Trajectories and Influencing Factors of Student Confidence Across a Semester

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Abstract—**This Research Full Paper presents the results of a longitudinal study about confidence and academic performance conducted at a large, R1, university over the course of a semester. We surveyed male (N = 226) and female (N = 67) students six times throughout the course of the semester and once after final grades were released. Each time, we asked students four questions designed to gauge students' overall confidence.**

Using a modified latent growth curve analysis, we found distinctively different patterns in confidence trajectories between students in CS-1, CS-2, CS-3, and CS-4; the four consecutive introductory courses. We found that students' confidence tended to show a significant decrease across all confidence variables for all four courses, though some courses showed a stronger decrease than others. We found a similar decline pattern for gender such that males initially reported higher confidence than females, but also showed a steeper decrease in confidence after receiving final grades. This declining trend was also predicted by grades, such that individuals who earned higher grades at the end of the semester initially began the semester with higher confidence, but these individuals also showed a steeper decrease in confidence after receiving their final grades.

This work has implications for researchers interested in developing interventions designed to help students gain confidence when they need it most and for those interested in the relationship between confidence and retention.

I. Introduction

Current literature suggests that when students' confidence in their computing ability falls, their interest in computing falls, making students more likely to switch out of Computer Science (CS) related majors. Confidence, and more broadly optimism and self-efficacy (i.e., belief in one's self to accomplish a given task), are well-known predictors of individuals' abilities to perform on specific tasks [1]. An individual's level of confidence influences said individual's persistence at a task and partially determines future success at key points in his/her life [2]. One such key point is during an individual's college years [3]. Specifically, greater student confidence has been linked to greater academic success, and thus generally greater success in other aspects of life [4]. While understood to be an important factor in student success, student confidence does not remain static. That is, student confidence changes as students progress in their studies. Relatively little is known about the influencing factors of this change. It is then important to understand how a student's confidence changes across time, and what factors influence trajectories of student confidence as students progress through their courses.

A. Related works

Many factors have been shown to influence student confidence such as student gender, emotional intelligence, and goal orientation [5]–[7]. However, less attention has been paid to how academic markers such as Grade Point Average (GPA) and which courses students are enrolled in effect student confidence over time. As such, we sought to understand how gender, GPA, and course choice affected student confidence across a semester. Research suggests that much of females' students' decisions to persist in STEM majors is influenced by their confidence [8]–[15]. Students' confidence can change dramatically throughout their college career [16], [17]. Even when controlling for American College Testing (ACT, a standardized college entrance examination) scores, females in the computer science major have been found to be significantly less confident of their computing ability than their male peers [18]. This is commonly referred to as a "confidence gender gap" and is wider in STEM majors than other majors [10].

Along with gender, student confidence may also be a function of student academic success. Previous research has shown a positive relationship between GPA and student confidence/self-efficacy in college students [3], [19]. Students who have stronger beliefs in their ability to achieve academically tend to have higher GPAs and higher academic success in general than students who have weaker beliefs in their ability to achieve academically.

Although gender and academic success have been shown to be related to student confidence in multiple cross-sectional studies, fairly little is known about how gender and academic success affect student confidence across a semester. In the remainder of this paper, we present findings regarding how student confidence changes across a semester, as well as how student confidence trajectories are influenced by gender, academic success, and course.

II. Method

A. Study Design

Departmental differences could be a major factor in explaining differences in retention rates across universities [20],

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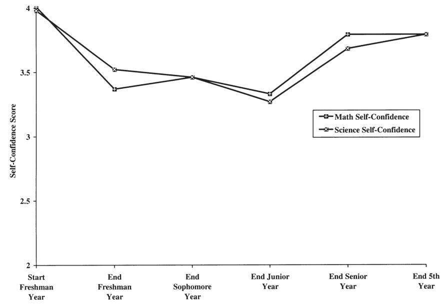

Fig. 1: "Main levels of self-confidence by year", figure reproduced from [16].

