**ABSTRACT** 

Title of Document: PREDICTING AND MOTIVATING

ACHIEVEMENT IN SELF-PACED

LEARNING: A FORMATIVE DESIGN,

STUDY AND EVALUATION

Alina Goldman, Master of Science, 2014

Directed By: Dr. Benjamin Bederson, Professor, Department

of Computer Science, Human Computer

Interaction Lab

Student motivation and retention is a notorious problem in self-paced and mastery environments. This thesis uses a formative study conducted during a self-paced mastery course at the University of Maryland to understand how background variables affect achievement and to explore whether student success can be positively influenced by: a) receiving a course credit suggestion; b) setting goals and sticking to self-made deadlines; c) viewing aggregated and individual progress feedback; and d) receiving game-inspired incentives and rewards. After evaluating the effectiveness of the integrated design, the thesis suggests design changes to improve motivation.

# PREDICTING AND MOTIVATING ACHIEVEMENT IN SELF-PACED LEARNING: A FORMATIVE DESIGN, STUDY AND EVALUATION

By

#### ALINA GOLDMAN

Thesis submitted to the Faculty of the Graduate School of the University of Maryland, College Park, in partial fulfillment of the requirements for the degree of Master of Science 2014

Advisory Committee:

Dr. Benjamin Bederson, Chair

Dr. June Ahn

Dr. Tamara Clegg

© Copyright by Alina Goldman 2014

# Acknowledgements

First and foremost, I would like to thank my committee chair, Ben Bederson, for giving me the opportunity to design and implement this research. Thank you for mentoring my progress over the past year, and for being wonderfully patient with me. Thank you also for teaching me to approach failures like a kitten: starting each morning with a new plan and renewed determination.

I cannot thank my family enough for their supportive. Mom and dad, you always protested my getting a job because you didn't want it to interfere with schoolwork – I guess you didn't realize I was planning to be in school forever! Grandma and Grandpa, thank you for offering to make me Borsht so that I wouldn't starve as I wrote this thesis.

Thank you also to my future family. Ben, I love you more every day. Thanks for reviewing, commenting, critiquing, and supporting my research: you always challenge my assumptions and push me to be the best. Carol and Sam, thank you for your kindness, support, and for the occasional 44 pounds of peaches.

The HCIL has been a remarkable support group over the past two years. Special thanks to Tammy Clegg and June Ahn for being on my thesis committee, and reviewing and critiquing my work. Tammy, I cannot thank you enough for helping

me figure out how I wanted to frame the research. Thank you also to Tak Yeon Lee, who helped me refine my thesis ideas, kept reminding me to simplify my work, and always brought me coffee.

# Table of Contents

Acknowledgements	ii
Table of Contents	iv
List of Tables	vii
List of Figures	viii
Chapter 1: Introduction	
1.1 Motivation	
1.2 Design Approach and Methods	3
1.3 Research Contributions	6
Chapter 2: Theoretical Motivations for Design	7
2.1 Nontraditional Learning Environments	
2.1.1 Nontraditional environment success	
2.2 Self-Paced Learning	9
2.3 Cognitive Biases in Academic Achievement	10
2.3.1 Self-Assessment	
2.3.2 Workload Assessment	
2.3.3 Planning and Procrastination	
2.3.4 Progress Monitoring	
2.4 Predicting Achievement in Self-Paced Courses	
2.4.1 Grades and Individual Differences	
2.4.2 Social and Contextual Influencers	
2.4.3 Predictors in Post-secondary Education	
2.5 Improving Achievement through Motivation	
2.5.1 Godis and Deddines	
2.5.2 Ferjormance Monitoring and Feedback	
Chapter 3: Study Goals and Research Questions	22
3.1 Background Predictors of Achievement	
3.2 Credit Goal Suggestion	
3.3 Motivation Intervention	
3.3.1 Goals and Deadlines	
3.3.2 Feedback	
3.3.3 Behavioral Incentives	26
Chapter 4: Description of Course	
4.1 Goals	
4.2 Structure	
4.3 Description of Content	30

4.3.	1 Online	30
4.3.	2 In Class	31
Char	oter 5: Description of Study	32
	Overview	
5.1.		
5.1.	1 9 1	
5.1.		
5.2	Description of Study	37
5.2.	•	
5.2.	2	38
5.2.	3 Course Credit Suggestion	39
5.2.	4 Course Plan	44
5.2.	5 Progress Monitoring and Feedback	49
5.2.	6 Incentive Structures	60
5.2.	7 Post-credit Survey	70
Char	oter 6: Results	
_	Background Predictors of Achievement	
6.1.	e e	
	2 Results	
	Credit Goal Suggestion	
6.2.	00	
	Motivation Intervention	
6.3.		
6.3.		
6.3.		
6.3.		
6.3.	5 Behavioral Incentives	95
Char	oter 7: Discussion	97
_	Background Predictors of Achievement	
	Credit Suggestion	
	Motivation	
7.3.		
7.3.	2 Feedback	
7.3.	3 Incentive Structures	104
	Implementation Limitations	
	Study Limitations	
7.5.		
7.5.		
Char	oter 8: Conclusion	111
	Design Considerations and Suggestions	
8.1.	9	
8.1.	9	
8.1.		
	4 Incentive Structures	
	Future Work	
Char	oter 9: Appendices	101
LILA	/LCI /. /IP/CIIMICC3	

Appendix A: Motivation Study Introduction	121
Appendix B: Student Consent Form	133
Appendix C: Pre-Course Survey	140
Appendix D: Course Plan	167
Appendix E: Overview of Incentive Structures	170
Appendix F: Post-Credit Survey	172
Appendix G: Summary of Data and Coding Key	184
Bibliography	199

# List of Tables

Table 1: Benchmark Course Plan	45
Table 2: Benchmark Schedule for Week 2	47
Table 3: Badges and Point Values	62
Table 4: Badge Colors	64
Table 5: Prizes	66
Table 6: Descriptive Statistics for Course Preparedness	74
Table 7: Descriptive Statistics for Programming Languages	75
Table 8: Summary of design considerations and implemented suggestions	

# List of Figures

Figure 1: Study Design Goals	5
Figure 2: Course Recruitment Poster	28
Figure 3: Credit Pace Differences	29
Figure 4: In Class Activities	32
Figure 5: Method Flowchart	35
Figure 6: Credit suggestion based on standard deviation of composite scores	44
Figure 7: Mockup of Student Dashboard	50
Figure 8: Mockup of Progress Leaderboard	51
Figure 9: Access Report showing individual student progress	54
Figure 10: Anonymous progress chart displaying the last module finished in we	eek
12	56
Figure 11: Anonymous progress chart showing the last assignment finished in v	week
12	57
Figure 12: Implemented Progress Leaderboard	58
Figure 13: Ranking of students who completed the top number of assignments .	59
Figure 14: Mid-Semester Credit Completion Forecast	60
Figure 15: Student nametag displaying sticker badges and prizes	64
Figure 16: Raffling off a 3D printed object	68
Figure 17: Sample multiple regression model in R. Credits completed was regre	ssed
on average self-efficacy, when controlling for procrastination	73
Figure 18: Credits completed by the days it took students to complete the pre-co	ourse
Survey. Students that completed fewer credits took longer to complete the	
survey	
Figure 19: Days to Return survey by number of programming languages. Stude	
that knew fewer programming languages took less time to return the Pre-c	ourse
Survey.	
Figure 20: Credits completed by Self-Efficacy for different programming experi-	ence
groups. Self-efficacy is a predictor of credits completed for students with	
medium or high programming experience, but not for students with little of	or no
	79
Figure 21: Days to Submit Survey By Self-Efficacy. Students with higher self-eff	icacy
took longer to submit the pre-course survey.	80
Figure 22: The credit goal students set in the course plan, number of credits students	dents
completed at the end of the fall semester, and total credits completed at the	
of the spring semester. Overall, students completed fewer credits than the	ir
credit goal	87
Figure 23: Credits completed in the fall by Credits Pursued	
Figure 24: Credits completed by credits pursued	88
Figure 26: The number of assignments students viewed on Canvas during the fa	all
semester for credits 1 and 2. At the beginning of the semester, students view	wed

pages more frequently and consistently during the week than at the en	d of the
semester.	90
Figure 27: The last module students completed between weeks 4 and 14	91

# Chapter 1: Introduction

New forms of online education have aroused tension with traditional college education by offering students flexible and interactive ways of learning. Online courses allow students to review lecture content multiple times, actively learn material through segmented "bite-sized" portions, and dynamically discuss problems with instructors and students on online forums. These courses have motivated researchers to enhance campus offerings using these technology advances, in order to make higher education "more mobile, visually stimulating and interactive" [86].

Although online education offers new opportunities, traditional classrooms offer value that online environments struggle to reproduce: face-to-face classrooms stimulate peer learning and group dynamics, and create rapport between students and instructors. Peer and instructor networks often lead to out-of-class social and academic connections, such as study groups and research opportunities. Additionally, students in face-to-face courses are directly monitored by instructors, and often feel commitment and obligation to complete their work[5].

Paths to Computer Science, an introductory programming course taught in Fall 2013, introduced a hybrid self-paced mastery model that aimed to combine the best of online and traditional education. During the semester, students watched lecture videos in the Canvas

learning management system, and spent class time asking questions and working on homework and in-class activities. In this thesis, I report on the design, implementation, and evaluation of a semester long study to understand whether background variables predict successful completion of the *Paths* course, and a motivation implementation to understand how students can be motivated to successfully set and meet goals.

#### 1.1 Motivation

Behavioral psychology and education research show that students have trouble succeeding in self-paced courses. Students often suffer from the planning fallacy, and underestimate the amount of time it takes to complete a task [39]. In self-paced environments, students also poorly set personal goals and deadlines, further magnifying the planning fallacy bias [2].

Students also have trouble balancing education goals with professional and personal goals [31][88]. Balancing multiple goals often causes people to procrastinate [29][2]; students taking self-paced courses may thus push of coursework in favor of harder deadlines. In self-paced courses, students also suffer from anonymity [5], which may further influence them to procrastinate. In addition to procrastinating, students often overestimate their abilities, and remember negative feedback as positive [25].

The problems demonstrated in the literature suggested that students would have trouble completing the *Paths to Computer Science* course. This consequently motivated the research in this thesis: I was curious whether background variables could predict whether students succeeded, and whether a motivation intervention could help students set and successfully complete the course.

The research thus strove to understand:

- 1. What factors predict student success in self-paced learning
- 2. How to encourage students to set realistic goals
- 3. How to motivate students to work persistently to meet course goals

To implement the study, this thesis drew on literature from behavioral and cognitive psychology, education research and technology design. Cognitive psychology and education literature informed the structure of the pre-course survey and implementation of the credit suggestion, and behavioral psychology, education and design literature informed the structure and assessment of the motivation implementation. The goal of this research is to inform the design of self-paced, blended, and online learning environments.

# 1.2 Design Approach and Methods

Education literature suggests that setting reasonable goals is important in self-paced

learning [2]. An important design goal was thus to help students set meaningful and achievable course credit goals. Equally important to setting good goals is achieving them. A central goal of the study was also to motivate students to meet their personal goals.<sup>1</sup>

Motivation literature suggests that feedback can motivate students [44][53], increase confidence, persistence, and effort [36], and help instructors assess performance [44]. A design goal was to create meaningful feedback that would help students assess how they were performing relative to their goals and classmates, and help the instructor monitor student progress.

<sup>1</sup> In this research, students set personal credit goals (1, 2 or 3 credits) using the course plan, so success was measured by how well students met these goals.



Figure 1: Study Design Goals

Fogg [33] suggests that monitoring is also key to successful academic performance: people being observed tend to work harder toward their goals. A secondary goal was thus to use peer monitoring to motivate students. Like feedback and monitoring, behavioral incentives can also effectively motivate students to pursue their goals [93][33], however insubstantial incentives can demotivate students [60]. Consequently, a tertiary goal was to implement a system of meaningful incentives to help students stick to their goals.

The implementation consisted of a course credit suggestion, a course plan, anonymized and personal progress feedback, a leaderboard, and a system of badges, points, and prizes.

At the beginning of the semester, students filled out a pre-course survey, and were given a credit suggestion based on computer background, time and goal commitments, and self-

efficacy. Student then chose on a credit goal (1, 2 or 3 credits) and created a course plan, setting personal deadlines for modules in each of the credits they planned to pursue. During the semester, students received anonymous group and personal progress feedback, were ranked on a progress leaderboard, and received badges, points and prizes based on how well they stuck to their goals. After completing each credit, students filled out a post-credit survey that was used to adjust the motivation implementation to fit student needs.

#### 1.3 Research Contributions

The overarching contribution of this thesis is the design, implementation, and evaluation of a motivation study and intervention to understand whether background variables contribute to successful completion of the *Paths* course, and to understand what motivation interventions can help students successfully set and meet course goals. This thesis offers both summative and formative contributions. Towards the former, I quantitatively assess the background variables that contribute to student success, and evaluate the predictive and motivational capacity of the credit suggestion. I also qualitatively assess the success of the motivation interventions. Towards the later, I offer insight into how students set personal goals, and how they respond to peer motivation and behavioral incentives, and suggest design considerations to help students better set and meet goals.

Considerations must also be made about the formative and summative research findings.

This thesis used a synthesis of field research methods to observe student behavior and assess the success of the motivation intervention, however data was biased in favor of students that filled out the post-credit surveys, and actively participated in the study. The research also used survey data and course completion statistics to propose conjectures about the role of background variables in student achievement; further studies are needed to validate these findings.

# Chapter 2: Theoretical Motivations for Design

# 2.1 Nontraditional Learning Environments

Students often struggle with academic achievement. This have been observed most often in Science Technology, Engineering and Math (STEM) courses, where the number of students majoring in a STEM field declines by approximately 40% from freshman to senior year [96]. A report by the Institution of Engineering and Technology found that STEM courses suffer high dropout rates because of the perception that STEM disciplines are 'out of reach' for most students [45].

Online, mastery, self-paced, and blended learning environments have created new ways for students to learn. Online courses, particularly Mass Online Open Courses (MOOCs),

integrate online course materials with interactive user forums [14], promoting flexibility and active learning [36]; online models create deep engagement by breaking learning content into short chunks and actively testing comprehension through quizzes and problems [95].

Mastery, self-paced, and blended learning environments have likewise offered new ways for students to learn. Bloom [9] suggests that most students can master a course when they are given flexible time to learn material, when they are judged on performance (rather than on a normal curve), and when they are given formative assessments that uncover problems with course objectives. Complementary to mastery learning, self-paced environments allow students to work at their own pace, giving them the opportunity to personally determine how long to spend on course material. Rather than learning during in class lectures, blended environments focus on engaging students, and often use a 'flipped' classroom model; students learn course material at home in a dynamic learning environment, and spend class time actively interacting with the instructor [95].

#### 2.1.1 Nontraditional Environment Success

While online, self-paced, and blended learning environments offer students flexibility and active learning, many have low completion rates [2][5][7]. For instance, completion rates in online environments are often less than 50% [37]. Even worse are MOOCs, which Skapinker [81] observes are "massively overhyped"; only half of registrants actively participate in

courses, and only 6.5% of students successfully finish [49]. Tauber [86] argues that online education models are unsuccessful because they don't work well for distracted twenty-first century learners; students often have personal and professional time commitments that compete for time and cognitive resources [31], preventing them from fully taking advantage of course offerings. Relatedly, a Duke University study found that a common reason for not completing MOOCs was "lack of time" [7].

# 2.2 Self-Paced Learning

There appears to be a discrepancy in the literature on the success of blended and self-paced courses. One body of research concludes that self-paced learning yields more positive results than instructor paced learning: Tullis and Benjamin [91] found that self-paced learners outperformed a control group on a memory recall task when they had control over study time allocation. Relatedly, Ironsmith et al. [46] found that students in a self-paced course achieved similar results to an instructor-paced course.

Other research has noted the pitfalls of self-paced learning. When Morris et al. [67] compared student achievement in a self-paced versus instructor-paced course, researchers found that students in the self-paced group procrastinated to such an extent that rates of test taking declined until the end of the semester, when students crammed to finish the coursework. The authors further noted that resources in the self-paced course were

ineffectively used; students only came to teaching assistants (TAs) at the end of the semester, and overcrowded study centers. Tullis and Benjamin [91] conclude that self-paced learning can be effective, however students must accurately monitor their learning progress and make appropriate choices during study.

# 2.3 Cognitive Biases in Academic Achievement

Students often plan how to allocate their time. Truthful self-assessment [25] and accurate time and workload assessment allows students to set pragmatic goals, select learning strategies, and monitor and adjust behavior to maximize progress [98]. Cognitive biases, irrational deviations in judgment about people and situations [47], often cause learners to inaccurately assess abilities and underestimate workload, poorly monitor and evaluate progress toward important goals, and to procrastinate.

# 2.3.1 Self-Assessment

Students often have trouble accurately predicting learning outcomes. The *optimism bias*, which is strongly exhibited in college age students [54], predicts that people estimate the odds of experiencing a good outcome as higher than average, and the odds of a bad outcome as lower than average [1]. Students even remain overconfident after receiving negative performance feedback: when Hacker, Bol, Horgan, and Rakow [40] asked students to predict how well they would perform on a future exam based on previous grades, poor

performers remained dramatically overconfident despite negative feedback. Although students tend to overinflate self-views, Dunning et al. [25] found that students in advanced courses calibrate self-assessments more accurately than in introductory courses, and that high-performing students predict performance more accurately than poor performing students.

Flyvbjerg [32] notes that self-assessment may be improved by benchmarking choices and performance against others. For instance, GradeCraft [44] let students compare their performance on assignments to classmates using a box-and-whiskers plot. While benchmarking may help high performing students gain insight, it does not help poor performers who most need to adjust their self-assessments [25]. Peer-assessments, which highly correlate with teacher evaluations and objective performance measures, may instead help students avoid biases.

# 2.3.2 Workload Assessment

Students also have trouble estimating workload. University courses often create biased assessments of difficulty: courses often start out easy and get more difficult, prompting students to misjudge difficulty at the beginning of a semester. This is especially true in introductory courses, where workload or material is new or unfamiliar [25]. Unfamiliar class structures and learning style may further contribute to biased predictions of achievement.

For instance, students taking a self-paced course may not work well without external motivation [22][68], but may not factor this into their decision to take the course [73].

Students can use peer assessment to decide whether to take a course, however individual differences in experience and ability make it difficult to make accurate judgments. Further, assessments are often biased; for example, students who reviewed instructors on *ratemyprofessors.com* rated sexy professors as easier and higher quality instructors [27].

#### 2.3.3 Planning and Procrastination

In addition to inaccurately assessing ability and setting unrealistic goals, students poorly plan their time and procrastinate. The *planning fallacy* is a well-documented phenomenon in which people underestimate the time and effort a task will take, and under allocate resources toward the task [39]. Students suffering from the planning fallacy may believe that they can accomplish more tasks than they actually can, and end up not achieving all of their goals. The planning fallacy is particularly problematic for students, because they often balancing course goals with other academic, personal and professional goals that compete

for time and cognitive resources [31][88]. For instance, Gross, and Dadashova [88] found that the number of hours a student worked impacted GPA to such an extent that full-time students who worked over 30 hours a week put themselves at risk of not completing college.<sup>2</sup>

Hyperbolic time discounting, another bias documented to cause procrastination, arises when the costs and benefits of an activity change in saliency over time, leading people to disproportionately favor immediate gratification over delayed rewards [2]. This bias may likewise contribute to the procrastination issue observed in self-paced courses (section 2.2).

Forecasting and education literature has explored different ways of helping students plan. For instance, Flyvbjerg [32] suggests that reference class forecasting can help people plan effectively by making projections based on actual performance from a reference class. Relatedly, GradeCraft [44] implemented an outcome prediction calculator that helped students predict what grade they would receive in a political science.

\_\_\_\_

<sup>&</sup>lt;sup>2</sup> Interestingly, Szafran [85] found that higher course loads were correlated with higher GPA, regardless of student major.

#### 2.3.4 Progress Monitoring

Cognitive biases also cause students to inadequately monitor and assess goal progress [31], particularly in self-paced learning [91]. For instance, the *discrepancy reduction theory* suggests that people stop studying once they meet a pre-set criterion [24], however people inaccurately judge items to be well learned and prematurely terminate self-paced study [68]. Likewise, *labor-in-vain effects* often cause students to terminate study prematurely when they believe they will not be able to master the material. Metcalfe and Kornell [64] explain that people stop studying once the "rate of return" (benefit per unit of study) falls below a criterion, when a student perceives no change in learning during a set amount of time.

Progress monitoring, Tullis and Benjamin [91] note, often determines the potential effectiveness of self-paced learning; self-guided learners must apply an effective learning strategy to a heterogeneously difficult set of items, and efficiently monitor how well they learned them; learners who are unable to distinguish between easy and difficult materials ineffectively monitor task learning, and overestimate test performance by up to 30% [40]. Tullis and Benjamin [91] also note that age affects this monitoring ability: while both younger and older students spend more time studying difficult items, younger students modulate study time based on item difficulty to a greater extent.

# 2.4 Predicting Achievement in Self-Paced Courses

Section 2.3 illustrates that students inaccurately assess abilities and course load, poorly monitor course progress, and often procrastinate. Since students differ in scholastic achievement [75], understanding the variables that predict success can significantly inform course and motivation design. The education and psychology literature principally shows that achievement can be predicted by grades, individual differences, and social and contextual factors, and that learning environment often affects predictor capacity.

#### 2.4.1 Grades and Individual Differences

Grades and GPA, indicators of previous achievement in one or more courses, are often cited as the best predictors of future achievement [75]; while high school grades and standardized exams are both used for college admission, grades were found to be stronger predictors of university GPA than either the SAT or ACT [99]. In addition to grades and GPA, individual differences significantly predict achievement [75].

Richardson et al. [75] cites cognitive intelligence, personality traits, and demographics as important predictors of performance. Intelligence tests reflect cognitive capacity to represent and manipulate abstract relationships [13], and personality, a sum of individual behaviors [75], often complements intelligence as a predictor of achievement [74]. Important

personality measures include conscientiousness, the capacity to remain attentive during academic tasks, need for cognition, intrinsic motivation to engage in effortful cognitive processing, and procrastination; Richardson et al. [75] found that the three measures were the largest personality correlates of GPA, and significantly predicted student achievement. Relatedly, Ferrari [29] observed that high scorers on the *Adult Inventory of Procrastination* (AIP) spent fewer hours studying and tended to engage in self-handicapping behaviors. Demographics, particularly age, sex and socioeconomic status (SES) also correlate with GPA. A meta-analysis of GPA correlates found that students from high socioeconomic backgrounds, older students, and female students obtained higher grades [75][99]. Interestingly, Sirin [80] found that the relationship between SES and academic achievement was a strong predictor of achievement for white students, but not a strong predictor for

# 2.4.2 Social and Contextual Influencers

minority students.

In addition to grades and individual differences, context plays a major role in student success [97]. When freshman students on-track to fail were placed into an academically rigorous chemistry course with a small class size, peer mentorship and supplemental instruction time, course grades paralleled those in a high achieving normal class. Further, the cohort of students that had taken the course had graduation rates above the university average [89][97].

To this effect, Richardson et al. [75] observed that overall stress and academic stress significantly predicted GPA, and Whalen and Shelly [96] found that financial aid significantly impacted whether STEM majors successfully graduated: students with one additional \$1,000 of work study were 96.8% more likely to graduate or be retained within six years. Conflicting personal, professional and academic activities likewise impact success [88]. As noted in section 2.3.3, social opportunities and personal factors can activate inconsistent motivations [57] that can impact performance [31].

# 2.4.3 Predictors in Post-secondary Education

Intelligence and personality tend to be important predictors of achievement, however these predictors may not accurately predict achievement in college environments. For this reason, intelligence and personality traits were not included in the credit suggestion (section 5.2.3).

Furnham, Chamorro-Premuzic, and McDougall [35] explain that the college selection process reduces variation in intelligence scores, so factors other than intelligence may more accurately predict performance. Like intelligence, personality traits may not accurately predict achievement in college students. Research suggests that personality stabilizes at age 30, and is most consistent in middle age [77]; college students are typically between the ages of 18 and 22, so their personality traits may not be fully developed. Even after maturation,

people demonstrate unique patterns of change at all stages of life [92]. For instance, Cobb-Clark and Schurer [15] found that women who experienced adverse income-related events became less conscientious, and men who experienced negative health-related events became less emotionally stable. Significant variation in genetics [76], gender and culture [18] may further make personality an unreliable predictor of achievement in diverse groups.

