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Motivation for and within Online College Courses

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Motivation for and within Online College Courses

DISSERTATION

Submitted in partial satisfaction of the requirements
for the degree of

DOCTOR OF PHILOSOPHY

in Education

by

Peter McPartlan

Dissertation Committee Members:
Distinguished Professor Jacquelynne Eccles, Chair
Professor Mark Warschauer
Assistant Professor Di Xu
Assistant Professor Teomara Rutherford

2019

DEDICATION

To

my parents and my wife, Denise

who have always made me feel like I belong

"Whether you think you can, or think you can't, you are right"

-Henry Ford

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ACKNOWLEDGEMENTS

This work was supported by the National Science Foundation [grant number 1535300].

An incredible amount of time, energy, and resources were given to me in order to support not only this dissertation, but also my overall experience as a doctoral student. I would like to thank my biggest supporters, Jacque Eccles and Mark Warschauer, for their time, which is clearly a coveted resource across campus. I decided to join the research community as a doctoral student because I felt it was just that: a community. Jacque and Mark's unwavering support of so many students, including myself, reaffirms more than anything that I made the right choice to join this group of academics. You have set a fantastic example of how to help others through the rigorous application of scientific principles to the study of education, all the while pushing for innovative approaches and strengthening the communities around you.

I'd also like to thank advisors Teya Rutherford and Di Xu. You showed your confidence in me by bringing me onto your own projects and always made me feel comfortable that I could ask you the questions I was too scared to ask others. I'm so excited to have you as mentors and look forward to working with you even more in the years to come.

My family has been incredibly supportive of my journey to this point. From my parents encouraging my young love of psychology to my wife Denise helping me understand entirely new cultures and experiences, I've had so many opportunities to grow my passion for this subject outside of school alone. Most importantly, you've nurtured an incredibly important life skill that also happens to be crucial for this field of study, which is the ability to put myself in the shoes of another. I can't thank you enough for how that has helped give me perspective both in my work and in my life.

Finally, I'd like to thank the peers with whom I completed this program. They've reluctantly discovered that every conversation can be related to sense of belonging somehow, but their support and camaraderie has been the biggest part of creating that sense of belonging for me. Osman, I'm so glad that we got to share so much of this experience. I can't imagine having had a better research partner, coteacher, and sounding board!

CURRICULUM VITAE

Peter McPartlan

EDUCATION

Ph.D. Education: Learning, Teaching, Cognition, and Development **June, 2019**
Advisor: Dr. Jacquelynne Eccles
School of Education, University of California, Irvine

B.A. Psychology, Global Studies minor **June, 2013**
University of California, Los Angeles

RESEARCH FOCUS

Evaluation of motivational interventions that target social-psychological experiences (e.g., sense of beloniging)

The impact of technology on classroom social dynamics and academic motivation

PUBLICATIONS

Wilton, M., Gonzalez-Niño, E., **McPartlan, P.**, Terner, Z., Christoffersen, R., & Rothman, J. (2019). Improving academic performance, belonging, and retention through an increased structure introductory biology course. *CBE – Life Sciences Education, Advance Online Publication.*

Solanki, S., **McPartlan, P.**, Xu, D., & Sato, B. K. (2019). Success with EASE: Who benefits from a STEM learning community? *PloS one*, *14*(3), e0213827.

Umarji, O., **McPartlan, P.**, & Eccles, J. (2018). Patterns of math and English self-concepts as motivation for college major selection. *Contemporary Educational Psychology*, *53*, 146-158.

Xu, D., Solanki, S., **McPartlan, P.**, & Sato, B. (2018). EASEing Students Into College: The Impact of Multidimensional Support for Underprepared Students. *Educational Researcher*, *47*(7), 435–450 DOI: 10.3102/0013189X18778559.

Manuscripts Under Review

McPartlan, P., Rutherford, T., Rodriguez, F., Shaffer, J., & Holton., A. (2019). Modality Motivation: Selection effects and motivational differences in students who choose to take courses online. Submitted to *The Internet and Higher Education*, August, 2019.

Lee., H. R., **McPartlan, P.**, Umarji, O., Li, Q., & Eccles, J. (2019). Hey Mr. Tambourine: The jingle-jangle of self-related beliefs in motivational measures. Submitted to *Contemporary Educational Psychology*, August, 2019.

McPartlan, P., Solanki, S., Xu, D., & Sato, B. Look before you leap: When we shouldn't expect mindset and belonging interventions to succeed among underrepresented college students. Submitted to *AERA Open*, May, 2019.

McPartlan, P., Umarji, O., & Eccles, J. Selective attention and exposure to encouragement: How multiple sources of ability feedback affect adolescents' math self-concept. Submitted to *Journal of Early Adolescence*, February, 2018.

Manuscripts in Preparation

Fischer, C., **McPartlan, P.**, Orona, G., Yu, R. *Design characteristics of online courses: Examining course syllabi*.

McPartlan, P., Dicke, A. L., Safavian, N., Rodriguez, F., Li, Q., Rutherford, T., Eccles, J., & Holton, A. *The utility of click data: Behavioral mediators of motivational interventions*

McPartlan, P., Rutherford, T., & Holton., A. *Belonging across contexts: Implications for theory and measurement of a popular motivational construct*.

Umarji, O., **McPartlan, P.**, Dicke, A. L., Rutherford, T., Eccles, J. *How the fish pond feeds the STEM pool: Middle school class composition associates with self-concept and choice of STEM major*

PRESENTATIONS

McPartlan, P. (2019, May). *How students with performance goals compare themselves when class is online*. Paper to be presented to the Association for Psychological Science annual meeting, New York, NY.

McPartlan, P. (2018, August). *Belonging in the blind spot: Do some students suffer negative effects in learning community programs?* Poster presented at the American Psychological Association annual meeting, New York, NY.

McPartlan, P., & Umarji, O., & Eccles, J. (2018, April). *"Fitting" sense of belonging in an Expectancy-Value framework: Directionality and development among first-year college students*. Poster presented at the American Educational Research Association annual meeting, New York, NY.

McPartlan, P., & Rutherford, T. (2018, April). *Are our measures offline? Critiquing measures of motivation in online courses*. Poster presented at the American Educational Research Association annual meeting, New York, NY.

McPartlan, P., Solanki, S., Xu, D., Sato, B., Hanselman, P., Duncan, G., & Eccles, J. (2017, November). *Growth mindset interventions in college: Considerations of gender, measurement, and combining interventions*. Paper presented at the Association for Public Policy Analysis and Management annual meeting, Chicago, IL.

McPartlan, P., Rutherford, T., Rodriguez, F., & Schaffer, J. (2017, August). *Modality motivation: Assessing motivational differences in online and face-to-face students.* Poster presented at the American Psychological Association annual meeting, Washington, D.C.

McPartlan, P. (2017, April). *What selective attention tells us about effective self-concept interventions*. Poster presented at the American Educational Research Association annual meeting, San Antonio, TX.

McPartlan, P. (2016, August). *"My momma loves me": Selective attention when developing math self-concept*. Poster presented at the American Psychological Association annual meeting, Denver, CO.

Umarji, O., **McPartlan, P.**, Rutherford, T., Dicke, A.L., & Eccles, J. (2016, April). *How the fish pond feeds the STEM pool: Middle school class composition associates with self-concept and choice of STEM major*. Poster presented at the Society for Research on Adolescence biannual meeting, Baltimore, MA.

McPartlan, P. & Banerjee, M. (2015, August). *The links between perceived competition in math classrooms and academic identity in adolescents*. Poster presented at the American Psychological Association annual meeting, Toronto, Canada.

Wu, M., Tjokrosurjo, J., Cortez, P., **McPartlan, P.**, Schenke, K., Tran, C. (2015, July). *What lactose intolerance, peristalsis, and chicken nuggets have in common: Using card sorting to inform the content of a digital game*. Poster presented at Games and Learning Society annual meeting, Madison, WI.

McPartlan, P. (2015, April). *Increasing STEM major persistence through social interactive pedagogies*. In-Progress Research presented at the American Educational Research Association annual meeting, Chicago, IL.

INVITED TALKS

McPartlan, P. (2019, May). *Instructor Presence in Online College Classrooms*. Digital Discovery Series, Division of Teaching Excellence and Innovation, UC Irvine.

McPartlan, P. (2018, March). *Battle to Belong: Keeping Underrepresented Students in STEM*. Graduate Research Advocacy Day at California State Capitol, Sacramento, CA.

McPartlan, P. (2016, October). *Science Games: Lying for the Sake of Learning*. Ignite! talk, the annual meeting of Digital Media and Learning, Irvine, CA.

McPartlan, P., Tulagan, N., Yang, Q., Simpkins, S. (2016, August). *Cultivating Academic Motivation in After School Programs*. Presented to the staff and college counselors of Boys and Girls Club, Orange County, CA.

WORKSHOPS

McPartlan, P. (2019, January). *Studying Psychology and Motivation in STEM Classrooms*. Society for the Advancement of Biology Education Research, Irvine, CA.

McPartlan, P. (2018, November). *Using Qualtrics to collect survey data*. Digital Learning Lab, UC Irvine.

HONORS AND AWARDS

Judge's Winner, UC Irvine Graduate Student Symposium **2018 & 2017**

Finalist, UC Irvine Grad Slam Competition **2018 & 2017**

Outstanding Graduate Student Poster, APA Division 15 **2017**

Graduate Student Seminar, APA Division 15 **2017**

Graduate Student Travel Award, APA **2017**

Honorable Mention, NSF Graduate Research Fellowship Program **2016**

Dean's Fellowship, University of California, Irvine **2014**

Latin Honors & College Honors, UCLA Bachelor's in Psychology **2013**

Eagle Scout **2007**

RESEARCH EXPERIENCE

Graduate Researcher, Collaborative Studies with UCI Biology Dept. **June 2016-July 2019**
University of California, Irvine
PI: Dr. Mark Warschauer, Dr. Jacquelynne Eccles, Dr. Di Xu

Organized multiple collaborative studies with Biology professors. The first compares Online and Face-to-face modalities of a single course, for which I spearheaded survey design. The second analyzes the effectiveness of a learning community program for retaining at-risk students in Biology, investigating the mediating roles of performance, motivation, and belongingness. Contributed to experimental design and theory sections of grant proposal. The third will replicate a promising Utility Value intervention for underrepresented students in an introductory Biology course.

Graduate Research Fellow, Multidisciplinary Design Project **2015-2017**
University of California, Irvine
PI: Dr. Cathy Tran

Led team of interdisciplinary undergraduates in the development of a research-based educational game called "Down With Food." Contributed knowledge of educational theory to game's development and facilitated play-testing sessions with children of target age range.

Graduate Student Researcher, Achievement Research Lab **2014-2019**
University of California, Irvine
PI: Dr. Jacquelynne Eccles

Worked on coding longitudinal data and creating scales. In charge of managing and guiding undergraduate research assistants.

Research Assistant, Middle School Diversity Project **2012-2014**
University of California, Los Angeles
PI: Dr. Jaana Juvonen

Worked on independent research project investigating links between identity formation and academic engagement as a function of extracurricular involvement. Spearheaded creation of lab's first digital version of its 30-page survey, increasing efficiency of data collection and analysis. Led teams of undergraduates through data collection at middle schools and trained over 50 lab members on data collection tasks.

Research Assistant, Relationships and Health Lab **2011-2013**
University of California, Los Angeles
PI: Dr. Theodore Robles

Worked directly with families in their homes to collect physiological data samples and administer Life Stress Interviews. Coded daily diary entries, recognizing presence of risk factors and categorizing their severity.

Research Assistant, Social Interaction and Social Stigma Lab **2011-2013**
University of California, Los Angeles
PI: Dr. Jenessa Shapiro

Lead experimenter as well as confederate in studies that investigated gender- and race-based stereotype threat in academic domains. Helped generate study design ideas, conducted literature searches, and recruited participants.

TEACHING EXPERIENCE

Instructor of Record, Statistics for Education **2018**
University of California, Irvine

Designed new syllabus for undergraduate students on introductory statistical methods. Due to students' low perceptions of interest and utility of math, changed traditional curriculum to emphasize the relevance and consumption of statistics in educational settings using project-based learning.

Teaching Assistant, Structural Equation Modeling **2016-2017**
University of California, Irvine
Advisor: Dr. George Farkas

Designed syllabus and taught lab sessions among undergraduate students on the statistical method of structural equation modeling.

Teaching Assistant, Technology and Education **2016**
University of California, Irvine
Advisor: Dr. Viet Vu

Online course about digital education techniques for online teaching and online collaboration.

Teaching Assistant, Multicultural Education in K-12 Schools **2015**
University of California, Irvine
Advisor: Dr. George Farkas

Led discussions among undergraduate students on the role of race and culture in educational inequality, and different paradigms through which the issue can be addressed. Shared lecturing responsibilities with the instructor and graded assessments.

Student Teacher, Undergraduate Student Initiated Education **2012-2013**
University of California, Los Angeles
Advisor: Dr. Jim Stigler

Conceived the idea for a seminar called "The Psychology of Gamifying Education," and taught the class to undergraduates at UCLA in spring quarter of 2013. Designed curriculum and syllabus, introducing students to "gamification," developmental psychology concepts, and how the two are beginning to converge within the school environment. Utilized academic articles and TED talks to generate discussion questions for class. Facilitated students' efforts to incorporate class sources into a final project.

PROFESSIONAL DEVELOPMENT

AERA Division C Graduate Student Seminar 2018

APA Division 15 Graduate Student Seminar 2017

AERA Division E Graduate Student Seminar 2016

Latent Class Analysis, Stats Camp Seminar 2016

PROFESSIONAL EXPERIENCE

ACT Tutor, Test Prep Gurus **2016-2019**
Irvine, CA

Taught 1:1 sessions on math and science sections of the ACT to aspiring college students.

SAT Tutor, Elite Educational Institute **2015-2019**
Irvine, CA

Designed class sessions and taught groups of 18 students for an 8-week SAT prep program.

Private Tutor, Brighter Minds Tutoring **2012-2014**
Los Angeles, CA

One-on-one, in-home tutor for 7^{th}-12^{th} grade students, teaching algebra, calculus, physics, world history, writing, and SAT prep. Discovered students' individual motives and learning styles by developing personal relationships with them.

User Experience Analyst, Kickstage **2012**
San Jose, CA

Recruited by a startup company to apply my knowledge of social psychology to build user loyalty strategy. Implemented "gamification" techniques into website to attract and retain users. Designed an outreach strategy to entice content contributors.

SERVICE

Graduate Student Co-Chair, Motivation in Education SIG **2017-2019**
American Educational Research Association (AERA)

Elected to represent international group of graduate students in AERA's Motivation SIG and manage events for them throughout the year. Authored initiatives including the Living Syllabus and online student collaborations. Managed regular events including peer mentorship program.

IT Manager and Peer Mentor, School of Education DECADE **2015-2019**
University of California, Irvine

Created and managed first SoE DECADE website for the purpose of informing students of events, opportunities for fellowships, important documents for program benchmarks, and member information.

Research Coordinator, Data Sciences Initiative Mini-symposium **2015-2018**
University of California, Irvine

Published submission standards for undergraduate and graduate research posters to be presented at interdisciplinary mini-symposium on Text and Data Mining for Interactive Online Learning. Coordinated accepted posters for presentation during mini-symposium and headed committee to determine top posters.

President, Delta Tau Delta Fraternity **2011-2013**
University of California, Los Angeles

In two years as president, tripled the size of Delta Tau Delta's UCLA chapter and created an awards/accreditation report for our chapter that was recognized as one of the top twelve in the country. Managed chapter's executive board while working closely with staff from both the national fraternity and UCLA's Greek Life Office.

Leadership Development Director, Alumni Scholars Club **2011-2012**
University of California, Los Angeles

Selected and managed a committee of eight Alumni Scholars Club members responsible for organizing workshops for other club members to learn professional skills from UCLA alumni. Implemented an original program, the Leadership Certification Program, which combined alumni workshops and tasks around campus to promote leadership skills.

Site Leader, UCLA Volunteer Partner Program **2011**
University of California, Los Angeles

Organized service project to beautify grounds of La Brea Tar Pits. Coordinated with staff from La Brea Tar Pits, planned volunteer tasks and schedule, and recruited student volunteers.

College Mentor, Los Angeles Team Mentoring **2009-2011**
Los Angeles, CA

Provided guidance to a group of ten middle school students at an underprivileged school. Worked with a teacher after school on a weekly basis and facilitated discussions and games designed to teach about health, study habits, and peer relationships.

ABSTRACT OF THE DISSERTATION

Motivation for and within Online Courses

By

Peter McPartlan

Doctor of Philosophy in Education

University of California, Irvine, 2019

Distinguished Professor Jacquelynne Eccles, Chair

Online courses have been heralded as efficient and cost-effective higher education solutions, but have negative associations with student learning and retention. In light of online learning's increasing prevalence, yet disappointing outcomes, it is imperative to investigate which features of online courses may be contributing to disparities in student performance. In this dissertation, I focus on a critical, yet understudied predictor of performance in online courses: motivation. I use Expectancy-Value Theory to investigate how motivation impacts who decides to take online courses, how motivation is affected by online courses, and how motivation can be improved within online courses. In my first study, I find that students select into online courses largely due to the need for flexibility, and that motivational, behavioral, and performance differences between OL and F2F students become more apparent once students are grouped by their reasons for selecting into an OL course. In my second study, I identify that by increasing the transactional distance between students, asynchronous online courses degrade belonging, increasing social uncertainty around classmates and a perceived lack of access to the instructor. Furthermore, interview data suggest that students conceptualize belonging differently across contexts, and that quantitative measures designed to measure school belonging may produce misleading results when adapted to the classroom level. In my final study, I address a gap in the theory behind the popular utility value intervention (UVI): the behavioral mechanisms linking greater motivation to greater performance. I was able to utilize click data to discover behaviors that are associated with both motivation and course performance, finding that motivated click behavior (i.e., interest) is best identified by the patterns of spacing one's engagement with the course across many days, especially days not surrounding course deadlines. I identify lingering questions about the directionality in the strengthening association between motivation and engaged behavior over time, discussing their implications for future intervention work. Overall, this study uses motivational theory to improve performance in online courses, and online course performance to inform motivational theory, demonstrating the potential for a symbiotic relationship between the fields of online learning and motivation.

INTRODUCTION – The state of online education in the U.S.

The prevalence of online education

Online courses have rapidly become available in the past decade. As of 2011, online course enrollment had grown by over 9% in each year of the previous decade (Allen & Seaman, 2013). This growth rate bears remarkable resemblance to the growth witnessed for school acquisition of computers and Internet connections before that time (Means, Bakia, & Murphy, 2014). In the years since, these growth rates have continued, with the most recent national report showing that one in three college students now takes at least one course online (Allen & Seaman, 2017). The uptake of online courses into the curricula of higher education institutions has only increased with every passing year (excluding private, for-profit institution), and has showed no signs of plateauing.

The growth of online courses throughout higher education institutions is largely because, amidst the growing expenses of and demand for higher education in the United States, online courses have been heralded as a cost-efficient remedy of the future (Bowen, 2012). In the wake of the United States' recent economic recession, political and education leaders alike have advocated for investments in online education as a means of meeting the increasing demand for higher education without exacerbating the heavy financial burden imposed on students (Means et al., 2014). From 2012 to 2015, this idea was reflected by decreasing on-campus enrollment coupled with increasing distance enrollment (Allen & Seaman, 2017).

This growth been especially evident in California following the 2008 recession, in which the CSU schools became the first university system in the country to cap enrollment even though applicant pools were increasing. Soon after, California's UC and community college systems followed suit (Bowen, Chingos, Lack, & Nygren, 2012). Since then, in response to Governor

Brown's call for increasing access to high-demand courses, California's CSU and UC universities have rapidly expanded their fully online course offerings, making hundreds of them available for "cross-campus" enrollment. The CSU system offers fully online programs for over 30 bachelor's degrees ("CSU Degree Programs", 2017), and the UC system's Innovative Learning Technology Initiative is actively prioritizing funding for transforming face-to-face courses to fully online courses ("ILTI Request for Proposals", 2017). Meanwhile, Governor Brown has even created a controversial new push within the community college system to create a fully-online college (Zinshteyn, 2017). Overall, both national trends and those among the hundreds of thousands of students in California alone suggest that fully online course development will receive ample funding in years to come.