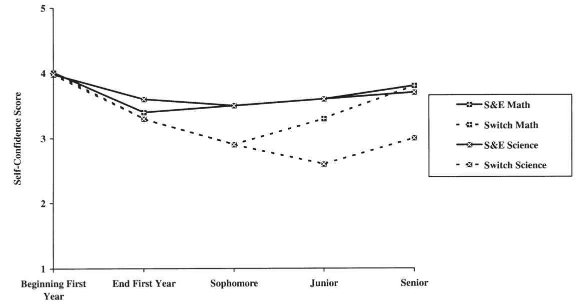

Fig. 2: "Academic self-confidence measures for women who remained in science and engineering vs. women who switched to another major.", figure reproduced from [16].

[21]. We therefore conducted a literature review to explore possible factors that impact retention rates across different CS departments [22].

While exploring factors that may increase retention, we read Brainard and Carlin's 1998 longitudinal study of female STEM students (collected over the course of six years at the University of Washington) [16]. Here we reproduce two figures from their study: in both Figures 1 and 2, show that freshmen initially lost self-confidence, but then slowly regained self-confidence over the following three years. Figure 2 shows a correlation between students loosing confidence and switching out of STEM.

Since then, other longitudinal studies have explored student confidence and self-efficacy. For example, researchers have used neural networks to predict students' success over time using 9 factors (including self-efficacy) defined by 166 items [23]. Other researchers have also asked introductory STEM students to self-report their proficiency technical tasks before asking them to perform tasks, and found that women underestimated their abilities while men overestimated theirs [24]. Researchers found in a multi-year, multi-institutional study of students in engineering degrees found that female students intention to persist in was positively and significantly related to five of the six subscales they used to measure self-efficacy [25].

We were curious whether students in courses with lower retention rates had lower self efficacy than students in courses with higher retention rates. We designed our study to continue exploring the impact of confidence on persistence and to explore the impact of courses, students' grades, and their gender on their confidence. In particular, we were interested in understanding whether we would see a drop in female students' confidence in CS-1 and CS-2 that correlates with high attrition rates of female students in these courses.

B. Participant Recruitment

Our study was conducted at a large, R1 university. On the day of the deadline for students to add and drop courses, we requested the email addresses for all 2467 students enrolled in courses taught by the CS department during the fall 2018 semester. All students were emailed and invited to participate in this study; if they consented to participate, they took the first survey and reported their major. Throughout the course of the semester, we emailed them an additional five times. In each of these six surveys, students were asked the following questions:

1) My experience in my CS course(s) in the past two weeks leads me to believe I would be successful in future computing activities.[1]
2) How likely is it that after graduation you will pursue a career that involves programming?[2]
3) I am better at CS than my current and previous grades in CS courses indicate.[3]
4) Are you better at your CS courses than your other courses at [this institution]?[4]

These questions were selected to measure students' confidence and their intent to persist with computing beyond the current semester.

After fall semester grades were released, we sent out a seventh and final survey. In addition to containing the four questions we had asked students during each previous survey, we also asked students to report their major, report their GPA, and report their gender, before reporting their grades for the CS course(s) they took during fall semester. We did not provide any extra credit or financial reward for the participants. The study was approved by the IRB[5].

C. Participants

We invited all students enrolled in a CS course during the fall semester to participate in this study. The number of participants and response rates are reported in table I. With data from this university's registrar office, we identified four courses with low retention rates: CS-1, CS-2, CS-3, and CS-4. At this university, these four courses are prerequisite courses for all but two CS courses; these courses cannot be taken concurrently and therefore take four semesters to complete.

[1] Seven point scale, from Strongly agree to Strongly disagree
[2] Seven point scale, from Extremely likely to Extremely unlikely
[3] Seven point scale, from Strongly agree to Strongly disagree
[4] Five point scale, from Definitely yes to Definitely no
[5] There was a clerical error where several of the initial respondents did not receive the proper consent document; this was remedied within an hour of the start of the study.

These courses are required for the CS minor and the CS major. Many other STEM majors at this university require one or more of these courses as well. We were particularly interested in the experience of both CS majors and non CS majors in introductory programming classes. We had responses from 84 participants in CS-1, 39 participants in CS-2, 31 participants enrolled in CS-3, 20 participants enrolled in CS-4, and 115 participants enrolled in other CS courses.

Although only 99 participants completed all seven surveys, we received at least five survey responses from 248 participants; on average each of the seven surveys received 276 responses. All missing data was considered missing at random and handled using full information maximum likelihood (FIML) [26].