# 2.5 Improving Achievement through Motivation

Post-secondary academic performance is heavily influenced by motivation, ability to calibrate, and ability to balance goals [72]. Motivation can be broad or domain-specific [33], intrinsic or extrinsic [60], and dynamic and contextual [73]. The thesis used motivation literature from persuasive computing and game design to inform the structure of goals and deadlines, monitoring and feedback, and behavioral incentive structures implemented in the motivation intervention.

Persuasive computing (captology) and game design fields often use psychology to motivate users. Persuasive computing studies how technology can help users to overcome cognitive biases, and motivate positive behavior through goals, feedback, monitoring, and behavior reinforcements [33][66]. Like captology, games use calibration, feedback, immersion and rewards to motivate and engage players [93]. Garris, Ahlers and Driskell [36] note that because games demonstrate the principles of active learning, a "holy grail" for training

professionals is to harness the motivational properties of games to enhance learning and instruction.

#### 2.5.1 Goals and Deadlines

Are deadlines necessary in self-paced learning? Should students be given the opportunity to set personal deadlines, or should external deadlines be imposed?

One body of literature argues that giving learners a sense of control leads to increased internal motivation and flow [19]. Games elicit this control by allowing users to select strategies, manage activities, and make decisions that affect outcomes [93]. For instance, when Holman, Aguilar and Fishman [44] allowed students to "spend" points on different assignment types in the GradeCraft LMS, they found that assignment flexibility gave students the option to self-correct, which improved achievement. Interestingly, Cordova and Lepper [17] found that providing elementary school students with control over instructionally irrelevant parts of a learning activity also led to increased motivation and greater learning.

In contrast, Garris, Ahlers and Driskell [36] describe how clear, specific, and difficult goals are necessary to create internal motivation and flow. Specific goals, the authors explain, help players perceive goal-feedback discrepancies, trigger attention and motivation, and lead to

increased effort and performance. Ariely and Wertenbroch [2] further note the importance of external goals; when the researchers gave students varying degrees of freedom to self-impose essay deadlines, students with externally imposed, evenly spaced goals received the highest grades, while students with maximally delayed deadlines receive the lowest grades. Students that were given some flexibility to set deadlines were aware of their tendency to procrastinate and used meaningful and costly deadlines to overcome their procrastination, but did not set these deadlines optimally.

# 2.5.2 Performance Monitoring and Feedback

Students need performance feedback to stay motivated [4][36][44]. For instance, an IDEO designed University of Phoenix course motivated students using a dynamic "impact score," that measured the degree to which student ideas sparked others to participate in the course [53]. Similarly, the GradeCraft dashboard [44] motivated students through progress feedback toward badges and course objectives. Instructor feedback is likewise instrumental to success. GradeCraft [44], for example, presented instructors with aggregated attendance and assignment consistency analytics; if a student suddenly stopped coming to class or stopped turning in assignments, the instructor noticed the problem and intervened.

Judgment, behavior, and feedback cycles interwoven with engagement can further lead to increased confidence, persistence, and effort [36], but must be effectively integrated to

facilitate learning [4]. In a particularly successful self-paced programming course, Gill and Holton [38] used cohesive feedback loops between students and TAs, TAs and instructors, and instructors and students to successfully motivate students. Students received participation credit for meeting with TA mentors weekly and documenting progress on assignments and exams; TAs monitored student progress and notified instructors if assistance was needed, and instructors consolidated tracked activities and TA feedback into a weekly progress report that students received by email.

#### 2.5.3 Incentives and Reward Structures

Incentives and reward structures also motivate behavior. Video games, for instance, trigger emotions by creating artificial systems of wealth and acquisition, and giving players wealth in that system [93]. Rewards, Tynan explains, can come in many different forms: games often motivate players using experience points, in-game money that 'powers-up' a player's character, achievement leaderboards, and story content.

Games keep players continuously motivated by pairing rewards with reinforcement schedules [30]. For instance, game designers might use the differential-reinforcement-of high-rates-of-behavior (DRH) schedule to award players for defeating five enemies in one minute [16]. To eliminate motivation gaps, games often superimpose reinforcement schedules, so that there is always a payout schedule producing high motivation [93].

These incentive and reward structures are often used in education. For instance, GradeCraft [44] used badges both as incentives for completing progress goals, and as meaningful replacements for course grades. Similarly, the Game2Learn computer science game [4] integrated a rewards system into gameplay that allowed players to collect hints from non-player characters and to receive discounts in a virtual shop; the research found that explicit rewards and punishments for right and wrong answers created positive differences in perceptions and attitudes, and improved learning effects. Although incentives can be motivating, Tynan [93] and LeBlanc [60] both note that when rewards are misaligned with intrinsic motivation, rewards can be harmful and demotivating.

# Chapter 3: Study Goals and Research Questions

The goal of the research was to understand what background variables affected student achievement, to help students to set achievable goals, and to motivate them to achieve those goals. The thesis evaluated background variables using a pre-course survey (Appendix C: Pre-Course Survey), and helped students set practical goals using a course credit suggestion (Figure 6). The study motivated students to meet course goals by creating a system of goals and deadlines, group and personal feedback, and behavioral incentives.

# 3.1 Background Predictors of Achievement

This thesis examines how background characteristics affected performance in the *Paths to Computer Science* course, and whether they were predictors of achievement and individual goals. The research uses data from the pre-course survey, the course plan and final grades to examine whether demographics, individual and contextual differences, and attitudes were potential predictors of achievement.

1. Which background variables predicted the total number of credits students completed?

The research examines background predictors, including course preparedness, number of programming languages, programming experience, procrastination, self-efficacy, and GPA. The thesis further examines how time and goal commitments affected success, including the number and hours devoted to academic, personal, and professional goals. From these findings, the research proposes conjectures about the effect of background variables on student success.

# 3.2 Credit Goal Suggestion

Students need help making optimal planning decisions (see sections 2.3.2 and 2.3.3). This thesis examines whether a credit suggestion based on programming background, time and goal commitments, and self-efficacy helped students in the *Paths* course set effective goals.

The study explores whether a) the suggestion used meaningful background predictors; and b) the goal suggestion was an effective way to help students set appropriate deadlines.

- 2. Did the background variables used to generate the suggestion (computer science background, time and goal commitments, and self-efficacy) predict student success?
- 3. How did students respond to the credit suggestion? Did they follow the suggestion when choosing a credit goal?

The course credit suggestion was implemented to help students overcome the planning fallacy. The research considers the benefit of the credit suggestion for students taking the *Paths* course, and suggests design changes to the background variables used to generate the suggestion, as well as to the suggestion's visual presentation.

#### 3.3 Motivation Intervention

# 3.3.1 Goals and Deadlines

A key challenge of the self-paced mastery model was to motivate students without externally enforced deadlines. Students taking the *Paths* course balanced coursework with other academic, personal, and professional goals, inciting them to discount coursework in favor of other goals. The study examines discrepancies between goals and outcomes to ascertain whether students met their personal goals.

4. How successful were students at meeting their goals? Did students exceed their goals? Did any patterns occur?

The literature suggests that students in self-paced courses procrastinate (see section 2.3.3), so an important goal was to motivate students to work consistently through the semester.

- 5. Did students meet their course plan deadlines? Did students work consistently during the semester? Did any patterns occur?
- 6. What did students think of the course plan and deadlines? Were students motivated to achieve their credit goals? Were students motivated to stick to personal deadlines? Did motivation change through the semester?

### 3.3.2 Feedback

Progress feedback increases confidence, persistence and effort, and helps instructors monitor whether students need guidance or support (see section 2.5.2). The study used anonymous group progress feedback, and individual feedback and forecasting to help students assess their weekly and overall progress toward their goals. The study also implemented a leaderboard as both a feedback structure and behavioral incentive.

- 7. Did students pay attention the feedback structures? Did any viewing patterns occur?
- 8. Were students motivated by the group feedback? Were students motivated by individual feedback? Were any structures particularly effective or ineffective?

### 3.3.3 Behavioral Incentives

The study also implemented a leaderboard, and a system of badges, points, and prizes to motivate students. Students were ranked weekly on the leaderboard, creating social competition. Students also received badges for working toward their goals that they could turn in for prizes during the semester.

- 9. Were students motivated by the leaderboard?
- 10. Were students motivated by badges points and prizes?

Performance is hugely impacted by the structure and presentation of motivation mechanisms (see sections 2.5.2 and 2.5.3). It was thus important to understand how well all of the intervention components (goals and deadlines, feedback, and behavioral incentives) integrated with one another.

- 11. Did the combined motivation strategies (monitoring and feedback, deadline structure and incentive design) work well together? Did incentives differ in effectiveness?
- 12. How did students respond to the intervention? Did students respond differently toward the incentives? Did affective responses toward the incentives change over time?

The thesis primarily used answers to the post-credit survey to assess the effectiveness of the motivation components. To assess how well students stuck to their goals, the thesis examined goal completion trends, student emails about credit goals, and informal

observations. To assess whether students paid attention to, and were motivated by feedback structure and incentives, the thesis also examines how often students viewed feedback and incentive progress information on Canvas, and how they responded to feedback and incentives during class.

The research considers the individual effectiveness of the intervention components, and how components affected one another. The study then suggests design changes to help students a) feel committed to meet deadlines; b) meaningfully visualize their progress; and c) stay motivated to meet their credit goals.

# Chapter 4: Description of Course

Paths to Computer Science was an introductory Python programming course taught in Fall 2013. During the course, I implemented a semester long motivation study and intervention to understand and influence how students set and met goals.

### 4.1 Goals

The course used an innovative self-paced and mastery based structure to support students who were interested in learning to program, but did not have a technical background, and may have been scared of the traditional gender-segregated [90] computer-science culture.

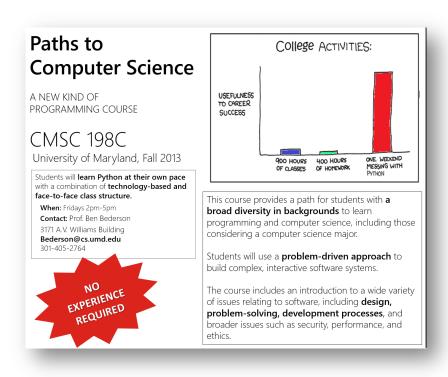


Figure 2: Course Recruitment Poster

#### 4.2 Structure

The *Paths To Computer Science* course united mastery, self-paced, and blended learning styles described in section 2.1. During the semester, students watched lectures and completed technical assignments online, and spent class time on mini-lectures on trends in computer science, peer learning and homework help. By dramatically decreasing classroom lecture time, the course encouraged learning centered teaching, which has been shown to improve learning outcomes for a wider array of students [23].

Borrowing from the Personalized System of Instruction (PSI) model popularized by Keller [51] in the 1970s and 1980s, the *Paths* course broke the 3 credits of course material into individual credits that students earned sequentially: students worked on one credit at a time and were only allowed to register for the next credit once they demonstrated mastery in the previous credit by earning an A in all of the homework assignments and assessments. Each credit was composed of 4 modules, each of which encompassed a set of lectures and online activities, an online homework assignment, and an in-class assessment. Students were required to score at least 90% on the HW to take the assessment, and score 90% on the assessment to start the next module.



Figure 3: Credit Pace Differences

In this way, students earned between one and three credits during the semester. Although a goal was to have as many students as possible earn the full three credits, the course's objective was to compel students to fully master the material they learned. Programming requires building a foundation of knowledge and skills, so rather than earning a "C" in a 3-credit course, students would master the material they learned well enough to earn an "A".

# 4.3 Description of Content

## 4.3.1 Online

The *Paths* course was set up using Canvas, the University of Maryland's Learning Management System. Each credit was divided into 4 modules. The first three modules were designed to take one week to complete, and the fourth module was designed to take two weeks to complete. Each module included approximately 90 minutes of video lecture broken up into short segments that were followed by simple comprehension quizzes. Video lectures were supplemented by additional activities, such as Python exercises and interactive step-by-step programming tutorials on *codecademy.com*.

The first credit of the course familiarized students with core programming concepts such as algorithms and debugging, and taught basic Python syntax and operations, writing lists and loops. In the second credit, students learned to structure code through classes, inherence, and event driven-programming, and were introduced to artificial intelligence and source code control. In credit 3, students learned to work with databases, to structure and store data using the Google app engine, and learned about data analysis and text processing using regular expressions.

Students learned and practiced programming fundamentals by building a simulation of virtual creatures that evolved, interacted with each other, and responded to a changing environment. The simulation taught students how programs interact with each other, and how computers process textual data and simulate complex environments [6].

## **4.3.2** In Class

Each in-class session was divided into three components. For 30 minutes, the instructor presented a "mini-lecture" on topics outside the flow of the technical Python sequence, including lectures on programming history, ethics, and coding style. These mini-lectures united the class, and helped students feel comfortable with one another. During this time, students also gave group presentations on current events in the computing field.

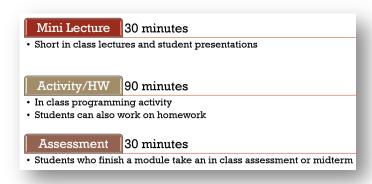


Figure 4: In Class Activities

The second segment of the course consisted of pair programming, a particularly effective method of learning and retention [63], and homework help. The pair-programming activities exercised skills taught in the online videos, and matched students by progress level, encouraging them to learn from each other. The homework time gave students the opportunity to ask the instructor comprehension and assignment questions. During the third part of the course, students who had completed a module took assessments in a separate classroom, while others continued to work on the in-class activities or homework.

# Chapter 5: Description of Study

The research in this thesis arose from literature suggesting that students in the *Paths* course would have trouble staying motivated: Students in self-paced courses procrastinate [2][91], underestimate time and effort required to complete tasks [39], and are demotivated to persevere when faced with a challenge [50][73].

The study strove to help students recognize planning biases and motivate them through the semester. The complementary research sought to understand whether the implementation components, the credit goal suggestion, student set goals and deadlines, feedback, monitoring, and incentive structures, could successfully motivate students to effectively choose and meet a goal. The study explores the success of the research design and effectiveness of the intervention methods, suggests motivation design changes to improve effectiveness, and generalizes observations to other non-traditional learning environments.

#### 5.1 Overview

# 5.1.1 Participant Demographics

Of the 36 students enrolled in the *Paths to Computer Science* course, 31 participated in the motivation study. The participant population was comprised of 17 men and 14 women that were diverse in age and ethnicity. Seventy-four percent of students were between the ages of 18 and 22, 10% of students were between 23 and 25, 13% were between 26 and 29, and 3% were older than 30 years old. Forty-five percent of students identified as white, 45% as Asian American, 6% as African American, and 3% as Hispanic.

Students came from 6 colleges across campus: the College of Arts and Humanities, the School of Business, the College of Behavior and Social Sciences, the College of Computer, Mathematical, and Natural Sciences, the School of Engineering, the Office of Letters and Sciences, and the Graduate School. Students were spread among freshman to seniors (6%, 25%, 25% and 38% respectively), including 6% graduate students. Students GPA varied from 1.5 to 4.0, however average GPA scores were approximately 3.5.

### 5.1.2 Study Design

The motivation study was developed for the first offering of the *Paths to Computer Science* course during Summer 2013, and was implemented during Fall 2013. Students taking the course were introduced to the study, and participants were recruited from the student population. Participants first took a pre-course survey online, and were given a credit goal suggestion based on how well they compared to peers in computer science background, time and goal conflicts, and self-efficacy. After receiving the suggestion, participants were asked to create a course plan, to explicitly choose a credit goal and set deadlines for modules in each credit they planned to pursue.

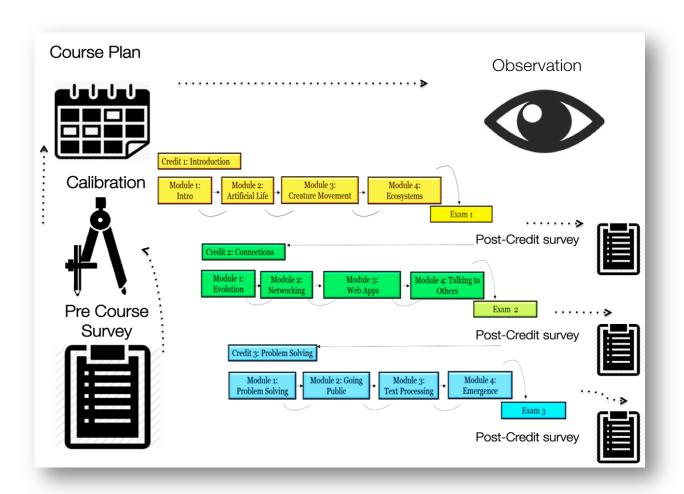


Figure 5: Method Flowchart

During the semester, students received group progress feedback through anonymous class progress charts (Figure 10) and a progress leaderboard (Figure 12); students also received personal progress updates and forecasting information (Figure 14). Group feedback showed students how well their progress compared to other students in the class, and individual updates and forecasting informed students of how well they were progressing toward their

credit goals, and whether they needed to modify their workload to successfully complete their goals.

The study also used incentives to motivate students to complete their course goals and to actively participate in the course. Students received badges for meeting goals, completing activities, and ranking on the leaderboard. Badges awarded students with 'points' that were turned in for prizes during the semester.

### Responsive Design

The overarching goal of the formative study was to improve student motivation, so the study used an informal responsive design to fix weaknesses exposed in the implementation. The study used formal and informal methods to recognize weaknesses. After students finished a credit, they completed a post-credit survey (Appendix F: Post-Credit Survey) that assessed their perception of the course and tools. In the middle of the semester, students were also polled to understand what they struggled with most in the course, and what changes they wanted to see in the course and motivation implementation. Informal face-to-face and email interactions with students also prompted study design changes.

### 5.1.3 Design Considerations

Several considerations must be made about the study design and implementation. The *Paths* course introduced a new learning environment, so the literature that informed the study may not have fully accounted for problems specific to the course. Additionally, course structure, technology, time constraints, and privacy considerations considerably shaped the implementation design. The course design and content were predefined, so the motivation implementation had to complement the course's pre-existing structure. The study also did not have time or resources to develop customized software, so the Canvas LMS shaped how students received feedback, and what data the study collected. Student privacy rights also shaped the study design; motivation is created through monitoring and social comparison [33], however the University of Maryland's Institutional Review Board (IRB) limited the information that could be made available to students about peer progress.

# 5.2 Description of Study

# 5.2.1 Participant Recruitment

On the first day of class, students were introduced to the course and the study. Students were invited to participate in the research, and were told that the voluntary research consisted of interacting with classmates and course tools during the semester, creating a

course plan, evaluating personal experience with the course and motivation tools, and filling out surveys. Students were further told that participants would have the chance to win small prizes based on how well they stuck to their goals.

Students who expressed interest in the course received a consent form to participate in the study (Appendix B). On the consent form, students opted into publically displaying their progress achievements, course plan deadlines, percentage of goals completed, and gold points earned to the class under a chosen pseudonym. Students who initially chose to participate in the study, but decided to stop participating were not included in the study, and students who signed up for the study after the first class were included from the date that they signed the consent form. Of the 36 students enrolled in the Paths course, 33 students signed up for the study at the beginning of the semester, and 31 participants completed the study at the end of the semester.

# **5.2.2 Pre-Course Survey**

Students took the pre-course survey (Appendix C) by logging into the Canvas LMS through their University of Maryland student portal. The 71 questions surveyed students on their demographics, computer science background, their experience with self-paced learning and nontraditional courses, familiarity with Canvas, expectations and motivation for taking the course, time and goal conflicts, and self-efficacy. Additionally, tendency to procrastinate

was measured from the number of days it took participants to complete the survey (based on the procedure described by Ferrari [29]). Procrastination on the survey was used as a benchmark for students' tendency to procrastinate over the semester, however student procrastination increases as a semester progresses [67], so the measure may not have fully accounted for the extent of students' procrastination.

The pre-course survey was created to assess the specific needs of the course and study, however questions from established questionnaires were used when possible. Self-efficacy measures were appropriated from Klobas, Renzi and Nigrelli [55], demographic and motivation questions were adapted from Benford and Gess-Newsome [8] and questions about computer background, course expectations and time and goal conflicts were developed for the study and approved by the instructor.

# 5.2.3 Course Credit Suggestion

After students completed the pre-course survey, they received a course credit suggestion to pursue 1, 2 or 3 credits during the semester. Research has shown that unfamiliar course subjects, structures and learning styles lead to biased predictions of achievement [25][73], and that explicit achievable goals often result in better performance[62][36]. The credit suggestion compared students to classmates on significant background predictors in order

to discourage biased predictions of achievement and to help students choose an explicit goal to pursue.

The goal suggestion was based on a composite score from three weighted achievement predictors (computer science background, time and goal commitments and self-efficacy) and suggested that students take 1-2 credits, 2-3 credits or 3 credits based on the standard deviation of the composite scores.

#### Credit Goal Predictors

The credit goal was calculated using three simple but powerful predictors of achievement. A student's background in a subject often affects their performance outcomes in that subject [25]. Computer science background was thus an important predictor for the *Paths* course: research suggests that people comfortable in one or more programming languages have a much easier time learning a second language [41], so students with more programming experience would be able to master more material than students with less experience.

Time and goal conflicts impact the cognitive resources that students have to allocate to a course [31]. Personal, professional and academic conflicts were thus also an important factor in the suggestion. Students with more conflicts and greater time devoted to conflicts had fewer resources to devote to the course [88], and thus would not be able to master as much

material as students with fewer conflicts.<sup>3</sup> Self-efficacy, a reflection of people's judgment of their ability to complete tasks and reach goals [29], was the third predictor used in the credit suggestion. Self-efficacy is critical to learning and performance, and predicts academic achievement better than other cognitive or affective processes [79]. The aforementioned predictors were assessed in the pre-course survey, and coded to create a composite score.

Several predictors were intentionally not included in the credit suggestion. Cognitive intelligence is an important predictor of achievement [13][74], however the college selection process reduces variation in intelligence scores, so factors other than intelligence more accurately predict performance [35]. Personality measures, usually significant predictors of achievement, are not consistent across age groups [77] [35], gender, and culture [18], making them difficult to use as predictors in a diverse class. Similarly, while grades normally predict post-secondary achievement [75], the diverse student population, made up of first-semester freshman, college seniors, graduate students, and working professions, made it

\_

<sup>&</sup>lt;sup>3</sup> Although research by Szafran (2001) found that higher course loads are correlated with higher GPA, the study treats academic conflicts in the same manner as professional and extracurricular conflicts, all of which compete for time and effort.

impractical to compare students using GPA. For a review of achievement predictors, see section 2.4.

#### Suggestion Development and Implementation

After completing the pre-course survey, students received a credit suggestion recommending that they work toward 1-2 credits, 2-3 credits, or 3 credits.

The suggestion was calculated using the following steps:

- 1. Questions in each of the predictor categories were coded using the coding scheme outlined in Appendix G: Summary of Data and Coding Key (questions used in the credit suggestion are bolded in the appendix).
- 2. Coded answers from each category were then summed and multiplied by a category percentage weight. The computer science predictor category had a 20% weight, and time and goal conflict and self-efficacy categories each had 40% weights.<sup>4</sup>
- 3. The weighted category totals were summed to calculate a composite score for each

42

<sup>&</sup>lt;sup>4</sup> The category weights were determined by the instructor rather than an academic source.

- student, and the mean and standard deviation of the composite scores were calculated.
- 4. The standard deviation of the composite scores determined the credit suggestion that students received: students whose composite score was one standard deviation or more below the mean received a suggestion of 1-2 credits, students whose score was less than one standard deviation from the mean received a suggestion of 2-3 credits, and students above one standard deviation from the mean received a suggestion of 3 credits.

After students completed the pre-course survey, they received a bar chart visualization that compared their composite score to other students (Figure 6) with a semester credit goal suggestion. To help students perceive the suggestion as meaningful, students also received an explanation of how the score was calculated.