Fortunately, research seems to support the merits of adopting online education as a cost-effective solution. Online courses are associated with lower costs for students (Deming et al., 2015; Means et al., 2014), along with less of a need for transportation and greater flexibility for balancing school with other responsibilities (Rickard, 2010). Meanwhile, university cost analyses have reported that transitioning from traditional courses to online formats result in a significant amount of savings to the school without sacrificing student learning (Twigg, 2003). More recent, rigorous studies of these economic issues have been skeptical that contemporaneous assessments of costs between traditional and online courses can provide accurate predictions of future, large-scale, state-wide expenses (Bowen, 2012). Still, there is optimism that online learning could help reduce the costs of higher education without reducing the quality of the educational experience (Bowen, 2012). Moreover, as the case of California depicts, policymakers have shown they are willing to use online learning to save money *without* rigorous cost-analyses to support the decision (Means et al., 2014).

Overall, the growing economic necessity of online education is coupled with optimism surrounding its other theoretical benefits, especially for traditionally disadvantaged students. Online courses have proven effective for granting access and flexibility to students who cannot travel to a physical campus, or for whom the residential experience is overly expensive (Rickard, 2010). Additionally, they offer the promise of differentiated instruction and the ability to go at one's own pace (Means et al., 2014). Furthermore, online courses also allow universities greater capacity to accommodate at-risk students who fail required courses (Means et al., 2014). This ability to offer cost-effective solutions that could be particularly helpful for at-risk and hard-to-reach students has led some researchers to predict that both public and private universities will make the growth of online courses and the courtship of online course-takers a focal point of their plans for growth (Allen & Seaman, 2013; Deming et al., 2015).

Defining online education

Synthesizing the body of literature on online education can be quite daunting if one does not understand the terms that help differentiate between various types of online learning. This is especially true when determining if studies on "hybrid" or "blended" courses should be lumped in with fully online courses. An overview of these terms is presented by Means and colleagues (2014), who point out that many interchangeable terms synonymous with online learning have emerged, including "Web-based learning" and "cyber learning." Importantly, though, a course involving the Internet is not considered an "online course" if the amount of the course experienced online is below a certain threshold. The Babson Survey Research Group, which has been heavily cited for its annual surveys on online learning in higher education, considers an "online course" one that presents more than 80 percent of its content online (Allen & Seaman, 2013; Means et al., 2014). "Hybrid" or "blended courses" are those that present over 30 percent of their content online, but have at least 21 percent of their content in person. Meanwhile, "Web-enhanced" courses are those that use online applications to support the face-to-face learning experience, with less than 30 percent of the course operating online. As several studies have noted, outcomes of hybrid and online courses are often quite different when analyzed separately (Alpert, Couch, & Harmon, 2016; Means, Toyama, Murphy, & Baki, 2013). In this dissertation, the courses examined will all be online courses that meet the criteria of having over 80 percent conducted online.

Online or blended: What is being prioritized?

Up-to-date national trends are slowly emerging around which *kinds* of online education are growing most rapidly, but preliminary reports suggest that colleges are prioritizing the growth of fully online programs rather than blended learning programs. These data, coming from Quality Matters' new Changing Landscape of Online Education (CHLOE) survey in 2017, were broken down among different types of institutions, including two-year public, four-year public, four-year private, and for-profit institutions. This breakdown showed that at public institutions, faculty are especially likely to be the main drivers of online course creation, and they are the least likely to have support available for designing their courses. This mirrors the situation in California's UC system described above. Its Innovative Learning Technology Initiative (ILTI) has put funding directly into the hands of faculty as principal investigators for the development of online courses. At the same time, the UC ILTI explicitly states that funding for online course development is being prioritized over funding for new hybrid courses. Importantly, the top funding priority for the ILTI is transforming a face-to-face course to a fully online course. In line with this trend of course *translation*, as opposed to *creation*, the studies of this dissertation draw from online courses that faculty have recently converted from face-to-face iterations.

Trouble with the effectiveness of online education

Working, shopping, and communicating with friends have all been made more convenient and efficient by the affordances of online tools. However, the quality of education has not experienced such benefits from the shift to online spaces. In fact, there is concern whether deficiencies in the quality of online education may end up overshadowing its cost-saving virtues (Bowen, 2012; Deming et al., 2015). Although a majority of chief academic officers at U.S. universities report that online learning is just as effective, if not better, than face-to-face offerings (Allen & Seaman, 2013), researchers have bemoaned the lack of hard evidence supporting this conclusion (Bowen, 2012). Though disappointing, the lack of rigorous research is unsurprising given the near impossibility of getting approval to randomly assign students to different course modalities (Means et al., 2014). Still, the most recent meta-analyses find that across a wide range of K-12, undergraduate, and graduate settings, only 45 studies rigorously compared equivalent face-to-face and online courses, and none involved random assignment between modalities. Results showed that whereas blended learning (combining face-to-face and Internet-based instruction) demonstrated a positive association with learning outcomes, there was no significant advantage to taking a course online (Lack, 2013; Means, Toyama, Murphy, Bakia, & Jones, 2009).

More recent analyses of online course effectiveness have not painted online courses more favorably. On top of persistent concern for the relatively poor retention rates of online courses (Bettinger & Loeb, 2017; Dupin-Bryant, 2004), new evidence from randomized studies suggests that equivalent online courses are no better (Bowen, Chingos, Lack, & Nygren, 2012), if not worse than, equivalent face-to-face courses (Alpert et al., 2016; Figlio, Rush, & Yin, 2013). Among college students, for whom the traditional, passive, lecture style of learning is already heavily criticized (Freeman et al., 2014; PCAST, 2012), it is troubling to think that online courses may be even poorer alternatives for learning. A recent study by Bettinger and colleagues (2017) used data from a for-profit institution in which the same instructors, curricula, and textbooks were used in both the online and face-to-face versions of its courses. Using a wide range of statistical controls with a very large sample (*N*=230,000), the authors were able to conclude that taking an online course was associated with higher rates of dropout. In addition, the decision to take a course online was associated with an average decrease in grade by one-third of a standard deviation. In line with results from smaller randomized studies, this is a compelling finding amidst a field of research often criticized either for small sample sizes or an inability to control for selection effects (Bowen, 2012).

Paradoxically, although one of the supposed benefits of online instruction is its potential to improve the experiences of low-performing students through differentiation of instruction, it is these very students for whom online instruction is often worse (Alpert et al., 2016; Bettinger & Loeb, 2017; Figlio, Rush, & Yin, 2013). This is particularly alarming considering the greater prevalence of online courses in less-selective public institutions (Deming et al., 2015). This includes community colleges, where online courses indeed have a significant negative impact on student grades and persistence (Xu & Jaggars, 2013). It is also concerning that online courses are often used as tools for remedial learning (Means et al., 2014) given the especially negative outcomes online courses have for below-average achievers (Figlio et al., 2013). In an American society that is experiencing the greatest levels of income inequality in nearly 50 years (Saez, 2010), it is troubling that even our educational institutions feel forced to adopt a system that may further disadvantage traditionally low-performing segments of society. These trends further emphasize the urgency with which researchers must identify the reasons for online education's poor outcomes.

Therefore, in this dissertation, I address theoretical and methodological questions associated with studying course outcomes in online education. I focus my studies on an increasingly relevant sample of online courses: those by California's UC faculty who are in the process of translating their face-to-face courses into online courses (in which > 80% of course is delivered online). As the following literature review outlines, these studies attempt to address the lack of literature on the role motivation may be playing in online course outcomes. Specifically, these studies will explore students' motivation *for* taking online courses and students' motivation *within* online courses, as well as ways that online students' motivation can be improved.

LITERATURE REVIEW – The role of motivation in online courses

Does motivation explain who selects into online courses? (Intro to Study 1)

Despite the need to improve the quality of online education, our ability to rigorously assess it can be difficult. Often, researchers design studies in which online (OL) courses are compared to equivalent face-to-face (F2F) courses. As the traditional form of education, F2F courses are standards by which we intuitively judge newly developed OL courses (Means et al., 2013). Although conducting randomized control trials would be ideal for this task, only a handful have ever been carried out (e.g. Figlio, Rush, & Yin, 2010) due to the near impossibility of getting approval to randomly assign students to different course modalities (Means et al., 2014). Without the benefit of randomization, the majority of researchers in this field must make do with quasi-experimental studies, using statistical techniques to estimate whether differences between OL and F2F course outcomes are caused by the course formats themselves, or are simply due to pre-existing differences in the students who choose OL courses. The validity of conclusions from these studies rests heavily on the assumption that selection effects can be statistically controlled.

Unfortunately, most research overlooks potentially important *psychological* differences between students who choose OL and F2F courses. A review of studies comparing OL and F2F courses cited by prominent meta-analyses (Lack, 2013; Means et al., 2013) reveals that these studies rarely consider group differences beyond superficial demographic variables such as age, race, gender, and SES. This is likely due to the convenience of collecting demographic variables. However, psychological variables are just as, if not more important for predicting student success in a course. Students' motivation when beginning a course, for example, is considered a much more proximal predictor of academic success than race or gender (Wigfield & Eccles, 2000). Yet, motivation has not been accounted for as a pre-existing difference between OL and

F2F students by even the most rigorously controlled studies (e.g. Xu & Jaggars, 2011). This is especially concerning considering recent qualitative findings suggesting that students prefer to take more "important" or "interesting" courses face-to-face (Jaggars, 2014). According to the Eccles and colleagues (1983) Expectancy-Value Theory of motivation, finding a course important or interesting indicates that the student is more likely to value participating and succeeding in the course. Valuing a course, in turn, is predictive of achievement. Therefore, if online students are more likely to believe a course is less interesting or important, they are often less likely to succeed.

Eccles and colleagues' Expectancy-Value Theory of motivation

Although the past couple centuries have seen many different ideas of how motivation should be defined and measured, the Eccles and colleagues (1983) Expectancy-Value Theory offers one of the most prominent and nuanced frameworks of motivation available today (APA, 2017). Building off the simple questions we often ask ourselves, "Can I do it?" and, "Do I want to do it?", Expectancy-Value theories of motivation (e.g., Atkinson, 1957) suggest that people will be motivated to engage in a task if they expect they can succeed and if they see value in succeeding. A key contribution of the Eccles and colleagues model is the delineation of different reasons one might assign value to a task: utility, interest, attainment, and cost. Whereas *utility value* is the usefulness the task holds for helping achieve future goals, *interest value* is the natural enjoyment one gets out of a task, similar to the idea of intrinsic motivation as defined by Deci and Ryan's Self-Determination Theory (Wigfield & Eccles, 1992). Meanwhile, tasks that are important to maintaining our desired personal identities hold *attainment value*. Finally, perceiving that there are *costs* to succeeding in a task detracts from its value. In recent years, an expanding body of research has even identified subcomponents of cost such as opportunity cost, effort cost, and psychological cost (Flake, Barron, Hulleman, McCoach, & Welsh, 2015; Perez, Cromley, & Kaplan, 2014). Altogether, assessments of students' expectancies of success and various values for school subjects have been used to successfully predict their choices, behavior, and performance (Eccles, 2005). Therefore, the present studies measure motivation by capturing students' expectancies for success and subjective values of the specific course subjects they are studying.

Who is more likely to choose online courses and why?

Compounding the lack of work on motivational differences in OL and F2F students, large scale data sets have yielded limited findings on how selection effects play out in OL and F2F courses, as these data sets are armed with little beyond basic demographic information. Women are generally more likely to enroll in online courses than men (Price, 2006). Additionally, online students are more likely to be older (Moore & Kearsley, 2005; Romero & Usart, 2014), employed, and single parents (Escueta, Quan, Nickow, & Oreopoulos, 2017), reflecting the flexibility desired for completing studies alongside employment and family responsibilities (Bailey, Ifenthaler, Gosper, Kretzschmar, & Ware, 2015). These demographic characteristics are therefore seen as important covariates for controlling for bias due to selection effects.

However, demographic differences such as being female or being older are not considered causes for poor performance in school. Rather, any observed associations between demographic characteristics and poor course performance should be mediated by behavioral or psychological processes conducive to poor course performance. Consequently, more nuanced information about students who choose OL courses is needed to understand what characteristics could make them predisposed to perform more poorly compared to F2F peers. To discover more meaningful differences between OL and F2F enrollees, students' actual reasons for selecting into

OL courses may offer insight. Understanding the core reasons that students choose OL courses can lead to a more nuanced understanding of who these students are more likely to be in terms of behavioral and psychological processes. This information could even be used to improve our understanding of why certain demographics of people tend to choose OL courses.

Only a handful of studies to date have explicitly examined students' reported reasons for choosing between OL and F2F courses. Several have found that students do so for the flexibility it provides (Bailey et al., 2015; Johnson, Stewart, & Bachman, 2015; Vanslambrouck, Zhu, Lombaerts, Philipsen, & Tondeur, 2018), and not because they believe it will provide a better learning experience (Aslanian & Clinefelter, 2013; Jaggars, 2014). On the other hand, students who choose F2F courses seem to do so after considering their learning preferences. Often, there is a concern that interactions with the instructor would be diminished in an online environment, which is cited as a common reason for choosing F2F courses (Jaggars, 2014; O'Neill & Sai, 2014). Similarly, students who believe online classes diminish interactional quality will often pick F2F courses if they value the social elements of their school experience or believe that interactional quality will help them self-regulate and manage their studies (Hagel & Shaw, 2010). Finally, qualitative work has suggested that, when weighing the flexibility of OL courses against the higher interactivity of F2F courses, students will consider the difficulty of the class. If students believe the class is "easy," and presumably, that they won't need to depend upon interactions with the instructor, they may be more willing to take the course online (Jaggars, 2014). Overall, the clear differences between OL and F2F students' reasons for selecting their respective course modalities hints that selection effects may be responsible for disparities in course performance. Yet no studies have related students' reasons for taking OL and F2F courses to their motivational, behavioral, and performance outcomes.

Research Questions

Online courses and the students that take them can vary dramatically from context to context. Therefore, it is important to consider that the present study was done in a large, research university of traditional college students.

1. Are there baseline motivational differences in students who take courses online?
2. What are the reasons that students take courses online and face-to-face at a large research university in the United States?
3. How are student reasons for choosing OL courses associated with their motivation, behavior, and performance?
4. How are demographic characteristics associated with choosing OL courses and reasons for choosing OL courses?

The first research question immediately addresses the lack of literature on the possibility that OL students may simply be less motivated to succeed than their F2F peers, as suggested by a recent qualitative study (Jaggars, 2014). The second research question then moves to a broader investigation of why students choose an OL or F2F course when both modalities are available. We anticipate that these results will largely reproduce previous findings in the literature. However, reproducing these findings in a large, American research university would confirm that patterns in students' reasons are consistent with those from community college (Jaggars, 2014), professional development (Vanslambrouck et al., 2018), and international settings (Bailey et al., 2015). The third research question extends this body of literature by connecting students' reasons to their motivational, behavioral, and performance outcomes, leaving us with the most nuanced evidence to date of how selection effects may be impacting comparisons between student performance in OL and F2F courses. The fourth research question connects the body of literature on the psychology of student choice to the quasi-experimental body of literature on estimating the effectiveness of OL courses relative to F2F courses.

Do online courses affect students' motivation? (Introduction to Study 2)

In light of the increasing prevalence of online course-taking, it is imperative to identify which features of online learning may be contributing to its relatively poor achievement outcomes. The phrase "distance" education itself highlights the most distinguishing characteristic of online courses: an increase in the physical distance between students and instructors. Since the advent of online education, scholars have noted how this physical distance impacts the "transactional" distance that colors interactions among instructors and students when those interactions are mediated by computers (Moore, 1993). Especially in asynchronous courses, students may be able to consume the entire curriculum of a course from wherever and whenever it most suits them, devoid of interpersonal interactions with both instructors and classmates. When they do interact, students are often forced to deal with the lower interactional quality afforded by computers. This may have important implications for online students' motivation and subsequent course achievement.

As Jaggars and Xu (2016) note, interpersonal interactions are hypothesized to promote students' psychological connection to their course. They outline that this is done by addressing two fundamental features of online courses detrimental to a strong psychological connection. First, interpersonal interactions reduce "transactional distance," or the separation of students and instructors from one another by space and/or time (Moore, 1993). At the same time, interpersonal interactions increase social presence, or the intimacy and immediacy that affect our perception of the other person as a "real person" (Short, Williams, & Christie, 1976). Theoretical and scale development on social presence have suggested that this concept comprises feeling connectedness and accessibility in psychological, emotional, and social manners. Ultimately, as one meta-analysis has concluded, the quality of interpersonal interactions has been found to positively affect students' performance outcomes (Bernard et al., 2009). This underscores the importance of addressing how a lack of quality interpersonal interactions may be undermining students' psychological connection to their online courses.

Potential motivational shortcomings of an online course – sense of belonging

Research has indeed supported the hypothesis that students have lower psychological connections to courses when they are online. Although no study has yet measured this in terms of expectancy-value motivational constructs, the literature suggests that online students feel less classroom connectedness, which is highly related to an increasingly popular construct called sense of belonging (Cho, Hathcoat, Bridges, Mathew, & Bang, 2014; Rovai & Lucking, 2003). Notably, sense of belonging has been found to be positively associated with both expectancies and values (Freeman, Anderman, & Jensen, 2007; Goodenow, 1993; Goodenow & Grady, 1993; Zumbrunn, McKim, Buhs, & Hawley, 2014), and has been an increasingly well-recognized motivational construct since the early 1990s (Faircloth, 2011).

The motivational frameworks of Maslow (1954) and Deci and Ryan (1985), all recognize the need to belong as a fundamental human need, a claim which has been supported by Baumeister and Leary's (1995) seminal review of empirical literature. As Eccles and Midgley (1989) point out, academic motivation is supported when the school environment meets these fundamental needs, making sense of belonging an important antecedent of students' motivation. This notion is reflected in seminal theories of college persistence (Spady, 1971; Tinto, 1993), which posit that students' sense of belonging is critical to their engagement and persistence (see Hurtado & Carter, 1997, for review). For this reason, sense of belonging has become a prominent motivational construct, defined as the extent to which one feels personally accepted, respected, included, and supported by others (Goodenow, 1993). Additionally, sense of belonging is thought to be closely tied to "fit" and valued involvement (Hoffman, Richmond, Morrow, & Salomone, 2003), and implies the importance of lasting, positive, and significant interpersonal relationships (Baumeister & Leary, 1995).

Given this definition, it is likely that students' sense of belonging may be degraded by the features of online courses. The "transactional distance" between students and instructors may decrease their perceptions of the instructor's respect and support for them. In asynchronous courses that offer few opportunities to interact with classmates, students may also be less likely to perceive that classmates will value the effort they invest in the course. Such hypotheses regarding these key components of belonging are supported by work showing that students report feeling less connected to both classmates and instructors in online courses (Cho et al., 2014; Jaggars, 2014). Overall, then, one of the most promising hypotheses regarding the effects of online courses on students' motivation is that it lowers their sense of belonging within the course.

Issues with measuring belonging in online courses

Though studies have compared OL and F2F students' perceptions of classroom connectedness (Cho et al., 2014; Rovai & Lucking, 2003), a construct similar to sense of belonging (Summers & Svinicki, 2007), researchers have yet to compare OL and F2F students' perceptions of belonging. However, an important theoretical and methodological issue may stand in the way of studying this. Due to a lack of theory regarding whether student's conceptualize sense of belonging differently across context, quantitative studies have largely operated under the assumption that sense of belonging develops the same way in different contexts. Carol

Goodenow's Psychological Sense of School Membership (PSSM) scale (1993) was created to assess belonging in the middle school context, but it has been adapted to measure belonging in universities and even in individual college classrooms (Freeman et al., 2007; Zumbrunn et al., 2014). However, differences in these contexts could conceivably change the way that students think about sense of belonging.

There are theoretical reasons to hypothesize that belonging in a university classroom context, not to mention an online classroom context, may occur differently than in the middle school context. Whereas middle school students are in early adolescence, college students are typically in late adolescence, which could potentially change collectively understood norms for the social interactions that form the foundation of belonging. Similarly, whereas middle school students are often in class sizes of 20-40, college students may experience class sizes of 200-400. These circumstances may deemphasize peer and instructor interactions, altering students' expectations and criteria for developing a sense of belonging. Finally, a student's experience in a college course can be as short as 10 weeks in duration, whereas their experience in middle school may last around three years. Such a short window of interacting with classmates may not afford the "temporally stable and enduring" interactions that Baumeister and Leary theorized are necessary conditions for developing belonging (Baumeister & Leary, 1995).

