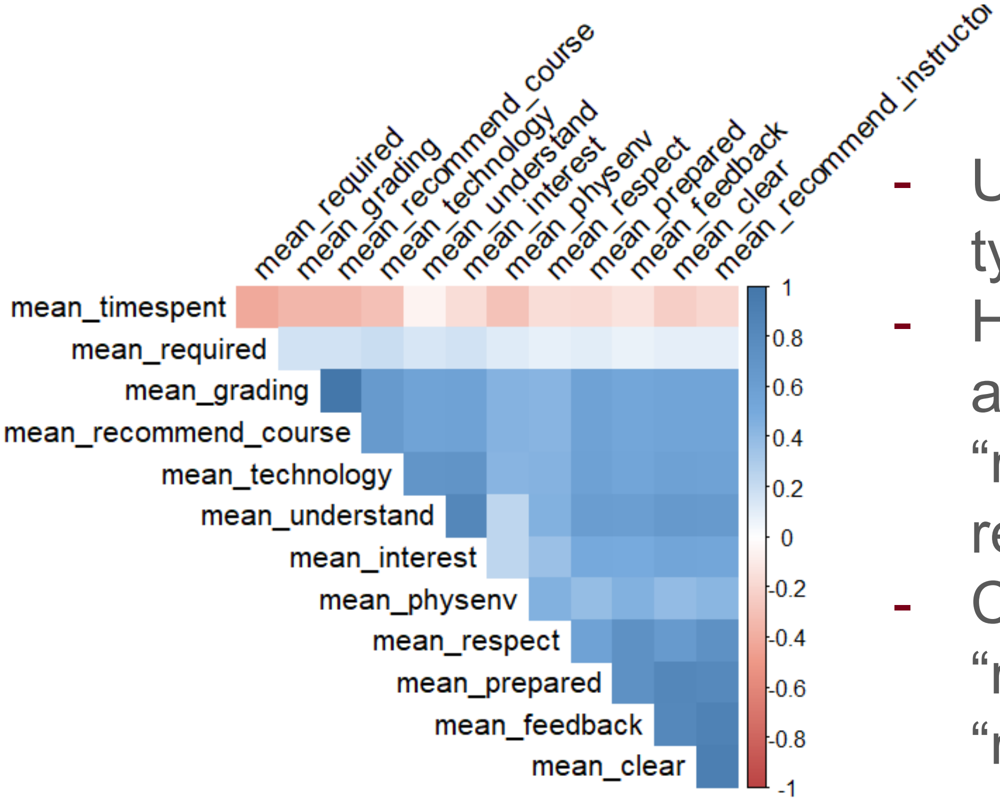
Course Characteristics

- 38 students in each section, on average
- 6.6% average DFWN rate overall
- On a 1-6 scale:
  - the average “mean_recommend_course” is 4.87
  - the average “mean_recommend_instructor” is 5.18
- On average, students spent 2.16 hours per week working outside of class
- 95.7% of courses are in person (4.3% online)
- ~56% are labs, 27% discussion, 16% lecture, and 1% independent study

Primary Instructor Characteristics

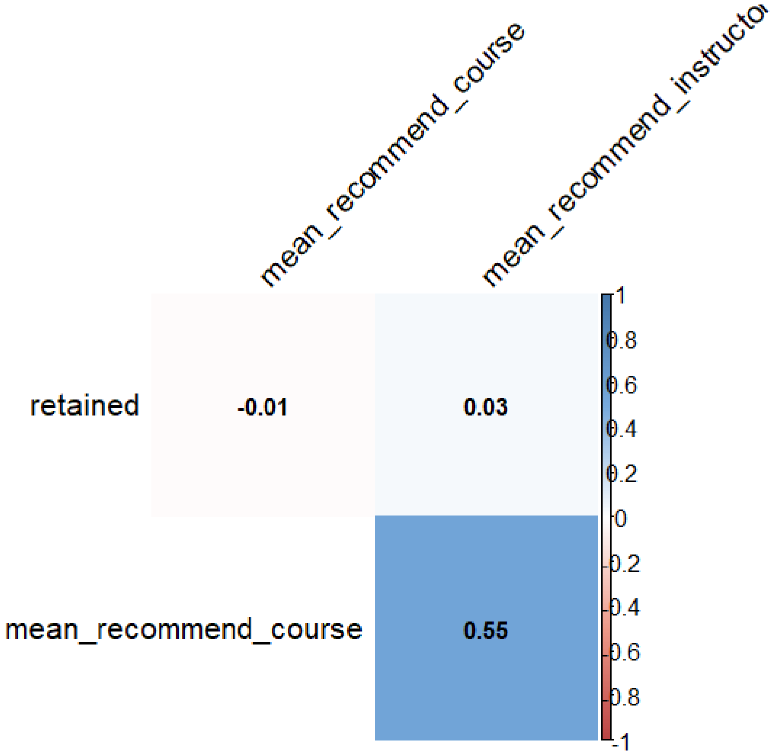
- Of the instructors with this information available:
  - 62% of instructors are white, 26% nonresident Alien (no race/ethnicity listed), and everyone else combined about 12% (n = 299)
  - 38% had Bachelor's degrees, 37% Master's, or 23% PhDs (n = 241)
  - 62% are graduate assistants, 21% have no faculty status, and 11% are either tenured or on the tenure track (n = 305)
  - 38% were female, 62% are male (n = 305)
  - they have worked at the University of Minnesota for 2 years and 8 months, on average (n = 305)