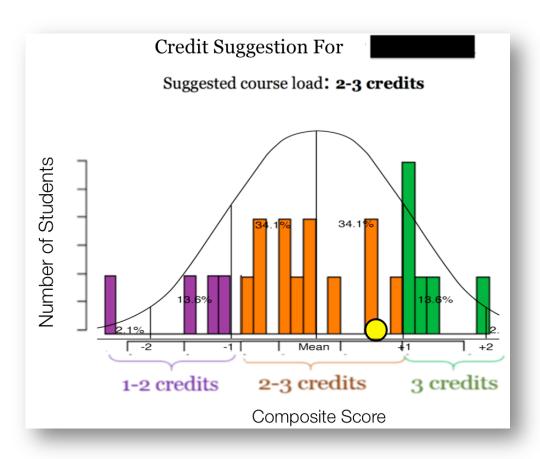


Figure 6: Credit suggestion based on standard deviation of composite scores.

# 5.2.4 Course Plan

After receiving the credit suggestion, students were asked to choose a credit goal, and to set personal deadlines for each of the modules they planned to complete. To help students set appropriate goals and deadlines and goals, participants received a semester benchmark illustrating an even-pace for the three credit schedules (Table 1) as well as an in-depth benchmark for the first week of the course.

After receiving the credit suggestion and testing out the sample workload, students were asked to create a course plan (Appendix D). The course plan asked students to choose a credit goal, and to set deadlines for each module in the credit goal.

Table 2 shows a benchmark schedule for week 2 of the course. Students were urged to test one of the credit goals during the sample week to help them better decide on an appropriate credit load.

Table 1: Benchmark Course Plan

Week	Class Date	3 Credits	2 Credits	ı Credit
Week 2	9/13	Artificial Life	Artificial Life	
Week 3	9/20	Intro to Python	Intro to Python	Artificial Life
Week 4	9/27	Creature Movement		
Week 5	10/4		Creature Movement	
Week 6	10/11	The 2nd Dimension		Intro to Python

TAT 1 7	10/18	Classes	The 2nd	
Week 7			Dimension	
Week 8	10/25	Interaction	Classes	
Week 9	11/1	Inheritance		
Week 10	11/8		Interaction	
Week 11	11/15	AI Search		Creature Movement
Week 12	11/22	Web Apps	Inheritance	
		THANKS	GIVING	
Week 13	12/6	Going Public		
Week 14	12/13	Test Processing		
Week 15	12/20	Evolution	AI Search	The 2nd Dimension

After receiving the credit suggestion and testing out the sample workload, students were asked to create a course plan (Appendix D). The course plan asked students to choose a credit goal, and to set deadlines for each module in the credit goal.

Table 2: Benchmark Schedule for Week 2

Day	Date	3 Credits	2 Credits	1 Credit
Sat	9/7	Pre-Course Survey	Pre-Course Survey	
Sun	9/8	Codeacademy Exercise (Python Syntax)	Codeacademy  Exercise (Python	Pre-Course Survey
			Syntax)	
		Codeacademy Exercise (Tip Calculator)		
Mon	9/9	Codeacademy Quiz –	Codeacademy	
Wion		Python Syntax	Exercise	
			(Tip Calculator)	
		Install Python Syntax and		
		Text Editor		

Tues	9/10	Intro to Python 1 -	Codeacademy Quiz:	Codeacademy
1000		Algorithms	Python Syntax	Exercise
				(Python Syntax)
		Quiz - Algorithms		
Wed	9/11	Intro to Python 2 -	Install Python	Codeacademy
vveu		Programming Languages	Syntax and Text	Exercise
			Editor	(Tip Calculator)
Thus	9/12	Quiz - Programming	Intro to Python 1 -	Install Python
111115		Languages	Algorithms	Syntax and Text
			Quiz - Algorithms	Editor

As students filled out the course plan, they were asked to think about the credit suggestion predictors, were reminded of the planning fallacy, and were nudged to be conservative when estimating how much time it would take to complete each module. Students that found the sample week workload too demanding were asked to consider choosing a less demanding credit target, and students that found the workload is not challenging enough were asked to consider increasing their credit goal. Students were also warned that they should account for the course material increasing in difficulty through the semester.

After filling out the course plan, students had one week to revise their credit goal and deadlines, and to confirm their course plan. After this period, the deadlines were considered permanent, and students were told that they needed to carefully plan their time to meet their goals. Participants were incentivized to meet course plan deadlines through positive and negative reinforcement; students that met their goals would earn points, and students that didn't meet their goals would lose points (see the Incentive Structures section for details). To account for planning and scheduling changes, students had an opportunity to revise their course plan after completing credits 1 and 2. Participants having trouble meeting goals also had the opportunity to spend earned points to modify their course plan.

# 5.2.5 Progress Monitoring and Feedback

### Initial Design

Education research shows that progress monitoring and feedback are essential to student success [44]. When woven together effectively [4], progress feedback motivates students to persevere [36][44] and engages students to actively participate [53]. In addition to feedback, peer benchmarking [32] and instructor monitoring has been found to improve motivation [44], particularly in self-paced learning environments [38].

The initial feedback and monitoring design combined a skill level tracker, a peer achievement newsfeed, a deadline reminder and a badge system in a comprehensive dashboard.

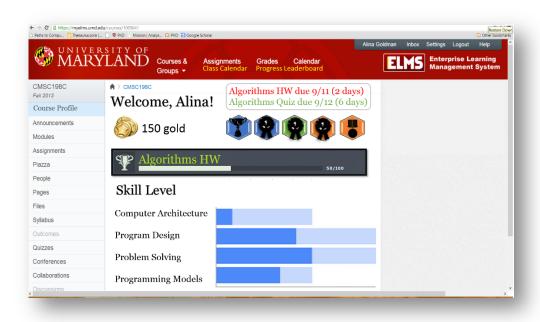


Figure 7: Mockup of Student Dashboard

The student dashboard was designed to be a personalized homepage that students saw when they logged into Canvas to work on assignments. Similar to the GradeCraft

Dashboard [44] and University of Phoenix's visual indicator of practice skills [53], the skill tracker was designed for students to visualize their learning progress by seeing how completed quizzes and assignment contributed to core knowledge areas; as students progressed through the course, they would see themselves gaining expertise in skill categories, making their progress feel more tangible. In complement to the skill tracker, the

dashboard would also remind students of approaching and past deadlines, and visually display earned badges and points.

In the original design, students could compare their progress in the course to other students using a dynamic progress leaderboard. The leaderboard would recognize students with the most progress in each credit, and the total number of points they had earned. The page would also show students how their progress compared to top ranking students, and include a newsfeed of recent peer achievements.

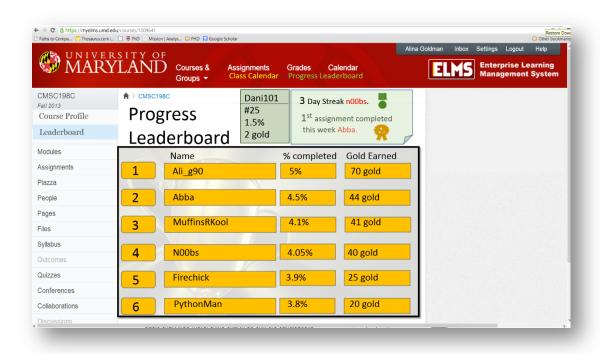


Figure 8: Mockup of Progress Leaderboard

The original design also incorporated a dynamic calendar of course plan deadlines. Student deadlines would turn green when a student completed a module on time, red if they didn't complete a module by the deadline, and orange if they completed a module after the deadline. In addition to facilitating peer monitoring between students, the calendar was also meant to help the instructor monitor progress.

This design planned to implement the monitoring, feedback, and incentive tools by customizing the ELMS homepage. Since the project did not have a development team, the design was going to be implemented using <u>Canvas Apps</u>, which could be integrated with the Canvas learning environment. The study planned to use the <u>Starfish Early Alert</u> application to monitor student progress and create reminders, the <u>Feed the Me</u> app to create the student progress newsfeed, <u>Google Charts</u> to visualize individual and course progress, and <u>Canvas Badges</u> to display earned badges.

# Design Modifications

The study planned to use Canvas Apps because the instructor implemented the online component of the *Paths* course in Canvas. Motivation information is most effective when people do not have to make a special effort to see progress and incentives [93][66], so using apps integrated into Canvas would have been an ideal solution.

Canvas Apps first came out in April 2013, and were untested when the study was developed. I worked with the University of Maryland's Canvas support team to integrate these applications into Canvas, but was ultimately unable to implement the customized display design; the apps I planned to use either didn't work, or required special information access and customization. There was little time to consider other integrated solutions for the study, so I developed medium and low-fidelity alternatives to track progress and motivate students.

### **Monitoring Progress**

Individual student progress information was collected manually using the *Access Report* feature built into Canvas (Figure 9). The Access Report logged the number of times students viewed a page, and time stamped the last time students viewed the page. If the page contained a quiz or assignment, the report also indicated the number of attempts students had made.

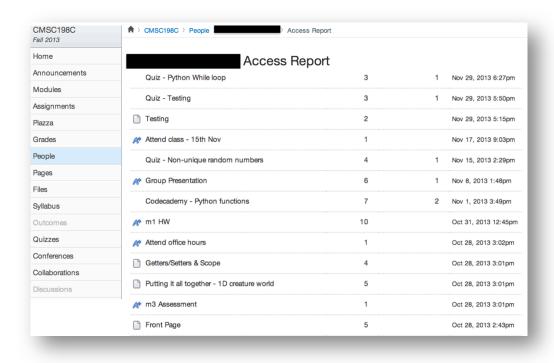


Figure 9: Access Report showing individual student progress

Every week, I used the student Access Reports to track course progress. I used the number of assignments students completed during the week, the last assignment completed, and the number of days that students logged into Canvas to generate an anonymous class progress chart and leaderboard, and to assign badges and points. <sup>5</sup>

<sup>5</sup> Since data was organized by *Last Date Viewed* in the student access reports, an assignment completed in a previous week but viewed during the current week could have erroneously been counted in the weekly tally. To

#### Shared Google Calendar

Once students confirmed their course plans, their module deadlines were displayed in a Google Doc calendar accessible from the Canvas course page. Deadlines that students met were highlighted in green, and deadlines that students didn't meet were highlighted in red. Although student privacy requirements prevented the calendar from using students' real names (the deadlines were displayed under pseudonyms), the goal of the calendar was to create the pressure of social monitoring and responsibility described by Fogg [33].

#### Anonymous Class Progress

Every week, two anonymous class progress charts showed aggregated student progress from the Friday of the last class to the Thursday before the next class. The *Last Module Finished* chart, shown in Figure 10, presented the last module that students had completed the Thursday before class.

account for this, I looked for obvious trends that clarified whether an assignment was viewed or completed during the week. For instance, Figure 9 shows that HW1 was viewed after the Module 3 assessment, however, assignments are completed sequentially, so it is clear that it was not completed on the last date viewed. Thus, it would have not been counted in the weekly tally.

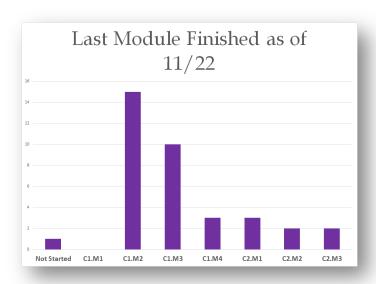


Figure 10: Anonymous progress chart displaying the last module finished in week 12.

The Last Assignment Completed chart (Figure 11) complemented the Last Module Finished chart with assignment progress information that helped the instructor assess where students were struggling in the course. For instance, Figure 10 shows that a majority of students completed C1.M2, the second module in credit 1, but it is unclear whether students had not started module 3, or had started but not completed the module. Figure 11 shows this information: a large group of students had finished the module 3 quizzes, but had not completed the homework, suggesting that they may have had a problem with the assignment. Seeing how students progressed over time was valuable feedback to both students and the instructor. Students used the information to compare themselves to the class, and the instructor used the trend data to track progress and uncover problems.

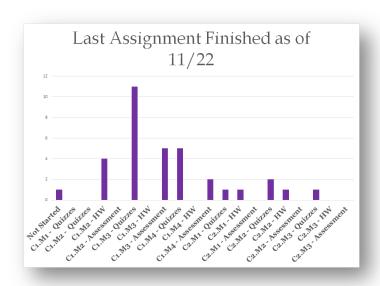


Figure 11: Anonymous progress chart showing the last assignment finished in week 12.

Weekly Canvas announcements reminded students to check the *Progress Chart Google Doc* to benchmark their personal progress against class progress. The progress charts were also displayed on the classroom projector at the beginning of each class to make sure that students saw them even if they did not look at the Google Doc on their own.

#### Progress Leaderboard

Every week, a *Progress Leaderboard* featured students who had made the greatest progress toward their credit goals. The progress leaderboard ranked students using a progress score that was calculated by tallying the number of assignments that a student completed that week, and dividing it by their credit goal; this normalized the data, ensuring that students

working toward more credits did not unfairly rank higher than students pursuing fewer credits.

The leaderboard, shown in Figure 12, displayed both the progress score and the credit goal, so that students could compare themselves against others pursuing the same credit load.

Students that opted out of displaying their leaderboard status with a pseudonym were included on the leaderboard as anonymous.

Pro	Progress Leaderboard 12/13					
Ranking	Pseudonym	Credit Goal	Progress Score			
1	AL AL	1	8			
2	PS	2	6.5			
3	Edi	2	4.5			
4	Anonymous	2	3			
4	avipacker	3	3			
5	Ying	1	2			
5	Anonymous	3	2			
6	T1 28	*** 3	1.67			
6	Heisenberg	3	1.67			
7	TheNumber	2	1.5			
7	Anonymous	2	1.5			
7	Jenny	2	1.5			
8	Peter	3				
8	Best Coder NA ssuplee	3	0.67			
10	Lin	2	0.67			

Figure 12: Implemented Progress Leaderboard

The *Progress Leaderboard* was biased in favor of students completing fewer credits (i.e. a student pursuing 3 credits would have to work much harder to get on the leaderboard than

a student pursuing 1 credit), so a *Most Assignments Completed* leaderboard also recognized students that made the most overall progress that week.

Most	Most Assignments Completed this Week				
***	A * *	Number of	Credit	Progress	
Ranking	Pseudonym	Assignments	Goal	Score	
1	PS	13	2	6.5	
2	Edi	9	2	4.5	
2	avipacker	9	3	3	
3	AL AL	8	_ 1	8	
4	Anonymous	6	3	2	
4	Anonymous	6	2	3	
*_5	Heisenberg	5	3	1.67	
5	T1 28	5	3	1.67	

Figure 13: Ranking of students who completed the top number of assignments

#### Individual Feedback and Progress Forecasting

In addition to group feedback, students received personal feedback detailing progress, badges and prizes through the Canvas message system every 3 weeks. Midway into the semester, students received a credit forecast that visually showed them how their progress (the gray line in Figure 14) compared to the benchmark course plan deadlines (the blue line) and their personal deadlines (the orange line).



Figure 14: Mid-Semester Credit Completion Forecast

In the forecast, students were also given a prediction of the number of credits they were expected to complete, and a suggestion with the number of modules they needed to complete per week in order to meet their credit goal by the end of the semester.

## **5.2.6 Incentive Structures**

Literature on games and education suggests that effective environments create immersive experiences [19][36], facilitate shared communities of practice through complex and diverse student and teacher roles [87] and use meaningful reward systems to motivate students [59]. Creating immersive experiences and multifaceted student and teacher roles require control over course structure and content, so the incentive structure primary focused on creating meaningful rewards.

#### Badges

Intrinsic and extrinsic reward systems are pervasive in game education environments [60][66][44]. While reward systems are most effective when they are intrinsic [4][93], extrinsic awards can also motivate students. Extrinsic incentives are most effective when they reward self-regulating behaviors (which can increase self-efficacy), performance quality (rather than participation), and when tasks being rewarded are not intrinsically motivating [60]. Further, extrinsic motivation is effective when award criteria are clear, and when students receive explicit feedback on how to improve performance.

During the semester, students had the opportunity to earn four types of badges: homework deadline badges, merit badges, activity badges, and survey badges (see Table 3 for badge details). Students received homework badges for completing modules by deadlines set in the course plan (*ModStar1*), completing deadlines early (*SpeedDemon*), and working

consistently toward their goals (*EnduranceStar*). Students also received individual merit badges for making significant progress during the week (*ProgressStar*), and group merit badges for completing a credit as a class (*TeamStar* badges). Further, students received activity badges for answering questions on the *Piazza* message forum (*QuestionStar*), and survey badges for completing study surveys (*SurveyStar*).

Table 3: Badges and Point Values

Type	Badge	Details	Points
HW	ModStar1	Complete module by deadline	+3
	SpeedDemon	Push module deadline forward by 2 or more	+5
		days and complete module by early deadline	
	EnduranceStar	3 day streak: Login in 3 days in a row and	+3
		work on module	
Merit	ProgressStar	Most progress for the week (top 6)	+1-6
	TeamStar	Class finishes Credit 1	+5
	TeamStar2	Class finished Credit 2 or Credit 3	+10
Activities	QuestionStar	Answer endorsed on the Piazza forum	+3
Survey	SurveyStar	Complete Intro Survey, post-exam survey or	+2
		Critical thinking questionnaire	

In line with the literature, the badges created for the *Paths* course focused on rewarding self-regulating behaviors (*ModStar1*, *SpeedDemon* and *EnduranceStar* badges) and performance (*ProgressStar* and *TeamStar* badges). The badges rewarded students for activities that were intrinsically engaging, however the goal was to create social contrast between achievers and non-achievers to motivate the students that were not making progress.

Rather than simply recognizing achievers, a goal of the badges was to motivate students that were doing well to help others. The *TeamStar* badge, for instance, was modeled after the *Undying* group achievement which students participating in the Just Press Play system [21] received if 90% of the freshman class passed an introductory programming course: upperclassmen were so motivated by the team badge that they organized study sessions for their peers, and successfully helped them pass. Similarly, the *QuestionStar* badge was designed to facilitate peer support by motivating students to answer each other's questions.

Rather than implementing the badges electronically, students received badges stickers to display on their nametag (*e.g.* Figure 15).





Figure 15: Student nametag displaying sticker badges and prizes

There were more badges than sticker colors, so the badge colors denoted difficulty rather than badge type. As shown in Table 4, silver badges were the easiest to attain, and red badges were the most difficult to attain.<sup>6</sup>

Table 4: Badge Colors

Color	Badge	Difficulty Rating
Silver	ModStar1, SurveyStar	1

<sup>&</sup>lt;sup>6</sup> The badge colors denoted the difficulty of the badge, not the badge itself. Students knew what badges they received through in class feedback and Canvas message updates.

Purple	EnduranceStar, QuestionStar	2	
Green	SpeedDemon	3	
Gold	Complete module correctly on first try	4	
Red	ProgressStar	5	

Students were initially given badges during the activity and homework portion of the course, however handing out badges while students were working in pairs was distracting. To avoid this distraction, badges were instead put on student nametags before the class began.<sup>7</sup>

#### Points and Prizes

Similar to the in-game currency described by Tynan [93], the badges students earned were worth points that could be turned in for small prizes during the semester. On prize days,

<sup>&</sup>lt;sup>7</sup> There was a tradeoff between giving students badges in class and putting them on before class. Although distracting, giving students badges during class made students more aware of why they earned their badges, and made the badges a very visible part of the implementation. Also, students used their badges to make unique shapes or designs on their nametags.

held every 3–4 weeks, students received a voucher based on the number of points they had earned (see prize voucher in Figure 15 and list of prizes in Table 5). Students could either collect a big prize, or turn in their voucher for smaller prizes (e.g. a student with 15 points could either select a folder or 3 truffles). Additionally, leftover points carried over to the next prize day (e.g. a student with 17 points would receive the folder and keep 2 points for the next prize day).

Table 5: Prizes

Level	Points	Prizes
Level 1	5	Lindt Chocolate Truffle
Level 2	15	Maryland Folder
Level 3	30	\$5 Starbucks card
Level 4	40	Personalized 3D printed item

At the end of the semester, students became primarily interested in winning the grand prize, a 3D printed object,<sup>8</sup> however most students did not have enough points to earn one. Instead of giving prize vouchers, the last prize day was a raffle that students could enter to win the grand prize. The raffle was worth 15 points, the average number of points students had.

<sup>&</sup>lt;sup>8</sup> During the class and over email, students asked how many points they needed to earn the 3D printed object, and made comments about what objects they wanted to print.



Figure 16: Raffling off a 3D printed object

On the final prize day, students put their names into a hat to enter the raffle, and the instructor drew the names of 3 winners. Winners were given the opportunity to create a 3D model, which the instructor agreed to print.

#### Deadlines

In addition to earning prizes, students could use points to push back deadlines. Students were heavily disincentivized from missing deadlines (they lost 7 points each time they missed a deadline), and were instead encouraged to modify their course plan. Updating the course plan encouraged students to consider how missing deadlines affected their credit goals, and was designed to prevent students from getting locked in failure traps described by Tynan [93]; students that missed one deadline were much more likely to miss the next deadline, and could easily become discouraged.

Pushing back deadlines initially cost a small number of points (1 point the first time), but cost more points the more students changed their deadlines. Increasing the cost of changing deadlines was meant to prevent students from whimsically changing deadlines when they did not want to work, and not being motivated to meet the goals they originally set.

#### **Incentive Amendments**

The incentive system was revised multiple times to account for data collection and student motivation issues. The badges implemented at the beginning of the semester focused more on merit than completion; the *ModMaster* badge awarded students for mastering a module on the first try, the *EarlyModMaster* badge awarded the first person to earn an A on a module, and the *ProgressSelf* badge recognized students that completed more than 8% of their credit goal during the week (students needed to complete at least 8% each week to stay on track).

Merit badges were removed from the badge system because the TAs graded assignments inconsistently, so it was difficult to obtain up-to-date grade information for all students.

Other badges were also removed because students found them confusing or not motivating. For instance, the *SpeedDemon* badge incentivized students to complete their deadlines early, however most students struggled to meet their deadlines.

The point system was also modified through the semester. When the study was first designed, the point system assumed that students would meet their goals, and incentivized them to complete their goals earlier. The system also predicted that the high penalty would discourage students from missing their deadlines. So many students missed their goals through the semester that the point system was changed; in addition to making the *ModStar* badge worth more, students received points for being ranked on the leaderboard. Also, many students had negative points (because they missed so many deadlines), so the penalty system was removed entirely.

## **5.2.7 Post-credit Survey**

After each credit exam, students were asked to complete a post-credit survey (
Appendix F) in order to understand how motivation changed, and which strategies were
most effective. Students were asked to reevaluate how prepared they felt for the course,
how interested they were in the course, and how much utility they received from the course.
Students were also asked to assess the motivation implementation: participants were asked
to rank motivation strategies in order of effectiveness, and were asked whether strategies
were particularly effective or ineffective.

In addition to evaluating the value of the implementation, it was important to understand whether students had motivation needs that weren't being addressed by the implementation. Students were asked how they approached the course, how many hours they spent working on the class per week, and what they did when they got stuck. Students were also asked how successfully they met their deadlines, and if and why they changed their deadlines and goals.

# Chapter 6: Results

The research uses a synthesis of quantitative and qualitative methods to answer the research questions posed in Chapter 3. The study uses multiple linear regression modeling to understand how background variables factored into student success, and whether the credit suggestion helped students pursue an achievable goal. The thesis blends the quantitative analyses with qualitative open coding methods to examine the role of background variables, effectiveness of the credit suggestion, goals and deadlines, feedback, and incentive structures on student achievement.

## 6.1 Background Predictors of Achievement

A primary research question was to understand what background variables predicted student achievement. As described in section 3.1, the research considers how course preparedness, number of programming languages, programming experience,

procrastination, self-efficacy, and time and goal commitments affected the total number of credits students completed. To understand how student background affected performance, I examined student responses in the pre-course and post-credit surveys, goals and deadlines in the course plan, and final grades.

Hypothesis 1: Course preparedness, number of programming languages, programming experience, procrastination, self-efficacy, and GPA variables will significantly predict the number of credits students completed at the end of the fall semester, and total number of credits completed.

Additionally, the number of conflicting academic, professional and personal time commitments will also predict the number of credits completed.

### 6.1.1 Analysis

In the pre-course survey, qualitative responses<sup>9</sup> were coded<sup>10</sup> into categorical, ordinal or interval variables (see Appendix G for coding key), and analyzed as multiple linear

\_

<sup>&</sup>lt;sup>9</sup> Qualitative responses in the pre-course survey were coded for quantitative statistical analysis, whereas qualitative responses in the post-credit survey were analyzed qualitatively using open coding techniques.