Recent qualitative work suggests that belonging is indeed conceptualized differently when the context in which it is studied changes. Slaten and colleagues, for instance, recently developed a separate scale for measuring university belonging informed by qualitative data suggesting that belonging is thought of differently in university contexts than middle school contexts (Slaten et al., 2014; Slaten, Elison, Deemer, Hughes, & Shemwell, 2017). When narrowing our focus on belonging within a single classroom setting, it may be important to consider that the context has a narrower range of valued outcomes: academic knowledge and achievement. Green and colleagues (2016) recently explored how belonging was conceptualized in a STEM school, noting the context as one that intentionally exudes a culture of advanced academic achievement. Importantly, they concluded from their interviews that belonging in that school context was tied more heavily to academic achievement than is typically discussed in other studies of school belonging. They therefore introduced the idea of complementary processes that can build belonging, social belonging and academic belonging. Whereas *social belonging* represents feelings of acceptance, respect, and inclusion that popular school belonging instruments are trying to measure as a result of interactions with others, *academic belonging* represents students' experiences of meeting academic expectations and participating in a range of activities and sharing in educationally-oriented experiences with peers. Similarly, shifting focus from a school to a classroom context that exalts a narrower set of achievement-based goals may de-emphasize the value of social belonging and instead make more salient belonging that is tied to one's academic achievement.

Quantitative analyses also imply support for the idea that sense of belonging should be measured differently in different contexts. Factor analyses of Goodenow's PSSM have consistently shown on multiple occasions that whereas school-level belonging can be broken down into three or more factors (Freeman et al., 2007; Ye & Wallace, 2013; You, Ritchey, Furlong, Shochet, & Boman, 2011), those same items produce only one factor when adapted to the classroom-level (Freeman et al., 2007; Zumbrunn et al., 2014). This is simply done by changing the word "school" to "class," but clearly this change alone is enough to change the way students interpret and answer questions about belonging. The disparity provides empirical evidence that sense of belonging is conceptualized differently in university-wide and classroom-level contexts. Considering the differences between university-wide and classroom-level belonging, it is certainly possible that online college courses require a different form of measurement as well.

Many different (often non-validated) measures of belonging have been used in college contexts for individual studies (e.g., Hausmann, Ye, Schofield, & Woods, 2009; Meeuwisse, Severiens, & Born, 2010; Summers & Svinicki, 2007), but Goodenow's Psychological Sense of School Membership (PSSM) is considered the gold-standard for measuring school belonging among adolescents (Faircloth, 2011). This is becoming true even among late adolescents in college, despite the existence of instruments designed for college students (e.g., Hoffman et al., 2003; Slaten et al., 2017). Likely, it is due to the positive reputation the PSSM has gained through its extensive use in middle school and high school (see You et al., 2011, for review). Because of this, we will use the PSSM in the present study to investigate whether belonging should be measured differently in different contexts and, if so, how.

Research Questions

This study will address the methodological issue of measuring sense of belonging in online courses and offer insight into the elements of online courses that may hinder the development of belonging. The study will be guided by the following research questions:

1. Do students conceptualize sense of belonging in different ways across contexts? (university, face-to-face classroom, online classroom)
2. Does a popular instrument measure sense of belonging when adapted to an online classroom context?
3. What are barriers to belonging in online courses?

These questions will address the theoretical gap regarding the measurement of sense of belonging across classroom contexts and test a promising hypothesis for the ways in which online courses impact students' motivation.

Are motivational interventions especially effective for online students? (Intro to Study 3)

To complement the previous study's investigation of students' motivation in online courses, I will also explore the potential of motivational interventions to help online course-takers. Documenting and addressing online students' motivation from an expectancy-value framework has yet to be done. This may be unsurprising given past studies that have found a disproportionately low number of publications regarding online students' motivation (Huett, Kalinowski, Moller, & Huett, 2008; Visser, Plomp, Amirault, & Kuiper, 2002). Nevertheless, two recent studies suggest that online students may have lower value for their courses. First, a qualitative study by Jaggars (2014) reported that when students take courses that they find "important" or "interesting," they prefer to take them face-to-face. According to Eccles and colleagues' expectancy-value theory, this would imply that online students are likely to have lower interest and utility value. Second, preliminary data analyses from the first study of this dissertation suggests that even if online students' baseline utility and interest values are equivalent to those of their face-to-face peers, their values are likely to go down over time, whereas, the values of face-to-face students are more likely to go up. This provides ample cause to examine how online students' expectancies and values both at the beginning of the course and throughout the course compare to those of their face-to-face peers.

Theoretically, though, why might online students have lower values for their courses? One simple explanation proposed above is that the students who don't value a particular subject are simply more likely to take the course online (Jaggars, 2014). However, the positive correlation between student's sense of belonging and their subjective task values hints at the possibility that it may be a process related to connectedness and belonging (Freeman, Anderman, & Jensen, 2007; Goodenow, 1993; Goodenow & Grady, 1993; Zumbrunn, McKim, Buhs, & Hawley, 2014), which is another way of referring to students' "psychological connection" to their class (Jaggars & Xu, 2016). When online courses increase the "transactional distance" between students, classmates, and instructors, and decrease students' connectedness and belonging in the class, students may find less utility value. Importantly, utility value can be derived from connecting course content to both professional and social goals. Whereas utility value is traditionally thought of as the connection that students make between course content and their academic/ professional goals, students may also find that engaging in a course is useful for engaging with and being accepted by peers (Gaspard et al., 2015). Therefore, if the online course context diminishes students' sense of belonging (Cho et al., 2014; Rovai & Lucking, 2003), students may have fewer reasons to actively engage with the course material.

Although this makes online courses an ideal context for interventions focusing on either sense of belonging or expectancy-value constructs, the far more established motivational interventions are those rooted in expectancy-value constructs (Harackiewicz & Priniski, 2018). Whereas a review of literature reveals no studies explicitly testing sense of belonging interventions at the college classroom level (Harackiewicz & Priniski, 2018), at least four studies specifically focusing on utility value in college classrooms have been conducted in the past several years (Canning et al., 2017; Harackiewicz, Canning, Tibbetts, Priniski, & Hyde, 2016; Hulleman, Godes, Hendricks, & Harackiewicz, 2010; Hulleman, Kosovich, Barron, & Daniel, 2017). These utility value interventions (UVIs) have successfully promoted students' value of and performance in both STEM and non-STEM courses (Harackiewicz & Priniski, 2018).

Because of the number of successful replications, as well as the increasingly nuanced understanding of the mechanisms driving that success (Wigfield, Rosenzweig, & Eccles, 2017), ample funding continues to be invested in the replication of this intervention in different university and classroom contexts. Yet, no research has investigated the effectiveness of UVIs in a classroom environment where they may be especially effective: online college courses. Therefore, the final study of my dissertation will investigate the effectiveness of a utility value intervention in an online college course.

Theoretical underpinnings of utility value interventions

Utility value is the perception that completing a task will hold relevance for one's future goals (Wigfield & Eccles, 1992). Although it is just one of several subcomponents of value in Eccles and colleagues' Expectancy-Value model, it is thought to be one of the most malleable, making it an appropriate target for intervention. As Harackiewicz and Priniski (2018) detail in their review, UVIs are driven by the hypothesis that if educators can help students connect course content to their short- or long-term goals, students will have stronger reasons, and thus stronger motivation, to engage with the material. Ultimately, this serves as a motivational mechanism responsible for improving students' performance.

The majority of utility value interventions accomplish these outcomes by having students self-generate connections between their goals and the course content they are studying, often through writing assignments. In these assignments, students are asked to choose a topic covered in the current unit of course material and write about the relevance of that topic to their lives. This treatment condition is then juxtaposed with a control condition in which students write a summary of that topic (Harackiewicz & Priniski, 2018). Although some variations of this intervention involve having a researcher or instructor simply tell students about the utility of a subject (e.g., Durik & Harackiewicz, 2007), or having students read quotes from other students (Gaspard et al., 2015), the majority of field-based experiments direct students to self-generate ideas. Because students essentially convince themselves of the benefits of learning the course material, researchers are able to limit the possibility that students actually view the exercise as an intervention, contributing to the theoretical validity of the findings by guarding against the possibility of a "good-subject" bias.

Although positive effects have been found in many studies, the heterogeneous effects that often emerge suggest that online courses may be a context in which UVIs are the most impactful. A strength of the evolving body of work on UVIs is the number of moderators that have been identified. Although several of these focus on the delivery of the intervention (e.g., Tibbetts et al., 2016), another line of work has focused on identifying subsets of students for whom these interventions have been most effective. Foremost among them are students who begin the course with low initial exam grades (Harackiewicz et al., 2016; Hulleman et al., 2010, 2017). Sometimes these subgroups of students are the only ones for whom the intervention actually has a significant effect (e.g., Hulleman et al., 2010), though this should not necessarily be considered a weakness of the intervention if the goal is to close achievement gaps. The takeaway, however, is that UVIs have proven to be especially effective among students who seem to struggle the most.

Although online college courses may be an especially appropriate context for motivational interventions, no researchers have implemented a UVI in this setting. That is not to say motivational interventions have not been tested in online settings. Recently, an unpublished study tested the effectiveness of a UVI on online *high school* students. This study had only modest findings regarding the success of a UVI featuring both quotes from other students and a writing assignment connecting course material to personal goals. However, this study may have underestimated the intervention's effectiveness because participants opted-in to the study, making it likely that many of the low-performing, less-motivated students who would stand to benefit the most were not represented in the sample (Rosenzweig, 2017).

Meanwhile, a separate line of motivation research that has targeted online college students has found positive effects for interventions based on the ARCS model of motivation (Keller, 1987). This model, which focuses on building students' (A)ttention, (R)elevance, (C)onfidence, and (S)atisfaction in their courses, is said to be based in several prominent motivational theories, including socio-cognitive theory and interest theories (Keller, 2010). Additionally, it is based in expectancy-value theory, as it reflects the importance of utility value (relevance) and expectancies of success (confidence) (Fritea & Opre, 2015). Studies have focused on the impact of things as simple as biweekly emails intended to convey the relevance of the course (Huett et al., 2008), to entire versions of courses intended to maximize links between content and learner's objectives (Fritea & Opre, 2015). Although these randomized studies found positive effects on students' motivation, effects on students' task values were often not measured as defined by expectancy-value theories. In the one study in which utility value was targeted and significantly improved, the intervention was incredibly resource-intensive, involving the entire design of the course around the idea of utility value (Fritea & Opre, 2015). Therefore, this body of research shows that motivational interventions can be effective in online courses, but that work remains to be done to discover whether short, cost-effective interventions such as UVIs can impact students' task value and performance in online college courses.

Using click data to uncover behavioral mediators of UVIs

Despite recent advances in the field of utility value interventions, a major question that remains is what behavioral changes mediate the well-documented relationship between higher motivation and higher course outcomes. Researchers of these interventions have insisted that the well-articulated nuances of the psychological theories behind their designs means they should not be regarded as “magic bullets” (Yeager & Walton, 2011). Yet, the conceptual models of these interventions are missing a long-overlooked link between higher motivation and higher performance (Harackiewicz, 2017). Implicit in all conceptual models linking motivation to higher performance are the behavioral or cognitive mechanisms directly responsible for academic performance. But it is still a mystery whether and how motivational interventions lead to behavioral and cognitive changes, as these mediational processes are overlooked in intervention researcher’s conceptual models and study designs.

Fortunately, online courses may offer a solution to the cause of this oversight. It is likely that behavioral data sufficient for addressing the question of behavioral and cognitive mediators are simply too difficult to collect. Does the motivational intervention lead students to study more? Does the motivational intervention lead students to procrastinate less? Although intensive longitudinal survey data collection methods might help capture students’ daily or weekly behaviors, these questions would still have to be answered largely based on students’ self-reports of their study patterns. Furthermore, the intensity of these types of studies can be burdensome for students and lead to high rates of attrition (Sugie, 2016). Therefore, it would be beneficial to this field if researchers could collect behavioral data without being overly intrusive and without relying upon the questionable validity of self-report measures.

Because of online courses’ ability to use clicks to collect *trace data*, online courses may provide the perfect context for answering long-standing questions about the behavioral processes behind motivational interventions. When learning takes place in technology-enhanced environments, the interactions between a learner and the environment can be used to "trace" a learner's actions during a task (Bernacki, Schunk, & Greene, 2018). In an online course, clicks on certain web pages can reflect important consequences of learners' motivation, such as help-seeking or challenge-seeking. Additionally, the timing of those clicks can be used to assess whether students are spacing their studying or procrastinating. In this way, the emerging field of learning analytics offers unique insights into behavioral processes that underlie student's learning outcomes (Siemens, 2013), all without requiring students to actively participate in the process of data collection.

Research Questions

Thus, the present study is driven by four research questions that explore the effectiveness of a utility value intervention in an online course:

1. Do online students' expectancies and values for their course differ from those of their face-to-face peers?
2. Is a utility value intervention differentially effective in online and face-to-face courses?
3. What are the behavioral correlates of expectancies and values in an online course?
4. What are the behavioral mediators of an online utility-value intervention, if any?

The first research question will use the control group in the present study to address the lack of literature documenting differences in values between OL and F2F students. This will involve measuring motivational constructs at the beginning of the course as well as changes in values throughout the course. Meanwhile, the intervention will compare the effectiveness of the intervention across the OL and F2F classes. Next, we will use correlational analyses to understand links between Expectancy-Value constructs of motivation and behavior in an online course. Finally, if any significant effects of the intervention are found, and if any significant associations between motivation and click-data are found, models will be tested to identify potential behaviors that may be mediators of the intervention in an online course.

Modality Motivation: Selection Effects and Motivational Differences in Students Who Choose to Take Courses Online

Research Questions

1. Are there baseline motivational differences in students who take courses online?
2. What are the reasons that students take courses online and face-to-face at a large research university in the United States?
3. How are student reasons for choosing OL courses associated with their motivation, behavior, and performance?
4. How are demographic characteristics associated with choosing OL courses and reasons for choosing OL courses?

The first research question immediately addresses the lack of literature on the possibility that OL students may simply be less motivated to succeed than their F2F peers, as suggested by a recent qualitative study (Jaggars, 2014). The second research question then moves to a broader investigation of why students choose an OL or F2F course when both modalities are available. We anticipate that these results will largely reproduce previous findings in the literature. However, reproducing these findings in a large, American research university would confirm that patterns in students' reasons are consistent with those from community college (Jaggars, 2014), professional development (Vanslambrouck et al., 2018), and international settings (Bailey et al., 2015). The third research question extends this body of literature by connecting students' reasons to their motivational, behavioral, and performance outcomes, leaving us with the most nuanced evidence to date of how selection effects may be impacting comparisons between student performance in OL and F2F courses. The fourth research question connects the body of literature on the psychology of student choice to the quasi-experimental body of literature on estimating the effectiveness of OL courses relative to F2F courses.

Methods

Participants

Participants were drawn from a large research university in the southwest United States. Because this university is both a Hispanic-serving institution (HSI) and an Asian-American serving institution (AASI), the racial-ethnic composition of the surveyed courses was diverse.

Setting

The courses under study all have both an OL and F2F version of the same course. In order to limit the potential for teacher effects to influence results, only courses with the same instructor teaching both versions of the course are considered for the study. Additionally, because students' reasons for choosing between OL and F2F has been shown to change over time (Bailey et al., 2015), we will survey courses at both introductory and advanced levels (see Table 1.1). These courses included Engineering, Chemistry, and Anatomy. Enrollment has been rapidly increasing at UCI, making it difficult for administrators to find space for all incoming Engineering students. Therefore, a small online section was added to supplement the limited number of spaces available in the traditional face-to-face introductory Engineering course. Furthermore, the Chemistry department's online courses were only offered to students who were behind the typical introductory Chemistry series. Therefore, this setting reflects the diverse reasons for which universities are turning to online courses; specifically, a lack of enough physical space, and the desire to offer more remedial courses for underperforming students (Means et al., 2014).

Table 1.1

Table 1.1 Overview of Courses Included in Study

Course	Modality	Typical student	Year	Term	Instructor	*N*
Intro Engineering	F2F	First year	2016	Fall	Mr. Yen	315
Intro Engineering	OL	First year	2016	Fall	Mr. Yen	57
Intro Chemistry	F2F	First year	2018	Winter	Ms. Hatha	447
Intro Chemistry	OL	First year	2018	Winter	Ms. Hatha	210
Adv. Anatomy	F2F	3-4 year	2016	Summer	Mr. Mina	47
Adv. Anatomy	OL	3-4 year	2016	Summer	Mr. Mina	37
Adv. Anatomy	F2F	3-4 year	2017	Summer	Mr. Mina	42
Adv. Anatomy	OL	3-4 year	2017	Summer	Mr. Mina	41

Note. All instructor names are pseudonyms.

Procedure

In the first week of each course under study, students were consented and took a survey asking about their motivation for the upcoming course, as well as their reasons for choosing either the OL or F2F version of the course. In the final week of each course, students were again surveyed. In the post-survey, students were asked about how much time they spent on different course-related activities and a variety of non-course-related activities. Depending on the course, students were either given course credit or a $5 gift card for completing each survey. Because this was a part of a larger study with many research interests, each course had slightly different surveys. Although all students were asked about their reasons for choosing the course and various questions regarding motivation, not all students received the exact same battery of motivation items.

Measures

Reasons for choosing modality. Students' reasons will be assessed by asking the question, "Why did you choose to take this course [online/ face-to-face] as opposed to [online/ face-to-face]?" This will be an open-ended response question, to which students are expected to give answers of 1-2 sentences.

Motivation. Motivation will be operationalized as students' expectancies of success within the course and the value they attach to the subject of study, consistent with Eccles and colleague's Expectancy-Value Theory of Motivation (Eccles et al., 1983). Specifically, we examined data on students' self-concept of ability, utility value, interest value, attainment value, and cost value for their respective courses. Often, each of the constructs was measured using scales of two to three items. These items were adapted from Gaspard et al. (2015), but response scales were changed from a true/not true scale to item-specific scales.

Relative motivation. We also measured students' perceptions of their course's importance and interest relative to the other courses that they were taking that term. We first asked students to list their other courses, then had students rank the courses from most to least important, and then from most to least interesting.

Time spent on academic activities. This included hours spent per week on course, time spent meeting with instructor, and time spent meeting with study groups (Flynn, 2014).

Time spent on non-academic activities. This includes caring for dependents, driving to-from class, and working for pay (Flynn, 2014).

Demographic variables. A wide array of variables provided by the university's office of institutional records after the course was completed included gender, race/ethnicity, age, major, low-income status, first-generation status, SAT scores, high school GPA, prior college GPA, academic year in school, and units attempted during the same term.

Grades. All graded assignments for the course were provided by the instructor. This included points assigned for all participations, homework, labs, projects, and exams.

Goal grades. During the survey, we also asked students to report the grade that they expected to get. For the Chemistry course, we were also able to ask students what grades they wanted to get and the worst grade that they would consider acceptable.

Goal grade achievement. The above variables allowed us to create an additional, meaningful measures of course performance, such as grade goal achievement, which we created by subtracting students' final grade from their expected grade.

Analysis Plan

First (RQ 1), quantitative data of students' self-reported motivation for the course was compared between OL and F2F versions of the same course. These comparisons were conducted upon the subsets of expectancies and task value outlined above, including self-concept of ability, utility value, interest value, attainment value, and cost value. For the introductory Chemistry course, we were also able to test for differences on measures of relative motivation and target grades. Although t-tests are normally conducted to compare two groups on normally distributed quantitative scales, many of the distributions of students' value for the respective course subject were non-normal. This is unsurprising because students in these courses are often majoring in the discipline and are therefore likely to see immense value in the course. However, the non-normality of the data required that non-parametric equality of medians tests be used to assess between-group differences. Importantly, this test of equal medians is much more robust to outliers and non-normality than those comparing means.