TABLE I: Response rates across gender and major

Sex	Invited	Responded	Response Rate
Male	2073	226	10.9%
Female	394	67	17.0%
Major			
CS Majors	1081	155	14.3%
Other	1386	138	10.0%
Total	2467	293	11.9%

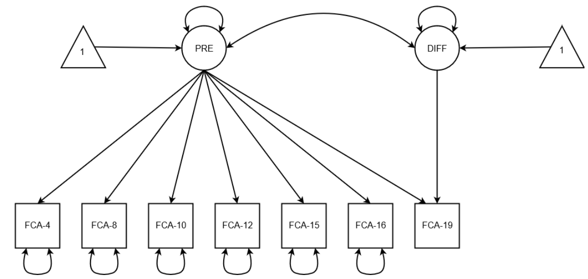

Fig. 3: Latent growth curve analysis (a form of structural equation model) is a multivariate method for analyzing longitudinal data. Latent growth curves are typically represented as a path diagram. This particular growth curve model is similar to a latent difference score model. As our data trends showed very little change before final grades, and then a large change after final grades, we modeled a system of equations to account for this longitudinal trend. Squares represent individual scores for a given variable at a given time, the PRE circle represents a latent distribution of average scores for individuals before final grades, the DIFF circle represents a latent distribution of average scores for individuals before final grades, triangles represent modeled means, single headed arrows represent regressions, and double headed arrows represent variances and covariances.

D. Analysis Method

We conducted a modified latent growth curve analysis, a type of structural equation model (SEM), to test each hypothesis. Latent growth curves are a popular statistical method for modeling longitudinal phenomenon [27], [28]. Latent growth curves allow for the estimation of both trajectories of intraindividual change in a given variable across time, as well as estimates of individual differences in intraindividual change across time. That is, latent growth curves estimate parameters associated with general group trends in change over time, while simultaneously estimating the degree to which these parameters vary by individual within a population. Additionally, as opposed to many other statistical methods, researchers using latent growth curves are able to obtain metrics relating how likely a particular data set was generated by a given model. These model fit statistics give researchers the ability to interpret not only parameter significance, but overall model fit as well. Model fit indices of CFI $> .9$, TLI $> .9$, RMSEA $< .08$, and SRMR $< .08$ are indicative of good fit [29]. As each of these metrics define model fit slightly differently and may not agree with one another, we have chosen to report each metric for all models.

Typically growth curve models take the form:

$$Y_{ij} = I + ST_j + u_{Ii} + u_{Si}T_j + \epsilon_{ij}, \tag{1}$$

$$COV(u_{Ii}, u_{Si}, \epsilon_{ij}) = \begin{bmatrix} \sigma^2_{u_I} & \sigma_{u_I u_S} & 0 \\ \sigma_{u_I u_S} & \sigma^2_{u_S} & 0 \\ 0 & 0 & \sigma^2_\epsilon \end{bmatrix}. \tag{2}$$

where Y_{ij} is the score for a variable of interest from person i at measurement occasion j, I is a general intercept term reflecting average scores at $T = 0$, S in a general slope term reflecting linear change in scores over time, u_{Ii} represents individual differences in intercept values by individual, u_{Si} represents individual differences in slope vales by individual, and ϵ_{ij} is an error term.

Typically, T is a linear process reflecting stable linear change as T increases (e.g., $T \in [0, 1, 2, \ldots, 9]$ for a process with 10 equally spaced time points). For our models, we fixed T such that $T \in [0, 0, 0, 0, 0, 0, 1]$, Figure 3. This is because a visual inspection of trends showed little intraindividual variation in slope across the first six measurement occasions. However at the 7^{th} measurement occasion (after students received final grades) there appeared to be rather drastic change. This constraint makes our model akin to a latent difference score model, but with multiple time points [30]. As such, instead of referring to intercept and slope of confidence, we will refer to average confidence values before students received final grades (PRE) vs. after final grades (POST). Additionally, as all predictor variables of interest were categorical in nature, we employed multiple-group model comparison techniques to assess group differences [31]. All missing data was considered missing at random and handled using full information maximum likelihood (FIML) [26].