<sup>10</sup> Some qualitative responses in the introductory survey answered multiple questions and were coded into two separate categories (e.g. question 32 in the introductory survey was coded into two variables: the number of total credits students took during the semester and the number of other courses students took).

regression models using R statistical computing software (see Figure 17 for sample regression model).

I analyzed categorical variables as coded indicator variables, and ordinal variables as continuous variables. I also measured procrastination by the number of days it took students to complete the introductory survey<sup>11</sup> (see [29]), and assessed self-efficacy as an average score of 22 variables in the pre-course survey.

```
lm(formula = CreditsCompleted ~ SelfEfficacy + Procrastination, data =
ThesisData)
```

Figure 17: Sample multiple regression model in R. Credits completed was regressed on average selfefficacy, when controlling for procrastination.

### 6.1.2 Results

<sup>11</sup> I measured procrastination after students completed the pre-course survey using timestamp data, however future experiments should assess procrastination as a measure and as a response item to improve accuracy.

Several variables identified in *Hypothesis 1* were significant predictors of total credits completed at the end of the spring semester. Programming experience, procrastination, and self-efficacy predicted total credits completed. While course preparedness and programming languages did not predict credits completed, they predicted the number of credits pursued in the course plan. Conversely, time and goal commitment variables and GPA did not significantly predict number of credits completed.

### Computer Background and Course Experience

Course preparedness (Beta=0.405, t=2.194, p=0.037) and number of programming languages (Beta=-0.352, t=-1.869, p=0.072) predicted credits pursued (the credit goal) but programming experience (Beta=0.122, t=0.663, p=0.513) did not (F(3,27)=2.606, p=0.072, adjusted r²=0.138).

Conversely, programming experience (Beta=0.672, t=2.945, p=0.007) predicted the number of credits completed, but course preparedness (Beta=-0.3163, t=-1.385, p=0.177) and number of programming languages (Beta=-0.359, t=-1.541, p=0.135) did not (F(3,27)=2.995, p=0.048, adjusted r<sup>2</sup>=0.166).

Table 6: Descriptive Statistics for Course Preparedness

Course Preparedness	Number of Students
1-not prepared	6

2-somewhat prepared, but lacking	14
important skills or knowledge	
3-prepared	11

Table 7: Descriptive Statistics for Programming Languages

Number of Programming  Languages	Number of Students
0	2
1	20
2	5
3	3
4	1

## Procrastination

Number of days to return the Pre-Course survey was used as a measure of procrastination [29]. The number of days it took students to return surveys ranged from 1 to 10 days, with a mean of 3.871, median of 3, and standard deviation of 2.680.

The number of days to return the survey (Beta=-0.12, t=-2.564, p=0.0158) predicted the number of credits completed (F(1,29)=6.577, p=0.016, adjusted  $r^2=0.157$ ). On average, participants that took ten days to return the survey completed one to two fewer credits.

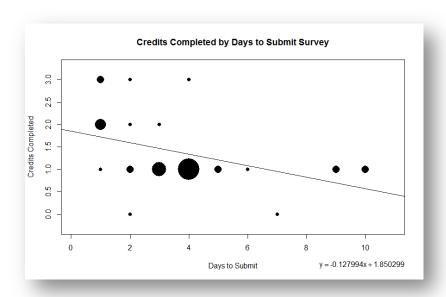


Figure 18: Credits completed by the days it took students to complete the Pre-Course Survey.

Students that completed fewer credits took longer to complete the survey.

Additionally, more programming experience (Beta=-1.5933, t=-2.370, p=0.0249) and a fewer programming languages (Beta=1.4083, t=-2.370, p=0.060) predicted fewer days to return the survey (F(2,28)=2.913, p=0.070).

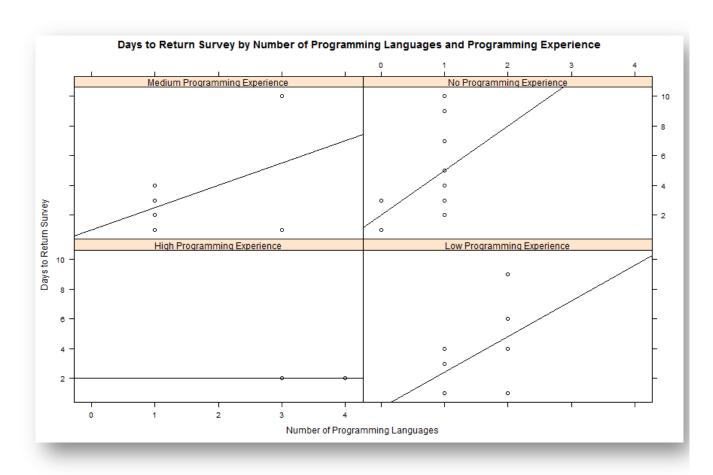


Figure 19: Days to Return survey by number of programming languages. Students that knew fewer programming languages took less time to return the Pre-course Survey.

Programming experience (Beta=0.575, t=2.606, p=0.015) predicted credits completed, however number of programming languages (Beta=-0.0384, t=-1.627, p=0.115) did not (F(2,28)=3.421, p=0.469, adjusted r²=0.139). Taken in combination, the number of days to return the survey (Beta=-0.125, t=-2.135, p=0.042) predicted number of credits completed but programming experience (Beta=0.376, t=1.652, p=0.110) and number of programming languages (Beta=-0.208, t=-0.878, p=0.387) did not (F(3,27)=4.09, p=0.016, adjusted r²=0.236).

## Self-Efficacy and Programming Experience

The self-efficacy score ranged between 3.09 and 6.91 with a mean of 5.33, median of 5.36, and standard deviation of 0.922. Self-efficacy (Beta=-0.816, t=-2.262, p=0.032), programming experience (Beta=-3.0651, t=-2.153, p=0.040) and the interaction between self-efficacy and programming experience (Beta=0.611, t=2.356, p=0.026) predicted credits completed (F(3,27)=3.054, p=0.0454).

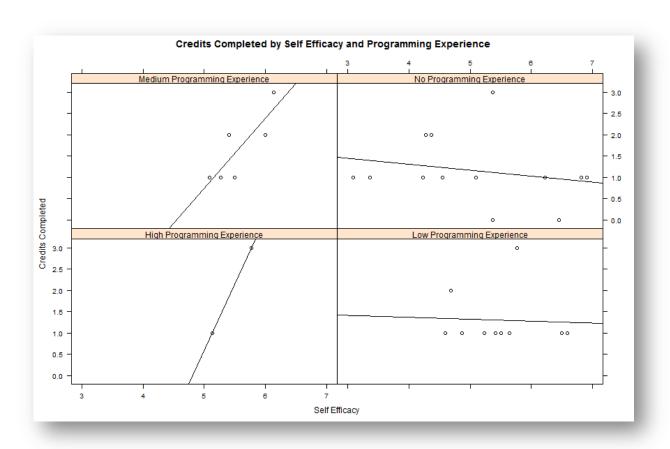


Figure 20: Credits completed by self-efficacy for different programming experience groups. Self-efficacy is a predictor of credits completed for students with medium or high programming experience, but not for students with little or no programming experience.

For participants with no or low programming experience, self-efficacy did not predict number of credits completed (F(1,21)=0.7833, p=0.386). However, for participants with medium or high programming experience, self-efficacy (Beta=1.848, t=3.476, p=0.013) was positively related to credits completed (F(1,6)=12.08, p=0.1321, adjusted  $r^2=0.613$ ).

### Self-Efficacy, Procrastination and Programming Experience

Self-efficacy was also a borderline significant predictor of the number of days to submit the survey (F(1,29)=3.283, p=0.080, adjusted  $r^2=0.071$ ).

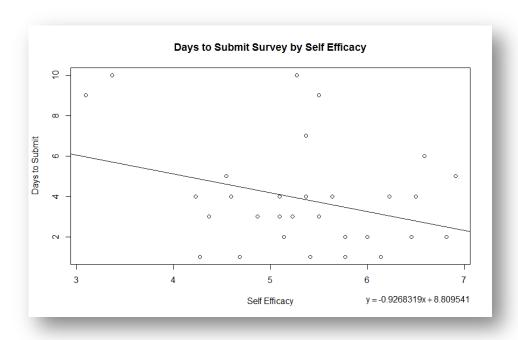


Figure 21: Days to Submit Survey By Self-Efficacy. Students with higher self-efficacy took fewer days to submit the pre-course survey.

Taken in combination, for participants with no or low programming experience, self-efficacy (Beta=-0.292, t=-1.837, p=0.0811) and days to submit the survey (Beta=-0.179, t=-2.810, p=0.011) were negatively related to credits completed (F(2,20)=4.468, p=0.025, adjusted  $F^2$ =0.240). Conversely, for participants with medium or high programming experience, self-efficacy (Beta=1.633, t=2.680, p=0.0.044) was positively related to credits completed, and days to submit the survey (Beta=-0.065, t=-0.804, p=0.458) was not (F(2,5)=6.008, p=0.047, adjusted  $F^2$ =0.589).

## 6.2 Credit Goal Suggestion

The credit suggestion used computer science background, time and goal conflicts, and self-efficacy variables to suggest an attainable credit goal. The goal of the research was to understand how well the variables used to generate the credit suggestion predicted student success, and how students responded to the suggestion.

Hypothesis 2: Students will use the credit suggestion as their credit goal in the course plan.

## 6.2.1 Analysis

To understand the effectiveness of the credit suggestion, total credits completed was regressed on computer science background, time and goal commitments, and self-efficacy (see Hypothesis 1). Likewise, to understand whether students used the credit suggestion as a guideline for their credit goal, the credit goal was regressed on the credit suggestion (Hypothesis 2).<sup>12</sup>

81

<sup>&</sup>lt;sup>12</sup> The credit suggestion was a range (e.g. Figure 6 suggests that the student should have pursued 2-3 credits), however the analysis was run using the lower limit of the suggestion range. 1-2 credit suggestions were analyzed as 1 credit, 2-3 credit suggestions were analyzed as 2 credits, and a 3 credit suggestion were analyzed as 3 credits.

In complement to the regression analysis, students' reasons for choosing a credit load (see Course Plan in Appendix D) and responses to the post-credit survey were examined using open coding techniques described by Miles and Huberman [65]. First, qualitative data was sorted and organized; irrelevant data was discarded, and remaining data was organized into study categories. After reading through the organized categories, data was further organized by the research questions posed in Chapter 3, and analyzed for general codes, patterns and causal relationships. After developing initial conclusions, I revisited the raw data to look for cases that illustrated and contradicted my findings, and revised my conclusions.

#### 6.2.2 Results

Hypothesis 1 predicted that the variables used in the credit suggestion would significantly predict the number of credits completed. As discussed in section 6.1.2, programming experience and self-efficacy were significant predictors of credits completed, but time and goal commitments, and number of programming languages were not. Although time and goal commitments were not quantitatively significant, qualitative analyses suggest that they considerably influenced student achievement.

Hypothesis 2 predicted that students would use the credit suggestion as their credit goal, however the credit suggestion did not significantly predicted the credit goal (Beta=-.1639, t=-0.2554, p=0.642), indicating that students did not follow the credit suggestion. Although the credit suggestion was not a significant predictor of the credit goal, open coding themes suggest that students considered the credit suggestion predictors when choosing a credit goal.

Several students noted that the credit suggestion influenced their credit goal.

For instance, students explained that they chose the credit load because of time and goal commitments. A freshman student explained, "ive been surprised by the amount of work that I've had in my classes lately... I'm also not used to college life yet and would like to reserve time for other extracurricular activities that are more tailored to my career interests." Another student explained that they "[planned] to complete all 3 credits, but realized my schedule is too busy."

Students also cited programming experience and self-efficacy as influencing their credit goal choice. One student said "I am very experience [sic] in programming [sic] and I am confident I can complete all the work," while another explained, "I am not at all familiar with coding and I don't know how difficult its going to be. Neither am I good at meeting goals," One student even factored the motivation implementation into their goal. "In order to avoid the planning fallacy I

thought it best to shoot for 2 credits and then constantly move up my deadlines if I get ahead. That way I will receive more points."

Although some students used the credit suggestion predictors to choose a credit goal, others cited programming and learning goals as their primary reason for their credit load. Students explained that their goal was "to be fluent in python" and wanted to "make the most of my time in this course and earn the most credit I can." Interestingly, some students cited multiple both credit suggestions predictors and learning goals: for instance, one student explained that "I have lots of other commitments this semester, such as GRE, grad school apps, service grap[sic], and research. I picked 2 credits instead of 1 because the course is really interesting."

Students additionally cited student status and financial reasons. One student explained that "I only need 1 credit to graduate this semester and I want to aim for an A" while another said that they "expect to be an in-state student next semester, so for financial reasons I am holding off on adding more credits."

#### 6.3 Motivation Intervention

The goal of the motivation study was to understand whether goals and deadlines, group and personal feedback, and behavioral incentives motivated students to meet their credit goals. The study strove to understand whether students successfully met their goals,

whether the intervention structures motivated students, and how students responded to the intervention components.

## 6.3.1 Goals and Deadlines

The study aimed to understand how successfully students met their goals, whether they worked consistently, and how they responded to goals and deadlines through the semester. Hypothesis 2 predicted that students would set achievable goals, so Hypothesis 3 predicted that students would successfully meet their goals.

Hypothesis 3: The credit goal will predict the number of credits completed.

## 6.3.2 Analysis

To understand the effectiveness of the goals and deadlines, I compared credits completed to credit goals. To examine whether students worked consistently, I examined page view trends. To understand student responses to goals and deadlines, I used open coding to analyze post-credit survey responses.

## 6.3.3 Results

#### **Credit Goals**

At the beginning of the fall semester, students in the *Paths* course decided on a credit goal and constructed a course plan to meet that goal. Four participants set a one-credit goal, 12 participants set two-credit goal, and 15 participants set a 3-credit goal.

At the end of the fall semester, 15 participants had not completed any credits, 14 participants had completed one credit, and 2 participants had completed two credits. Students that had not finished a credit by the end of the semester were given the opportunity to take an incomplete and finish the credit during the spring semester. At the end of the spring semester, 2 participants had not completed any credits, 20 had completed one credit, 5 completed two credits, and 4 completed three credits.

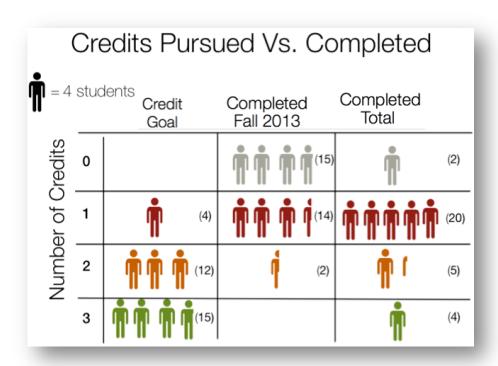


Figure 22: The credit goal students set in the course plan, number of credits students completed at the end of the fall semester, and total credits completed at the end of the spring semester. Overall, students completed fewer credits than their credit goal.

Quantitative analyses found that participant credit goals did not predict the number of credits that students completed in the fall (F(1,29)=0.439, p=0.512) nor overall(F(1,29)=0.380, p=0.542). Many students that pursued three credits completed one or no credits, and two students that pursued two credits completed three credits.

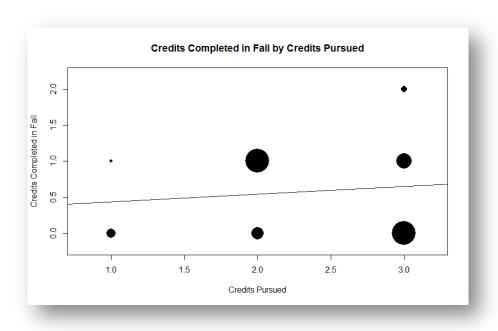


Figure 23: Credits completed in the fall by Credits Pursued

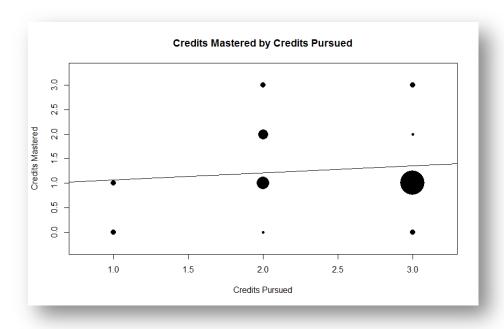


Figure 24: Credits completed total by credits pursued

## Consistency

Student effort and progress declined significantly through the fall semester. As shown in Figure 25, students viewed credit 1 pages approximately 1500 times per day in September, and approximately 150 times per day in December. Although half of the class worked on credit 2 during the fall, the total views for credit 1 and 2 were approximately 500 per day, three times less than in September.

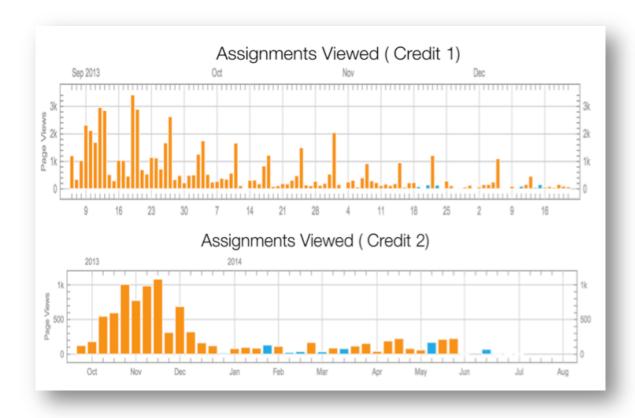


Figure 25: The number of assignments students viewed on Canvas during the fall semester for credits 1 and 2. At the beginning of the semester, students viewed pages more frequently and consistently during the week than at the end of the semester.

Students also worked less consistently at the end of the semester. At the beginning of semester, page views on course days corresponded to page views on non-course days, but as the semester progressed, students viewed course pages primarily on class days. For instance, during week 2, students viewed 2860 pages on the course day, and approximately 1750 pages per day on non-course days. Consistently declined so sharply that by week 4, students viewed 2634 pages on the course day, and only 992 pages per day on non-course days.

Figure 26 further shows how course progress stagnated through the semester. The benchmark course plan (Table 1) suggested that students pursuing 3 credits finish credit 1, module 3 (C1.M3) by week 4, students pursuing 2 credits finish the module by week 5, and students pursuing 1 credit finish the module by week 11. Students were so far behind that at the end of week 14, only two thirds of the class (24 of 36 students) had finished the C1.M3 module.

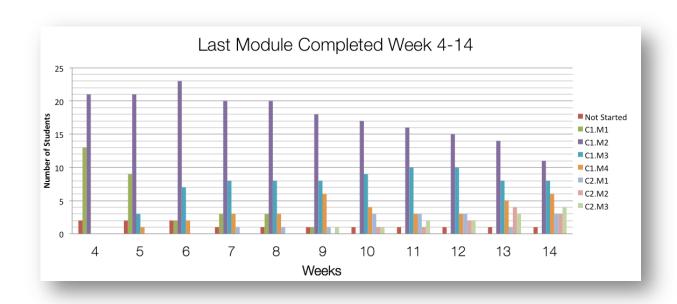


Figure 26: The last module students completed between weeks 4 and 14.

#### Attitudes toward the Course Plan and Deadlines

Students enjoyed setting and pursuing deadlines. A student commented that they "found the course deadlines and plan a good outline" and another student explained, "I liked setting my own schedule. I had actually planned when I should finish each credit before I got to the first class, but it helped me to be able to schedule each module." Another student noted that "knowing I was falling behind on a deadline was certainly a motivating factor."

Although students found the deadlines useful, some had trouble with the study implementation. One student noted that she "couldn't actually see the calendar deadlines…and then when I could, I was already done with the first credit. I just saved them to my iPad, so I could

keep track." Other students wanted to have stricter deadlines and smaller goals increments.

"I wish that we had some more hard deadlines," one student commented. "Although I think I did

pretty well with [budgeting time and making sure not to cram all the course work into the last weeks

of the semester], it would have been useful to have one or two hard deadlines." A student who had

completed an incomplete credit after the fall semester ended further explained "although we

didn't use a course plan in the spring, we did have a much harder deadline (May 30th) to finish all

our work. This helped me manage my time and finish the work accordingly."

A few students did not have trouble keeping up with deadlines. After finishing Credit 1, one student explained that they "liked to keep a week ahead of those goals to be safe...for when life happens and I fall behind." Many more students, however, seemed to have significant trouble with the deadlines. A student said that they "lost track of time, struggling with other classes" while another said explained that her "deadlines were set really high and after I fell behind I never saw a reason to catch up to them." Students also wanted more flexible ways of recovering from missed deadlines. A student explained "once someone is behind, they might as well not even try, as the motivators are unattainable," and suggested that incentives should reward students for weekly progress rather than overall progress "so if a person falls far behind, but then starts doing really well (meaning their rate of progress gets faster), they can still get the stars/points."

At the beginning of the semester, some students that were having trouble meeting their deadlines spent points to change their course plan. "I [changed my deadlines] maybe twice in the beginning ... because I wasn't investing enough time into the work...[and] because of internal factors (the projects were hard or I got stuck)" a student explained, but added that these deadlines lost meaning to students as the semester progressed. "I never pushed back the rest of my deadlines because I started to cease to care about the prize system--and therefore, the deadline calendar as well. As I fell even further behind, I became discouraged and, emotionally, didn't think the original 'planned calendar (aka 3 credits)' applied to me any more." Another student explained that they "didn't make modifications---I threw the whole thing out entirely. I didn't complete Module 1 till May of ... Spring 2014. It was kind of embarrassing."

## 6.3.4 Feedback

The study aimed to understand whether students paid attention and were motivated by group and individual feedback and whether viewing patterns occurred. Similar to goals and deadlines, I examined feedback trends using post-credit survey, email data, and in class observations using open-coding.

#### Results

### **Attention to Feedback and Viewing Patterns**

Students that progressed quickly in the course enjoyed seeing the class's progress. One student explained, "I like seeing where I am compared to my classmates," and another noted that they "found the leaderboard pretty motivating just because once you're in the top three, you feel like you want to keep going." Dynamically seeing progress from week to week also sparked curiosity about the study and motivation. "It was interesting to see that not one single student managed to keep up to their planned schedule" one student said, mentioning that "it would have been nice to know why." Social motivation seemed to extend beyond simply tracking classmates progress. One student said that they were "motivated to answer more questions on Piazza because of the points... [but] I also just like answering questions and being helpful to my classmates."

Interestingly, students were discouraged to see that their peers were performing poorly. "Everything is fine for me, [but] I have been noticing that a lot of other students are having trouble understanding a lot of the core concepts needed to complete the assignments," a student observed, and another noted that "watching half of the class fall behind at the same time was definitely a non-motivating factor."

Some students were more interested in seeing their personal progress through the course rather than seeing how the class was progressing. A student explained that they motivated by visually seeing their progress on the Canvas. "I find it motivating to track my progress

through each credit with the little check marks and such," they explained. Other students enjoyed being recognized on the leaderboard, but wanted more meaningful recognition of their work. "In other courses, a real motivator (for me and for others) was to get some recognition each session, "a student explained. I had a chemistry teacher who would ask those students who had done an especially nice job with a problem on a test to describe what they had done ...in front of the whole class. It was an honor to be called up, and a really motivator."

## 6.3.5 Behavioral Incentives

A primary study goal was to understand whether students were motivated by the leaderboard, and system of badges, points, and prizes, and whether the motivation strategies worked well together. As with goals and deadlines and feedback, I examined behavioral incentive trends using the post-credit survey, email data, and in class observations.

#### Results

Students in the *Paths* course struggled to balance their self-paced coursework. One student noted that "other classes got in the way and this [course] got pushed to the back burner," and another student noted that they "needed to blend the coursework in with all ... other coursework."

Students that were busy with other courses noted that they "didn't find the [motivation incentives] especially motivating because I was very busy with my other courses," but wish they had had more time "to really participate."

Many students were motivated by the badge and prizes system at the beginning of the semester, but lost interest as the semester progressed. "At first, getting badges... was exciting, but it did not continue to be motivating because it became normal. I liked getting stars and stuff, but it wasn't particularly motivating." Another student noted that their motivation decreased when they fell behind their progress goals. "At first, the gold stars were somewhat motivating, but they lost that power when I fell behind, as there was no obvious way to reset."