Second (RQ 2), students' qualitative reasons for choosing the OL or F2F modality were analyzed. Importantly, students were also asked if they were aware that the course had been offered both OL and F2F, and the responses of those who reported they were not aware of this choice were excluded. Two lead authors first agreed upon a coding scheme after reviewing a subset of responses of both OL and F2F students. This was done through initial coding (Saldaña, 2014), and was informed by a combination of previous findings and considerations relating to expectancy-value theory (Vanslambrouck et al., 2018). The coding scheme consisted of general themes, and subcategories for each of those themes. Responses were coded for whether they fell under any general themes, then given an additional code if they fit a subcategory of that theme. Some responses were given multiple codes, as they implied multiple reasons for making the choice. The coding scheme was then used by two to three research assistants to code the entirety of the data. After inter-rater reliability was assessed, these results were then examined for differences between course modality (OL and F2F), course subject (Engineering, Chemistry, Human Anatomy), course level (introductory and advanced), and term (regular academic year and summer terms).

Third (RQ 3), OL students' reasons for selecting the OL version of the course were associated with their academic outcomes, time on academic activities, time on non-academic activities, and motivational measures throughout the term. We collapsed the reasons students gave for choosing the OL course into a smaller number of categories in order to explore ether whether theoretically interesting distinctions were associated with course experiences. OL students who chose their course for each of these respective reasons were compared to all F2F students. Course experience variables were standardized within each course (combining OL and F2F distributions for each course, respectively). This eliminated variance due to course format while retaining variance associated with course modality. This was done to reflect the practical question of whether there were detectable differences between OL students and their F2F peers.

We conducted equality of medians tests between broad categories of reasons for selecting OL courses and the course experience variables described above.

Finally (RQ 4), students' demographic characteristics were associated with the same broad categories of reasons for choosing the course described above. Because each reason for selecting either OL or F2F courses is coded as either a 0 or 1, we used Chi-square tests to determine their associations with gender, race/ethnicity, low-income status, and first-generation status, whereas we will use t-tests to determine their association with age, SAT scores, high-school GPA, prior college GPA, academic year in school, and units attempted during the same term (these variables are all Normally distributed).

Results

RQ1: Are there baseline motivational differences in students who take courses online?

Quantitative comparisons of motivational differences presented in Table 1.2 show there are no consistent significant differences between OL and F2F students in their expectancies or values for their courses. Only in introductory Chemistry was the interest of OL students less than that of F2F students. Similarly, when introductory Chemistry was also examined by conceptualizing motivation hierarchically, we saw that students who chose the OL version of the course believe that the course is less interesting when compared to interest in their concurrent other courses.

Importantly, results did not show that OL students tend to desire or expect lower grades than their F2F peers. Table 1.3 displays these additional analyses, which were conducted on variables that were only in the introductory Chemistry course. Much like the literature on performance in MOOCs, it is important to consider that students' differences in overall performance simply stem from differences in desired and expected performance at the beginning of the course. But we do not see evidence here that OL students have less lofty performance goals than their F2F peers. However, students who chose the OL chemistry course reported that the lowest grade they would be satisfied with receiving was significantly lower than students in the F2F course.

Table 1.2

Table 1.2 Comparison of Motivation Variables by Course Modality

	Intro Engineering			**Adv. Anatomy**			**Intro Chemistry**		
	F2F Mean (Median)	OL Mean (Median)	Test X^2 (*p*-value)	F2F Mean (Median)	OL Mean (Median)	Test X^2 (*p*-value)	F2F Mean (Median)	OL Mean (Median)	Test X^2 (*p*-value)
Expected course grade	11.4 (12)	11.2 (12)	0.00 (p=0.99)	11.4 (12)	10.9 (12)	1.32 (p=0.25)	10.4 (11)	10.2 (10)	0.23 (p=0.63)
Self-concept of Ability	4.00 (4)	3.98 (4)	0.09 (p=0.76)	4.93 (5)	4.82 (5)	0.00 (p=0.99)	5.17 (5.25)	5.08 (5)	1.38 (p=0.24)
Utility Value	6.67 (7)	6.78 (7)	0.11 (p=0.73)	6.25 (6.5)	5.93 (6.25)	3.61 (p=.06)	5.00 (5)	4.78 (5)	0.13 (p=0.72)
Interest Value	8.96 (10)	8.70 (9)	2.06 (p=0.15)	5.15 (5.5)	5.36 (5.5)	1.00 (p=0.31)	4.41 (4.4)	3.92 (4)	**10.15 (p<0.01)**
Attainment Value	6.55 (7)	6.47 (7)	0.59 (p=0.42)	6.16 (6.5)	6.05 (6.5)	0.01 (p=0.91)	4.30 (4.25)	4.12 (4.13)	0.39 (p=0.53)
Opportunity Cost				5.64 (6)	5.08 (5)	3.21 (p=0.07)	4.63 (5)	4.65 (5)	0.00 (p=0.93)
N	312	59		88	77		324	139	

Note. Expected course grade was letter grade recoded numerically, from A+ (13), A (12), A- (11), B+ (10), B (10), through D- (2), and F (1).

Table 1.3

Table 1.3 Comparison of Relative Importance and Target Grades by Course Modality

	Intro Chemistry		
	F2F Mean (Median)	OL Mean (Median)	Test X^2 (p-value)
Relative importance	1.82 (2)	1.70 (1)	3.10 (p=0.08)
Relative interest	2.12 (2)	2.58 (2)	**13.6** **(p<0.01)**
Desired grade	11.49 (12)	11.48 (12)	0.36 (p=.55)
Expected grade	9.46 (9)	9.26 (9)	0.58 (p=0.45)
Worst acceptable grade	7.88 (8)	7.40 (7)	**10.0** **(p<.01)**
N	318	146	

RQ2: What are the reasons that students take courses online and face-to-face at a large research university in the United States?

After initial coding, four overarching themes emerged for why students chose online courses, including preference for flexibility, need for flexibility, university constraints, and learning preferences. As we detail the results, we note that the final coding scheme, including sample quotes, are available in the Appendix B. A visualization of the results can be seen immediately below in Figure 1.1. Of the 219 OL students who offered reasons for their choice, the most common overarching reason was a preference for flexibility (n = 86, 39%). Many of these students simply mentioned their general desire for flexibility (n = 54, 25%). Others included specific reasons for preferring flexibility, such as not wanting to commute to class (n = 26, 12%), wanting to simplify the balance between school and employment (n = 6, 3%), and wanting to simplify the balance between school and family (*n* = 2, 1%). The second most common theme was need for flexibility (*n* = 55, 25%). These students suggested they would not have been able to attend the course without the flexibility of an online option. Some of these students simply mentioned their general inability to attend the F2F version of the class (*n* = 17, 8%). Others included specific reasons for needing the flexibility, including conflicts with other courses offered at the same time (*n* = 23, 11%), having to work during the F2F course (*n* = 8, 4%), and living too far away to make commute to campus (*n* = 8, 4%). The third most common theme was university constraints (*n* = 52, 24%), or that the F2F course was full when they enrolled, so the OL option was the only one that remained. The final, least cited theme was learning preferences (*n* = 42, 19%). These students said that they generally liked the format of OL classes better than that of F2F classes (*n* = 12, 5%), that they liked the freedom to control the pace of the course material (*n* = 14, 6%), that they felt OL course environments improved their ability to self-regulate (*n* = 13, 6%), and that they preferred online peer interactions (*n* = 4, 2%).

Only two of these overarching themes were relevant for the 500 students who offered reasons why they chose F2F courses. By far, the most prominent of these was learning preferences (*n* = 469, 94%). Many students cited their general belief that face-to-face courses were better for their learning (*n* = 197, 39%), but many fell into one or more specific subcategories. Students commonly said that they were concerned about their self-regulation, referring to distractions in OL courses or feeling more engaged in F2F courses (*n* = 114, 23%). Students also said they desired peer interaction (*n* = 78, 16%), professor interaction (*n* = 62, 12%), and the belief that they learn better when they can see/hear the professor giving a lecture from the same room (*n* = 49, 10%). Some students said that they had previous experiences with online courses and simply disliked them (*n* = 26, 5%). Finally, students also cited the theme of

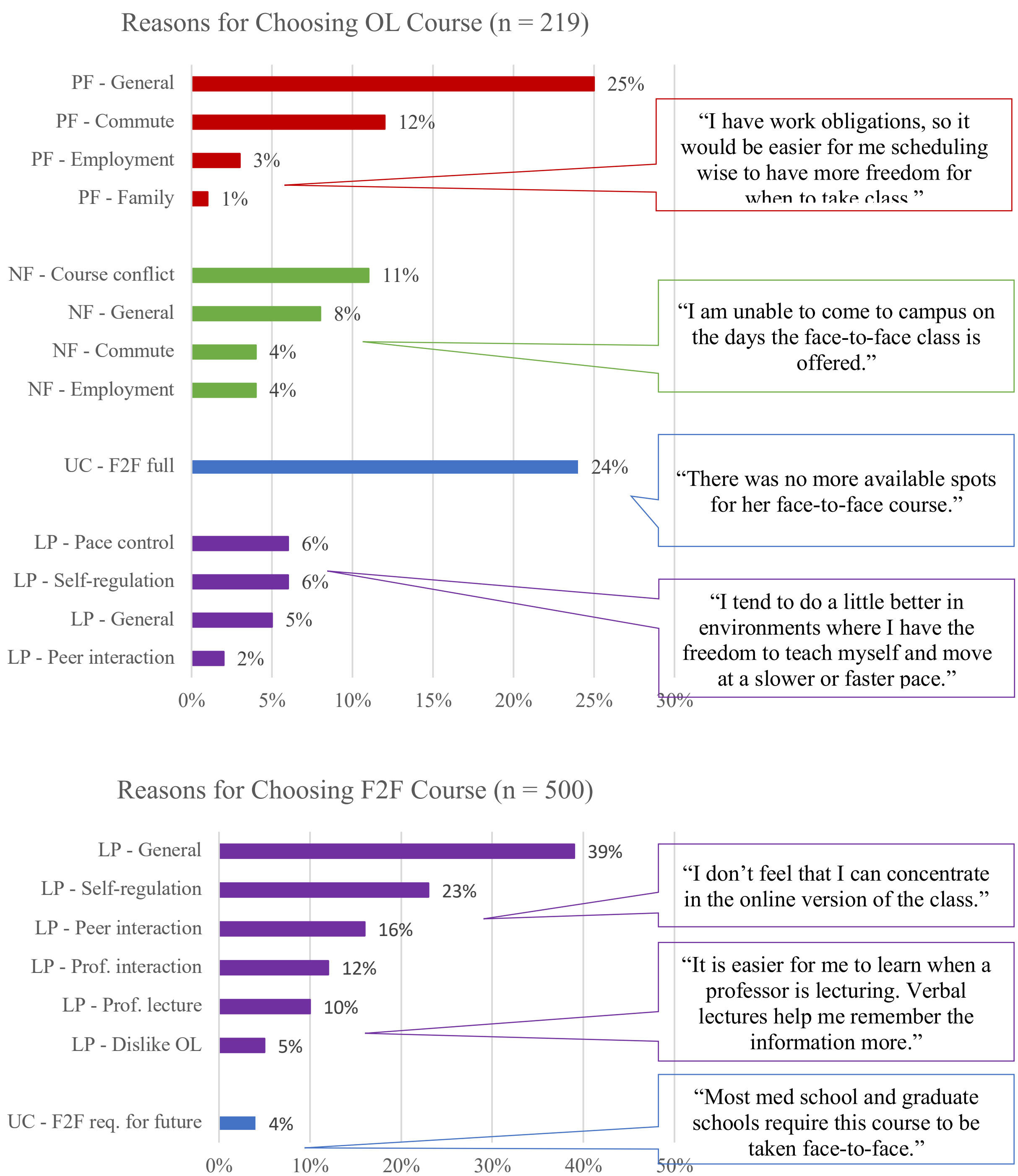

Figure 1.1. PF = prefer flexibility. NF = need flexibility. UC = university constraint. LP = learning preference. For a full explanation of the coding scheme, see Appendix A.

university constraints (n = 23, 3%), saying they believed the OL version of required courses would not be accepted when applying to post-graduate programs.

There was a considerable amount of between-course heterogeneity when comparing online courses (see Appendix A for full breakdown). In the introductory courses, Engineering and Chemistry, only 16% and 36% of the students, respectively, chose the online courses due to preference for flexibility. Meanwhile, preference for flexibility was a reason given by 59% of the online advanced summer students cited a preference for flexibility. Conversely, introductory students were much more likely to cite university constraints. 54% and 21% of introductory Engineering and Chemistry students, respectively, said that they chose the OL course simply because the F2F version of the course was full. Zero students in the advanced summer course mentioned the impact of university constraints. The OL and F2F versions of the advanced summer course were evenly enrolled, and the F2F course did not reach its enrollment capacity.

Among F2F students, learning preferences were slightly different among Engineering students. Whereas Chemistry and Anatomy students most frequently cited self-regulation concerns (29% and 35%, respectively) and a desire for professor interaction (29% and 9%, respectively), Engineering students cited peer interactions as the most common factor (20%). Detailed responses revealed that they wanted this peer interaction because the course involved groupwork assignments for building vehicles. This provided a clear, discipline-related reason for why many Engineering students chose the F2F course. Additionally, the advanced Anatomy students were far more likely to say they avoided the OL course because it would not count for graduate school requirements (15%) compared to introductory Chemistry (1%) and Engineering (3%) students. This may suggest that advanced students are more likely to consider the implications of their modality choice for graduate admissions.

RQ3: How are student reasons for choosing OL courses associated with their motivation, behavior, and performance?

To begin assessing this question, we collapsed the large array of codes given for choosing an OL course. The main themes that emerged from the codes were preferring flexibility, needing flexibility, learning preferences, and university constraints. However, we collapsed the codes to represent theoretically plausible ways in which selecting an OL course could be associated with an experience different from that of F2F students. We started by looking only at students who said they were in the OL course because the F2F course was full. Because these students implied that they would otherwise be in the F2F course if not for university constraints, we expected these students would be the least likely to differ from their F2F peers. Next, we broke down the large number of students who talked about flexibility, classifying them by whether they specified what other responsibilities led to their desire for flexibility (flexibility – specific), or whether they gave a general, unspecific reason for desiring flexibility (flexibility – general). We reasoned that students with general, unspecific reasons for desiring flexibility may not have competing responsibilities, and simply may not want to attend a F2F class. From a motivational perspective, we imagined that these students may struggle due to a lack of utility, interest, or attainment value for the course. Conversely, we believed that students who cited specific reasons for desiring flexibility, whether needed or preferred, might face challenges engaging in the course due to competing responsibilities. We imagined that these students would perceive higher cost to engaging in the course and that they would report doing more non-academic activities. Finally, we examined the experiences of students who cited learning preferences for OL courses, hypothesizing that these students were the most well-suited to have more motivation and report more academic behaviors than their F2F peers. The composition of each collapsed coding category is presented in Table 1.4. Each of these groups was compared one at a time to the F2F students (n = 493).

Table 1.4

Table 1.4 Collapsed categories of reasons for choosing OL course

	F2F full	Flexibility (general)	Flexibility (specific)	Learning Preferences
	"F2F full"	"prefer flexibility - general"	Any other "prefer flexibility"	Any "learning preference"
		"need flexibility - general"	Any other "need flexibility)	
N	48	67	66	38

In contrast to Tables 2 and 3, which compared all OL students to all F2F students, Table 1.5 shows the results when comparing F2F students to specific subsets of OL students grouped by their reasons for selecting OL courses. As expected, students who were in OL courses simply because the F2F course was full showed no pre-survey differences in motivation, did not exhibit any significant behavioral differences, and did not significantly differ in their performance when compared to F2F students. The only significant difference that did emerge was significantly lower interest in the course at post-survey. Overall, the lack of pre-survey motivational differences mirrored the aggregate results present in Table 1.2.

As opposed to the results in Table 1.2, Table 1.5 shows that OL students did exhibit less motivation than their F2F peers when focusing only on the OL students who picked the course out of a general desire for flexibility. These OL students did not show differential engagement in academic or nonacademic activity and did not perform significantly lower than their F2F peers.

OL students who cited specific reasons for desiring its flexibility (e.g., commuting, employment) did perform significantly worse than their F2F peers. However, unlike those who chose the OL course for the sake of general flexibility, those citing specific reasons for wanting flexibility actually did report more time on nonacademic behaviors like working for pay and caring for dependents. Additionally, they reported significantly less time on academic behaviors, like time spent in study groups. They also reported significantly less pre-course interest, and significantly lower expectancies for success at the end of the course. Interestingly, although they simultaneously reported less time on academic activities and more time on nonacademic activities, these students did not report less cost at either the beginning or end of the course. This may be due to the fact that conceptualizing measures of cost may be contextualized differently within the F2F and OL versions of the course, which we discuss below.

OL students who cited learning preferences reported patterns of motivation, behavior, and performance contrary to our hypotheses. These students said they believed the OL course format better suited the way they preferred to learn. Understandably, then, these students had significantly higher expectancies for success than their F2F peers. However, these students also reported significantly less utility, interest, and attainment value for the course, significantly less time spent in study groups, and significantly lower course performance.

Table 1.5

Table 1.5 Medians for Course Outcomes by Course Modality and Reasons for Selecting OL Course

	F2F	OL			
		F2F full	General flexibility	Specific flexibility	Learning preferences
Academic outcomes					
Final grade	0.22	-0.06	0.08	**-0.16**	**-0.05**
Goal grade achievement	0.14	0.07	-0.11	-0.15	-0.43
Desired grade	0.37	0.37	0.37	0.37	0.37
Expected grade	0.40	-0.17	0.53	0.47	0.40
Worst acceptable grade	0.15	-0.36	-0.39	0.15	-0.39
Academic behaviors					
Time on course	-0.23	-0.48	-0.55	-0.20	-0.48
Speaking with faculty	-0.05	-0.05	-0.17	-0.17	-0.17
Study groups	-0.12	0.32	-0.68	**-0.72**	**-0.72**
Non-academic behaviors					
Working for pay	-0.40	-0.40	-0.58	**-0.40**	-0.40
Caring for dependents	-0.41	-0.41	-0.41	**-0.01**	-0.51
Socializing	-0.23	-0.23	-0.23	-0.04	-0.23
Commuting	-0.11	-0.11	-0.20	-0.20	-0.20
Expectancies and values					
Expectancies (pre)	0.00	0.00	0.11	-0.02	**0.22**
Utility (pre)	0.49	0.49	**0.17**	0.44	**-0.03**
Interest (pre)	0.10	0.02	0.05	**-0.27**	**-0.26**
Attainment (pre)	0.62	0.26	**-0.16**	0.38	**0.36**
Cost (pre)	0.25	0.25	**-0.28**	-0.28	0.25
Expectancies (post)	0.15	-0.02	0.08	**-0.21**	-0.18
Utility (post)	0.15	-0.07	-0.43	0.15	0.11
Interest (post)	-0.03	**-0.43**	-0.32	0.08	-0.16
Attainment (post)	0.29	-0.14	**-0.14**	0.29	0.17
Cost (post)	0.22	NA	0.22	0.22	0.22

Note. Bolded cells represent statistically different distributions from those of the F2F course, as concluded from equality of medians tests ($p < .05$). All variables were first standardized within course to remove between-course variation and create a standard scale so that all courses could be analyzed together. NA is entered for measures of cost because the Anatomy course was the only one in which cost items were asked at post-survey, and in that course, no students selected into the OL course because the F2F version was full.

RQ 4: How are demographic characteristics associated with choosing OL courses and reasons for choosing OL courses?

Demographic characteristics are indeed associated with selection into the OL courses in our sample. Table 1.6 shows that women, older students, and part-time students were more likely to enroll in face-to-face courses. Associations between these demographic variables and reasons for selecting OL courses showed that women in OL courses were more likely than men to make that selection due to employment conflicts. Men in OL courses, conversely, were more likely than women to cite that the F2F course was full, or that they had course conflicts. Part-time students in OL courses were more likely to cite long commutes as the reason for their choice relative to full-time students, who were more likely to cite that the F2F course was full. Finally, older students exhibited a similar trend, citing long commutes as the reason for their choice relative to younger students, who were more likely to cite that the F2F course was full. Overall, this trend suggests that certain demographics, such as gender, age, and part-time enrollment status, are associated with specific competing responsibilities as well as the decision to take the course online. Selecting OL courses and reasons for selecting OL courses were not associated with ethnicity, low-income status, first-generation status, home language, transfer student status, SAT score, or high school GPA.