III. RESULTS

At each measurement occasion, students were shown 4 items measuring student confidence (Cronbach's $\alpha = .62$). These items measured students' beliefs in future success ("My experience in my CS course(s) in the past two weeks leads me to believe I would be successful in future computing activities."), post graduation plans ("How likely is it that after graduation you will pursue a career that involves programming?", CS efficacy relative to each student's current grades ("I am better at CS than my current and previous grades in CS courses indicate."), and CS efficacy relative to each student's general education courses ("Are you better at your CS courses than your other courses at [this institution]?"). For each question, we created a multiple group modified latent growth curve models testing for effects of gender, grades (B- or higher Vs. C+ or below), and course (CS-1, CS-2, CS-3, or CS-4) on students' responses before receiving final grades (PRE), after reciving final grades (POST), and the difference between students responses before vs. after receiving final grades (DIFF). Students' responses are show in Figures 4-7.

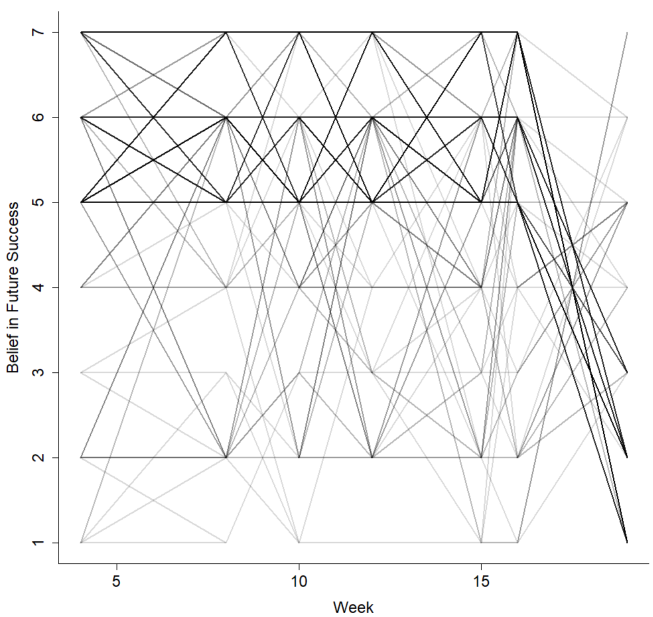

Fig. 4: Spaghetti plot of student responses to the question "My experience in my CS course(s) in the past two weeks leads me to believe I would be successful in future computing activities." Each line represents a single student's response over the course of the study. Darker lines indicate more students showing similar trajectories.

A. Gender

We found significant differences in the trajectories of belief in future success, post graduation plans, CS efficacy relative to each student's current grades, and CS efficacy relative to each student's general education courses between males and females, table II. On average males reported higher PRE scores on all of these items compared to women. After receiving final grades, males' scores significantly dropped an average of 3.49 points (SD = 2.23) for beliefs in future success, 4.45 points (SD = 2.85) for post graduation plans, 1.72 points (SD = 2.58) for CS efficacy relative to each student's current grades, and 1.51 points (SD = 2.06) for CS efficacy relative

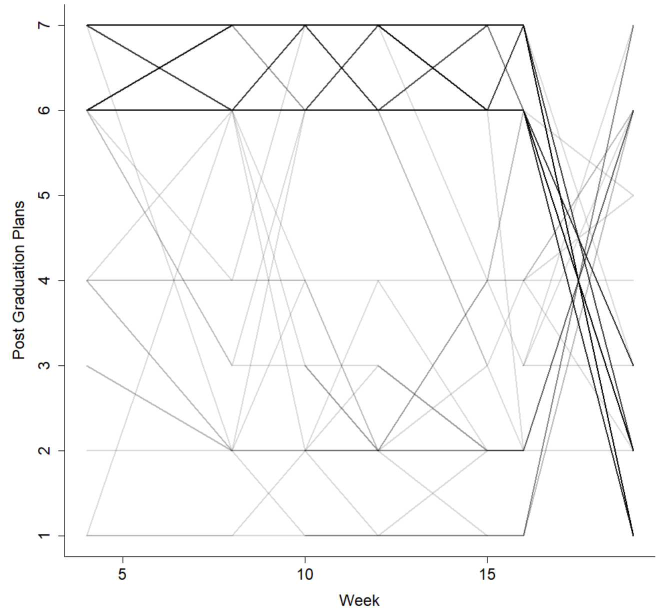

Fig. 5: Spaghetti plot of student responses to the question "How likely is it that after graduation you will pursue a career that involves programming?" Each line represents a single student's response over the course of the study. Darker lines indicate more students showing similar trajectories.

to each student's general education courses. Females' scores significantly dropped an average of 2.40 points (SD = 2.45) for beliefs in future success and 3.09 points (SD = 3.03) for post graduation plans. We also found significant negative covariances between PRE and POST scores for males and females for all models, indicating that the higher males' and females' PRE scores, the lower males' and females' POST scores.