Students were divided on the motivation incentives. Students noted that the incentives were "cute" and one explained that they found the "prizes system motivating, because [they] wanted to make a 3D printed item." Another student stated that they were "excited to get the 3D printing prize... [but], I guess the motivation wasn't enough to get me to stick to my plan." Some students did not like the prizes. One student said that they "[liked] chocolate, but ...didn't really like the top prize." Still others found the prizes not related to the course goal. "There were no motivation practices that could make up for the difficulty of the class," one student explained. "Chocolate doesn't really matter when the object is to learn something."

A few students noted problems with the structure of the badges and prizes. One student said that they were "somewhat confused by how exactly the gold system works" and another noted that they didn't like that the sticker badges were distributed during class. "When I was working on an in class assignment, [it] felt rude [to] ... interrupt our work to get stickers." Further, some students did not appreciate the visibility of the badges. "I don't really care about the stickers, and I don't like other people seeing how many I got," one student explained.

# Chapter 7: Discussion

This research explores how background variables affected achievement, whether a course credit suggestion influenced student goals, and whether goal and deadlines, feedback, and incentive structures motivated students to meet their goals.

The analysis of background predictors found that programming experience, procrastination and self-efficacy quantitatively predicted the number of credits students completed, however time and goal commitments also influenced achievement. Relatedly, the study found that students did not explicitly follow the credit suggestion, but considered it when choosing their credit goal.

The motivation intervention found that goals and deadlines, feedback, and incentive structures were both motivating and demotivating. Students found the deadlines useful, but

had trouble meeting credit goals. Similarly, students paid attention to aggregate progress feedback, but were demotivated by stagnation. Further, some students were motivated by the leaderboard and prizes at the beginning of the semester, however many wanted meaningful recognition of achievement.

## 7.1 Background Predictors of Achievement

To understand whether student background influenced achievement, predictors were regressed on number of credits completed in the fall and total number of credits completed. Predictors were examined individually through linear regression and in groupings through multiple linear regression, and were also examined for interaction effects.

The study found that programming experience significantly predicted the number of credits students completed, however course preparedness and the number of languages students were familiar with did not. Interestingly, course preparedness and number of programming languages predicted the number of credits students pursued, but did not predict the number of credits students completed.

Hypothesis 1 predicted that computer background variables would predict the number of credits completed because students with more programming experience find it easier to

learn new programming languages [41]. Although programming experience and number of programming language variables are related, number of programming languages predicted credits pursued, while experience programming predicted credits completed. This unusual pattern of significance suggests that survey framing may have contributed to this discrepancy. In the pre-course survey, number of programming languages is an abstract assessment of skill: the measure asks students to list which languages they have "at least a little experience with" (see Appendix G: Summary of Data and Coding Key for details). Conversely, the experience programming measure concretely describes the different choices (e.g. high programming experience indicates that the student has" taken a programming class or studied on [their] own and has written short (10-50 line) programs"), making it easier for students to accurately respond to the question. After taking the survey, students may have considered the abstract variable when setting their credit goal, when in fact the more concrete measure was a better predictor.

Procrastination also significantly predicted the number of credits completed, supporting Hypothesis 1: more days to finish the pre-course survey (greater procrastination) negatively predicted performance, and on average, participants that took ten days to return the survey completed one to two fewer credits. Interestingly, fewer number of days to finish the survey was positively predicted by programming experience and negatively predicted by number of programming languages, indicating that student with significant programming experience in fewer programming languages were less likely to procrastinate than students with less programming experience, but experience with many languages. This finding suggest that programming "specialists" are less likely to procrastinate than programming "generalists," which is reasonable; learning a skill deeply requires persistence, however surface learning does not.

Self-efficacy and programming experience together positively predicted the number of credits students completed, supporting *Hypothesis 1*, however self-efficacy was only a predictor for students with medium or high programming experience; these students procrastinated less and completed more credits when they had relatively higher self-efficacy scores. An explanation for this may be how students interpreted the context of the self-efficacy questionnaire. The questionnaire asked students to assess their ability to understand material on their own (e.g. a measure asks students to rate " I am always able to identify useful information on the web for a project" on a 7-point Likert scale), but did not specify a context for this rating. Students with more programming experience may have rated their self-efficacy in the context of computer science, whereas others may have rated their self-efficacy more abstractly, or relative to other disciplines or experiences. Self-efficacy is subject-specific [28], so the measure may have only been predictive for students that rated themselves in the context of computer science.

Overall, the study findings partially support *Hypothesis 1*. Findings suggest that self-efficacy, procrastination, and programming experience significantly predicted the number of credits students completed, however course preparedness, number of programming languages, and GPA did not. Although time and goal commitments did not quantitatively predict number of credits completed, students cited time and goal conflicts as a primary reason for not meeting module deadlines and completing credit goals, suggesting that it was an important factor in achievement.

## 7.2 Credit Suggestion

Hypothesis 2 posits that students would use the credit suggestion as their credit goal in the course plan. The research found that the credit suggestion was not a significant predictor of the number of credits students chose to pursue, however qualitative findings suggest that students considered the credit suggestion factors; In the course plan, several students mentioned that programming experience, time commitments, and self- efficacy influenced their credit goal.

The number of credits students pursued did not predict the total number of credits completed. Many students that pursued three credits completed one or no credits, and two

students that pursued two credits completed three credits. This suggests that students were not able to set effective goals, even when they actively considered achievement predictors into their decision.

#### 7.3 Motivation

The post-credit survey, the course plan, email exchanges, and informal observations were primarily used to evaluate the effect of goals and deadlines, feedback, and incentive structures on student motivation. Overall, the motivation intervention did not motivate students to work consistently and to meet personal goals. Students were excited by motivation components at the beginning of the semester, however motivation decreased as the semester progressed.

## 7.3.1 Goals and Deadlines

Students responded positively to setting goals and deadlines, but were unmotivated by their flexibility. In the post-credit survey, many students suggested implementing stricter deadlines; one student explained, "although we didn't use a course plan in the spring, we did have a much harder deadline to finish all our work...[which] helped me manage my time and finish the work."

As the semester progressed, students struggled with their coursework. Students that started the semester actively participating in the study lost motivation when they couldn't keep up with deadlines: As one student explained, "I fell even further behind, I became discouraged and, emotionally, didn't think the original 'planned calendar... applied to me any more." This is consistent with Soman and Cheema [83], who find that violating a behavioral goal can often decrease subsequent performance.

Students that could not meet their goals were not motivated by badges and prizes. One student summarized that "once someone is behind, they might as well not even try, as the motivators are unattainable." Because students had trouble recovering from missed deadlines, they wanted to be able set deadlines for smaller goal increments, and create more flexible and meaningful ways of earning badges and prizes. This way, a student explained, " if a person falls far behind, but then starts doing really well…they can still get the stars/points."

## 7.3.2 Feedback

Students paid attention to aggregate feedback but were demotivated by stagnation. One student explained that "watching half of the class fall behind at the same time was definitely a non-motivating factor." Seeing other students performing poorly demoralized students, and a student noted that "Everything is fine for me, [but] I have been noticing that a lot of other students are having trouble understanding a lot of the core concepts needed to complete the assignments."

It was difficult to assess the effect of individual progress feedback because students did not actively discuss it in the post-credit survey, over emails, or in class. Interestingly, students mentioned that they were motivated to see their progress. For instance, one student said, "I find it motivating to track my progress through each credit with the little check marks and such."

## 7.3.3 Incentive Structures

In the beginning of the semester, participants enjoyed comparing themselves to other students and receiving badges and prizes. One participant explained that the leaderboard was motivating because "once you're in the top three, you feel like you want to keep going," and another said that the prizes were motivating "because I wanted to make a 3D printed item."

While many students said that they liked the study, they were not motivated by the extrinsic rewards, and wanted meaningful recognition for their achievements. Several students did not find the prizes were meaningful, and one student summarized that "there were no motivation practices that could make up for the difficulty of the class. Chocolate doesn't really matter when the object is to learn something." This is consistent with LeBlanc [60], who notes that extrinsic rewards can shift focus away from the material to be learned and instead concentrate solely on the reward. Like to meaningful prizes, some students did not find the leaderboard motivating, instead wanting meaningful recognition for their work.

In addition to not being motivated by the incentives, some students struggled with study implementation flaws. One student, for instance, was confused how the gold point system worked, and another noted that they could not see the deadlines on the shared calendar. " I couldn't actually see the calendar deadlines…and then when I could, I was already done with the first credit." Additionally, some students did not like the way the badges were implemented. "I don't like other people seeing how many [stickers] I got," a student commented, and another pointed out that "[it] felt rude [to] … interrupt our work to get stickers."

## 7.4 Implementation Limitations

The implementation was limited by several factors. The literature highlights that self-paced study often makes students feel isolated and results in less social visibility [37], and that self-paced learning is most effective when students feel that they are being constantly monitored [38]. Since the course only met face-to-face once a week, there was limited opportunity for students to interact with peers and for instructors, and for TAs to monitor progress. The instructor and TAs accounted for this by offering office hours on the four days that the course did not meet (9 hours, in total), however, Karabenick [48] has shown that students who are anxious and perform poorly often avoid seeking help, so students who needed the most help may not have proactively used this resource.

The predefined course structure additionally limited the incentive structures that the study could use to motivate students through the semester. Tynan [93] suggests that rewards should be aligned with intrinsic motivation that enhances the experience that is being motivated [4], however, it was difficult to convincingly integrate an intrinsic rewards structure into a preexisting design.

Limited technology resources further limited the implementation design. Research suggests that interventions are most successful when delivered "just-in-time" [33][66] and several education motivation platforms have created customized dashboards that give users immediate feedback on goal progress[44], and impact on other students [53]. Since the study was developed in three months, and the research did not have a development team or budget, the study relied on pre-implemented and freely available software that could perform motivationally similar tasks. The study thus relied on the Canvas system, that students were using to watch videos and complete assignments, to display progress information and collect data. The Canvas display and analytics data were inflexible, so the design made use of announcements, private messages, and Google docs to display information, and paired analytics data with additional measures to collect progress data.

The study was also heavily defined by student privacy concerns. Like instructor monitoring, peer and social monitoring is an instrumental motivation tool; Taylor and

Backlund [87] observe that a shared community of practice contributes to flow and immersion, and Fogg [33] notes surveillance as an important design principle of effective motivation technology. Students may have profited from being aware of each other's progress, however publically available data had to be anonymized or use pseudonyms, which decreased visibility effects.

Course structure, technology and privacy concerns were further magnified by time constraints. After reviewing literature, there was limited time to design the study before the research had to be submitted to IRB. There was thus little time to determine what methods would be most effective, and what technology would best implement these methods. Once the review board approved the study and the semester began, several issues appeared that were difficult to amend without completely rethinking the study and implementation structures.

## 7.5 Study Limitations

## 7.5.1 Survey responses

The pre-course survey assessed student goal and time commitments, however activities and hours devoted to activities may have changed during the semester, making these measures a poor predictor of achievement. Pintrich [73] notes that self-reporting assessments are

useful for measuring general aptitudes and propensities to use different self-regulatory processes, but that retrospective and self-reported measures may lead to validity problems [26]. Further, students may favor certain numbers on a scale (e.g. always picking 7 on a Likert scale) so answers may have been biased. To overcome this bias, studies often use several questions to assess a measure, however the introductory study was complex, so I decided to only include duplicate assessments of self-efficacy, which was a central measure in the research. Different background variables may have also moderated how students interpreted and answered questions. For instance, question 36 in the pre-course survey assessed the typicality of student workload, however students with different college experiences or majors may have interpreted this question differently.

Unlike on the pre-course survey, missing data was a significant problem on the post-credit survey. The survey was designed for students to complete immediately after they finished each credit, and thus assess the motivation implementation multiple times during the semester. Most students in the course finished their credit goals after the fall semester, so it was difficult to collect data from these students. Further, data collected during the spring semester asked students to assess their experience with the study from the previous semester, potentially leading to biased assessments of the implementation. For instance, the *negativity* cognitive bias asserts that people have a better recall of unpleasant memories compared to positive memories [42], while the fading affect bias suggests that emotions

associated with unpleasant memories fade more quickly than emotions associated with pleasant memories [94]. Students could have thus recalled the implementation as more positive or negative than their actual experience.

## 7.5.2 Collected Data

Progress data, which was collected weekly before class, determined the anonymous progress feedback, badges, and the leaderboard. Progress data collected from the student access report (Figure 9) showed a timestamp and number of times an assignment was viewed and attempted. This created opportunities for incorrectly assessing student progress; trends were used to assess whether an assignment had been completed on a given day or was viewed after previously being completed (see footnote 5 for details), however the misleading data structure created opportunities for error. Further, the last-viewed data changed every time students accessed a page, so it was difficult to assess the reliability of the collected data. Anonymous progress feedback, badges, and the leaderboard data may have thus been compromised.

Several important motivation measures were also not evaluated. To be effective, extrinsic motivation must have clear award criteria and explicit information on how to improve performance [60]. The implementation was updated several times to better motivate students, however it is not clear how well students understood the changes made to the

study. Students had access to the motivation study document (Appendix A) that explained the badges, prizes and points system, however the study did not assess how well they paid attention to and understood the changes. For instance, students that looked at the motivation study Google Doc more frequently may have had a better understanding of the badge and point system, and may have been more motivated by the incentives. Incentive amendments (see page 69), may have also made some of the data collected not meaningful. For instance, when the study began, students lost points for not completing their goals on time, however this penalty was removed because students were demotivated by negative points, making the point data not representative of actual performance.

Extending the amount of time that students worked on the course may have further biased the motivation implementation. The course plan, and credit goals were designed to help students set clear, specific goals, and the module deadlines were designed to help student evenly space deadlines [36][2] and help students assess whether they were making adequate progress toward those goals [52]. Students procrastinated until the end of the semester, however the *Goal Looms Larger* effect, which makes goals feel all-consuming [34], should

have nudged students to work intensely to meet their goals. Instead, students were given the opportunity to complete up to two credits<sup>13</sup> during the spring semester, which eliminated pressure to make progress during the fall; students that decided to finish a credit during the spring may have not found the progress data and forecasting information meaningful, and may have not been motivated to stick to their goals [31].

## Chapter 8: Conclusion

In this thesis I have predicted and motivated achievement in the *Paths to Computer Science* course. First, I considered what background variables predicted achievement in the self-paced mastery environment, and designed, implemented, and evaluated a motivation intervention to help students set a reasonable credit workload and stay motivated through the semester.

<sup>13</sup> Although students were only supposed to have the opportunity to complete a credit they had already started,

the instructor allowed some students to sign up for an additional credit.

Overall, students in the course struggled with poor planning, balancing coursework with other time commitments, and procrastination; my analysis found that procrastination, self-efficacy, and programming experience were significant predictors of credits completed. In the motivation intervention, I found that students profited from deadlines and feedback and considerably benefited from the credit suggestion, but were largely not motivated by the incentive structures: the study found that students wanted meaningful recognition for their work rather than physical prizes.

## 8.1 Design Considerations and Suggestions

In the discussion, I observed and identified prominent open coding themes. Based on these themes, I propose design considerations and implementation suggestions to effectively motivate students in self-paced mastery learning environments.

## 8.1.1 Background Variables and the Credit Suggestion

The research found that programming experience, self-efficacy, procrastination and time and goal commitments significantly contributed to student achievement (see section 6.1.2). The study also found that students used the credit suggestion as a guide, and noted that individual predictors influenced their decision to take a credit load. Although students considered the suggestion when choosing a credit goal, many chose a higher goal that the credit suggestion.

The credit suggestion could help students set meaningful and attainable goals if it was based on significant predictors, compared students on individual measures, and accounted for goal inflation. In the study, the suggestion used several measures to assess computer science background, however only programming experience was a significant predictor of achievement. Relatedly, procrastination was not considered in the credit suggestion, but also significantly predicted achievement. Programming experience should thus replace the other computer science variables, and procrastination should be incorporated in the credit suggestion calculation.

The credit suggestion showed students how they compared to one another on an aggregate measure that subsumed computer science background, time and goal commitments, and self-efficacy measures (Figure 6). Although the suggestion did not compare students on individual measures, participants justified their course plan goals using specific predictors: several students referred to their time and goal commitments and self-efficacy in their responses. Rather than comparing students solely on an aggregate measure, comparing them on individual predictors would make the measures more salient, and help students readily benchmark their background and experience to their peers. While students used credit suggestion measures to choose a credit goal, they chose overly demanding goals. Goal

inflation could be accounted for by giving students lower credit suggestions, so that when they adjust upward, they would choose appropriate goals.

#### 8.1.2 Goals and Deadlines

The study found mixed results on the effectiveness of the credit goal and course plan (section 7.3.1). Students considered the deadlines useful and necessary, but had trouble sticking to the course plan and actively meeting deadlines. Once students fell behind on their goals, they became discouraged and stopped paying attention to the course plan completely.

Motivation literature notes that evenly spaced [2], hard deadlines [34] are important to student achievement, and in the post-credit survey, students indicated that the hard deadline at the end of the spring semester motivated them to complete their goals. Evenly spaced, hard deadlines are a standard practice in traditional college courses, however Bloom [9] advocates that students require different amounts of time to master course material. To help students both successfully master course material and complete their credit goals, students could choose from a set of predetermined, evenly spaced paces to follow (e.g. the benchmark credit schedules in Table 1). Unlike the personal deadlines students created in the course plan, the predefined deadlines should affect course grades, and should not be easily extended.

#### 8.1.3 Feedback

Students received aggregated anonymous feedback and personal feedback and forecasting during the course. The discussion on *Attention to Feedback and Viewing Patterns* in section 6.3.4 found that students paid more attention to aggregate feedback than individual feedback, and enjoyed the process of tracking their progress through the course.

The study findings suggest that progress comparisons to the class were concurrently motivating and demotivating. Students that progressed quickly enjoyed seeing that they were ahead the class, but became demotivated when class progress stagnated. Relatedly, students that had trouble meeting goals became demotivated when they saw that they were not making as much progress as the class. Rather than being compared to the entire class, students should be compared in progress cohorts to simultaneously motivate high and low achievers. Small cohorts would allow students to benchmark weekly progress based on peers at similar paces, and would increase the perception of social monitoring [33].

It was difficult to assess the effectiveness of individual feedback and forecasting because students did not discuss it in the post-credit survey or over email. Students received individual progress through Canvas messages, but may have not seen or paid attention to the progress information. While it was not possible to implement in this research, future work should make individual feedback dynamic and easily accessible. For instance,

students could see personal progress feedback when they logged into Canvas to work on course assignments. Although students did not address goal and deadline progress feedback in the post-credit survey, they enjoyed the process of tracking the progress path. Future work could generate intrinsic motivation by giving students the opportunity to manually check off completed assignments online, and signal that they completed a module by pressing a "That Was Easy" button during class, which would create social visibility and competition between students.

#### 8.1.4 Incentive Structures

Students were predominantly not motivated by the leaderboard, badges, points, and prize structures (see section 6.3.5). At the beginning of the semester, some students were excited to be on the leaderboard and earn badges and prizes, however many noted that the incentive structures were superficial, and didn't actively motivate them to make progress toward their goals. Further, students who missed module deadlines became demotivated by the incentives because they could not earn prizes once they fell behind. Rather than being motivated to catch up to their peers, participants that fell behind became disinterested in earning badges and prizes.

In the post-credit survey, student highlighted the importance of meaningful recognition, and suggested that they were intrinsically motivated to help classmates understand course

material. Rather than distributing prizes, students could be rewarded with skill badges that let them engage in leadership roles. For instance, students that completed assignments with an exceptionally high grade could be awarded *Skill TA* badges that would publically recognize their achievement and nudge them to help other students learn the skill they mastered. Helping others learn would refine students' mastery of the skill, and free the instructor and TAs from repeating simple explanations.

In addition to creating meaningful incentives, students who fall behind must be able to recover quickly from mistakes. To do this, the incentive structure should only use positive reinforcement, and reward students for incremental rather than overall progress. This could be achieved by rewarding effort in the course (e.g. hours spent on coursework) rather module completion. This would help students who normally underestimate the amount of time assignments take [32] to accurately plan out a number of hours to devote to the course per week.

*Table 8: Summary of design considerations and implemented suggestions* 

Structure	Design Consideration	Implementation Suggestions
Credit Suggestion	Programming experience, time and goal commitments, self-efficacy, and procrastination contributed to student achievement	Use significant predictors to construct the suggestion

Credit Suggestion	Students considered individual predictors when choosing a credit goal	Compare students on individual predictors, and visualize them meaningfully
Credit Suggestion	Students anchored and adjusted from the credit goal	Suggest a lower credit goal expecting that students will adjust upward
Deadlines	Students considered deadlines useful and necessary, but were not motivated by the credit goal and personal deadlines	Deadlines should be broken into smaller increments and spaced more evenly Students need multiple "hard" deadlines
Feedback	Social comparison to the class was both motivating and demotivating: Students paid attention to aggregate feedback, but were demotivated by stagnation	Compare students in small progress cohorts rather than against a full class
Feedback	Students did not pay attention to personal feedback	Students should receive dynamic feedback whenever they log in to work on assignments
Feedback	Students enjoyed tracking their progress path	Give students an opportunity to meaningfully "check off" assignments
Incentive Structures	Students wanted meaningful recognition and incentives	Recognize students through leadership roles (e.g. TA skill badges)
Incentive Structures	Students need to be able to recover from mistakes	Only give positive reinforcement  Reward students for weekly progress instead of overall progress

## 8.2 Future Work

Future studies to motivate students in self-paced and mastery courses should consider the motivation suggestions described in section 8.1 (see Table 8). Course load suggestions should be based on significant predictors, should meaningfully visualize and compare students on individual predictors, and account for goal inflation. Further, deadlines structures should be divided into small, evenly spaced increments, and should affect student grades. Likewise, group feedback structures should compare students in progress cohorts, and personal feedback should be dynamic and readily accessible. Lastly, intrinsic motivation should be generated from progress monitoring and meaningful rewards; incentive structures should only use positive reinforcement and reward students for incremental, rather than overall progress.

The research found that students considered the credit suggestion when setting workload goals. Future work might consider how a credit or workload suggestion could help students in online courses and MOOCs set effective goals. For instance, a course suggestion calculator could suggest a course or learning style based on background predictors of achievement.

The study also demonstrated that for self-paced courses to be successful, students need meaningful personal and relative feedback, easily achieved but rigorous deadlines, and persistent progress monitoring. Previous research has devoted significant resources to implementing automated or instructor dependent motivation structures, however a next step might explore how to *nudge students to motivate each other*. Similar to online open source projects, peer motivated learning in MOOCs and online courses could create viable alternatives to traditional college environments.

Chapter 9: Appendices

Appendix A: Motivation Study Introduction

Paths to Computer Science - Fall 2013

Prof. Ben Bederson

CMSC 198 (C, D, E) Motivation Study

**Experimental Study to Improve Motivation** 

During the semester, Professor Bederson and graduate student Alina Goldman will use the CMSC 198 (C, D, E) course to conduct a study about motivation in a self-paced mastery based environment. We invite students to participate in this research.

If students choose to participate, they will **not be required to complete any** assignments beyond the normal class requirements. Participation in this **research is completely voluntary**, and students may choose not to take part at all.

The study will involve (a) interacting with classmates and course tools during the semester, (b) creating a course plan, (c) evaluating personal experience with the course and these tools, and (d) filling out surveys.

121

Study participants will have the chance to win small prizes based on how well they stick to their goals.

### **Study Consent**

At the beginning of the semester, students will receive a consent form to participate in the study. On the consent form, students will be able to opt into displaying the following:

- Student achievements, including badges for completing deadlines early or on time, helping others, and making progress in the course
- deadlines from student course plan
- Percentage of my goals completed
- Gold points earned

If students decide to participate in this research, they may stop participating at any time. If students decide not to participate in this study or if they stop participating at any time, they will not be penalized or lose any benefits to which they otherwise qualify.

## **Course Expectations**

Students that participate in the study will:

- Create and stick to a course plan
- Interact with "motivation" tools

Fill out introductory and post-exam surveys

### Course Plan

#### Determining a target credit goal

Students who choose to participate in the study will be asked **choose a target goal** of completing 1, 2 or 3 credits during the semester **on Friday September 13**<sup>th</sup>. Before this date, students should test the pace of a credit workload by following one of the week 2 workloads outlined below. However, you should be aware that this first week includes less material than ensuing weeks, and the difficulty of the material increases during the semester.