Table 1.6

Table 1.6 Association of Demographic Variables with Course Modality Choice and Modality Selection Reason

Demographic variable	obs	More likely to select OL?	obs	OL – Associated with reasons for selection?	Interpretation
Gender	896	Women	188	Women = employment Men = course conflict & F2F full	Women more likely to list specific reasons for desiring flexibility
Ethnicity	800		167		
Low income	886		184		
Part time status	899	Part-time students	189	Part time = prefer flexibility, citing commute Full time = F2F full	Part-time students more likely to list specific reasons for desiring flexibility
First generation	866		177		
Home language	886		184		
Transfer student	878		184		
Age	898	Older students	189	Older = prefer flexibility, citing commute Younger = F2F full	Older students more likely to list specific reasons for desiring flexibility
SAT score	859		180		
High school GPA	853		176		

Note. Each conclusion for course modality choice is supported by a X^2 test for which $p<.05$, associating the demographic variable with the decision to select an OL or F2F course. Each conclusion for specific reason for selecting the OL or F2F course when limiting the sample to OL or F2F students, respectively.

Robustness Check: Are women, part-time students, and older students doing worse in OL courses?

Results from research question three suggest that students who choose OL courses desiring flexibility for specific purposes perform worse than F2F students, and results from research question four suggest that women, part-time students, and older students are significantly more likely to select into OL courses for those types of reasons (e.g., employment, commuting). Therefore, we should expect that women, part-time students, and older students in OL courses are performing worse than their counterparts in F2F courses. We compared OL and F2F students' final grades and goal grade achievement after breaking down the sample by gender, part-time status, and age.

Table 1.7 reflects the accuracy of these hypotheses. Whereas females did worse in OL courses than F2F courses, males did not. Whereas part-time students did worse in OL courses than F2F courses, full-time students did not. Whereas older students (over age 18) did worse in OL courses than F2F courses, younger students did not. Except for women, these patterns also held true when comparing OL and F2F students' grade goal achievement.

Table 1.7

Table 1.7 Associations of Demographic Variables and Course Performance by Course Modality

		Final grade			*Goal grade achievement*		
	obs	F2F Mean (Median)	OL Mean (Median)	Test X^2 (*p*-value)	F2F Mean (Median)	OL Mean (Median)	Test X^2 (*p*-value)
Female	285	0.19 (.27)	-0.12 (-.09)	**6.75 (*p*=.009)**	0.32 (.37)	0.01 (.05)	2.99 (*p*=.084)
Male	340	.09 (.16)	-0.09 (.07)	0.35 (*p*=.552)	0.07 (.02)	-0.13 (-.03)	0.11 (*p*=.745)
Part-time	38	0.49 (.68)	-0.51 (-.31)	**5.22 (*p*=.022)**	0.94 (.99)	-0.29 (-.53)	**8.62 (*p*=.003)**
Full-time	590	0.11 (.17)	-0.06 (.04)	2.96 (*p*=.085)	0.14 (.07)	-0.03 (.05)	0.14 (*p*=.710)
Age > 18	201	0.31 (.44)	-0.26 (-.04)	**8.15 (*p*=.004)**	0.31 (.36)	0.11 (0.02)	**6.88 (*p*=.009)**
Age <= 18	452	0.08 (.15)	-0.02 (.03)	2.38 (*p*=.123)	-0.20 (-.16)	0.02 (.07)	0.31 (*p*=.580)

Discussion

Past research has suggested that OL courses are associated with lower performance when compared to F2F course formats (Bettinger et al., 2017). With the exception of a small number of randomized control trials (e.g., Alpert et al., 2016), these conclusions have relied heavily on the presumption that variance due to selection effects is being partialed out by controlling for demographic variables. In this study, we find evidence that specific demographic variables are indeed associated with selection processes and differential performance outcomes in online courses. More importantly, we used qualitative data and an Expectancy-Value motivation framework to depict how these selection effects may be occurring. We began by capturing students' reasons for selection into OL courses, then used the heterogeneity that we found among those reasons to guide quantitative analyses. Doing so revealed potential processes by which OL students may struggle to perform as well as their F2F peers. Finally, we connect these processes back to specific demographic characteristics, such as gender, age, and part-time status, and confirmed that only students with demographic characteristics associated with those processes had significantly lower grades in OL courses. Below, we discuss the implications of knowing OL students' selection reasons for predicting students most likely to struggle and potential ways they can be helped.

We found that students select into OL courses for a variety of different reasons, and the value of understanding those reasons became apparent in our quantitative analyses. One of the most important realizations was that many OL students in our sample did not willingly select into the OL version of the course. These students serve as a representation of the growing necessity of OL courses to exist as a cost-effective means of accommodating growing numbers of students in higher education (Bowen, 2012). Therefore, in our examination selection effects, it was important to begin by considering that many students did not willingly select. It is certainly likely that there are characteristics associated with not enrolling early enough to gain a spot in the F2F version of the course that we might also hypothesize are associated with worse course performance, such as lower academic standing or less motivation. However, even if these were true in our sample, we did not see these differences bear out in the form of motivational, behavioral, or performance differences compared to F2F peers. These students did not seem to struggle, and separating them from the others who did willingly select into the OL course helped paint a clearer picture of the selection effects that were at play.

In our aggregated analyses, Table 1.2 seemed to suggest that students do not take courses OL due to lower levels of motivation, contrary to recent qualitative findings (Jaggars, 2014). However, breaking down the students by their selection reasons told a different story. We did find that students who simply wanted the flexibility of an OL version of the course without pressure from outside responsibilities (i.e., general flexibility) found the course material less important to accomplishing their goals (utility value) and less important to their identity (attainment value). However, these students still reported spending an equivalent amount of time on the course, including conversations with faculty and time spent in study groups when compared to their F2F peers. Ultimately, these students did not perform significantly worse than their F2F peers. This suggests that many students may indeed choose OL courses due to lesser motivation for the course, but that these students are among many other OL course takers whose choice does not seem to be associated with a lack of positive value so much as higher amount of cost value.

The role of cost emerged much more clearly when examining students who cited specific reasons for selection into OL courses. The Expectancy-Value measures of motivation that we used were context-specific, meaning comparing them across contexts can produce misleading results. The item we were most concerned about when comparing across OL and F2F contexts was the cost item, asking students how many opportunities they would have to give up in order to succeed in the course. OL students' responses likely differed from those of their F2F peers simply because having chosen the OL version of the course implied less commuting and more flexibility to plan coursework around other valued activities. Although our aggregated comparisons suggest OL and F2F students don't differ in terms of their cost, the selection reasons that we qualitatively capture suggest a different story: that selection into the OL course is associated with competing responsibilities (e.g., employment conflict, long commute) that may create barriers to engaging in the course as much as their F2F peers. This represents the construct of opportunity cost construct by showing that in order to fully engage in the course, OL students would often have to prioritize the course above the competing responsibilities they face. As expected, this qualitative representation of cost was simultaneously associated with less interaction with peers (i.e., study groups) and greater time spent working for pay and caring for dependents. As Vanslambrouck and colleagues (2018) concluded after taking an Expectancy-Value approach to understand OL selection patterns, students engage in an weighing of positive and negative value when considering whether to take a course online. Our evidence again suggests that this is true, but additionally sheds light on the mechanisms by which this choice may be impacting students' performance.

Although we intentionally chose to study only courses that had identical OL and F2F versions of the same course, leading scholars have argued that the field of online education needs to move beyond studies that ask whether online learning "works." In order for a truly unbiased test, all instructional elements must be held constant (Clark, 1994). When this is the case, outcomes will never theoretically differ, however, because instructional content drives learning outcomes, not its medium. Therefore, there has been a push to instead investigate the ability of technology to provide learning affordances that the traditional classroom cannot (Means et al., 2014, p. 24). In other words, attempting to find an ideal comparison that holds everything imaginable about OL and F2F courses constant holds few practical implications because we should not merely aspire to make our OL courses duplicates of our F2F courses.

Rather, OL and F2F course modalities offer different benefits (Means et al., 2014), and it should be incumbent upon future researchers and practitioners to help students identify which course modality is best suited for their learning preferences. Unfortunately, this well-intentioned line of research seems far off, given the reality that many students base their decision to take OL courses due to F2F enrollment caps and competing responsibilities with which they must balance their coursework. In its current state, online learning is simply a necessity for many students due to a lack of space in F2F classrooms, and for many more who have competing responsibilities outside of school.

Considering this, the most important affordances of online learning to take advantage of right now are those that can help tailor online learning experiences specifically to students who face the challenges of juggling online education with competing responsibilities. Additionally, instructors should be especially wary of the possibility that by virtue of enrolling in an online course, their OL students may be signaling greater amounts of competing responsibilities than students in their F2F courses.

Importantly, though, even the students who chose OL courses due to the belief that it would provide a superior learning experience ended up performing worse than their F2F peers, contrary to our hypothesis that they would perform better. As we have learned from the lack of validity surrounding “learning styles” (Pashler, McDaniel, Rohrer, & Bjork, 2008), students’ preferences for content delivery does not seem to be causally related to their performance in a course. What these students may actually prefer is not interacting with their classmates as much, as evidenced by the lower amount of time they spent in study groups. Therefore, even once it becomes a priority to help students select the appropriate course format, it will be important to consider that students may not know which modality is best suited for them.

A model of selection effects in OL courses

Both the hypothesis testing and exploratory work done in this study can be taken together to suggest a model explaining how demographic variables may be successfully controlling for selection effects. We assert that demographic variables predict students’ competing responsibilities and motivation. This, in turn, should inform students’ decision about whether to select into an OL course when F2F versions of the course are available. Because the choice to enter an OL course is often associated with greater amounts of competing responsibilities, and lesser value for the course (either absolute or relative), OL students are more likely to underperform compared to their F2F peers. This implies that demographic variables like age and gender that are associated with greater amounts of competing responsibilities or lesser motivation are important to control for when evaluating how OL delivery formats compare to F2F delivery formats.

The findings of the present study suggest a model by which demographic characteristics are associated with competing responsibilities, motivation, and one's reason for selecting between an OL and F2F course. This, in turn, is hypothesized to lead to differences in behavior and changes in motivation throughout the course, ultimately impacting students' performance. We offer this model both to organize our findings as well as suggest avenues for future empirical work. In this study, we didn't test such a model due to the conflation of course modality with our cost measure. In addition, directionality must be carefully considered between students' motivation and their reason for choosing the course. Depending on the time point at which measures are collected, one could argue either that motivation predicts one's reason for choosing a course, or vice-versa. Additionally, although it seems likely that the role of one's prior achievement would be a mediating mechanism by which demographic characteristics are associated with course modality selection, we did not explore these links in the present study. Finally, when selecting an appropriate venue for further hypothesis testing, it is important to select the appropriate context. We discovered that students who do not willingly select into OL courses (i.e., "F2F full") may be more likely to be found in introductory courses in which the OL course was developed as an accommodation for student overflow. In these situations, performance differences between OL and F2F courses were very slight. Conversely, in advanced summer courses where OL course selection was more willfully enacted, motivation, behavior, and performance differences were readily apparent. Therefore, researchers attempting to limit the impact of selection effects when comparing OL and F2F courses are advised to choose impacted introductory courses in which students are unlikely to be making willful selection into the OL version of the course.

Limitations

One important assumption underlies many of the comparisons that we made in this study between OL and F2F students: that the delivery of the OL course format was actually of equal quality compared to the F2F delivery formats. Of course, one of the reasons that students in OL courses may be doing worse than their F2F peers is simply because the OL delivery of the course is simply worse for students' learning than the F2F version of the course (e.g., Bettinger et al., 2017). Whether this might be due to less engaging or less comprehensible presentation of material, students in the OL version of the course would still be expected to exhibit lower performance, regardless of whether the mechanisms proposed in the present study are at play. Each of the courses under study were conducted in partnership with teaching faculty well known on campus for the quality of their teaching. Yet, transitioning one's F2F course to an OL course may actually be even more difficult for instructors who benefit from the opportunities that in-person lectures afford for delivering course material through charisma and an ability to articulate complex topics.

Additionally, it is important to consider the context of the present study before generalizing to other contexts. We were able to replicate the notion that students select into OL courses due to a desire for flexibility, which has also been found in community college (Jaggars, 2014), professional development (Vanslambrouck et al., 2018), and international settings (Bailey et al., 2015). However, the associations of these selection reasons with motivation, behavior, and performance must be tested and replicated beyond the three courses. The heterogeneity observed even among the few courses in this study exemplifies the importance of considering the context of online courses when understanding reasons for selection and the subsequent experiences that may follow.

Finally, we should note that of the 721 students of students who completed the pre-survey measures and explained why they selected into their course, 31% did not complete the post-survey and 6.5% of dropped out of the course. OL students were significantly more likely to be missing post-survey data or have dropped out of the course. Because our study focused mainly on understanding how student's outcomes are associated with their reasons for selecting the course, we analyzed whether missingness was associated with these reasons. Students who said they took the OL course due to a general desire for flexibility were overrepresented among those missing post-survey data and among those who dropped out of the course. Because these students showed less motivation during the pre-survey compared to their F2F peers, disproportionately missing their post-survey data suggests that we may be underestimating the behavioral and performance differences between students who select into OL courses due to general flexibility and their F2F peers.

Conclusion

Improving the quality of online course-taking should be an increasingly important priority among higher education administrators. Assessing the extent to which we are succeeding in doing so, however, must account for the differences of those who choose to take our online courses. Although accounting for demographic variables has been instrumental in accounting for selection effects, our field stands to benefit greatly from understanding the processes by which people from different backgrounds select into and approach online courses. In the present study, we describe a variety of ways in which OL course selection occurs, and also identify the processes by which selection students may end up leading to poorer course performance. In doing so, we not only uncover key assumptions about how demographic characteristics may be helping researchers control for selection effects, but also highlight the ways in which online learning may be able to improve its effectiveness through a better understanding of challenges specific to its students.

Belonging Across Contexts: Implications for Theory and Measurement of a Popular Motivational Construct

Research Questions

This study will address the methodological issue of measuring sense of belonging in online courses and offer insight into the elements of online courses that may hinder the development of belonging. The study will be guided by the following research questions:

1. Do students conceptualize sense of belonging in different ways across contexts? (university, face-to-face classroom, online classroom)
2. Does a popular instrument measure sense of belonging when adapted to an online classroom context?
3. What are barriers to belonging in online courses?

These questions will address the theoretical gap regarding the measurement of sense of belonging across classroom contexts and test a promising hypothesis for the ways in which online courses impact students' motivation.

Methods

Participants

Participants were drawn from an online, introductory Chemistry course at a large, ethnically diverse research university in the southwest United States. Because this is an introductory course, almost all students (85%) were in their first year of college, with a mean age of 19.0 years-old. The students in this course were 58% female, 39% Asian, 41% Hispanic, 15% White, and 5% Black. 71% of students were from households that primarily spoke a non-English language or a mix of English and non-English. 56% of students represented the first-generation in their family to attend college, and 37% were from low-income backgrounds (30% both first-generation and low-income). 59% of the online students said this was the first online course they had ever taken.

Setting

The introductory Chemistry course will be taught in Winter 2018. This course will be offered both OL and F2F. The online course will be taught asynchronously by giving students access to recorded lectures often given by someone other than the course's instructor. In-person interactions with the instructor will only be during office hours or exams. Weekly discussion sections, which will be led by a teaching assistant, will be available either online or in-person.

Measures for cognitive interviewing and surveys

Sense of belonging. This will be measured using the Goodenow (1993) *Psychological Sense of School Membership* scale, which was developed to assess the extent to which students feel accepted, respected, supported, and included in their school. Several studies that measure sense of belonging at the classroom level have adapted items from this scale (Freeman et al., 2007; Zumbrunn et al., 2014). In the present study, its 18 items will be adapted to investigate sense of belonging in three different contexts: university, a face-to-face classroom, and an online classroom. As has been done in previous studies, this will be accomplished simply by changing references to one's "school" to their "class" (Freeman et al., 2007; Zumbrunn et al., 2014).

Procedure

Participants will be asked to complete baseline surveys in exchange for $5 as part of a larger study. These surveys will focus on a broad range of motivational constructs, including class-context sense of belonging. To elicit sense of belonging questions in alternative contexts, students will be asked to complete mid-term surveys in exchange for a small amount of extra credit. Splitting up these measures is done primarily to protect the validity of the data by keeping the pre-surveys short enough so as to avoid fatigue from participants. These mid-term surveys will ask students to indicate their sense of belonging in their university context. Then, an additional midterm survey will ask online students to reflect on their sense of belonging in a current face-to-face science or mathematics course that they are taking. Finally, post-surveys will be administered in the final week of the term and will include class-context sense of belonging items that match with those from the baseline pre-surveys. This design will allow me to collect data from online students on their sense of belonging in three different contexts, as well as measure the class-context sense of belonging of all students at the beginning and end of the course.

After completing the course, students in the online class will be given the opportunity to volunteer to participate in a 30-minute interview (either online or in-person) in exchange for a $15 gift card. Students will be asked to describe a time that they experienced a sense of belonging in the different contexts (university, face-to-face classroom, online classroom). In addition, the interviews will feature think-aloud cognitive interviews (Dillman, Smyth, & Melani, 2011) that will ask participants to answer and reflect upon items from the PSSM.

Analysis Plan

Interviews (RQ 1). Audio data from the interviews will be transcribed and coded. Initial descriptive coding (Saldaña, 2014) will include theoretically grounded codes consistent with popular components of sense of belonging, including acceptance and respect (Carol Goodenow, 1993), and "fit" and valued involvement (Hoffman et al., 2003). This deductive approach, based on prior definitions of belonging emphasizing social interactions, will be balanced with an inductive approach that will allow us to detect other processes related to belonging (e.g., academic belonging). Because participants' descriptions of belonging are likely to be intimately associated with the interpersonal interactions that precede them (Hoffman et al., 2003), pattern coding will then conducted to identify links between components of belonging and the interpersonal interactions associated with them (Saldaña, 2014). These themes will be expressed in a case dynamics matrix for each context of belonging: university, classroom, and online. They will then be compared for discrepancies across contexts (Miles & Huberman, 1994, 148-149).

Cognitive interview data (RQ 2) will be coded using an open coding process framed around cognitive theories of how survey questions are answered (Tourangeau, Rips, & Rasinski, 2000). This framework describes that questions are answered through the process of 1) comprehension of the item, 2) retrieving relevant information, 3) using that information to make required judgments, and 4) selecting an answer. I first report themes present in student's general comprehension of the item and their retrieval of information relevant to the construct of belonging. In addition, I report themes that arose regarding the impact of online course context on the way students answer the questions. First, I report how online course contexts are affecting students' interpretation of the question. This gives an idea of whether the instrument may be measuring a different construct when adapted to the online course context. Second, I report on whether elements unique to online course contexts are affecting students' judgment of their answer, which represents how online courses may be impacting students' sense of belonging.

Ways of improving belonging in online courses (RQ 3) will be assessed through inductive coding of the interviews described above. As part of the semi-structured interviews, students who spoke about belonging in their OL courses were asked to elaborate on what could be done to improve their sense of belonging in their online course. These data will be coded to identify themes in students' recommendations for how sense of belonging could be improved in online courses.

Results and Discussion

RQ 1: Do students conceptualize sense of belonging in different ways across contexts?

Many of the *a priori* codes regarding acceptance, respect, "fit," and valued involvement consistently appeared across all contexts, suggesting that many of the social processes that characterize belonging can and do appear in different contexts. As expected, these emerged through a variety of processes involving interpersonal interactions. As can be seen in the Case Dynamics Matrices (Table X), common experiences, interest-driven discussions, and content-driven discussions with either peers or the instructor appeared to support students' feelings of acceptance, respect, "fit," and valued involvement in various ways. Participant 12 highlighted how a common experience with peers led to a sense of valued involvement, "So I guess having to see each other and having to interact with each other and work together to that extent to get the job done made me feel like I was part of their group." After describing interest-based discussions with classmates, Participant 13 emphasized how that experience could lead to feelings of respect and care from the group, saying "It's like they care about you being there. It's not like you're this random person and a benchwarmer. That's where I feel like I belong because it's like they want me to be there."