B. Grades

We also found significant differences in the trajectories of belief in future success, post graduation plans, CS efficacy relative to each student's current grades, and CS efficacy relative to each student's general education courses between students with higher grades (B- or higher) Vs. students with lower grades (C+ or below), table III. On average students with higher grades reported higher PRES scores belief in future success, post graduation plans, and CS efficacy relative to each student's general education courses compared to students with lower grades. Students with lower grades however, on averaged scored higher than students with higher grades on PRE scores for CS efficacy relative to each student's current grades. After receiving final grades, students with higher grades' scores significantly dropped an average of 3.65 points (SD = 1.97) for beliefs in future success, 4.34 points (SD = 2.72) for post graduation plans, 1.23 points (SD = 2.61) for CS efficacy relative to each student's current grades, and 1.37 points (SD = 2.03) for CS efficacy relative to each student's

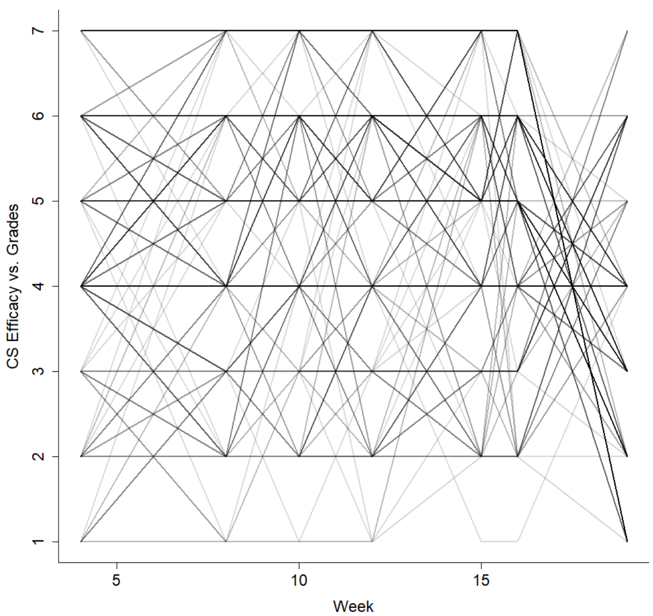

Fig. 6: Spaghetti plot of student responses to the question "I am better at CS than my current and previous grades in CS courses indicate." Each line represents a single student's response over the course of the study. Darker lines indicate more students showing similar trajectories.

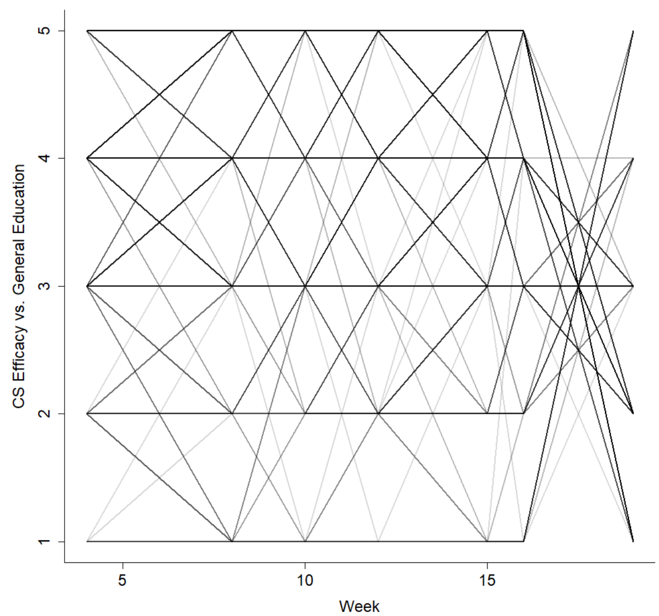

Fig. 7: Spaghetti plot of student responses to the question "Are you better at your CS courses than your other courses at [this institution]?" Each line represents a single student's response over the course of the study. Darker lines indicate more students showing similar trajectories.