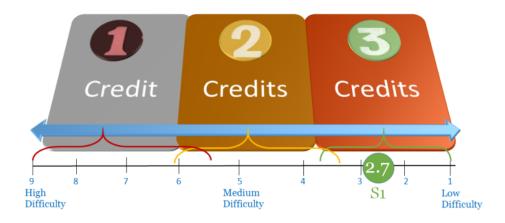
Day	Date	3 Credits	2 Credits	1 Credit
Sat	9/7	Introductory Survey	Introductory Survey	
Sun	9/8	Codeacademy Exercise (Python Syntax)  Codeacademy Exercise (Tip Calculator)	Codeacademy Exercise (Python Syntax)	Introductory Survey
Mon	9/9	Codeacademy Quiz – Python Syntax Install Python Syntax	Codeacademy Exercise (Tip Calculator)	

		and Text Editor		
Tues	9/10	Intro to Python 1 - Algorithms  Quiz - Algorithms	Codeacademy Quiz – Python Syntax	Codeacademy Exercise (Python Syntax)
Wed	9/11	Intro to Python 2 - Programming Languages	Install Python Syntax and Text Editor	Codeacademy Exercise (Tip Calculator)
Thus	9/12	Quiz - Programming Languages	Intro to Python 1 - Algorithms  Quiz - Algorithms	Install Python Syntax and Text Editor
Fri	9/13			

If a student finds the workload too demanding, they should consider choosing a less demanding credit target. If a student finds that the workload is not challenging enough, they should consider increasing their credit target.

Calibrating Workload Difficulty and Suggesting a Target Goal

After participating students complete the introductory survey, the instructor will use responses about time commitments, programming background, and self-efficacy to calibrate how difficult each credit would likely be for individual students. The instructor will use this difficulty calibration to suggest a target goal. This should additionally help students calibrate what course difficulty may be most appropriate.



#### Creating the Course Plan

On September 13th, students will be asked to set their target credit goal.

When setting the target goal, students should consider:

- How many other courses are you taking? Do you have other time commitments, such as a job or extracurricular activities? How much time will they take per week?
- How comfortable do you feel with technology? How familiar are you with programming?

• How good are you at working at your own pace? How good are at following through with goals?

Students should also remember to:

Be conservative when estimating how much time it will take to
 complete each module. The <u>planning fallacy</u> shows that people often
 underestimate how long they will need to complete a task, even when they have
 done the task before.

Students will then be asked to **create deadlines** for each credit they plan to pursue.

Students will have **one week** to revise this plan.

Please refer to the credit schedule below for a sample pace for each of the three credits.

Week	Class Date	3 Credits	2 Credits	1 Credit
Week 2	9/13	Artificial Life	Artificial Life	
Week 3	9/20	Intro to Python	Intro to Python	Artificial Life
Week 4	9/27	Creature Movement		
Week 5	10/4		Creature Movement	
Week 6	10/11	The 2nd Dimension		Intro to Python
Week 7	10/18	Classes	The 2nd Dimension	
Week 8	10/25	Interaction	Classes	

Week 9	11/1	Inheritance		
Week 10	11/8		Interaction	
Week 11	11/15	AI Search		Creature Movement
Week 12	11/22	Web Apps	Inheritance	
		THANKS	GIVING	
Week 13	12/6	Going Public		
Week 14	12/13	Test Processing		
Week 15	12/20	Evolution	AI Search	The 2nd Dimension

## On September 23<sup>st</sup>, deadlines for the first credit will be considered

**permanent**. Students will be expected to complete modules by the chosen deadlines, and should carefully consider other time commitments when setting these deadlines.

Deadlines for credits 2 and 3 are considered to be tentative. Students will have the chance to **revise their course plan after finishing each credit**.

Once students confirm their deadlines, we will post these deadlines to a shared google calendar via a pseudonym. This will help students feel a sense of social responsibility toward their peers. (See Shared Calendar under tools for more details)

If students are unable to complete a module by the deadline, they will have the chance to revise the course plan in exchange for gold points. The more deadlines a student pushes back, the more gold points it will cost (see points and prizes for more details). If students do not complete a deadline in time, they will be penalized by losing additional gold points (see badges and points).

#### Playing a Game

We have created several tools to help students meet their target deadlines. During the semester, students will have the chance to earn badges and gold points. Students that make the most weekly progress will also have the chance to be featured on a Top 10 leaderboard.

#### Badges

Students will have the chance to earn 4 types of badges: deadline badges, early completion badges, merit badges, and miscellaneous badges.

- Homework badges are awarded for completing modules early or on time
- Early completion badges are awarded for pushing module deadlines forward
- Merit badges are awarded for making progress in modules and mastering modules on the first try
- Misc. badges are awarded for tasks such as answering questions, completing surveys, and working on modules several days in a row.

Earned badges will be given to students in class, and students will have opportunity to display them publicly. See the chart below for badge details.

### **Badge Colors and Sizes**

Silver	complete deadlines by date, complete surveys
Gold	Personal achievement: complete module correctly on first try
Green	Set and meet deadlines earlier
Purple	Login streaks, answering questions
Red	Most Progress/first to achieve a goal

Type	Badge	Details	Points
HW	1. ModStar1	Complete module by deadline	+3
	2. SpeedDemon	Push module deadline forward by 2+ days and complete module by early deadline.	+5
	3. ProgressStar	Most progress for the week (top 3)	+6, 5, 4 (1, 2, 3)

Type	Badge	Details	Points
Misc.	4. QuestionStar	Get your answer endorsed on the Canvas forum	+3
	5. EnduranceStar	4 day streak: Login in 4 days in a row and work on module	+3
	6. SurveyStar	Complete Introductory Survey or Critical thinking questionnaire	+2
	7. SurveyStar2	Complete post-exam survey	+1
	8. TeamStar1	Class achievement if everyone finishes credit 1	+5
	9. TeamStar2	Class achievement if everyone finishes credit 2, 3	+10

#### **Points and Prizes**

Students will earn badges to collect gold points. These gold points may be turned in for prizes at specific times during the semester. Prizes may change throughout the semester.

Participants turn in their points for prizes every 3 weeks: turn in for highest level prize, keep left over points (e.g. if you have 17 points, get level a level 2 prize, keep 2 points)

Level 1	5	Lindt chocolate
Level 2	15	small fun prizes
Level 3	30	\$5 starbucks card, YogiBerry card
Level 4	40	Personalized 3D printed item

Students will also have the chance to push back deadlines. **Pushing back deadlines**will cost gold, and the more deadlines a student pushes back, the more gold points it
will cost. Students who miss a deadline will lose 7 gold per deadline missed.

Change Per Credit	Cost
#1	1 gold
#2	2 gold
#3	4 gold
#4	5 gold

#### Progress Leaderboard

Every week, a leaderboard will show **the scores and achievements of the top 10 students** who have made the greatest progress toward their goal.

If students want to have their scores posted to the leaderboard during the semester, they will have the chance to **opt in on the Consent Form** (see study explanation below). Otherwise, students will not be included in the leaderboard.

Shared Google Calendar

Once students confirm their deadlines, we will post these deadlines with pseudonyms to a shared google calendar, which will be shared with other students in the class. This will help students feel a sense of social responsibility toward their peers. Students will not be obligated to post these deadlines, and will opt in on the consent form to post their deadlines to the calendar.

Additional Tools and Strategies

During the semester, additional tools, such as deadline reminders, may be added to improve student motivation. These tools will be fully explained and students will be asked to use and evaluate them.

# Appendix B: Student Consent Form

Project Title	Motivation in Mastery Based Coursework
Purpose of the Study	This research is being conducted by <b>Dr. Ben Bederson</b> at the University of Maryland, College Park. We are inviting you to participate in this research project because you are enrolled in CMSC 198 (C,D,E) during the Fall 2013 semester. The purpose of this research is to understand how best to motivate students in a self-paced mastery based environment.
Procedures	The experiment will take place during the Fall 2013 academic semester. Participants will not be required to complete any assignments beyond the normal class requirements. Participants will be compensated with small prizes based on how well they stick to their goals.
	The procedures involve (a) interacting with students and course tools during the semester, (b) creating a course plan, (c) evaluating your experience with the course and these tools, and (d) filling out surveys about your experience with computers, non-traditional learning environments and answering questions about motivation, time commitments and demographics. The questionnaire and course plan will take no more than 30 minutes to complete.
	Participants will complete 5 surveys over the over the course of the semester. Surveys will be completed in Canvas at the beginning of the semester and after each exam.

Project Title	Motivation in Mastery Based Coursework	
	Sample Survey Questions:	
	1. What is your experience with traditional online courses (e.g. online class at UMUC)? Do you prefer traditional or online courses? Why?	
	2. How useful do you feel this course will be relative to the academic/personal activities you are currently engaged in?	
Potential Risks and Discomforts	Risks associated with this research potentially include unease associated	
	with having information about course progress visible to other students.	
	To avoid these risks, the amount of personal progress information is up to	
	the participant, and participants will be able to use pseudonyms.	
	Additional risks include the potential loss or breach of confidentiality about	
	student progress. Precautionary methods will be performed, such as	
	performing security testing on online tools.	
Potential Benefits	The purpose of this study is to understand how best to motivate students to	
	help them successfully complete their intended goals in the CMSC 198(C,	
	D, E) course. By participating in this study, participants may be more	
	motivated to follow through with their personal goals for the course. We	
	also hope that, in the future, others might benefit from this study through	
	improved understanding of appropriate motivation practices for self-paced	

Project Title	Motivation in Mastery Based Coursework
	learning environments.
Confidentiality	Any information collected in this study is confidential to the extent
	permitted by law. The data you provide will be stored in locked cabinets
	and password-protected computers. Only authorized researchers will have
	access to these data.
	Your anonymity will be maintained in the following ways: (1) Your name
	will not be associated with collected data (2) your subject ID will label all
	of the questionnaires and collected data (3) researchers will be able to link
	to your identity only through the use of an identification key; and (4) only
	authorized researchers will have access to the identification key.
	Additionally, this identification key will be stored in a locked cabinet or on
	a password-protected computer with restricted user access. All collected
	data will be secured in a locked cabinet within an office after the end of the
	project.

Project Title	Motivation in Mastery Based Coursework
	If we write a report or article about this research project, your identity will
	be protected to the maximum extent possible. Your information may be
	shared with representatives of the University of Maryland, College Park or
	governmental authorities if you or someone else is in danger or if we are
	required to do so by law.
Compensation	Participants will be compensated with small prizes based on how well they stick to their goals. Prizes will be worth no more than \$10 each and will consist of small toys, UMD logo items, and simple fun things.
	☐ Check here if you expect to earn \$600 or more as a research participant in UMCP studies in this calendar year. You must provide your name, address and SSN to receive compensation.
	☐ Check here if you do not expect to earn \$600 or more as a research participant in UMCP studies in this calendar year. Your name, address, and SSN will not be collected to receive compensation.
Medical Treatment	The University of Maryland does not provide any medical, hospitalization or other insurance for participants in this research study, nor will the University of Maryland provide any medical treatment or compensation for any injury sustained as a result of participation in this research study, except as required by law.
Right to Withdraw and Questions	Your participation in this research is completely voluntary. You may choose not to take part at all. If you decide to participate in this research, you may stop participating at any time. If you decide not to participate in this study or if you stop participating at any time, you will not be penalized or lose any benefits to which you otherwise qualify.  If you decide to stop taking part in the study, if you have questions,

Project Title	Motivation in Mastery Based Coursework
	concerns, or complaints, or if you need to report an injury related to the
	research, please contact the investigator:
	Ben Bederson, PhD
	Department of Computer Science
	A.V. Williams Building,
	University of Maryland
	College Park, MD 20742
	bederson@cs.umd.edu
	301-405-2764
Participant Rights	If you have questions about your rights as a research participant or wish to
	report a research-related injury, please contact:
	University of Maryland College Park
	Institutional Review Board Office
	1204 Marie Mount Hall
	College Park, Maryland, 20742
	E-mail: <u>irb@umd.edu</u>
	Telephone: 301-405-0678
	This research has been reviewed according to the University of Maryland,
	College Park IRB procedures for research involving human subjects.
Statement of Consent	

Project Title	Motivation in Mastery Based Coursework
	This research involves procedures that involve interacting and evaluating motivation practices during the semester and interacting with other students to best understand how to motivate students in self-paced environments.
	For each of the following kinds of information, I give permission for the checked options to be made visible to other students in the class under the following pseudonym. If at any point I decide to stop displaying this information to other students, or if I wish to change my pseudonym, then I will contact the instructor at which point the change will be made within 24 hours.
	Pseudonym:
	My achievements, including badges for completing deadlines early or on time, helping others, and making progress in the course  My deadlines from my course plan  Percentage of my goals completed  Gold points earned

Project Title	Motivation in M	lastery Based Coursework
	read this consent form or have has answered to your satisfaction ar	ou are at least 18 years of age; you have ad it read to you; your questions have been ad you voluntarily agree to participate in ceive a copy of this signed consent form.
Signature and Date	NAME OF SUBJECT	
	[Please Print]	
	SIGNATURE OF	
	SUBJECT	
	DATE	

### Appendix C: Pre-Course Survey

This purpose of this survey is to understand your background to better design this course.

Please rate the extent to which you agree with the statement. Mark your answer by choosing 1 - 7 below.

Question 1: I can easily find information about what I need online

1 - Strongly Disagree
2
3
4 - Neutral
4
6
7 - Strongly Agree

Question 2: I can quickly find information about what I need online

1 - Strongly Disagree

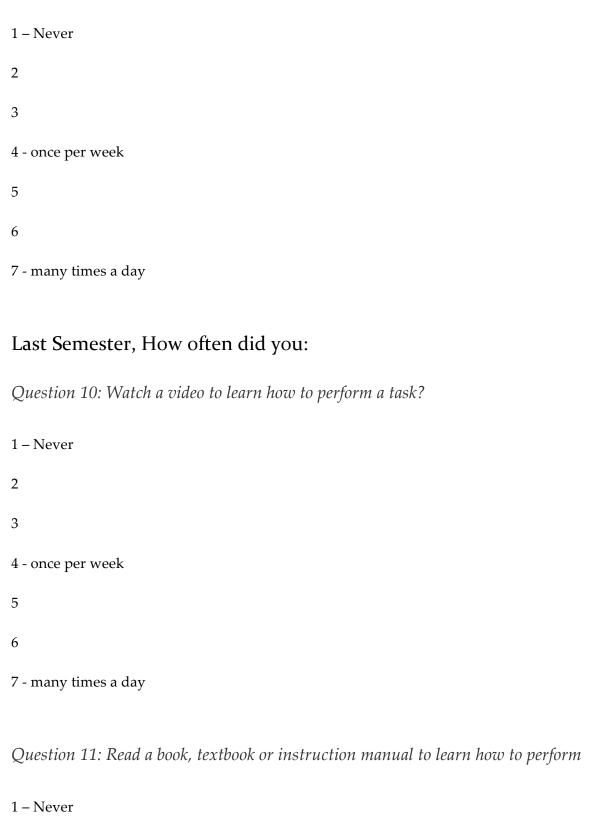
2
3
4 – Neutral
4
6
7 - Strongly Agree
Question 3: I have at least a little experience with the following programming languages
Basic
JavaScript
C, C++, Objective C, or Java
Python
Other
Question 4: My experience with programming a computer is:
None - never programmed a computer
Low - I wrote a short script or use macros or automation
Medium - I've taken a programming class or studied on my own and have written short (10
50 line) programs

High - I've written some reasonably complicated programs (> 100 lines)

Last Semester, how often did you:

## Question 5: Log into and out of Canvas during the semester? 1 – Never 2 3 4 - once per week 5 6 7 - many times a day Question 6: Read announcements and view calendar events in Canvas? 1 – Never 2 3 4 - once per week 5 6 7 - many times a day

Question 7: Access, read, reply to, and attach files to messages in the Canvas discussion board?
1 – Never
2
3
4 - once per week
5
6
7 - many times a day
Question 8: Ask or answer questions about homework on Canvas?
1 – Never
2
3
4 - once per week
5
6
7 - many times a day
Ouestion 9: Submit homework through Canvas?



```
2
3
4 - once per week
5
6
7 - many times a day
Question 12: What is your experience with traditional online courses (e.g. online
class at UMUC)? Do you prefer traditional or online courses? Why?
Question 13: What is your experience with Mass Online Open Courses (MOOC)
courses (e.g. Udacity, Coursera, EdX)? Have you ever started a MOOC? Have you
ever finished one? Did you enjoy the experience?
Question 14: The reasons I am taking this course are:
Question 15: How much overall benefit do you expect to get from this course?
1 (no benefit)
2
3
4(some benefit)
5
6
7 (a lot of benefit)
```

Question 16: Relative to other college courses you have taken, how much utility will you get from this course?

```
1 (much less utility)

2

3

4 (equal utility)

5

6

7 (much greater utility)
```

Question 17: Please explain your answer to the previous question (how much utility will you get from this course?)

Question 18: How useful do you feel this course will be relative to the academic/personal activities you are currently engaged in?

```
1 (much less useful)234 (equally useful)5
```

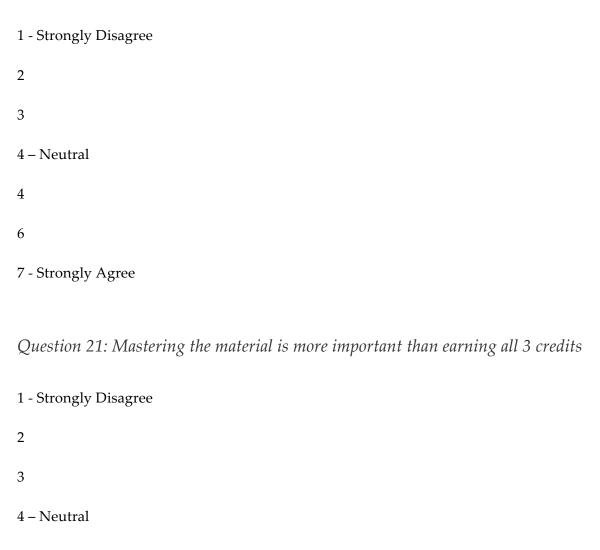
6

7 (much more useful)

Question 19: Please explain your answer to the previous question (How useful do you feel this course will be relative to your academic/personal activities)

# Please rate the extent to which you agree with the statement. Mark your answer by choosing 1 - 7 below.

Question 20: I am interested in earning a high grade in this course



4
6
7 - Strongly Agree
Question 22: I am interested in learning to program in Python
1 - Strongly Disagree
2
3
4 – Neutral
4
6
7 - Strongly Agree
Question 23: I would rather earning more credits overall than earning a high grade in each credit
1 - Strongly Disagree
2
3
4 – Neutral
4

6
7 - Strongly Agree
Question 24: Even if I don't earn all 3 credits, I will feel good about my achievements
1 - Strongly Disagree
2
3
4 – Neutral
4
6
7 - Strongly Agree
Question 25: Earning all 3 credits is very important to me
1 - Strongly Disagree
2
3
4 – Neutral
4
6

7 - Strongly Agree

Question 26: 1nis class is:
Required for my major
Required for my minor
Satisfies a GenEd
An elective
Other
Question 27: The primary motivation you are pursuing a college degree is to: Be financially successful
Pursue a career I love
Satisfy a personal interest or goal
Follow the advice of a parent or guardian
Interact socially with other college students
Other
Question 28 What is your age?
18 or younger
19-20
21-22

23-25
26-29
30 or older
Question 29: What is your gender?
Female
Male
Question 30: Which category best describes your ethnicity?
African American
Asian American
Hispanic
Native American
White/Caucasian
Other
Question 31: Which category best describes your major?
Arts, humanities, or communication
Business, accounting, or information technology

Social services (social science, social work, health care), or education

Math, physical science, life science

Undecided

Other

Question 32: How many total credits are you taking this semester? How many other courses?

Question 3: Do you have a job? How much time do you spending working each week?

Question 34: In addition to having a job, do you regularly participate in non-academic activities? (e.g. sports, theatre groups, etc.) How many different activities do you participate in?

Question 35 How many hours do you plan to devote weekly to non-academic activities during this semester?

Question 36: Is this workload typical for you? Please Explain. Is this workload typical for you? Please Explain.

Question 37: How do responsibilities outside of school affect your success at school?

They don't ever affect my success at school

They seldom affect my success at school

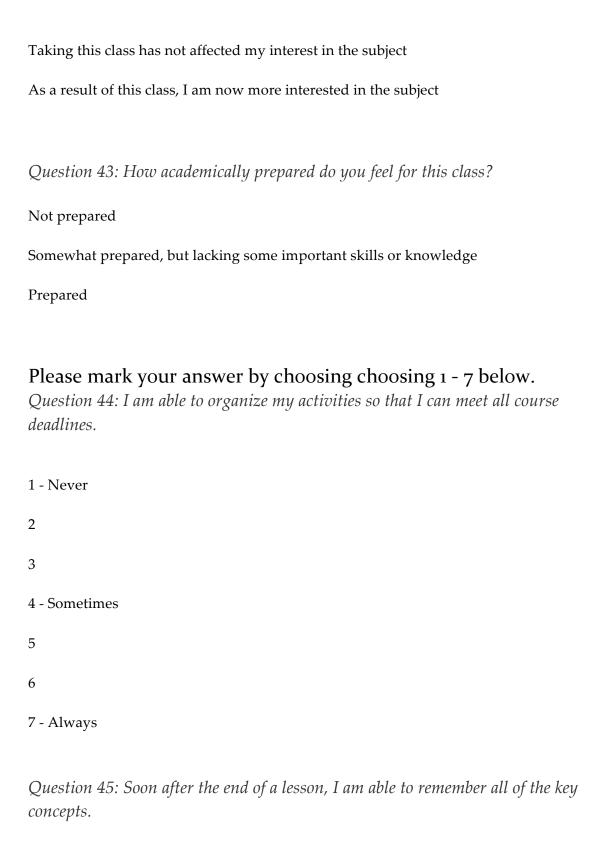
They occasionally affect my success at school

They often affect my success at school

They always affect my success at school		
Question 38: What non-academic factor most influences your success in this class?		
Work and/or financial situation		
Family obligations		
Physical and/or emotional health		
Athletics		
Social and/or recreational activities		
Interest and/or motivation in this class or in school		
Please rate the extent to which you agree with the statement. Mark your answer by choosing 1 - 7 below.  Question 39: What grade do you expect to get in this class?		
A		
В		
C		
D		
F		
Other		
Question 40: What is your overall college GPA?		

Below 1.5
1.5-1.9
2.0-2.4
2.5-2.9
3.0-3.4
3.5-4.0
Question 41: How will your level of success in this class affect your academic, career, or personal goals?
It definitely will not affect my goals at all
It probably will not affect my goals
It probably will affect my goals
It definitely will affect my goals
I'm not sure how it will affect my goals
Question 42: How do you think taking this class will affect your interest in the subject?

As a result of this class, I am now less interested in the subject



1 - Never
2
3
4 - Sometimes
5
6
7 - Always
Question 46: I can understand all of the key concepts covered in my course.
1 - Never
2
3
4 - Sometimes
5
6
7 - Always

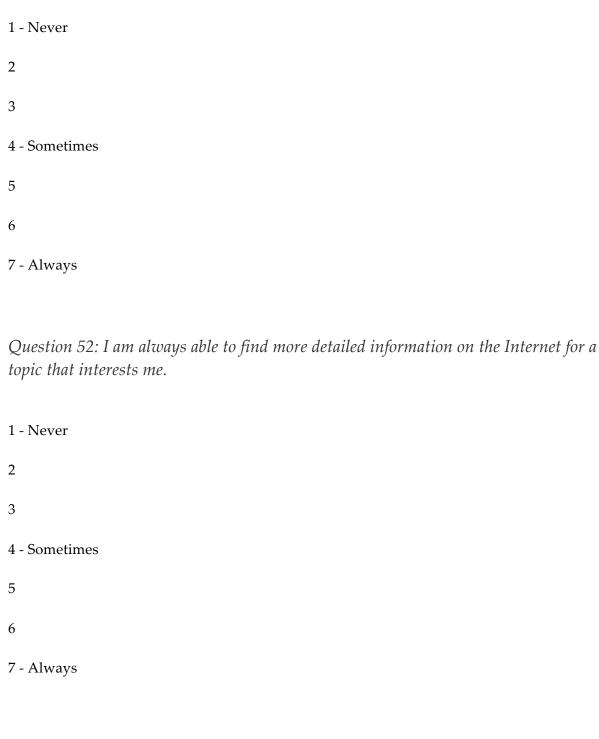
Question 47: I am able to explain to my fellow students, in a way they can understand, all of the key conce covered in a course.