However, results also suggest that students do indeed conceptualize belonging differently across contexts because belonging does not solely comprise interpersonal interactions in some contexts. An important emergent code was students' focus on the role of ability when describing their belonging. The role of ability and achievement came up only when describing belonging in face-to-face and classroom contexts, as opposed to describing belonging in more general contexts that they offered (e.g., campus clubs, dorm floors, church groups). Several students talked about how feeling a sense of belonging in a classroom was about knowing that their ability was at an appropriate level to signal that they belonged to the class. Participant 21 said, “Like I would say my belonging, my sense of belonging came more from knowing that I was supposed to be taking the class in general. It wasn't from like people interactions, like how I was talking about earlier.” They chose to focus on belonging by describing the “fit” of their academic ability in the classroom rather than social phenomena such as acceptance or respect. Interestingly, students reported that academic belonging could be established through both objective and comparative standards. Whereas some students justified their sense of belonging by referring to the fact that they had satisfied the course’s prerequisites, others spoke about belonging by comparing their ability in their course to their ability in other courses. Participant 16 explained, “Knowing more about the subject ... you actually know what you're doing, so that will make you feel like you belong into that class. Rather than like you trying to learn like a whole new kind of thing.” Others mentioned that their sense of belonging was related to how their ability compared to the ability of classmates, as Participant 8 mentioned, “Anytime we would do an assignment, and there was a hard question that no one understood, the teacher would call on me and ask if I knew it. If the teacher had that expectation from me, it made me feel like I'm doing well and I belong here.” Belonging also wavered when realizing that they weren’t keeping up with coursework. Interestingly, one of the experiences most closely tied to belonging was attending office hours and feeling reassured by the fact that other students were also struggling. This suggests not only that student’s sense of belonging is tied to their ability in the course, but also that assessing whether their ability is strong enough to signal belonging is a comparative process that may benefit from comparing oneself with peers who are also struggling. Because these comparison processes seemed to involve comparisons against ability in other courses and against ability of other students, we see strong similarities between the construction of academic belonging and the I/E Model of academic self-concept construction (Marsh, 1986).

Although students spoke primarily of social processes typically associated with belonging in classroom contexts, their focus on academic belonging is consistent with the findings of Green and colleagues (Green et al., 2016), who qualitatively captured students' sense of belonging in a STEM-focused high school context. Although existing scales like the PSSM do have items measuring peer and teacher recognition of the students' ability (e.g., "Teachers here know I can do good work"), our findings suggests that peer recognition may not be necessary for belonging. Instead, personal assessments of whether one's ability is sufficient for a given context may affect perceptions of belonging regardless of peer recognition. Overall, a major theme that our findings reiterate is the likelihood that the criteria for belonging change as the context shifts. In classroom settings, this criterion seems to become much more heavily related to academic ability and performance.

Building upon this idea, it is important to recognize that the growing body of literature on social belonging interventions also implies that we should expect belonging to be constructed differently across contexts. As interventions have attempted to replicate the results of seminal works such as Walton and Cohen (2011), a common issue has been the overlooked importance of thoroughly understanding what criteria compose belonging in a specific group (e.g., Broda et al., 2018; Walton, Logel, Peach, Spencer, & Zanna, 2015). Discovering the criteria for group membership that students struggle with has become a critical component of adapting belonging interventions to the target population. "Tailoring" belonging interventions in this way underscores the different social and academic processes at play in different contexts as students calibrate their perceptions of belonging.

If the criteria for belonging can shift across contexts, an important question that arises is who determines the criteria for membership in a given group? By comparing general and classroom contexts, we found that authority figures, such as teachers, may play a larger role in classroom contexts. Students spoke much more about the role of teachers in reassuring them of both social and academic belonging when they spoke of belonging in their classrooms. Participant 1 mentioned the importance of interest-driven discussions with the teacher for conveying respect and care, “When our labs would finish early…[the instructor] would talk to us. She wouldn't just go on her phone, she would interact with her students.” Similarly, a *lack* of visibility and content-driven discussions with the instructor could have the opposite effect, as Participant 11 explained, “The teacher gave the impression that she was very busy and doesn't have time for questions because she would say we're college students and could figure it out.” In contrast, talking about belonging in more general contexts focused much more on acceptance and valued involvement with respect to peer groups. When we discovered this theme and prompted students to reflect on the role of authority figures in general contexts, a few did bring them up (e.g., church group leaders, club captains, senior students). However, most of these instances described the role of the authority figure as someone who simply facilitated interactions among students within that group. This suggests that as contexts change, so too may the authority figure’s role in signaling the criteria necessary for membership and helping students judge whether or not they meet these criteria.

Subsequently, we conclude that the experience of belonging does indeed change across contexts. Specifically, our data highlight that typical conceptualizations and measures of belonging emphasize the social element of belonging, but not the ability-based or academic element of belonging that students frequently reference at the classroom level. Measures that only measure the social element may therefore be missing a critical element of belonging, depending on the context. Furthermore, the extent to which interactions with peers and teachers are important for one's overall sense of belonging may be different as the context changes. As factor analyses of the popular PSSM scale and SOBS show, scales of school belonging often measure interactions with both peers and teachers (Hoffman et al., 2003; Ye & Wallace, 2013; You et al., 2011). Yet, as we demonstrate, the relative importance of these interactions to one's overall sense of belonging depends on the context.

RQ2: Does a popular instrument measure sense of belonging when adapted to an online classroom context?

Results from cognitive interviewing suggest that when scales such as the PSSM are adapted to gauge belonging in contexts other than the whole schools, it may provide misleading and incomplete results. One big issue with many of the items is that students' answers are conflated with reasoning unrelated to social belonging. Whether students wish they were in a different class (item 16) is influenced by preferences for the timing of the class, and whether students sometimes feel as if they don't belong in a classroom (item 6) is likely to be influenced by academic and/or social considerations. Importantly, this item is the only one out of the 18-item scale that explicitly uses the word "belong." Therefore, the salience of academic achievement when answering this question echoes recent findings about the role of academic achievement in one's overall sense of belonging (Green et al., 2016; Slaten et al., 2017). This suggests that earlier scales that do not explicitly attempt to gauge academic belonging may be incomplete.

Another issue is that some items attempt to gauge belonging through experiences that are not as relevant to college course contexts as they might be at the school-level. Pride for belonging in one's class (item 17) is not an emotion students report experiencing at the classroom level. And in online classes, specifically, students often recognize that there are few opportunities for classmates to notice when one is good at something (items 2 and 15), few opportunities for them to be included in activities (item 10), and few opportunities for the instructor to show interest in them (item 5). For such items, students occasionally said that they would skip this question if they could due to a lack of relevant information on which to make a judgment. Students admitted that variations in their perceptions may be influenced more by their personality traits rather than objective variations in classroom experiences.

What may be the most dangerous issue with some of these items is that the nature of online courses inhibits students' recognition that their responses are based on inaccurate information. Students were quick to report that their judgment of whether their instructor is interested in them (item 9), whether they are treated with as much respect as other classmates (item 11), and whether they can be themselves in the class (item 13) is based on a comparison between how they themselves are treated relative to how their classmates are treated. However, upon probing, students admitted that they don't really get to see how their classmates are treated in online courses because most interactions occur through private email conversations. When students offered high endorsements of these items, they cited that it was not so much that they could recall experiencing respect or acceptance, but rather because they were unaware of experiences suggesting they were not respected or accepted. As the wording of these items implies, whether or not students believe that they belong to a group can be based on a subjective judgment of their experience in that group relative to that of others. However, students in online courses report that they have little access to information about others' experiences in the course to which they can compare their own.

As students made their judgments, they reported that this lack of information about interactions in online courses had a double-edged effect on their responses: it simultaneously reduced both their endorsement of positive indicators of belonging and negative indicators of belonging. When answering positively worded items about feeling like a real part of the class (item 1), instructor interest (item 5), and others knowing that they can do good work (items 2 and 15), students often cited the lack of interactions when offering a low level of endorsement. Conversely, when answering negatively worded items about it being hard to be accepted in class (item 3), feeling as if you don't belong in the class (item 6), the instructor not being interested in you (item 9), and feeling very different from other students (item 12), students often cited the lack of negative experiences when offering a low level of endorsement. Subsequently, the lack of interactions that often characterize online course contexts may inhibit the development of students' social belonging, but it may also protect students from witnessing interactions that suggest they don't belong.

These results have several general implications for measuring belonging in different contexts. First, researchers should carefully consider whether the specific experiences (e.g., involvement in activities) and emotions (e.g., pride) are actually relevant in the context to which an existing instrument is being adapted. When these experiences and emotions are not relevant, students may be inclined to skip the question or provide a judgment based more on personality traits than their experiences and emotions. Conversely, researchers should consider that belonging may be constructed from experiences (e.g., academic achievement) that previous instruments have not explicitly attempted to capture. Finally, it should be considered that certain phrases evoke different interpretations when adapted to different contexts, leading students to retrieve different information. Being a "real part" of a group may shift from considering the quality of one's social participation in that group (e.g. a school) to simply considering one's ability to meet the prerequisites needed to gain entry into the group (e.g., a class). Similarly, whether "people" is interpreted to refer to classmates, instructors, or a combination of both may change depending on the salience of interactions with classmates and instructors, respectively (Ye & Wallace, 2013). Although it is important to understand how the interpretation of such phrases changes between contexts, it is just as important to understand how interpretation can vary within contexts. When this occurs, the validity of the instrument is reduced because variation is not due to differences in belonging, but differences in what the instrument is measuring. To combat variability in belonging caused by different interpretations, it is recommended that researchers ask questions using specific phrasing (e.g., "classmates" or "teachers" as opposed to "people"; "me" as opposed to "people like me"), and relevant experiences ("belong with my classmates" as opposed to "belong in this class").

These results also have implications for measuring belonging in online course contexts, specifically. A critical assumption of any self-report measure is that respondents have the ability to access relevant information. Here, we see that this is an especially problematic assumption in online course contexts. As the results of research question one show, judgments about belonging are largely tied to interactions we have with others. But as cognitive interviewing shows, whether these interactions are indicative of belonging is often judged through a process of social comparison. Similar to the way other motivational constructs are measured (e.g., self-concept of ability), when absolute standards of judgment do not exist, social comparisons are used as a standard of judgment (Festinger, 1954). On top of the fact that some belonging items explicitly tap these comparison processes (e.g., "I am treated with as much respect as other students"), students engaged in social comparison when judging their answers to other items as well (e.g., “people in this class are friendly to me”). Students pointed out that when they are in an online course, expectations for friendliness can be different from face-to-face contexts, and they are therefore uncertain of an absolute standard of friendliness. This realization, for instance, seemed to lead students to judge the quality of their interactions with classmates by comparing them to other classmates’ interactions.

Importantly, though, online courses make social comparisons incredibly difficult to execute because they naturally hide the information needed to compare one’s experiences to those of another. Participants said that their answers to many items would be affected by knowing that their classmates had been treated differently, either by seeing the instructor respond to other students more promptly or fully, or by seeing classmates offer more thoughtful to other students. Yet participants also admitted that they could not see whether this was happening, and they likely would not know if it was. Therefore, when measuring belonging in online courses, researchers must be especially cautious not to ask questions that respondents do not have enough information with which to make an accurate judgment. Adding a “not applicable” or “I am unsure” option to response scales would be especially useful for eliminating variance unrelated to belonging. And thoroughly understanding the full range of interactions within the course will be crucial for assessing students’ ability to answer questions that lead to social comparisons.

Considering the above findings, it seems clear that research on belonging has thus far not provided clear enough theoretical or methodological resources for understanding how belonging should be measured in online contexts. Those who seek to assess belonging in online course contexts by simply adapting an existing measure from a different context will product misleading results. For the present time, qualitative work is best suited to capture students’ belonging in online courses.

RQ3: What are barriers to belonging in online courses?

Students reported two themes regarding how the transactional distance created by their online course created to barriers to belonging. Unsurprisingly, they focused on issues with the social nature of belonging in an online course, highlighting the social uncertainty and frustration when dealing with peers and the perceived lack of access to the instructor. Students spoke about the importance of knowing information about their peers when considering the quality of their relationships with their classmates. Participant 10 said, “When you don't know anything but someone's name, it's kind of hard to assume, like, would they even answer if I asked them any questions? When you don't really know about anyone, you're less likely to even ask them ‘cause you don't really know what expect.” It became clear that “knowing what to expect” depended heavily on cues normally gained from face-to-face interactions, as Participant 1 explained: “You can’t feel comfortable enough to ask them a question if you don’t really see them ever and you don’t know how they’ll react to your question.” Not being able to see classmates’ reactions to one’s questions or comments was a repeatedly brought up as a factor that degraded the likelihood interactions with classmates would produce feelings of belonging, as Participant 15 echoed, “ I like [face-to-face] interactions and I feel like it’s more genuine than online interaction. I think it would be more about seeing the other person’s emotions and reactions to what you say.” Laboratory studies have found that computer-mediated interactions often deprive people of bonding cues that are used to signal acceptance and respect (Greenfield, 2018). The students in our sample seemed to be missing out on these cues, emphasizing that acceptance and respect are best judged by others’ reactions to what one says, and that nonverbal cues may be especially helpful in this regard.

Another element of online courses that degraded the quality of peer interactions was the long, disjointed nature of digital conversations. Participant 3 said, "If I had to ask a question in a discussion online, I expect that question to be answered in a matter of minutes. But I have to wait an hour and then I'm like you know 'why did you even ask?'" Altogether, the social uncertainty of not being able to see others' reactions and the frustration that accompanied conversations drawn out over long pauses between communication culminated in the recognition that meaningful relationships with others are unlikely to be established in online courses, as Participant 4 summarized, "But like online you can't be like 'I'm going to email this person and try to be friends with them' and try to study with them because I don't think it works that way."

The second theme that emerged was a perceived lack of access to the instructor. Similar to students' insistence that nonverbal signals from classmates would have helped signal acceptance and respect, a lack of synchronous interaction with the course's instructor seemed to signal that the instructor did not want to be bothered. Participant 8 explained, "I don't think belonging is possible in an online class. The teacher has to deal with so many students, and she's not physically there." Although students described how important physical, or at least synchronous, presence was for classmates and the instructor to indicate how they felt, Participant 11 explained that the lack of presence itself can be interpreted as a powerful message, "You never really saw the person face-to-face unless, you like, Skyped. There was not really encouragement like 'Oh, visit me after hours' kind of thing. I kind of saw it like 'I'm very busy like I don't have time for questions.' Like 'You're college students, you should be able to figure it out,' kind of thing."

Other seemingly innocuous details about the way an instructor manages their class can send similar messages about a lack of availability, as Participant 18 described her instructor posting lecture videos recorded by other faculty members, “If the videos are of other professors, it seems like my professor doesn’t care about the course. Even if they posted really good videos, it seems like the professor is lazy, and I don’t ask questions to teachers who seem pressed for time.” Several students reported reluctance about reaching out to faculty due to a fear of wasting professors’ time. Several students felt that their professor was busy and disinterested in discussing course material with students, and their conclusions seemed to be based on characteristics inherent to online courses that limit students’ exposure to their instructor, such as a lack of physical interactions and posting lectures of other professors. This makes it all the more critical for instructors to send explicit messages about their openness to discussions with students, as participant 13 offered, “I feel like it would have made a bigger difference if the teacher talked more and showed more of herself on the PowerPoints and probably said ‘Oh if you have any questions about this specific slide, not just in general, you can definitely shoot me an email.’ Just that reassurance that the teacher is there.”

Many other suggestions were offered for how to improve the social elements of students’ belonging in their online courses, centering on introductions, synchronous elements, and signaling instructor openness. Students felt that interactions with classmates would be improved through higher quality introductions. Participant 10 suggested, “If we even had like pictures of people so we could actually even see who they are, maybe they could introduce themselves. Something you can be like ‘okay I can talk to them for help.” Participant 26 admitted “I know it’s annoying, but icebreakers would help. Like, now you at least know *something* about them.”

Whereas those suggestions could theoretically be done asynchronously through a course management system, many students jumped at the chance to recommend that more synchronous elements be worked into the course. Participant 17 articulated a common sentiment to demonstrate this need, saying "I only felt like I belonged when I came to the in-person discussion. Getting a laugh or a 'I had the question too' was very validating," which Participant 27 echoed by saying, "The in-person part of her OL class was most helpful." Addressing this topic, online students advocated most strongly for video chatting, like Participant 3 explained, "Like my idea…it takes a lot of time to do this…kind of like Skype. I feel like if we did that at least once." And Participant 26 agreed, "Discussion sections on zoom were great. Being able to ask questions or expand helps with engagement.

Finally, students further addressed the problematic perception that the instructor was not open to being approached by students. Participant 23 suggested how the teacher could prevented this perception in her eyes, saying "She sent a message that had a picture of herself and her dogs. You can see she tried to get to know us." This advocated for the use of self-disclosure as a means of showing students respect and care. Conversely, Participant 26 lamented, "In that class I literally never saw the professor, just slides and audio of her voice. It would help to understand who my teacher is." Overall, the ideas that students had, from sharing pictures to doing icebreakers to hosting video discussions were quite simple, and certainly not new. But the implication that they can make a difference for students' sense of belonging conveys just how easily asynchronous online courses can increase transactional distance and degrade interactional quality, leading to social uncertainty regarding classmates and a perception that the instructor does not want to be bothered.

General Discussion

Theoretical implications

In order to understand how to assess students' sense of belonging across contexts, we need quantitative measures that are built with an understanding of how belonging conceptually changes across contexts. Yet, researchers in this field have not purposefully conducted cross-context studies outside of Freeman's (2007) work, leaving us with little understanding of what these findings mean for how belonging develops at a fundamental level, and how it is understood differently across people and across contexts. Considering this, the above findings may lay the foundation for a new theory of belonging by comparing and contrasting conceptualizations across all contexts, as well as the differences that can emerge between people even when the context is the same. A few themes that emerged from this study may be helpful in creating a general theory of belonging that can be more easily adapted to specific contexts and specific individuals.

First, when we speak about belonging, it is important to recognize that we are implying a defined group for which there is membership criteria. What that membership criteria is can certainly change from group to group, and it likely depends on the goals of who is in the group. Consider two classroom contexts. In a class of advanced Biology students, recognition that many students share the desire to go to medical school can lead to the perception that strong academic ability is part of the criteria for belonging in the classroom. Conversely, in a middle school math classroom composed of students in the low-ability track, students may recognize that mathematics achievement is not a shared goal among peers. It is likely that there is a "collective negotiation" of what the group's common goals are, which may drive perceptions of what attributes are valued in that group, thereby creating criteria for membership.

Second, signals of membership may change in different contexts. Satisfaction of membership criteria may come in the form of payment (Mercedes owners) or prior accomplishment (Eagle scouts), participation (hiking groups), performance of ability (MENSA), or social contributions (undergraduate fraternities). It is crucial to consider who decides what these signals are. As described in our results, teachers may play an especially important role in students' perceptions of belonging once the context is limited to a single classroom. Academic settings may offer different ways for students to signal their belonging depending on the negotiation of what the group's goals and valued attributes are. Whereas a performance-oriented science teacher may signal to students that consistently finding the correct answers represents membership, a mastery-oriented science teacher may signal to students that simply attempting to support an argument with facts meets the criteria for membership regardless of the outcome. In both cases, the teacher had control over signaling whether criteria for belonging were being met, but chose to emphasize different valued attributes that aligned with their respective goals for the class. In other contexts, peers, other authority figures, or even personal assessments may be in control of determining whether one belongs to a group.

Finally, even as a group and membership criteria are defined and signals of membership are decided upon, one's satisfaction of membership criteria ("fit") may be discovered through experiences with the group. Interactions with others are likely key for gaining recognition from peers or an authority figure that membership is being satisfied. Such was the case when students described the acceptance from peers in clubs that they had joined or the respect and care from teachers in their classrooms. In some instances, however, it may be possible that peer or authority recognition may not be needed to feel a sense of belonging to a group, such as our students who maintained that they belonged in their classes because they had satisfied the prerequisites to enter the course.