TABLE II: Results Table for Confidence Variables by Gender

Outcome	Gender	Latent Scores	Estimate	z	p	Model Fit
FCA	Male	PRE	5.54	74.60	<.001*	CFI = .928
		POST - PRE	-3.49	-22.96	<.001*	TLI = .937
	Female	PRE	5.06	35.61	<.001*	RMSEA = .084
		POST - PRE	-2.40	-7.77	<.001*	SRMR = .014
PGP	Male	PRE	6.24	65.62	<.001*	CFI = .954
		POST - PRE	-4.45	-23.41	<.001*	TLI = .960
	Female	PRE	5.65	30.27	<.001*	RMSEA = .081
		POST - PRE	-3.09	-8.19	<.001*	SRMR = .080
BCG	Male	PRE	4.87	59.12	<.001*	CFI = .903
		POST - PRE	-1.72	-9.87	<.001*	TLI = .915
	Female	PRE	4.41	28.73	<.001*	RMSEA = .109
		POST - PRE	-0.50	-1.43	0.152	SRMR = .091
BCO	Male	PRE	3.74	53.90	<.001*	CFI = .928
		POST - PRE	-1.51	-10.93	<.001*	TLI = .937
	Female	PRE	2.99	23.12	<.001*	RMSEA = .129
		POST - PRE	0.12	0.46	0.643	SRMR = .075

Outcome	Group Comparison	Chisq diff	df	p
FCA	Male vs. Female	9.60	2	0.008*
PGP	Male vs. Female	10.35	2	0.006*
BCG	Male vs. Female	9.58	2	0.008*
BCO	Male vs. Female	27.91	2	<.001*

FCA = My experience in my CS course(s) in the past two weeks leads me to believe I would be successful in future computing activities.
PGP = How likely is it that after graduation you will pursue a career that involves programming?
BCG = I am better at CS than my current and previous grades in CS courses indicate.
BCO = Are you better at your CS courses than your other courses at [this institution]?
*$p < .05$

TABLE III: Results Table for Confidence Variables by Grades

Outcome	Grades	Latent Scores	Estimate	z	p	Model Fit
FCA	High	PRE	5.58	86.98	<.001*	CFI = .933
		POST - PRE	-3.65	-28.72	<.001*	TLI = .941
	Low	PRE	4.36	18.30	<.001*	RMSEA = .078
		POST - PRE	-0.39	-0.82	0.410	SRMR = .098
PGP	High	PRE	6.18	71.99	<.001*	CFI = .932
		POST - PRE	-4.34	-25.25	<.001*	TLI = .941
	Low	PRE	5.56	16.36	<.001*	RMSEA = .143
		POST - PRE	-2.68	-4.01	<.001*	SRMR = .080
BCG	High	PRE	4.70	61.71	<.001*	CFI = .883
		POST - PRE	-1.23	-7.08	<.001*	TLI = .898
	Low	PRE	5.36	22.08	<.001*	RMSEA = .119
		POST - PRE	-3.08	-6.89	<.001*	SRMR = .106
BCO	High	PRE	3.69	57.24	<.001*	CFI = .952
		POST - PRE	-1.37	-10.96	<.001*	TLI = .958
	Low	PRE	2.79	13.24	<.001*	RMSEA = .105
		POST - PRE	0.44	1.33	0.285	SRMR = .071

Outcome	Group Comparison	Chisq diff	df	p
FCA	High vs. Low	30.85	2	<.001*
PGP	High vs. Low	9.87	2	0.007*
BCG	High vs. Low	15.80	2	<.001*
BCO	High vs. Low	16.18	2	<.001*

FCA = My experience in my CS course(s) in the past two weeks leads me to believe I would be successful in future computing activities.
PGP = How likely is it that after graduation you will pursue a career that involves programming?
BCG = I am better at CS than my current and previous grades in CS courses indicate.
BCO = Are you better at your CS courses than your other courses at [this institution]?
*$p < .05$

general education courses. Students with lower grades' scores significantly dropped an average of 2.68 points (SD = 3.84) for post graduation plans, and 3.08 points (SD = 2.54) for CS efficacy relative to each student's current grades. Again, we also found significant negative covariances between PRE and POST scores for all models, indicating that the higher individuals' PRE scores, the lower individuals' POST scores.