1 - Never
2
3
4 - Sometimes
5
6
7 - Always
Question 48: After sitting an exam, I am able to remember all of the key concepts covered in the course.
1 - Never
2
3
4 - Sometimes
5
6
7 - Always

Question 49: When I find something new about a topic that I am studying, I am always able to connect it with other things that I know about the topic

1 - Never
2
3
4 - Sometimes
5
6
7 - Always
Question 50: I always know how to get up to date on a topic if my knowledge of it is dated
1 - Never
2
3
4 - Sometimes
5
6
7 - Always

Question 51: Even when I haven't participated in a lesson, I can always understand the concepts covered in the lesson by reading a textbook



Question 53: I am never embarrassed to ask the teacher for clarification

1 - Never
2
3
4 - Sometimes
5
6
7 - Always
Question 54: I am always able to identify the most appropriate person to help me resolve a problem related to my study
1 - Never
2
3
4 - Sometimes
5
6
7 - Always

Question 55: I am always able to relate the notes I have made during a lesson with the topics covered in the course text or readings

1 - Never
2
3
4 - Sometimes
5
6
7 - Always
Question 56: It is always easy for me to understand new information, even on a topic that does not interest me very much
1 - Never
2
3
4 - Sometimes
5
6
7 – Always

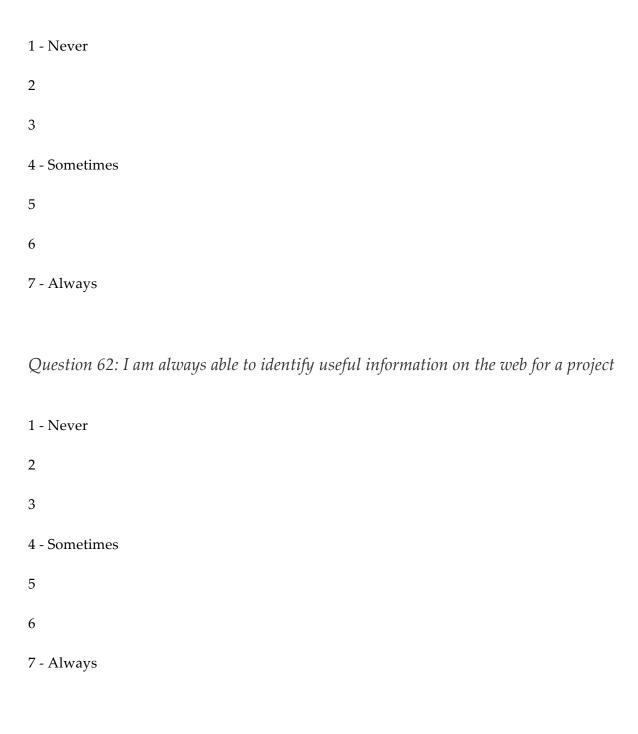
Question 57: It is always easy for me to connect new information about a topic that interests me with other pieces of information

1 - Never
2
3
4 - Sometimes
5
6
7 - Always
Question 58: During a course, if we are given a new task to complete, I can always complete it by applying the knowledge that I obtained from lessons
1 - Never
2
3
4 - Sometimes
5
6
7 - Always

Question 59: Soon after the end of a lesson, I am always able to distinguish the most important concepts from concepts of less importance

1 - Never
2
3
4 - Sometimes
5
6
7 - Always
Question 60: If, as part of a course, I participate in a forum or online discussion, I am always able to identify those messages, which will improve my understanding of the material covered in the course
1 - Never
2
3
4 - Sometimes
5
6
7 - Always

Question 61: I always find it easy to join a group of fellow students to study or complete course activities



Question 63: After a lesson, I am always able to integrate concept described by the teacher with those presented in course texts and readings

1 - Never
2
3
4 - Sometimes
5
6
7 - Always
Question 64: When I complete a project for a course, I am always able to incorporate knowledge gained from other sources
1 - Never
2
3
4 - Sometimes
5
6
7 - Always

Question 65: I am always able to help other students solve problems based on concepts described in a lesson

1 - Never

2

3

4 - Sometimes

5

6

7 - Always

## Appendix D: Course Plan

### **Course Plan**

#### Setting Initial Goals

How many total credits do you plan to complete this semester?	
Please explain how you came to this decision:	

During the semester, you will have the chance to earn achievements based on your progress in the course, ability to stick to deadlines, and initiative to help other students. Achievements are worth gold points that can be turned in for small fun prizes.

In the chart below, please set deadlines for individual modules in each of the three credits.

Please note that:

- You have the option of modifying your deadlines until September 20nd. Deadlines will be finalized
  and posted to a shared calendar by September 21st ONLY if you opt-in on the consent form.
- Deadlines for credits 2 and 3 are tentative; after completing each credit, you will have a chance to revise your schedule for the next credit.
- You are allowed to change deadlines up to 2 days before your assignment is due. Please note that
  pushing back a deadline will cost gold points:

Change per Credit	Cost
#1	2 gold*
#2	10 gold*
#3	12 gold*
#4	15 gold*

- Pushing forward a deadline will earn you 1 point\* for each day the deadline is pushed forward.
- Not completing an assignment in time results in 20 gold points\* being subtracted.

<sup>\*</sup> Note that gold points are tentative

### Course Plan

Credit	Module	Deadline
1	Artificial Life	
1	Intro to Python	
1	Creature Movement	
1	The 2nd Dimension	
2	Classes	
2	Interaction	
2	Inheritance	
2	AI Search	
3	Web Apps	
3	Going Public	
3	Text Processing	
3	Evolution	

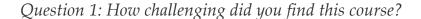
# Appendix E: Overview of Incentive Structures

HW	Progress toward	+ gold for completing each assignment on the
Badges for	individual goals	first try
completin		+ gold for pushing deadline forward
g all HW		– gold for pushing deadlines back
(basically		
a progress		
bar)		
Merit	Badges for doing	1. Complete a certain number HW
Badges	assignments/exams	assignments early (e.g. completed last 2 HW
	early/well	assignments 2 days early)
		2. Get an A on 3 HW assignments on the first
		try
		3. First, 2 <sup>nd</sup> , 3 <sup>rd</sup> to complete exam 1, 2, and 3
		with an A
		4. Most progress for the week (from progress
		leaderboard)

Non HW	Badges for additional tasks	Answer other people's questions correctly
badges	G	on the Canvas forum
		2. 5 day Login streak (logging in 5 days in a
		row and doing some amount of HW)
		3. Take notes on 5 videos
		4. Journal entry reactions to 3 assignments
		5. Complete post-exam survey
Gold	Students earn gold to buy	1. Different badges earn different amounts of
	accessories for their	gold
	creature	2. Students can save up gold to win prizes
		3. Changing deadlines "costs" students a
		certain number of gold
Progress	Weekly leaderboard	1. Students compete to have made the most
Leaderboa	showing whose made the	progress that week
rd	most progress in the	2. Students with the highest progress are
	previous week	awarded badges

# Appendix F: Post-Credit Survey

Please think about the last credit you completed for this course. If you completed the last credit during the Fall semester, please try your best to remember your experience.



Easy

Not very challenging

Somewhat challenging

Considerably challenging

Difficult

Question 2: How academically prepared did you feel for this class?

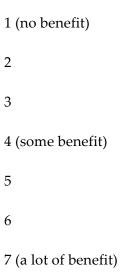
Not prepared

Somewhat prepared, but lacking some important skills or knowledge

Prepared

Question 3: Please explain your answer to the previous question (how academically prepared did you feel for this class?)

Question 4: How much overall benefit do you expect to get from this course?



Question 5: Please explain your answer to the previous question (how much overall benefit did you get from this course?)

Question 6: Relative to other college courses you have taken, how much utility did you get from this course?

```
1 (much less utility)
```

2

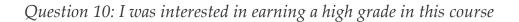
```
3
4 (equal utility)
5
6
7 (much greater utility)
```

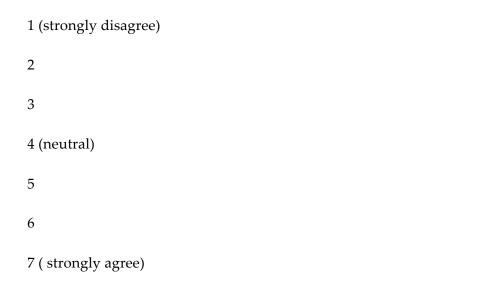
Question 7: Please explain your answer to the previous question (how much utility did you get from this course relative to your other college courses?)

Question 8: How useful was this course relative to the academic/personal activities you are currently engaged in?

```
1 (much less useful)
2
3
4 (equally useful)
5
6
7 (much more useful)
```

Question 9: Please explain your answer to the previous question (How useful was this course relative to the academic/personal activities you are currently engaged in?)





Question 11: I am interested in learning to program in Python

```
1 (strongly disagree)

2

3

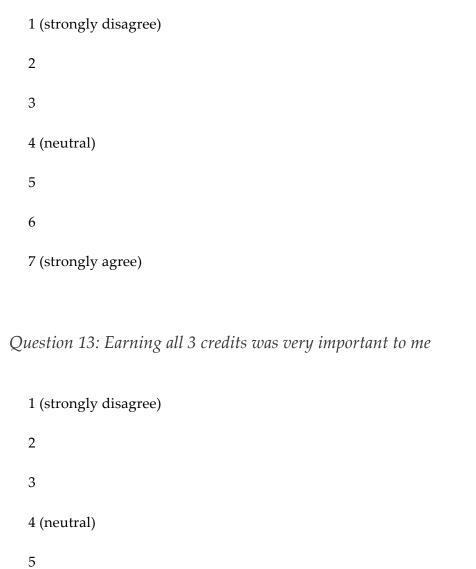
4 (neutral)

5

6

7 (strongly agree)
```

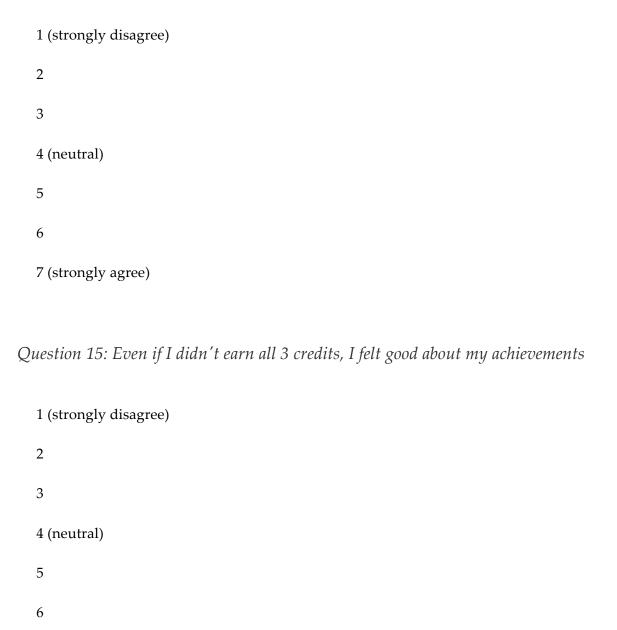
Question 12: Mastering the material was more important than earning all 3 credits



6

7 (strongly agree)

Question 14: I would have rather earned more credits overall than a high grade in each credit



Question 16: How will your level of success in this class affect your academic, career, or personal goals?

7 (strongly agree)

It definitely will not affect my goals at all

t probably will not affect my goals

It probably will affect my goals

It definitely will affect my goals

I'm not sure how it will affect my goals

In the following questions, think about your work on the modules for the LAST credit you completed.

Question 17: On average, how many hours did did you spend working on the last credit you completed [credit 1, 2, 3] per week? How many hours did you spend overall?

Question 18: Please explain how you approached each module in the last credit you completed. In your explanation, address the following:

- 1. Did you work on the modules in a systematic way? What did you do first? Second? Third?
- 2. What did you do if or when you got stuck in a module?

In this section, think about the LAST CREDIT YOU COMPLETED DURING FALL 2013. For example, if you finished credit 1 during the Fall semester and finished credit 2 during the spring semester, think about your experience with credit 1.

Question 19: What was the last credit you completed during Fall 2013?

Credit 1 Credit 2 Credit 3 Question 20: How motivated were you to complete this credit [credit 1, 2 or 3] on time? 1 (not at all motivated) 2 3 4 (neutral) 5 6 7 (very motivated) Question 21: Please number the motivations strategies used during the Fall semester from the most motivating to least motivating (most motivating) Course Plan/ Deadline [Tool1]

Shared Deadline Calendar

[Tool2]

[Tool3] Leaderboard

[Tool4] Anonymous Class Progress Info

[Tool5] Badges

[Tool6] Gold Points

[Tool7] Prizes

[Tool8] Individual Progress Updates(message on canvas)

(least motivating)

Question 22: Did you find any of the motivation practices (refer to question above) used during the Fall semester especially motivating? Did any of these practices help you stick to your course plan? Please explain.

Question 23: During the Fall semester, did you find any of the motivation practices (including the course plan) annoying or distracting? Please explain.

Question 24: Is there anything you wish we had done differently? Are there any tools you wish you had access to? Please explain.

Question 25: Think about the course plan you created for the last credit you completed during Fall 2013. Try to remember as well as you can.

Question 26: For the last credit you completed during the Fall semester: Did you successfully meet all of the deadlines you set in your course plan (original or modified)?

Yes

No

Question 27: If you made modifications to the course plan (pushed deadlines back or forward), please explain why you decided to make those modifications, e.g. was it because of internal factors (relating to material difficulty) or external factors (other events that conflicted with the deadline).

Question 28: For the last credit you completed during fall 2013, if you didn't successfully met all of your deadlines please explain what happened. Try your best to remember why.

## For students who worked on a credit during Spring Semester:

Question 29: What was the last credit you completed during Spring 2014?

Credit 1

Credit 2

Credit 3

Question 30: Are you satisfied with the grade you received for this credit?

1(not satisfied)

2

3
4 (somewhat satisfied)
5
6
7 (very satisfied)
Question 31: Are you glad to have had the opportunity to finish this credit during the Spring semester or would you have preferred to have been required to finish the credit during the Fall? Please explain.
Question 32: Did you feel more or less motivated to complete the credit during the Spring than during the Fall? Why?
Think about your experience with the course plan (during the Fall) and without the course plan (during the Spring):
Question 33: Did you prefer having to stick to a course plan or not having a course plan?
Preferred course plan
Didn't prefer course plan

Question 34: Did you prefer having to set deadlines or working without deadlines?

Preferred Deadlines

Didn't Prefer Deadlines

Question 35: Did you perform better with deadlines or without deadlines? Please explain your reasoning.

Thank you for your time and have a wonderful summer!

# Appendix G: Summary of Data and Coding Key

### **Pre-Course Survey**

Procrastination

- Submitted (order): Order of intro surveys submitted (1-31)
- Submitted (days): Relative to first submission, number of days it took students to submit. 1(students submitted 1st day)-10(9 days after 1st student)

### Computer Background

- EasilyFindInfoOnline: I can easily find information about what I need online (1-Strongly Disagree, 4-Neutral, 7 - Strongly Agree)
- QuicklyFindInfoOnline: I can quickly find information about what I need online
   (1- Strongly Disagree, 4-Neutral, 7 Strongly Agree)
- NumProgrammingLang: I have at least a little experience with the following programming languages. Count of how many have experience with: [Basic],
   [JavaScript], [C, C++, Objective C, or Java], [Python], [Other]
- ExperienceProgramming: My experience with programming a computer is: 1:

  None never programmed a computer, 2: Low I wrote a some short scripts or use macros or automation, 3:Medium I've taken a programming class or studied on my own and have written short (10-50 line) programs

#### Experience with Canvas

- FreqLoggingIntoCanvas: Log into and out of Canvas during the semester? (1- Never,
   4-Once Per Week, 7-Many Times a Day)
- FreqCanvasCalendarEvents: Read announcements and view calendar events in Canvas? (1- Never, 4-Once Per Week, 7-Many Times a Day)
- FreqCanvasMessagesDiscussion: Access, read, reply to, and attach files to messages in the Canvas discussion board? (1- Never, 4-Once Per Week, 7-Many Times a Day)
- FreqCanvasHWQuestions: Ask or answer questions about homework on Canvas? (1-Never, 4-Once Per Week, 7-Many Times a Day)
- FreqSubmitHWCanvas: Submit homework through Canvas? (1- Never, 4-Once Per Week, 7-Many Times a Day)

### Self-Paced and Online Learning

- FreqVideoLearn: Watch a video to learn how to perform a task? (1- Never, 4-Once
   Per Week, 7-Many Times a Day)
- FreqBookLearn: Read a book, textbook or instruction manual to learn how to perform a task? (1- Never, 4-Once Per Week, 7-Many Times a Day)
- TakenOnlineCourse: Taken online Course? (1-No, 2-Yes, 3-no answer)
- CourseTypePreference: Do you prefer traditional or online courses? (1-Traditional, 2-Online, 3-not sure/combination)

ExperienceMoocs: What is your experience with Mass Online Open Courses
 (MOOC) courses (e.g. Udacity, Coursera, EdX)? Have you ever started a MOOC?
 Have you ever finished one? Did you enjoy the experience? (1- no experience, 2-signed up for MOOC, 3-completed MOOC, 4-Completed several MOOCS)

#### Course Expectations

- ReasonsTakingCourse: The reasons I am taking this course are: (1-to learn
  programming foundations, 2-decide if want CS major, 3-foundation for CS major, 4supplement to other career goal, 5-learn to program in Python, 6-general interest in
  computer science/programming, 7-course structure)
- ExpectedBenefit: How much overall benefit do you expect to get from this course?
   (1- No Benefit, 4-Some Benefit, 7-A Lot of Benefit)
- ExpectedUtility: Relative to other college courses you have taken, how much utility
  will you get from this course? (1 Much Less Utility, 4-Equal Utility, 7-Much Greater
  Utility)
- ExpectedRelativeUsefulness: How useful do you feel this course will be relative to
  the academic/personal activities you are currently engaged in? (1- Much Less Useful,
  4-Equally Useful, 7-Much More Useful)
- gradeExpected: What grade do you expect to get in this class? (1-A, 2-B, 3-C, 4-D, 5-F, 6-Other)
- CourseSuccessAffectGoals: How will your level of success in this class affect your

- academic, career, or personal goals? (1-Definitly not affect, goals 2-probably not, 3-I'm not sure how will affect, 4-probably will affect, 5-definitely will affect)
- CourseAffectInterest: How do you think taking this class will affect your interest in the subject? (1-less interested, 2-not affected interest, 3-more interested)
- CoursePreparedness: How academically prepared do you feel for this class? (1-not Prepared, 2-somewhat prepared, but lacking important skills or knowledge, 3prepared)

#### Interest in Course

- InterestHighGrade: I am interested in earning a high grade in this course (1-Strongly Disagree, 4-Neutral, 7-Strongly Agree)
- InterestMasteringMaterial: Mastering the material is more important than earning all 3 credits (1-Strongly Disagree, 4-Neutral, 7-Strongly Agree)
- InterestProgrammingPython: I am interested in learning to program in Python (1-Strongly Disagree, 4-Neutral, 7-Strongly Agree)
- PreferenceCreditsOverGrade: I would rather earning more credits overall than earning a high grade in each credit (1-Strongly Disagree, 4-Neutral, 7-Strongly Agree)
- AchievementFeelingCredits: Even if I don't earn all 3 credits, I will feel good about my achievements (1-Strongly Disagree, 4-Neutral, 7-Strongly Agree)
- ImportanceEarningCredits: Earning all 3 credits is very important to me (1-Strongly

- Disagree, 4-Neutral, 7-Strongly Agree)
- CourseSatisfyReq: This class is: (1-Required for Major, 2-Required for Minor, 3-GenEd, 4-Elective, 5-Other)

### Demographics

- MotivationCollege: The primary motivation you are pursuing a college degree is to:
   (1-Be Financially Successful, 2-Pursue a career I love, 3-Satisfy Personal Interest or
   Goal, 4-Follow advice of a parent or guardian, 5-Interact Socially with other College
   Students, 6-Other)
- Age: What is your age? (1- 18 or younger, 2- 19-20, 3-21-22, 4-23-25, 5-26-29, 6-30+)
- Gender: What is your gender? (1-Male, 2-Female)
- Ethnicity: Which category best describes your ethnicity? (1-African American, 2-Asian American, 3-Hispanic, 4-Native American, 5-White/Caucasian, 6-Other)
- Major: 5. Which category best describes your major? (1-Arts/humanities/comm, 2 Business/info tech, 3-social services/education, 4-Math/physical sciencs, 5-undecided,
   6-other)
- GPA: What is your overall college GPA? (1-below 1.5, 2-(1.5-1.9), 3-(2.0-2.4), 4-(2.5-2.9), 5-(3.0-3.4), 6-(3.5-4.0))

#### Goal and Time Commitments

•	TotalNumCredits Total Credits
	5 points: 1-3
	4 points: 4-7
	3 points: 8-11
	2 points: 12-15
	1 point: 16+
•	NumOtherCourses: How many other courses?
	5 points: 0
	4 points: 1
	3 points: 2
	2 points: 3
	1 point: 4+
•	NumHoursWorking: Do you have a job? How much time do you spending
	working each week?
	5 points: 0
	4 points: 1-10
	3 points: 11-20
	2 points: 21-30

1 point: 31-40

0 points: 41+

NumActivities: In addition to having a job, do you regularly participate in non-academic activities? (e.g. sports, theatre groups, etc.) How many different activities do you participate in?

5 points: 0

4 points: 1

3 points: 2/no resp

2 points: 3

1 point: 4+

 HoursActivities: How many hours do you plan to devote weekly to non-academic activities during this semester?

5 points: 0

4 points: 1-4

3 points: 5-9/ or not sure

2 points: 10-14

1 point: 15+

• TypicalityWorkload: Is this workload typical for you? Please Explain.

5 points: very typical

4 points: almost typical, less

3 points: atypical, less

2 points: almost typical, more

1 point: atypical, more

NonacademicInfluences: What non-academic factor most influences your success

in this class? (1-Work/financial, 2-Family Obligations, 3-Physical/emotional

healths, 4-Athletics, 5-Social/recreational, 6-interest/motivation in course)

OutsideResponsibilitiesAffectSchool: How do responsibilities outside of school

affect your success at school?