The field of belonging in academic settings has highlighted the positive relationship between belonging and achievement, often suggesting a causal path from belonging to achievement (Zumbrunn et al., 2014). Yet it may not be the case that belonging in a group is always related to success within that group. Two examples of belonging in academic contexts may illustrate why. The first offers an example of a mismatch between the "collective negotiation" of goals and valued attributes of the students and the goals and valued attributes of the authority figures. Stage-environment fit theory illustrates how students' desire for autonomy and relatedness can contrast with teachers' desire for control and limited socializing among students, leading to declining levels of motivation (J. S. Eccles & Midgley, 1989). In the example of a middle-school math class whose students see more value in socializing, feeling like you belong to the group may be associated with lesser motivation.

Second, despite the recognition that relatedness, or belonging, is a fundamental human need, theories of belonging do not suggest that belonging to every context one encounters is a fundamental human need (Baumeister & Leary, 1995; Deci & Ryan, 1985a). Students in our online course mentioned that discussing belonging in that context was a foreign concept to them, admitting they had never thought about the course as a place that they even could belong. As one student said when qualifying the importance of belonging to the university, more generally, "It's important to me, but it doesn't have to be. Like a lot of commuting students can just go home on the weekend anyway and belong back with their family, but for me I live here, so belonging is important." Understanding whether belonging is actually important for predicting success in a given context may depend on the centrality of that context to the students' life. In contrast to the majority of studies on school belonging, which focus on middle school, high school, or university contexts, individual courses may only last several weeks, and can be just one of many courses students may be taking. If students are able to retreat from a given context to another place that they belong or are unable to form "temporally stable and enduring" relationships within a course, then belonging may not be an important predictor of success. The disruption of temporally stable and enduring relationships, as well as uncertainty over standards for achievement and academic belonging, may be the reason why transition periods (e.g., first year of college) are considered so crucial for students' belonging and long-term achievement.

Quantitative implications

What does this mean for the researcher who wants to measure belonging in a manner appropriate for a given context? First and foremost, to those interested in studying online courses, I would recommend the connectedness subscale of Rovai's sense of classroom community scale (Rovai, 2002). This scale is specifically designed for online students. Although it does not exactly measure students' sense of belonging (and certainly does not capture any sense of academic belonging), it does not require comparative judgments of how the individual is being treated with respect to other classmates.

Considering the skepticism we may have over whether belonging is actually important in all contexts, we may instead choose to adopt measures that account for students' own perceptions of whether or not they need to feel like they belong in that context. The relatedness subscale of the Basic Psychological Needs Scale – Revised builds items that adjust for this (Chen et al., 2015). Items like "I feel that people I care about also care about me" or "I feel that people who are important to me are cold and distant from me" may be better at capturing the experiences of students by accounting for their experience of belonging relative to their needs. A scale like this may measure a more meaningful construct: the gap between the social belonging we experience in a context and the social belonging we *need* in that context. A limitation is that this focuses on social relationships, not academic relationships.

Moving forward, it seems two important improvements must be made to quantitative measures of belonging in order to understand how belonging is associated with outcomes in academic settings. The first is that academic belonging must be measured, as its role in students' conceptualization of belonging is becoming particularly pronounced as research on belonging moves to contexts in which we might consider the "collectively negotiated" goals and values are increasingly aligned with academic achievement (i.e., undergraduate classrooms and STEM high schools). The second is that interindividual differences in the importance of social and academic belonging must be accounted for. When answering one of the most straightforward questions, "sometimes I feel I don't belong in this class," some students exclusively described their academic experiences, whereas others exclusively spoke about their social experiences. Future work in this area may uncover that individual differences in how students conceptualize belonging even within the same contexts has implications for their experiences.

Conclusion

Sense of belonging has emerged as an increasingly popular motivational construct in educational psychology. Despite the lack of theory regarding how belonging may develop and operate differently in different contexts, attempts to quantitatively measure belonging in new contexts have proliferated. With a lack of theory to guide the development of measures appropriate for new contexts, data-driven approaches such as factor analyses have been relied upon to discover items that are not appropriate, leaving hints that belonging is conceptualized differently in different contexts. In this study, we discuss students' conceptualizations of belonging across several different contexts, cementing the theoretical tenet that belonging is conceptualized differently across different contexts, but also why it is conceptualized differently, and just how misleading existing measures of school belonging may be when adapted to different contexts (specifically online college courses). The implications suggest a new model of contextualized belonging is needed, identifying elements of belonging that are constant across contexts in order to situate the elements that can differ from context to context and even person to person. Meanwhile, qualitative descriptions of belonging offer helpful insight into the sophisticated processes behind belonging, and practical solutions for those in settings where belonging may be most difficult to cultivate (e.g., online courses).

The Utility of Click Data: Behavioral Mediators of Motivational Interventions

Research Questions

The present study is driven by four research questions that explore the effectiveness of a utility value intervention in an online course:

1. Do online students' expectancies and values for their course differ from those of their face-to-face peers?
2. Is a utility value intervention differentially effective in online and face-to-face courses?
3. What are the behavioral correlates of expectancies and values in an online course?
4. What are the behavioral mediators of an online utility-value intervention, if any?

The first research question will use the control group in the present study to address the lack of literature documenting differences in values between OL and F2F students. This will involve measuring motivational constructs at the beginning of the course as well as changes in values throughout the course. Meanwhile, the intervention will compare the effectiveness of the intervention across the OL and F2F classes. Next, we will use correlational analyses to understand links between Expectancy-Value constructs of motivation and behavior in an online course. Finally, if any significant effects of the intervention are found, and if any significant associations between motivation and click-data are found, models will be tested to identify potential behaviors that may be mediators of the intervention in an online course.

Methods

Participants

Participants were drawn from an online, introductory Chemistry course at a large, ethnically diverse research university in the southwest United States. Because this is an introductory course, almost all students (85%) were in their first year of college, with a mean age of 19.0 years-old. The students in this course were 58% female, 39% Asian, 41% Hispanic, 15% White, and 5% Black. 71% of students were from households that primarily spoke a non-English language or a mix of English and non-English. 56% of students represented the first-generation in their family to attend college, and 37% were from low-income backgrounds (30% both first-generation and low-income). 59% of the online students said this was the first online course they had ever taken.

Measures

Motivation. Students' motivation will be measured according to Eccles and colleagues' Expectancy-Value theory, capturing their perceived competence, competence valuation, affective interest, behavioral interest, attainment value, utility value, and behavioral intentions. Items for the each of these constructs are taken directly from recent studies on utility value interventions by Harackiewicz and colleagues (e.g., Harackiewicz et al., 2016), and are scales of two to six items each. Items were phrased as statements about each of these respective constructs that participants answered on a scale from 1 = Not at all true to 7 = Very true. A full list of items composing each construct, along with means and Cronbach's alphas, can be found in the Appendix C.

Demographic variables. A wide array of variables provided by the universities office of institutional records after the course was completed included gender, low-income status, part-time status, first-generation status, race/ethnicity, age, SAT scores, and high school GPA.

Grades. All graded assignments for the course were provided by the instructor. This included points assigned for all participation, homeworks, labs, projects, and exams.

Click data - course activity. This will be tracked using students' total number of clicks per day. We will sum up total clicks throughout the entire course, number of days during which students made at least one click on the course. We will also combine clicks from certain days to capture course activity immediately after midterm exams and on specific days of the week.

Click data – video pages. The course was delivered through assigned lecture videos that needed to be watched so that video quiz assignments could be completed by each Wednesday at midnight. Links to these videos were available each week on a web page specific to that week. We counted students' total number of clicks on these pages per day. We will sum up total video page clicks throughout the entire course, as well as number of days during which students made at least one click on a video page.

Click data - procrastination. This will be generated from the date and time data associated with the video quiz assignments due each Wednesday at midnight. There were roughly 7 video quiz assignments due each Wednesday. By subtracting the time of students' first click to attempt a video quiz from the time associated with that assignment's due date, we will be able to calculate how much time students had left before the deadline when they first attempted their weekly assignments. Because greater procrastination is indicated by a smaller amount of time between accessing the assignment and the assignment due date, this measure will be reverse-coded throughout analyses.

Click data - Spacing. Because weekly video quizzes in this course are intended to be completed on a cyclical, weekly schedule, the spacing of students' clicks on assignment pages throughout the week (Monday through Sunday) will indicate whether their course activity was spaced out or completed all at once. After obtaining the time difference between completing a video quiz and its deadline, these standard deviation of these values for (roughly seven per week) for each student will indicate how much they "spaced" their work.

Click data - challenge-seeking. In the present course, the instructor makes available sets of “toughie” problems. These are challenging sets of questions that the instructor tells students are designed for advanced students who want to cement their understanding and prepare themselves to earn the highest possible grades on exams. We hypothesized that clicking on the link to access the page with these problems would be considered an indicator of challenge-seeking.

Procedure

Within the OL and F2F versions of the course, students will be randomly assigned to the treatment or control conditions. In the first week of the term, students will be given the opportunity to complete a baseline survey, in exchange for a $5 gift card. Throughout the term, students will be given two writing assignments. For students in the control condition, these writing assignments will consist of choosing a topic that has been covered in lecture in the preceding two-week period. They will then have to formulate a question related to that topic and write roughly 500 words summarizing that topic. Students in the treatment condition will similarly be asked to formulate a question for a recent topic, but then will be asked to write about how the topic is relevant to their own life. They will be advised to either write an essay about this or to write a letter either to a friend or to a family member. Finally, at the end of the term, the students will be given the opportunity to complete another survey, in exchange for a $5 gift card. This procedure will be repeated in the second quarter of the study.

Analysis Plan

First, I will compare the OL and F2F versions of the class on measures of motivation at pre-survey. Concurrently, I will conduct a missing data analysis to understand whether expected differences between OL and F2F students' motivation may be being underestimated or overestimated.

Second, I will compare whether the effects of the intervention are greater for OL or F2F students. I will start by conducting a randomization check in both OL and F2F courses, separately. Randomization will be assessed with respect to demographic data and pre-survey motivation data. I will then calculate the treatment effects of the intervention using an Intent-to-Treat (ITT) design, followed by a Treatment on the Treated (TOT) design (Shadish, Cook, & Campbell, 2002). TOT effects will be measured as those who participated in both of the two treatment assignments. These may be especially different because this intervention was merely offered as a source of extra credit, not required. This will be done for each modality separately. Because these studies often reveal heterogeneous effects, these same procedures will also be conducted for subsets of the sample. In particular, I will focus on whether the intervention's effectiveness is moderated by initial performance level, as defined by performance on the first exam (which will take place before the first intervention writing assignment). Additionally, I will test for moderation of intervention effectiveness by first-generation status, URM status, and gender. Finally, I will compare the distributions of the separate treatment effects to determine if the intervention worked significantly better for online students.

Next, I will use correlational analyses to establish relationships between motivational measures and behavior measurable through click data. I will start by establishing associations between expectancy-value constructs of motivation and course performance. Because this will be done for the purpose of gaining insight into how motivation constructs might influence performance, I will use partial correlations. Partialing out the variance due to prior performance will better control for the likelihood that performance may also be causing motivation. Then, I will establish associations between click behaviors and course performance. This will include associations between course performance and totaled click behaviors for the course, as well as daily click behaviors for the course.

Although it would make theoretical sense to jump directly to associations between motivation and click behaviors, it is important in this exploratory work to begin by establishing associations between motivation and course performance, as well as click behaviors and course performance. I will then examine relationships between specific expectancy-value constructs and click behavior, limiting my analysis to motivational and behavioral measures positively associated with course performance.

Finally, if the intervention is successful among any subset of students, I will investigate whether receiving the intervention is associated with changes in course-related behavior, as indicated by students' click patterns. Because much more click-data related to course activity is recorded in the online version of the course, this portion of the analyses will only include online students.

Results

RQ 1: Do online students' expectancies and values for their course differ from those of their face-to-face peers?

Results show that largely, OL students' expectancies and values do not differ from those of their F2F peers. As can be seen in Table 3.1, the only significant difference is students' interest in the course, with OL students exhibiting less interest (both affective and behavioral). Furthermore, significant differences in OL and F2F students' value of their coursework does not appear over time, as indicated by students' change in motivation.

However, motivational differences between OL and F2F students may be underestimated due to missing data. Table 3.2 shows that online students were significantly less likely to complete the pre-survey. Moreover, we can see that students with lower math ability (as determined by SAT scores), poorer exam performance, and lower overall course grades were less likely to complete the surveys. Under the assumption that lower-achieving students are likely to have lower motivation for the course, it is reasonable to hypothesize that missing data would have lowered the average means of motivational variables more for the OL course than the F2F course.

Table 3.1

Table 3.1 Summary Statistics and Randomization Check of Demographic and Motivational Variables by Intervention Condition

	Summary statistics			Randomization Check					
					F2F			OL	
	F2F	OL	p-value	Control	UV	p-value	Control	UV	p-value
Demographics									
Male	47%	31%	**0.000**	48%	45%	0.502	31%	31%	0.970
Low-income	37%	38%	0.949	36%	38%	0.647	37%	38%	0.868
Full-time status	100%	99%	**0.010**	100%	100%	1.000	100%	97%	0.078
First-generation status	58%	52%	0.157	60%	57%	0.571	58%	46%	0.086
Asian	37%	47%	**0.027**	36%	38%	0.696	45%	49%	0.644
Black	5%	6%	0.727	4%	6%	0.485	7%	4%	0.322
Hispanic	44%	35%	0.056	44%	43%	0.937	37%	33%	0.585
White	15%	13%	0.530	17%	13%	0.404	11%	15%	0.446
Age	18.92	19.15	0.097	18.8	19	0.228	19.1	19.2	0.828
N	438	198		218	220		100	98	
Motivation (Pre-survey)									
Perceived Competence	5.23	5.10	0.059	5.27	5.18	0.750	5.21	4.97	0.474
Competence Valuation	6.44	6.48	0.279	6.45	6.43	0.852	6.49	6.47	0.687
Interest (Affective)	4.88	4.32	**0.002**	4.83	4.92	0.277	4.38	4.25	0.868
Interest (Behavioral)	3.76	3.43	**0.044**	3.66	3.87	0.486	3.51	3.34	0.068
Attainment Value	4.33	4.12	0.147	4.34	4.32	0.942	4.31	3.92	0.098
Utility Value	5.04	4.81	0.320	5.07	5.01	0.557	4.98	4.63	0.094
N	304	116		149	155		61	55	
Motivation (Change)									
Perceived Competence	-0.25	-0.78	0.089						
Competence Valuation	-0.49	-0.65	0.542						
Interest (Affective)	-0.07	-0.22	0.534						
Interest (Behavioral)	0.35	0.22	0.621						
Attainment Value	0.00	-0.01	0.969						
Utility Value	-0.41	-0.31	0.679						
N	93	31							

Note. Bolded cells are statistically significant at the p<.05 level. p-values are for X^2 tests for Male, full-time status, first-generation status, and all race categories. All other p-values are for t-tests of differences between Control and UV groups. Change in motivation is reported for students in control group.

Table 3.2

Table 3.2 Associations of Missing Pre-survey Data with Means of Demographic and Achievement Variables

	Non-missing	Missing	p-value
Course Modality			
Online student	28%	38%	**0.008**
Demographics			
Male	35%	55%	**0.000**
Low-income	39%	34%	0.169
Full-time status	100%	99%	**0.040**[a]
First-generation status	60%	49%	**0.010**
Asian	38%	43%	0.356
Black	5%	6%	0.551
Hispanic	43%	37%	0.267
White	15%	14%	0.922
Age	18.88	19.25	**0.009**
Achievement			
SAT math	589.7	622.9	**0.001**
SAT verbal	554.8	559.6	0.627
SAT writing	544.5	552.1	0.105
SAT total	1689	1734.6	**0.001**
High school GPA	3.907	3.88	0.380
Final grade	67.05	59.45	**0.000**
Exam grades	109	97.74	**0.001**
N	420	216	

Note. Bolded cells are statistically significant at the $p<.05$ level. *p*-values are for X^2 tests for Male, full-time status, first-generation status, and all race categories. [a]Fisher's exact test used because expected cell sizes < 0. All other *p*-values are for t-tests of differences between Control and UV groups in each modality.

RQ 2: Is a utility value intervention differentially effective in OL and F2F courses?

A randomization check showed that there were no statistically significant differences between the treatment (UV) and control conditions in either the OL or F2F courses (see Table 3.1). Results then showed that the main effects of the UVI were not statistically significant in either OL or F2F course modalities, whether assessing ITT or TOT estimates. This was true regardless of whether the outcomes measured were with respect to performance (i.e., overall grade and final exam) or motivation (e.g., affective interest, utility value, behavioral intentions).

Interaction effects were also not statistically significant, except for the interaction of first-generation status by treatment on the attainment value of students in the OL condition. This suggests that the effect of the UVI on OL students' attainment value was significantly greater when the students came from a first-generation background. However, a similarly positive interaction between first-generation status and the UVI was not observed when analyzing the targeted mechanism of utility value or the targeted performance outcomes, suggesting that the statistical significance observed here may be due to chance.

Additional analyses show that the UV treatment did not interact with course modality. Table 1.5 shows that although the UVI did have a statistically significant main effect on overall course grades when analyzed across both courses using ITT estimates, this effect was not moderated by the course modality. It is important to note that the main effect of the UVI on overall course grades dropped to zero when analyzing the TOT estimates. Furthermore, the UVI did not show a positive main effect on any of the motivational variables that are proposed to mediate the UVI's effect on performance outcomes. This suggests that the UV's statistically significant main effect using an ITT model was likely due to a combination of chance variation and a sample size larger than any other estimated models.

Table 3.3

Table 3.3 Effects of UVI in F2F Course - ITT and TOT Estimates

	Overall Grade	Final Exam	Affective Interest	Behavioral Interest	Attainment Value	Utility Value	Behavioral Intentions
ITT - Main effect							
UVI	0.16	0.13	-0.01	-0.04	-0.11	0.00	-0.13
	(0.10)	(0.10)	(0.14)	(0.14)	(0.14)	(0.14)	(0.14)
ITT - Interactions							
Performance level	-0.06	-0.04	-0.14	-0.14	-0.21	-0.13	-0.29
	(0.07)	(0.08)	(0.15)	(0.15)	(0.15)	(0.15)	(0.15)
	0.27	0.31	0.21	0.37	0.25	-0.09	-0.07
First generation	(0.20)	(0.20)	(0.29)	(0.30)	(0.30)	(0.29)	(0.30)
	0.15	0.13	-0.07	-0.16	-0.21	-0.23	0.03
Low income	(0.20)	(0.20)	(0.28)	(0.28)	(0.28)	(0.28)	(0.29)
	-0.03	0.00	0.33	0.43	0.39	0.34	0.50
URM	(0.20)	(0.20)	(0.27)	(0.28)	(0.28)	(0.27)	(0.28)
	-0.07	-0.10	-0.18	0.00	-0.39	-0.03	-0.01
Male	(0.19)	(0.19)	(0.29)	(0.30)	(0.30)	(0.29)	(0.28)
TOT - Observations	438	438	216	205	206	216	202
TOT - Main effect							
UVI	-0.06	-0.01	-0.34	-0.09	-0.09	-0.26	-0.25
	(0.14)	(0.14)	(0.19)	(0.20)	(0.21)	(0.21)	(0.20)
TOT - Interactions							
Performance level	0.00	-0.02	-0.10	-0.10	-0.08	-0.10	-0.19
	(0.10)	(0.11)	(0.21)	(0.22)	(0.22)	(0.22)	(0.22)
	0.35	0.32	0.72	0.77	0.60	0.28	-0.13
First generation	(0.29)	(0.28)	(0.39)	(0.42)	(0.44)	(0.43)	(0.43)
	0.29	0.19	-0.67	-0.37	-0.34	-0.61	-0.19
Low income	(0.30)	(0.29)	(0.40)	(0.42)	(0.43)	(0.42)	(0.41)
	0.14	0.11	0.65	0.75	0.49	0.76	0.46
URM	(0.29)	(0.28)	(0.38)	(0.40)	(0.42)	(0.41)	(0.40)
	-0.11	-0.10	-0.45	-0.41	-0.84	-0.55	-0.37
Male	(0.29)	(0.29)	(0.42)	(0.46)	(0.44)	(0.43)	(0.41)
TOT - Observations	150	150	95	90	91	95	88

Note. * $p<.05$, ** $p<.01$, *** $p<.001$. All coefficients are standardized. Standard errors in parentheses. Main effect estimate is from model in which UVI treatment was only predictor. Interaction estimates are from separate models in which each interaction term was entered as the only additional predictor.