Data Exploration - SRT Variables



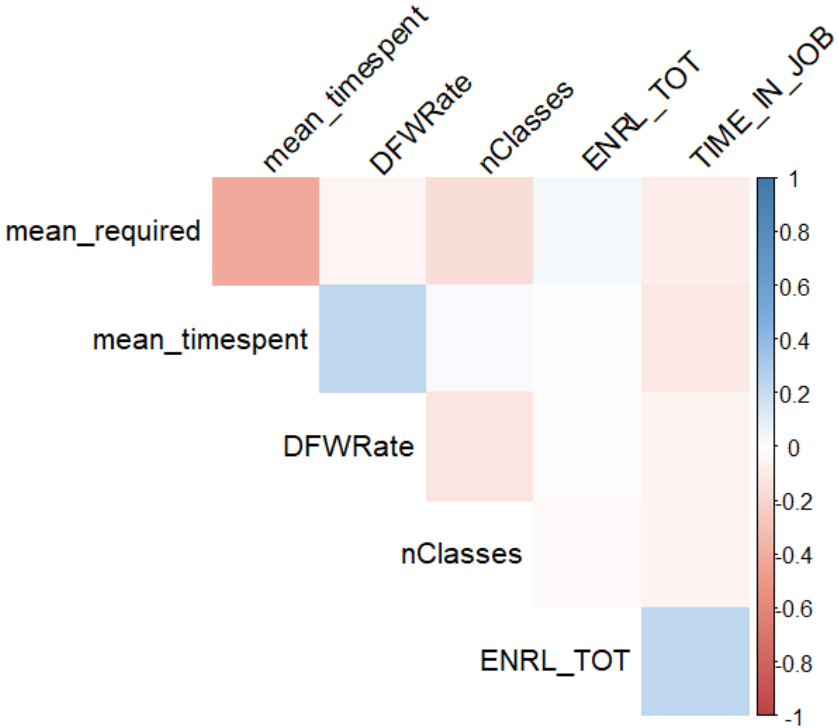
- UMN SRTs have 12 Likert-type items
- High degree of correlation among items, aside from “mean time spent”, and “mean required preparation”
- Collapsing other variables into “mean recommend course”, “mean recommend instructor”

Data Exploration - Retained/SRT Correlation



- Low correlation between main SRT variables and main outcome variable...
- This is why we control for other variables.

Data Exploration - Covariates



- Little correlation in other quantitative variables
- Each will be treated separately in the final model
- Of note: DFWN Rate and Workload

Baseline Model

Selecting a Baseline Model

$$\log\left(\frac{\pi_{ij}}{1-\pi_{ij}}\right) = \beta_0 + b_{0j}, b_{0j} \sim \mathcal{N}(0, \sigma_{b0}^2)$$

- Where π_{ij} is the probability student *i* in course *j* is retained, β_0 is the intercept, and b_{0j} is a random effect specific to course *j*.

Models	Parameters	AIC	BIC	logLik	deviance	χ^2	χ^2 Df	*p*
Linear	1	12974	12982	-6485.9	12972			
2-Level: S:C	2	12122	12138	-6058.9	12118	853.88	1	<.0001
3-Level: S:I:C	3	12124	12147	-6058.9	12118	0	1	0.9994

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Final Model

Selecting a Final Model (that Converges)

$$\log\left(\frac{\pi_{ij}}{1-\pi_{ij}}\right) = \beta_0+(\beta_{\text{instructor}}+\beta_{\text{course}})+(\beta_{\text{Student ACT}}+\beta_{\text{Student Courseload}})+(\beta_{\text{Instructor Education}}+\beta_{\text{Instructor Ethnicity}})+(\beta_{\text{Course DFWN}}+\beta_{\text{Course Workload}}+\beta_{\text{Course Format}}+\beta_{\text{Course Online}})+b_{0j},\ b_{0j} \sim \mathcal{N}(0, \sigma^2_{b0})$$

	Parameters	AIC	BIC	logLik	deviance	χ^2	χ^2 Df	p
Reduced (Final) Model	19	7262.9	7403.6	-3612.5	7224.9			
All Covariates	26	7273.7	7466.1	-3610.8	7221.7	3.2618	7	0.8598

Main SRT Estimates

To what extent are students' course and instructor evaluations predictive of student retention after controlling for individual student, instructor, and course characteristics?