C. Course

Finally, we found significant differences in the trajectories of belief in future success, CS efficacy relative to each student's current grades, and CS efficacy relative to each student's general education courses between students enrolled in different courses (CS-1, CS-2, CS-3, or CS-4), table IV. We were unable to run a model for students' post graduation plans as this model was unable to converge with the given data. Although no clear pattern exists between CS courses as did with our gender and grade models, there is still significant heterogeneity between students' PRE and POST scores for all courses. That is, different courses effected students' PRE and POST scores on all questions differently. However, for most cases, the pattern of change was similar across course even though the magnitude of change was not constant. We still observed a pattern for each measure of student confidence to drop significantly from PRE to POST. Again, we also found significant negative covariances between PRE and POST scores for all models.

TABLE IV: Results Table for Confidence Variables by Course

Outcome	Course	Latent Scores	Estimate	z	p	Model Fit
FCA	CS-1	PRE	5.27	36.51	$<.001$*	CFI = .768
		POST - PRE	-3.00	-9.72	$<.001$*	TLI = .797
	CS-2	PRE	5.70	35.43	$<.001$*	RMSEA = .172
		POST - PRE	-3.88	-13.67	$<.001$*	SRMR = .229
	CS-3	PRE	4.73	18.7	$<.001$*	
		POST - PRE	-1.37	-2.44	0.015*	
	CS-4	PRE	5.54	23.77	$<.001$*	
		POST - PRE	-3.44	-8.99	$<.001$*	
BCG	CS-1	PRE	4.49	32.65	$<.001$*	CFI = .769
		POST - PRE	-0.84	-2.86	0.004*	TLI = .798
	CS-2	PRE	4.79	25.57	$<.001$*	RMSEA = .170
		POST - PRE	-1.51	-3.91	$<.001$*	SRMR = .173
	CS-3	PRE	4.86	21.10	$<.001$*	
		POST - PRE	-1.96	-3.87	$<.001$*	
	CS-4	PRE	4.85	20.84	$<.001$*	
		POST - PRE	-1.80	-3.75	$<.001$*	
BCO	CS-1	PRE	3.61	32.87	$<.001$*	CFI = .900
		POST - PRE	-1.23	-5.23	$<.001$*	TLI = .913
	CS-2	PRE	3.59	20.60	$<.001$*	RMSEA = .147
		POST - PRE	-1.18	-3.56	$<.001$*	SRMR = .122
	CS-3	PRE	2.91	14.63	$<.001$*	
		POST - PRE	0.12	0.30	0.768	
	CS-4	PRE	3.57	14.82	$<.001$*	
		POST - PRE	-1.17	-2.34	0.019*	

Outcome	Group Comparison	Chisq diff	df	p
FCA	CS-1 vs. Others	14.27	4	.006*
	CS-2 vs. Others	9.63	4	.047*
	CS-3 vs. Others	4.82	4	.306
	CS-4 vs. Others	15.81	4	.003*
BCG	CS-1 vs. Others	2.31	4	.679
	CS-2 vs. Others	6.40	4	.171
	CS-3 vs. Others	3.65	4	.456
	CS-4 vs. Others	6.11	4	.191
BCO	CS-1 vs. Others	7.12	4	.130
	CS-2 vs. Others	8.94	4	.063
	CS-3 vs. Others	0.10	4	.999
	CS-4 vs. Others	9.09	4	.059

FCA = My experience in my CS course(s) in the past two weeks leads me to believe I would be successful in future computing activities.
BCG = I am better at CS than my current and previous grades in CS courses indicate.
BCO = Are you better at your CS courses than your other courses at [this institution]?
*$p < .05$

IV. Discussion

A. Findings

We began this study searching for a point, or points, in introductory courses where lower confidence could be causing lower retention rates. However, we did not find any significant trends in confidence that correlated with lower retention rates.

Student confidence does indeed change across a semester, however this change appears to be most apparent at the end a semester. Because different universities cover different material in their introductory CS courses and teach with different methods, different departments can certainly expect to see different patterns of confidence. However, our data suggests that the end of the semester may be when students confidence is the most volatile.