5 points: don't ever

4 points: seldom

3 points: occasionally

2 points: often

1 point: always

Self-Efficacy

AvgSelfEfficacy

o I am able to organize my activities so that I can meet all course deadlines. (1-

191

- never, 4-sometimes, 7-always)
- Soon after the end of a lesson, I am able to remember all of the key concepts. (1-never, 4-sometimes, 7-always)
- I can understand all of the key concepts covered in my course. (1-never, 4-sometimes, 7-always)
- I am able to explain to my fellow students, in a way they can understand, all of the key concepts covered in a course. (1-never, 4-sometimes, 7-always
- After sitting an exam, I am able to remember all of the key concepts covered in the course.( 1-never, 4-sometimes, 7-always)
- When I find something new about a topic that I am studying, I am always able to connect it with other things that I know about the topic (1-never, 4-sometimes, 7-always)
- I always know how to get up to date on a topic if my knowledge of it is dated (1-never, 4-sometimes, 7-always)
- Even when I haven't participated in a lesson, I can always understand the concepts covered in the lesson by reading a textbook (1-never, 4-sometimes, 7always)
- I am always able to find more detailed information on the Internet for a topic that interests me. (1-never, 4-sometimes, 7-always)
- o I am never embarrassed to ask the teacher for clarification (1-never, 4-sometimes,

7-always)

- o I am always able to identify the most appropriate person to help me resolve a problem related to my study (1-never, 4-sometimes, 7-always)
- I am always able to relate the notes I have made during a lesson with the topics
   covered in the course text or readings (1-never, 4-sometimes, 7-always)
- It is always easy for me to understand new information, even on a topic that does not interest me very much (1-never, 4-sometimes, 7-always)
- It is always easy for me to connect new information about a topic that interests
   me with other pieces of information (1-never, 4-sometimes, 7-always)
- During a course, if we are given a new task to complete, I can always complete it
   by applying the knowledge that I obtained from lessons (1-never, 4-sometimes,
   7-always)
- Soon after the end of a lesson, I am always able to distinguish the most important concepts from concepts of less importance (1-never, 4-sometimes, 7always
- If, as part of a course, I participate in a forum or online discussion, I am always able to identify those message which will improve my understanding of the material covered in the course (1-never, 4-sometimes, 7-always)
- I always find it easy to join a group of fellow students to study or complete course activities (1-never, 4-sometimes, 7-always)

- I am always able to identify useful information on the web for a project (1never, 4-sometimes, 7-always)
- After a lesson, I am always able to integrate concepts described by the teacher with those presented in course texts and readings (1-never, 4-sometimes, 7always)
- When I complete a project for a course, I am always able to incorporate knowledge gained from other sources (1-never, 4-sometimes, 7-always)
- I am always able to help other students solve problems based on concepts described in a lesson (1-never, 4-sometimes, 7-always)

# **Credit Suggestion**

- CalibrationPercentage: % of calibration total Percent
- CreditPrediction: Number of Credits Predicted (1, 23)

#### Course Plan

- CreditsPursued: Number of Credits Pursued (1, 2 3)
- PlanAvgDaysPerModule

# **ELMS Progress**

#### Motivation Data

- AvgViews\_M
- AvgAttempts\_M
- NumTasks\_M
- SDDate\_M

### Course Data

- AvgViews\_C
- AvgAttempts\_C
- NumTasks\_C
- SDDate\_C: Standard Deviation of Number of Days Viewed

# ProgressData

• AvgProgressPerWeekActual

### **Emails**

- TotEmails
- MessageFromStudents

# Badge Data

# Badges

- BadgePointsTotal
- NumBadgeTypes
- NumBadges
- ModStar
- EnduranceStar
- Leaderboard

### Subtracted

- PointsSub
- NumTimesPointsSub

### Deadlines

• NumChangedDeadlines

### Leaderboard

- Avg ProgressScore
- NumTimesRanked

# Post-Credit Survey

#### Course Assessment

- How challenging did you find this course?
- How difficult did you find this course?
- How academically prepared did you feel for this class?
- How much overall benefit do you expect to get from this course?
- Relative to other college courses you have taken, how much utility did you get from this course?
- How useful was this course relative to the academic/personal activities you are currently engaged in?

#### Interest in Course

- I was interested in earning a high grade in this course
- I am interested in learning to program in Python
- Mastering the material was more important than earning all 3 credits
- Earning all 3 credits was very important to me
- I would have rather earned more credits overall than a high grade in each credit
- Even if I didn't earn all 3 credits, I felt good about my achievements (1, 2 3)

### **Final Grades**

• CreditsCompletedFall: Number of Credits completed in the Fall (1, 2, 3)

- CreditsCompletedTotal: Total Credits Completed (0=no,1=yes)
- tookIncomplete: Did student take incomplete? (0=no, 1=yes, 2=didn't take)
- CompletedIncompleted: Did student Complete Incomplete credit Successfully?
   (0=no, 1=yes, 2=didn't take)

# **Bibliography**

- [1] Ariely, D. (2009). The Curious Paradox of 'Optimism Bias.' *Bloomberg Business Week*. Retrieved from http://www.businessweek.com/magazine/content/ 09\_34/b4144048821798.htm [accessed June 4, 2014].
- [2] Ariey, D., & Wertenbroch, K. (2002). Procrastination, Deadlines, and Performance: Self-Control by Precommitment. *Psychological Science*. 13: 219
- [3] Bailey, C., & Katchabaw, M. J. (2005). An Experimental Testbed to Enable Auto-Dynamic Difficulty in Modern Video Games. *Proceedings of the 2005 GameOn North America Conference*, Montreal, Canada.
- [4] Barnes, T., Powell E., Chaffin, A., & Lipford, H. (2008) Game2Learn: improving the motivation of CS1 students, Proceedings of the 3rd international conference on Game Development in Computer Science Education, p.1-5, February 27-March 03, 2008, Miami, Florida.
- [5] Bauman, P. (2002). Student Retention: What You Can Control, & How. *Distance Education Report*, 6(16).
- [6] Bederson, B. (2013). Paths to Computer Science Overview. Retrieved from http://www.cs.umd.edu/~bederson/classes/paths-f13/ [accessed June 22, 2014].
- [7] Belanger, Y., & Thorton, J. (2013). Bioelectricity: A Quantitative Approach, Duke University's First MOOC. *Duke University Libraries*. Retrieved from http://hdl.handle.net/10161/6216 [accessed June 1, 2014]
- [8] Benford, R. & Gess-Newsome, J. (2006). Factors affecting student academic success in gateway courses at Northern Arizona University. Flagstaff, AZ: Center for Science Teaching and Learning, Northern Arizona University.
- [9] Bloom, B. S. (1968). Learning for mastery. *Evaluation Comment*, 1(2), 112. Retrieved from http://programs.honolulu.hawaii.edu/intranet/sites/programs.honolulu.

- hawaii.edu.intranet/files/upstf-student-success-bloom-1968.pdf [accessed July, 24, 2014]
- [10] Brophy, J. (1999). Toward a model of the value aspects of motivation in education: Developing appreciation for particular learning domains and activities. *Educational Psychologist*, 34(2), 75-85.
- [11] Brehm, J.W. (1956). Postdecision changes in the desirability of alternatives. The *Journal of Abnormal and Social Psychology*, Vol. 52(3), May 1956, 384-389.
- [12] Buehler, R., Griffin, & D., Ross (2002). Inside the Planning Fallacy: The Causes and Consequences of Optimistic Time Predictions. *In Heuristics and Biases: The psychology of intuitive judgment* (250-270). Cambridge University Press, Cambridge, UK.
- [13] Carpenter, P. A., Just, M. A., & Shell, P. (1990). What one intelligence test measures: A theoretical account of the processing in the Raven Progressive Matrices Test. *Psychological Review*, 97 (3): 404-431. Retrieved from http://kryten.mm.rpi.edu/COURSES/LOGAIS02/carpenter.pdf
- [14] Clow, Doug (2013). MOOCs and the funnel of participation. *Third Conference on Learning Analytics and Knowledge* (LAK 2013), 8-12 April 2013, Leuven, Belgium.
- [15] Cobb-Clark, D. A., & Schurer, S. (2012). The stability of big-five personality traits, *Economics Letters*, Elsevier, vol. 115(1), pages 11-15.
- [16] Cooper, J.O., Heron, T.E., & Heward, W.L. (2007). *Applied Behavior Analysis* (Second Edition). Upper Saddle River, NJ: Pearson Education, Inc.
- [17] Cordova, D. I. & Lepper, M. R. (1996). Intrinsic motivation and the process of learning: Beneficial effects of contextualization, personalization, and choice. *Journal of Educational Psychology*, 88(4), 715-730.
- [18] Costa, P.T. Jr., Terracciano, A., & McCrae, R.R. (2001). "Gender Differences in Personality Traits Across Cultures: Robust and Surprising Findings". *Journal of Personality and Social Psychology*, 81 (2): 322–331.
- [19] Csikszentmihalyi, M. (1990). Flow: The Psychology of Optimal Experience. New York: Harper and Row.

- [20] DeBoer, J., Ho, A.D., Stump, G.,&Breslow, L. (2014). Changing "Course": Reconceptu alizing Educational Variables for Massive Open Online Courses. *Educational Researcher*, vol. 43 no. 2 74-84
- [21] Decker, A., Lawley, E.L. (2013). Life's a Game and the Game of Life: How Making a Game Out of it Can Change Student Behavior. *SIGCSE'13*, March 6–9, 2013, Denver, Colorado, USA.
- [22] Do, T. (2013). Learning from Data [video file]. *Panel at Coursera Partner's Conference*. Retrieved from https://www.youtube.com/watch?v=aED8oHfSLUs
- [23] Doyle. T. (2011). Learner-centered teaching: Putting the research on learning into practice. Stylus Publishing, LLC, **Sterling**, **VA**.
- [24] Dunlosky, J., and Thiede, K.W. (1998). "What makes people study more? An evaluation of factors that affect self-paced study." *Acta Psychologica* 98, no. 1 (1998): 37-56
- [25] Dunning, D., Heath, C., & Suls, J. (2004). Flawed self-assessment: Implications for health, education, and the workplace. *Psychological Science in the Public Interest*, 5, 69-106.
- [26] Fan, X., Miller, B. C., Park, K., Winward, B. W., Christensen, M., Grotevant, H. D., & Tai, R. (2006). An exploratory study about inaccuracy and invalidity in adolescent self-report surveys. *Field Methods*, 18, 223–244.
- [27] Felton, J., Mitchell, J. & Stinson, M. (2004). Web-based student evaluations of professors: the relations between perceived quality, easiness and sexiness *Assessment & Evaluation in Higher Education*, Vol. 29, No. 1
- [28] Ferla, J., Valcke, M., & Cai, Y. (2009). Academic self-efficacy and academic self-concept: Reconsidering structural relationships. Learning and Individual Differences, 19, 499-505. Retrieved from http://jamiesmithportfolio.com/EDTE800/wp-content/Self-Efficacy/Ferla.pdf [Accessed August 6, 2014]
- [29] Ferrari, J. (1992). Psychometric Validation of Two Procrastination Inventories for Adults: Arousal and Avoidance Measures. *Journal of Psychopathology and Behavioral Assessment*, Vol. 14, No. 2

- [30] Ferster, C. B., & Skinner, B. F. (1957). *Schedules of Reinforcement*. New York: Appleton-Century-Crofts.
- [31] Fishbach, A., & Dhar, R. (2005). Goals as Excuses or Guides: The Liberating Effect of Perceived Goal Progress on Choice. *Journal of Consumer Research*, Vol. 32, No. 3 p. 370-377.
- [32] Flyvbjerg, B. (2006). Curbing Optimism Bias and Strategic Misrepresentation in Planning: Reference Class Forecasting. *Practice European Planning Studies*, Vol. 16, Iss. 1, 2008.
- [33] Fogg, B.J. (2003). Persuasive Technology: Using Computers to Change What We Think and Do. Morgan Kaufmann Publishers, San Francisco, CA.
- [34] Forster, J., Higgens, T., & Idson, L. (1998). Achievement and Avoidance Strength During Goal Attainment: Regulatory Focus and the "Goal Looms Larger" Effect. *Journal of Personality and Social Psychology*, 1998, Vol. 75, No. 5, 1115-1131.
- [35] Furnham, A., Chamorro-Premuzic, T., & McDougall, F. (2003). Personality, cognitive ability, and beliefs about intelligence as predictors of academic performance. *Learning and Individual Differences*, 14, 49–66.
- [36] Garris R., Ahlers R., & Driskell, J. (2002). Games, motivation and learning: a research and practice model. *Simulation & Gaming, Vol. 33*, No. 4, 2002, 441-467
- [37] Gleason, B. J. (2004). Retention issues in online programs: A review of the literature. *Second AIMS International Conference on Management*, Calcutta, India.
- [38] Gill, G.T., Holton, C. F. (2006). A Self-Paced Introductory Programming Course. *Journal of Information Technology Education*. 2006, Vol. 5, p 95-105.
- [39] Gilovich, T., Griffin, D., & Kahneman D. (2002) *Heuristics and Biases: The psychology of intuitive judgment*. Cambridge University Press, Cambridge, UK.
- [40] Hacker, D. J., Bol, L., Horgan, D. D., & Rakow, E. A. (2000). Test prediction and performance in a classroom context. *Journal of Educational Psychology*, 92, 160–170. doi: 10.1037/0022-0663.92.1.160

- [41] Hagan, D. and Markham, S. (2000). Does it help to have some programming experience before beginning a computing degree program? *Proceedings of the 5th annual SIGCSE/SIGCUE ITiCS E conference on Innovation and technology in computer science education*, p.25-28, Helsinki, Finland
- [42] Haizlip, J.A,. May, N., Schorling, J., et al. (2012). The negativity bias, medical education, and the culture of academic medicine: why culture change is hard. *Academic Medicine*, 87(9): 1205–9.
- [43] Haselton, M. G., Nettle, D., & Andrews, P. W. (2005). The evolution of cognitive bias. In D. M. Buss (Ed.), The Handbook of Evolutionary Psychology: Hoboken, NJ, US: John Wiley & Sons Inc. pp. 724–746.
- [44] Holman, C., Aguilar, S., & Fishman, B. (2013). GradeCraft: what can we learn from a game-inspired learning Management system? *Third Conference on Learning Analytics and Knowledge* (Leuven, Belgium, April 8-12, 2013), LAK '13
- [45] Institution of Engineering and Technology (2008). Studying STEM: What are the barriers? Retrieved from http://www.theiet.org/factfiles/education/stem-report-page.cfm [accessed June 1, 2014.]
- [46] Ironsmith, M., Marva, J., Harju, B., & Eppler, M. (2003). Motivation and performance in college students enrolled in self-paced versus lecture-format remedial mathematics courses. *Journal of Instructional Psychology*, 30(4), 276–284.
- [47] Kahn, C. (2014). The Road to Better MOOCs [web log comment]. Retrieved from https://medium.com/teaching-learning/the-road-to-better-moocs-1c7bf6e5eb53Kahneman, D., Slovic, P., & Tversky, A. (1982). Judgment under uncertainty: Heuristics and biases (1st ed.). Cambridge University Press.
- [48] Karabenick, S. A. (2001). Seeking Help in Large College Classes: Who, Why, and from Whom. *Annual Meeting of the American Educational Research Association* (Seattle, WA, April 10-14, 2001).
- [49] Jordan, Katy (2014). Initial trends in enrolment and completion of massive open online courses. *International Review of Research in Open and Distance Learning*, 15(1) pp. 133–160.

- [50] Kearsley, G. (2002). Is online learning for everybody? *Educational Technology*, 42 (1), pp. 41-44.
- [51] Keller, F. (1968). Good by Teacher. Journal of Applied Behavioral Analysis, 1(1): 79-89.
- [52] Kernan, M.C., Lord, R.G (1990). Effects of valence, expectancies, and goal-performance discrepancies in single and multiple goal environments. *Journal of Applied Psychology*, 75(2), 194-203. doi: 10.1037/0021-9010.75.2.194
- [53] Kim, J. (2013). Lessons from U of P's Innovator's Accelerator Online Course. *Inside Higher Ed.* Retrieved from http://www.insidehighered.com/blogs/technology-and-learning/lessons-u-ps-innovators-accelerator-online-course#ixzz2Nv3jMMcb [Accessed June 2, 2014]
- [54] Klein, C., & Helweg-Larsen, M. (2002). "Perceived Control and the Optimistic Bias: A Meta-analytic Review". *Psychology and Health* 17 (4): 437–446.
- [55] Klobas, J., Renzi, S., & Nigrelli, M.L. (2007). A scale for the measurement of self-efficacy for learning (SEL) at university. *Doneda Working Papers*, Doneda Center for Social Dynamics, Universita Bocconi, Milano. Retrieved from www.dondena.unibocconi.it/wp2. [Accessed June 22, 2014]
- [56] Kraus, J. (2012, April 12). *Slow Tech* [YouTube Transcript]. Retrieved from http://joekraus.com/were-creating-a-culture-of-distraction
- [57] Kruglanski, A., Shah, J., Fishbach, A., Friedman, R., Chun, W., & Sleeth-Keppler D. (2002), "A Theory of Goal Systems," in *Advances in Experimental Social Psychology*, Vol. 34, ed. Mark P. Zanna, New York: Academic Press, 331–78.
- [58] Lawrence, S.A. (2014). Critical Practice in P-12 Education: Transformative Teaching and Learning. *Information Science Reference*, Hershey, PA.
- [59] Lee, J. J., & Hammer, J. (2011). Gamification in Education: What, How, Why Bother? *Academic Exchange Quarterly*, 15(2).
- [60] Leblanc, G. (2004). Enhancing intrinsic motivation through the use of a token economy. *Essays in Education*, 11(1). Retrieved from http://www.usca.edu/essays/vol112004/leblanc,pdf.pdf

- [61] Likert, R. (1932). A Technique for the Measurement of Attitudes. *Archives of Psychology*, 140, 1–55.
- [62] Malone, T.W., & Lepper, M. R. "Making learning fun: a taxonomy of intrinsic motivations for learning." *Aptitude, Learning and Instruction* 3(1987) 223-253.
- [63] McDowell, C., Werner, L., Bullock, H., & Fernald, J. (2006). Pair Programming Improves Student Retention, Confidence, and Program Quality. *Communications of the ACM*, 49(8). Vol. 49, Issue 8, pp. 90-95. Retrieved from http://www.soe.ucsc.edu/~charlie/pubs/cacm.pdf
- [64] Metcalfe, J., & Kornell, N. (2003). The dynamics of learning and allocation of study time to a region of proximal learning. Journal of Experimental Psychology: General, 132, 530–542.
- [65] Miles, M.B., & Huberman, A.M. (1994). *Qualitative Data Analysis*. Sage Publications, Inc., Thousand Oaks, California.
- [66] Mintz, J., & Aagaard, M. (2012). The Application of Persuasive Technology to Educational Settings. *Educational Technology Research and Development*, 60(3), 483-499.
- [67] Morris, E. Surber, C. Bijou, S. (1978). Self- versus instructor-pacing: Achievement, evaluations, and retention. *Journal of Educational Psychology*, Vol 70(2), Apr, 1978. pp. 224-230.
- [68] Nelson, T.O., & Leonesio, R.J. (1988). Allocation of self-paced study and the "labor in vain" effect. *Journal of Experimental Psychology*: Learning, Memory and Cognition, 14, 476-486.
- [69] Ning, H.K., & Downing, K. (2012). Influence of student learning experience on academic performance: the mediator and moderator effects of self-regulation and motivation. *British education research journal*, 38 (2), 219-237.
- [70] Oinas-Kukkonen, H., & Harjumaa, M. (2008). A systematic framework for designing and evaluating persuasive systems. In H. Oinas-Kukkonen, P. Hasle, M. Harjumaa, & K. Segerstahl (Eds). New York: Springer

- [71] Pappano, L.(2012). The Year of the MOOC. *The New York Times*. Retrieved from http://www.nytimes.com/2012/11/04/education/edlife/massive-open-online-courses-are-multiplying-at-a-rapid-pace.html?pagewanted=all&\_r=1&
- [72] Phye, G. D. (Ed.). (1997). Handbook of classroom assessment: Learning, achievement, and motivation. San Diego: Academic Press.
- [73] Pintrich, P. (2004). A Conceptual Framework for Assessing Motivation and Self-Regulated Learning in College Students. *Educational Psychology Review*, Vol. 16, No. 4.
- [74] Poporat, A. (2009). A Meta-Analysis of the Five-Factor Model of Personality and Academic Performance. *Psychological Bulletin*, Vol. 135, No. 2, 322–338
- [75] Richardson, M., Abraham, C., and Bond, R. (2012) Psychological correlates of University students' academic performance: A systematic review and meta-analysis. *Psychological Bulletin*.138 (2) 353-387.
- [76] Riemann R., Angleitner A., & Strelau J(1997). Genetic and environmental influences on personality: A study of twins reared together using the self- and peer report NEO-FFI scales. *Journal of Personality*. 65(3): 449–475.
- [77] Roberts, B.W., DelVecchio, W.F., (2000). The rank-order consistency of personality traits from childhood to old age: A quantitative review of longitudinal studies. *Psychological Bulletin* 126, 3-25.
- [78] Roberts, B. W., & Mroczek, D. (2008). "Personality Trait Change in Adulthood". *Current Directions in Psychological Science* 17 (1): 31–35. doi:10.1111/j.1467-8721.2008.00543.x.
- [79] Shen, D., Cho, M., Tsai, C., & Marra, R. (2013). Unpacking online learning experiences: Online learning self-efficacy and learning satisfaction. *Internet and Higher Education*, 19, 10-17.
- [80] Sirin, S. R. (2005). Socioeconomic status and academic achievement: A meta-analytic review of research. *Review of Educational Research*, 75, 417–453.

- [81] Skapinker, M. (2013). Open Web Courses Are Massively Overhyped. *Financial Times*. Retrieved from http://www.ft.com/intl/cms/s/0/84f6cd3e-8a50-11e2-bf79-00144feabdc0.html#axzz2NXRfkenu
- [82] Smith, A. (2012). The Best (and Worst) of Mobile Connectivity. *Pew Research Internet Project*. Retrieved from http://www.pewinternet.org/2012/11/30/the-best-and-worst-of-mobile-connectivity/ [Accessed June 2, 2014]
- [83] Soman, D., & Cheema, A. (2004), "When Goals Are Counterproductive: The Effects of Violation of a Behavioral Goal on Subsequent Performance," *Journal of Consumer Research*, 31 (June), 52–62.
- [84] Srivastava, S., John, O. P., Gosling, S. D., & Potter, J. (2003). "Development of personality in early and middle adulthood: Set like plaster or persistent change?" *Journal of Personality and Social Psychology* 84 (5): 1041–1053. doi:10.1037/0022-3514.84.5.1041.
- [85] Szafran, R.F. (2001). The Effect of Academic Load on Success For New College Students: Is Lighter Better? *Research in Higher Education*, Vol. 42, No. 1.
- [86] Tauber, T. (2013). The Dirty Little Secrets of Online Learning: Students are Bored and Dropping Out. Retrieved from http://qz.com/65408/the-dirty-little-secret-of-online-learning-students-are-bored-and-dropping-out/ [accessed, June 22, 2014]
- [87] Taylor, A-S., Backlund, P. (2011). Letting the students create and the teacher play: Expanding the roles in serious gaming. In *Proceedings of the Academic Mind Trek conference* (MindTrek'11) (pp. 63–70), Tampere, Finland, September 28-30, 2011. doi: 10.1145/2181037.2181049
- [88] Torres, V., Gross, J. & Dadashova, A. (2010). Traditional-Age Students Becoming At-Risk: Does Working Threaten College Students' Academic Success? *Journal of College* Student Retention, Vol. 12(1) 51-68.
- [89] Tough, P.(2014). "Who Gets to Graduate?" *The New York Times*. Retrieved from http://nyti.ms/1gjJOoU
- [90] Tufeki, Z. (2012). Change the Cowboy Culture. *The New York Times*. Retrieved from http://www.nytimes.com/roomfordebate/2011/06/15/computer-sciences-sputnik-moment/change-the-cowboy-culture-in-computer-science [accessed, June 22, 2014]

- [91] Tullis, J. G. & Benjamin, A. S. (2011). On the effectiveness of self-paced learning. *Journal of Memory and Language*, 64, 109-118.
- [92] Turiano, N.A., Pitzer, L., Armour, C., Karlamangla, A., Ryff, C.D., & Mroczek, D.K. (2012). Personality trait level and change as predictors of health outcomes: findings from a national study of americans (midus). *The Journals of Gerontology, Series B: Psychological Sciences and Social Sciences*, 67(1), 4–12, doi:10.1093/geronb/gbr072. Advance Access published on July 15, 2011
- [93] Tynan, S. (2013). *Designing Games: A Guide to Engineering Experiences. O'Reilly Media, Inc.* Retrieved from http://proquest.safaribooksonline.com.proxyum.researchport.umd.edu/book/-/9781449338015
- [94] Walker, W. R., Skowronski, J.J., Thompson, C.P. (2003). "Life Is Pleasant—and Memory Helps to Keep It That Way!". Review of General Psychology 7 (2): 203–210.doi:10.1037/1089-2680.7.2.203.
- [95] Waldrop, M.M. (2013). Online learning: Campus 2.0. *Nature*, 495 (7440), 160-163. Retrieved from http://www.nature.com/news/online-learning-campus-2-0-1.12590
- [96] Whalen, D. F., & Shelley, M. C. (2010). Academic success for STEM and non-STEM majors. *Journal of STEM Education*, 11(1–2), 45–60.
- [97] Yeager, D., Walton, G., & Cohen, G. (2013). Addressing Achievement Gaps with Psychological Interventions. Kappan Magazine, V95, N5. Retrieved from https://labs.la.utexas.edu/adrg/files/2013/12/PDK-Yeager-Walton-Cohen-2013.pdf
- [98] Zimmerman, B. J. (2008). Investigating self-regulation and motivation: Historical background, methodological developments, and future prospects. *American Educational Research Journal*, 45(1), 166–183.
- [99] Zwick, R. (2012). The Role of Admissions Test Scores, Socioeconomic Status, and High School Grades in Predicting College Achievement. *Pensamiento Educativo, Revista de Investigación Educacional Latinoamericana* 2012, 49(2), 23-30