- Based on significance, after accounting for other variables, neither are significant predictors of retention
- Similar models were fitted with the same covariates and only 1 SRT predictor each to account for multicollinearity between SRT variables, but the terms were still not significant and had worse model fit

	Estimate	Std. Error	*z*	*p*
Recommend Course	-0.02119	0.10805	-0.196	0.844491
Recommend Instructor	0.09235	0.09152	1.009	0.312986

Student Covariates

After controlling for other covariates, is student retention predicted by student characteristics?

- Both ACT score and course load were significant predictors of retention, after controlling for other factors
- A student with an ACT score of 29 (.45 more than average) is 24% more likely to be retained
- A student taking 3 courses (.38 courses more than the average) is 22% more likely to be retained

	Estimate	Std. Error	*z*	*p*
(ACT Score)/6	0.4734	0.04458	10.62	< .001***
# Classes	0.52366	0.04479	11.69	< .001***

Instructor Covariates

After controlling for other covariates, is student retention predicted by instructor characteristics?

- Compared to instructors with PhDs, students taught by professors with:
  - Professional degrees are 8.7% less likely to be retained
  - Bachelor's degrees are 32.1% more likely to be retained
  - Master's degrees 41.9% more likely to be retained

Degree type	Estimate	Std. Error	*z*	*p*
Bachelor's	0.27807	0.14855	1.872	0.06122*
Master's	0.35009	0.13232	2.646	0.008149**
Professional	-0.09062	0.28129	-0.322	0.747324

Course Covariates

After controlling for other covariates, is student retention predicted by course characteristics?

- Compared to Lectures, students in:
  - Discussion sections are 18.4% less likely to be retained
  - Lab sections are 47.2% less likely to be retained
- Students in online courses are 43.3% less likely to be retained over in person courses

	Estimate	Std. Error	z value	Pr(>|z|)
Discussion	-0.20293	0.18228	-1.113	0.265581
Laboratory	-0.63795	0.15412	-4.139	< .001***
Online	-0.57536	0.24941	-2.307	0.021063*

Course Covariates

After controlling for other covariates, is student retention predicted by course characteristics?

- Students in courses with a DFWN rate 1 percentage point above the grand mean (7.6%) are 86.3% less likely to be retained

- Students in courses that take 1 additional hour in outside class work time above the grand mean (3.16 hours) are 48.5% less likely to be retained

	Estimate	Std. Error	z value	Pr(>|z|)
DFWN Rate	-1.98689	0.61624	-3.224	0.001263**
Work load	0.39531	0.10555	3.745	0.00018***

DISCUSSION

Main Takeaways

- SRT course and instructor ratings not significant

- Retainment was associated with students who: (a) took more STEM courses and (b) had higher ACT scores

- Lower retention was associated for classes with
  - higher DFW have much lower retention rates
    - higher DFW for courses with higher workloads
  - Lab component
  - Online instruction

Limitations

- We were unable to match individual students (and their demographic characteristics) with their responses on course evaluations
  - Many classroom-based gateway courses use paper forms, which are completely anonymous
- Students who drop or withdraw from a class did not complete ratings
- Student evaluations were aggregated at the classroom and instructor level

Implications for SRT Evaluations

- Our results show the utility of linking student evaluation variables (e.g., reported workload) with student outcomes, which has implications for how UMN collects evaluation data
  - Currently, 60% of all courses still evaluations on paper (and an even higher rate with gateway courses)
  - Senior stakeholders had expressed interest in a more proactive push to transition a much larger proportion of evaluations online, which with the pandemic was the case last semester
  - Our findings may increase the likelihood of keeping evaluations online rather than permitting units to revert to paper if they wish

Potential Institutional Implications

- Share the results with senior stakeholders to discuss potential:
  – professional development initiatives for instructors of STEM gateway courses with low DFW rates
  – course design characteristics that can be implemented to improve student learning in online STEM gateway courses
  – additional supports for students who are enrolled in a STEM gateway course with prior low DFW rates, particularly for students with low ACT scores or those take few STEM courses

- If such interventions were implemented, student evaluations could be used as one important outcome measure

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