The strength of this volatility is at least partially explained by gender, GPA, and course. Females had lower average confidence across all of our metrics compared to males, but did not tend to drop as much as males once students received final grades. One probable explanation for this finding is a floor effect for student confidence. That is, student confidence may only be able to drop to a point. Once this point is reached, student confidence may not be able to drop further or may simply need stronger negative events to show a larger drop. Females drop less than males simply because females begin closer "floor" relative to males. It is also probable that students who fall below even this "confidence floor" choose to drop out of STEM majors as opposed remaining [32].

We found a similar "confidence floor" effect for student grades in which higher performing students showed a larger drop in confidence for most of our measures of student confidence, than lower performing students. This pattern in student confidence as a function of grades may be explained by the Dunning-Kruger effect [33]. The Dunning-Kruger effects is a well-established psychological phenomenon in which individuals with relatively low competence in a given subject appraise themselves as being highly competent, and individuals highly competent in a given subject appraise themselves as being less competent than they truly are. In the case of this study, students with higher grades may be interpreting final grades as confirmation of their own incompetence, while students with lower grades may be buffering their loss of confidence through positive self-appraisal.

Our findings for confidence as a function of course shows that the common trajectory of student confidence observed in this study remains fairly invariant across course. Although there may be heterogeneity for some measures of confidence between courses, for the most part models for each course were statistically indistinguishable from one another given our data. This gives evidence for a stable pattern of confidence regardless of course.

These findings have direct implication for individuals interested in developing interventions to increase retention in STEM courses. Assuming student confidence in their STEM skills is a key factor in retention, individuals interested in creating interventions should focus on having students set realistic goals and focus on mindfulness before finals, and focus on recovering student confidence after finals [34]. By behaving students set realistic goals and focus on mindfulness before finals, students may not show a steep of a decline in confidence after finals [35]. Realistic goals give students something to focus on and mindfulness training may allow students to buffer their loss of confidence after finals [36]. This may also help reduce student overconfidence in their own abilities. However, student confidence may still decrease after finals and thus be in need of recovery.

B. Limitations

Although informative regarding the change in confidence of students across a semester, our study does have a number of limitations which may limit the generalizability of our findings. One such limitation is that not all participants filled out the survey each week. It seems likely that the students who did not respond during a particular week did so because they were particularly busy or stressed. Thus, it is possible that unmeasured variables influenced response rates and drop out in our study. For the purposes of this study, all missing data was considered missing at random and handled using FIML [26].

Another possible limiting factor to this study is that individuals who responded to this survey did so voluntarily, as opposed to being truly randomly sampled from the population of students taking CS courses at this institution. This self-selection bias may mean that only individuals whose confidence was already being affected by their respective course work were those who chose to volunteer for this study [37]. While we believe this is unlikely, it is still a possible factor influencing our findings.

There are also obvious differences between these four classes. For example, in CS-1, many students find it easy to earn high grades on homework and projects, but struggle to earn high grades on the midterm and final. On the other hand, in CS-4, many students find the pace of the class challenging and earn lower grades on homeworks and projects. Grade perception for these four courses are likely to be different.

A final possible limitation of our study is that all measures of student confidence were collected as self-report type items. Self-report items are known to have a myriad of biases and error sources. Although the use of SEM as our analytic method helped to mitigate any effects of error sources, such biases as social desirability bias are not fully able to be controlled with statistical modeling alone [38], [39].

C. Future Directions

This work has implications for future interventions designed to help students gain confidence when they need it the most. Understanding these trends in students' confidence across a semester will be valuable for professors, faculty, and staff alike. As such, individuals interested in designing interventions based around improving student confidence for STEM majors should focus on mitigating student confidence loss after final grades have been released, as well as increasing the confidence of female students and students with lower grades.

Student confidence is considered to play a key role in student persistence in STEM majors [40]. It is them imperative that the significant decline in student confidence after receiving final grades be considered a target for intervention as this point may be where students are most venerable to dropout. Targeted interventions should cater differently to different student needs. This is evident by the differential effects of gender and grades on PRE and POST confidence scores. By finding means of buffering student confidence before final grades are released, and means of mitigating loss of student confidence after final grades are released, those interested in intervention may be able to greatly increase student persistence in STEM majors and improve quality of life for STEM students. This research could influence course design.

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