Table 3.4

Table 3.4 Effects of UVI in OL Course - ITT and TOT Estimates

	Overall Grade	Final Exam	Affective Interest	Behavioral Interest	Attainment Value	Utility Value	Behavioral Intentions
ITT - Main effect							
UVI	0.17	0.12	-0.12	-0.057	-0.22	-0.14	-0.09
	(0.14)	(0.14)	(0.22)	(0.22)	(0.22)	(0.22)	(0.23)
ITT - Interactions							
Performance level	0.15	0.21	0.11	0.06	-0.11	0.17	0.22
	(0.10)	(0.11)	(0.22)	(0.23)	(0.23)	(0.23)	(0.24)
First generation	0.04	0.06	0.31	0.77	0.91*	-0.04	-0.27
	(0.29)	(0.29)	(0.44)	(0.45)	(0.44)	(0.44)	(0.46)
Low income	-0.20	-0.18	0.08	0.59	0.40	-0.52	-0.32
	(0.30)	(0.30)	(0.45)	(0.45)	(0.45)	(0.43)	(0.46)
URM	0.16	0.09	-0.09	-0.40	-0.47	-0.55	-0.97
	(0.30)	(0.30)	(0.47)	(0.48)	(0.48)	(0.47)	(0.49)
Male	-0.30	-0.28	-0.71	0.32	-0.17	-0.16	0.63
	(0.31)	(0.31)	(0.49)	(0.51)	(0.50)	(0.49)	(0.49)
TOT - Observations	198	198	86	81	81	86	78
TOT - Main effect							
UVI	0.12	0.03	-0.02	-0.40	-0.25	-0.12	-0.07
	(0.20)	(0.20)	(0.31)	(0.35)	(0.35)	(0.34)	(0.29)
TOT - Interactions							
Performance level	0.17	0.25	-0.11	-0.34	-0.55	0.22	-0.44
	(0.12)	(0.15)	(0.32)	(0.36)	(0.37)	(0.36)	(0.34)
First generation	-0.35	-0.18	0.31	0.76	1.42*	0.09	0.61
	(0.40)	(0.42)	(0.66)	(0.72)	(0.69)	(0.71)	(0.60)
Low income	-0.60	-0.67	-0.28	0.89	0.90	-0.54	0.62
	(0.41)	(0.43)	(0.68)	(0.72)	(0.73)	(0.72)	(0.60)
URM	0.13	0.23	0.89	-0.76	1.41	1.07	0.36
	(0.45)	(0.48)	(0.87)	(1.21)	(1.20)	(0.93)	(0.98)
Male	-0.76	-0.73	1.15	1.65	1.78	0.46	0.90
	(0.49)	(0.52)	(0.97)	(1.02)	(1.02)	(1.04)	(0.84)
TOT - Observations	68	68	38	35	35	38	34

Note. * $p<.05$, ** $p<.01$, *** $p<.001$. All coefficients are standardized. Main effect estimate is from model in which UVI treatment was only predictor. Interaction estimates are from separate models in which each interaction term was entered as the only additional predictor.

Table 3.5

Table 3.5 Effects of UVI by Course Modality - ITT and TOT Estimates

	Overall Grade		Final Exam		Affective Interest		Behavioral Interest		Attainment Value		Utility Value		Behavioral Intentions	
	m1	m2	m1	m2	m1	m2	m1	m2	m1	m2	m1	m2	m1	m2
ITT - Main effects														
UV	0.16*	0.15	0.13	0.12	-0.04	-0.01	-0.05	-0.04	-0.14	-0.10	-0.04	0.00	-0.12	-0.13
	(0.08)	(0.09)	(0.08)	(0.09)	(0.12)	(0.13)	(0.12)	(0.14)	(0.12)	(0.14)	(0.12)	(0.14)	(0.12)	(0.14)
OL		-0.47***		-0.54***		-0.35		-0.25		-0.10		-0.13		0.05
		(0.12)		(0.12)		(0.18)		(0.19)		(0.19)		(0.18)		(0.19)
ITT - Interaction														
OL x UVI		0.03		0.00		-0.11		-0.02		-0.13		-0.14		0.04
		(0.17)		(0.17)		(0.25)		(0.26)		(0.26)		(0.26)		(0.27)
ITT - Observations	636	636	636	636	303	302	287	286	288	287	303	302	281	280
TOT - Main effects														
UV	0.00	-0.05	0.00	-0.01	-0.28	-0.34	-0.19	-0.08	-0.14	-0.09	-0.24	-0.26	-0.19	-0.25
	(0.11)	(0.13)	(0.11)	(0.13)	(0.16)	(0.19)	(0.18)	(0.21)	(0.18)	(0.21)	(0.18)	(0.21)	(0.17)	(0.20)
OL		-0.53**		-0.55**		-0.59*		-0.11		-0.01		-0.36		0.05
		(0.17)		(0.17)		(0.26)		(0.29)		(0.29)		(0.28)		(0.27)
TOT - Interaction														
OL x UVI		0.19		0.04		0.32		-0.35		-0.17		0.15		0.18
		(0.24)		(0.24)		(0.36)		(0.39)		(0.41)		(0.39)		(0.37)
TOT - Observations	218	218	218	218	133	133	125	125	126	126	133	133	122	122

Note. * *p*<.05, ** *p*<.01, *** *p*<.001. All coefficients are standardized. Standard errors in parentheses.

RQ 3: What are the behavioral correlates of expectancies and values in an online course?

Surprisingly, students' pre-survey measures of motivation did not show consistent, significant associations with their final grade in the course. This was the case even when using partial correlations (Table 3.6), which removed variance in these associations due to prior ability. Taken alone, these results could be used to suggest that motivation for a course is not a significant predictor of performance in that course. A more likely explanation, however, is that students' responses during the first week of the course regarding their anticipated motivation throughout the course were simply not well-calibrated. Tellingly, even students' perceived competence for the course was not significantly associated with their final grades (the raw correlation of perceived competence with final grade was also $r = .09$).

Table 3.6

Table 3.6 Partial Correlations of Final Grade with Expectancy-Value Constructs by Wave

	Pre-survey	Post-survey	Change
Perceived competence	0.09	**0.57***	**0.33***
Affective interest	**0.18***	**0.40***	**0.39***
Behavioral interest	0.1	**0.24***	0.12
Attainment value	-0.08	0.17	**0.27***
Utility value	0.02	**0.28***	**0.33***

Note. Correlations partial out variance associated with prior ability. Prior ability is represented by student's SAT math score.

Meanwhile, students' post-survey motivational measures were much more strongly associated with course performance. The relationship between motivation and performance is certainly bi-directional. However, it is unlikely that this association appeared more strongly at the end of the term purely because course-related behavior caused motivation to develop. Rather, it is more likely that students' self-reported pre-survey measures of motivation were not well-calibrated enough to offer insight into how motivated students would actually be as they learned more about the course. Because pre-survey affective interest, as well as post-survey perceived competence, behavioral interest, and utility value are significantly associated with students' final grade, these motivational measures will be tested for associations with click behaviors.

Click behavior showed many more significant associations with students' final grade in the course. The weakest associations between click behavior and course performance were observed when looking at raw number of total clicks and raw number of clicks on different types of course pages. Although clicking on the course website more times was positively associated with course performance, it was one of the weaker associations observed. Meanwhile, number of clicks on video pages and number of clicks on "toughie problems" page were not significantly associated with course performance.

A theme apparent from the results in Table 3.7 is that course performance is not so much associated with the raw numbers of clicks or even the amount of time spent on each course page as it is with the spacing of study behavior throughout the duration of the course. Procrastination (not accessing assignments until closer to the Wednesday deadline) and spacing (accessing assignments with more time between assignments) showed the strongest correlations between click behavior and course performance. Similarly, when the percentage of days students spent accessing videos was more heavily concentrated on Thursdays (the day after assignments were due), students were likely to have a lower course grade.

Table 3.7

Table 3.7 Correlations of Final Course Grade with Click Behavior

General course behavior		*General clicks on course website*		*Video watching*	
Clicks on course website	0.22*	Days with at least one click on course website	0.62*	Days with at least one click on video pages	0.46*
Clicks on video pages	0.00	Mondays clicked at least once on course	0.52*	Mondays with at least one click on video pages	0.39*
Clicks on "toughie problems" page	0.06	Tuesdays clicked at least once on course	0.46*	Tuesdays with at least one click on video pages	0.30*
Time on task	0.07[a]	Wednesdays clicked at least once on course	0.47*	Wednesdays with at least one click on video pages	0.33*
Procrastination	-0.33*	Thursdays clicked at least once on course	0.39*	Thursdays with at least one click on video pages	0.16*
Spacing	0.27*	Fridays clicked at least once on course	0.44*	Fridays with at least one click on video pages	0.22*
Days with at least one click on video pages in 5 days following each exam	0.27*	Saturdays clicked at least once on course	0.46*	Saturdays with at least one click on video pages	0.32*
Percentage of days viewing video pages falling day after video due date	-0.19*	Sundays clicked at least once on course	0.39*	Sundays with at least one click on video pages	0.27*

Note. * $p<.05$. $n = 199$. [a] Correlation with time on task is partial correlation, partialing out variance associated with number of days with at least one click on course. Clicks with longer than one hour between subsequent clicks were rounded down to one hour for time-on-task. Because the final click during each day's online session would always be longer than one hour, students who accessed the course more days per week would be likely to exhibit more time on task due to larger numbers of artificially long. The correlation between time-on-task and days with at least one click on the course is $r = 0.91$.

Following the logic that course grades are more strongly associated with the spacing of study behavior, we then see that the number of separate days with at least one click on the course website and days with at least one click on video pages were even more strongly associated with course grades. Breaking down these associations across days of the week adds further detail to our understanding of the relationship between spacing and course performance. Engaging with the course on Mondays (the beginning of the week and two days before assignments were due) showed the strongest association with course performance for both general clicks on the course website and video-watching, whereas the weakest associations fell on Thursdays (the day after assignments were due).

Finally, motivational measures showed that they were indeed associated with patterns of click behavior (Table 3.8). Suggesting the most compelling example of motivation influencing behavior, higher affective interest at the beginning of the course was associated with more consistently accessing the course and doing so well before the deadlines. By the end of the course, students who had higher levels of perceived competence, affective interest, behavioral interest, and utility value were exhibiting similar trends, along with less procrastination and more spacing. When broken down by weekday, we see that higher levels of interest was significantly associated with accessing the course and watching videos specifically on Mondays, whereas it was unrelated to watching videos on Thursdays. This trend also appeared when examining post-survey measures of motivation. Coupled with our previous findings showing that spacing out course engagement is the strongest behavioral predictor of course performance in this study, it seems that greater interest in the course may be what is leading students to engage in more beneficial study habits.

Table 3.8

Table 3.8 Correlations of Motivational Variables with Click Behavior

	Pre-survey	*Post-survey*			
	Affective interest	*Perceived Competence*	*Affective interest*	*Behavioral interest*	*Utility value*
Clicks on course website	0.06	0.03	-0.08	-0.02	0.05
Procrastination	-0.02	**-0.34***	**-0.27***	-0.23	-0.15
Spacing	0.13	**0.34***	**0.28***	**0.35***	0.17
Days with at least one click on video pages in 5 days following each exam	0.01	0.14	0.13	0.03	0.06
Percentage of days viewing video pages falling day after video due date	-0.09	-0.14	-0.15	0.05	-0.15
Days with at least one click on course website	**0.20***	**0.34***	**0.31***	**0.20***	**0.23***
Mondays clicked at least once on course	**0.20***	**0.33***	**0.33***	0.05	**0.22***
Thursdays clicked at least once on course	0.00	0.09	0.10	0.12	0.04
Days with at least one click on video pages	**0.16***	**0.30***	**0.27***	**0.23***	0.15
Mondays with at least one click on video pages	**0.22***	**0.32***	**0.37***	**0.24***	**0.23***
Thursdays with at least one click on video pages	-0.02	-0.09	-0.07	0.05	-0.06
N	118	87	87	82	87

Note. * $p<.05$. $n = 118$.

RQ 4: What are the behavioral mediators of a utility-value intervention, if any?

Due to the lack of significant effects from the intervention, we did not attempt to test an overarching model that positioned click behaviors as a mediator between the UVI and performance outcomes. Analyses of the intervention in the OL course suggested that the UVI did not work as intended, even among the students who did indeed participate in the treatment. With no direct effects of the UVI observable on either motivation or performance outcomes, we had no reason to hypothesize or test whether the UVI would change any of the click behaviors associated with motivation.

Discussion

In this study, we attempted to understand behaviors that might mediate motivational processes by examining click data within an online course. We conducted our analyses within the larger context of a Utility Value Intervention, with the intent of addressing a large gap in the conceptual model of task-value interventions regarding the behavioral differences that are promoted by the UVI treatment. Though we did not attempt a full mediation model in this study due to the lack of significant main effects of the UVI or interactions by various subgroups, we offer new insights regarding the behavioral correlates that future research can study in order to test for behavioral mediators of task value interventions or any other motivational processes.

Effectiveness of a UVI in an online course

The intervention itself proved ineffective in the present study, which must be discussed in light of the need to understand the conditions under which psychological interventions should be expected to replicate (Pashler & Wagenmakers, 2012; Schwartz, Cheng, Salehi, & Wieman, 2016). During this pilot phase of data collection within a larger study, it may have been an issue that many students did not engage in the treatment. Likely because it was offered as an extra-credit assignment, only 34% of F2F students and 34% of OL course actually participated in both treatment assignments. The TOT estimates may have been biased more than usual due to an association with higher baseline levels of ability and motivation. Presence in the TOT analysis subset was significantly associated with higher baseline perceived competence at the 0.10 level, higher utility value at the 0.10 level, and higher exam scores at the .01 level. The fact that many of the students who would be hypothesized to benefit most from the intervention did not engage in the treatment may be the reason that we did not see consistently positive effects of the treatment even on those who did engage in the treatment. In addition, it is likely that the relatively small number of short treatments (two) may not have been enough to significantly impact students' beliefs. Even if students' beliefs were positively affected, though, the brevity of the academic term (10 weeks) may not have left enough time for students to put those beliefs into action to a statistically significant degree.

Importantly, the intervention was not more effective for OL students than for F2F students. After conducting our initial analyses and finding no differences between OL and F2F students' expectancies and values emerged over time, however, a large reason for suspecting that the UVI would be more effective among OL students proved unsubstantiated. We must note that the lack of a UVI x course modality interaction cannot be ruled out from an analysis of one OL course alone. Due to the large variations in how online courses are delivered, and the different reasons students select into OL and F2F courses (see Study 1), it will be important to test this hypothesis again in different types of OL courses. Given the results of Study 1, we might expect that the UVI x course modality interaction would be more likely to be seen when done by students who select into OL courses due to a general desire for flexibility or learning preferences. The results of Study 1 show that it is these OL students who seem to exhibit lesser positive value for their courses when compared to their F2F peers.

Behavioral correlates of motivation

Despite the lack of significant effects in this pilot UVI intervention study, there exists a growing body of literature demonstrating the potential for short, motivational interventions that improve academic performance by targeting students' task value. Yet, the question remains how exactly higher task value might be leading to higher grades for students. In the latter, exploratory phase of our study, we use the click data available in our online course to offer evidence of how higher task values may be impacting students' behavior.

Our data show that expectancies and values, spacing one's study behavior out over time, and higher grades are all positively associated with each other. This echoes emerging trends in educational data mining showing that procrastination is associated with lower grades (Park et al., 2018), and then extends this work by identifying the motivational characteristics most likely to predict spaced study behavior and a lack of procrastination. Although almost all expectancy-value constructs of motivation are associated with spacing behavior and higher grades when measured during the post-survey, only one construct appeared associated with behaviors and outcomes when measured at pre-survey: affective interest. It may be that students' interest in this introductory STEM course may be the more important for predicting their choice to regularly engage with a course regardless. This emphasizes the critical role that interest plays in predicting students' choices in STEM-related fields in higher education, perhaps more so than expectancies or even other sources of task value (Renninger, Nieswandt, & Hidi, 2015). Fittingly, the work of Hulleman and colleagues (2010, 2017) has demonstrated the potential of UVIs to increase students' perceived interest in the course along with other expectancy-value constructs.

The patterns of association observed in the present study between motivation and behaviors also underscores important questions about the directionality of that relationship. One explanation for why pre-survey measures of motivation were not correlated with final grades for the course, whereas post-survey measures were, was that students do not have enough information about the course they will be taking to be able to predict what their motivation will actually be as the course goes on. Predicting behaviors on course-specific tasks through click data should be most accurate when students' self-reported motivation is judged with those specific tasks in mind. But the students in this class, many of whom have never taken an online course before, may have been unaware of how motivated they would be as the course went on. It is possible, then, that predicting students' behavioral engagement with a course from their baseline motivational measures can be best accomplished by surveying students after they have had one to two weeks to familiarize themselves with a course's weekly routine and calibrate their motivation.

An alternative explanation, though, is that the behaviors that students engage in during the course are what lead students to develop greater motivation. Even using the example of surveying students one to two weeks into a course, this effect could be at play. While we may argue that students are using that time to better calibrate their motivation for the course, these motivational changes may very well be happening as a result of the decisions to spend more time on the course during the first few weeks. More consistent time spent on the course may be creating opportunities to find value in the course, or simply leading students to reason that something they spend more time on must be more valuable.

The puzzle surrounding how motivation and behavior become more correlated over time have implications for what types of interventions should be prioritized. Whereas task-value interventions such as UVIs may be able to improve student's consistency of engagement in the course through motivation, "nudging" or implementation intention interventions seek to improve motivation and performance by improving students' consistency of engagement in the course (Baker, Evans, Li, & Cung, 2018). If one directional pathway were to reveal itself as the strongest, it would make a strong case for which interventions are best for driving motivation, behavioral engagement in the course, and performance. However, it is likely that these processes are mutually reinforcing, as has been shown in interventions focused on self-concept enhancement (Moller, Retelsdorf, Koller, & Marsh, 2011). Our own data suggest how this might be true. Greater interest at the beginning of the course may be leading some students to engage more consistently with the course, and this engagement in turn may be driving the growth of students' perceived competence, interest, attainment value, and utility value. Researchers conducting further work in this area would be also be wise to investigate the role of self-regulated learning in the trajectories of students' motivation throughout a course, although it is worth noting that students' self-reported self-regulation may also be poorly calibrated at the beginning of a course.

Issues with uncovering motivated behavior using click data

Although the lack of correlations between pre-survey measures of motivation and click behavior led us to conclude that students' pre-survey self-report data was poorly calibrated, more consistent associations may have appeared if we had generated "better" click measures. We specifically sought to generate click measures that would be theoretically associated with students' expectancies and values. Number of total clicks, for instance, was not especially strongly associated with course performance and was not associated at all with motivation. Clicks may occur because students are simply confused with how the course website works. Additionally, understanding the context of the specific course under study and the student population under study is also critical for identifying click measures that are most likely to signal motivated behavior. Although our data supports the idea that procrastination and cramming (the opposite of spacing) are negatively associated with grades, researchers studying online courses should be aware that many students select into online courses due to the amount of competing demands on their time (see Study 1). Students who decide to take a course despite commitments to work, family, and other courses may be highly motivated, but relatively unable to access the course every-other day. In our introductory course, among students who were mostly 19-year-old first-years, this seemed to pose less of an issue.

The future of this field would therefore benefit greatly from cognitive interviewing with students regarding how their course context and their personal contexts combine to determine what types of clicks signal motivated behavior. We believed that accessing “toughie problems” would be associated with perceived competence and higher value. However, a very small number of students accessed this page a very small number of times. The instructor later suggested that this may be because students print the page out at the beginning of the term. By sitting with students to discover how they navigate their course website, researchers will be better able to identify specific types of *course pages* that signal student motivation. Asking students about the *timing* of their course access will also shed light on what behavior is driven by motivation, such as whether late-night or before-the-deadline clicking is a signal that students are losing motivation for the course or have prioritized other courses ahead of this one. Furthermore, students can be asked about how their course activity *evolves over time*. If clicks during the first few weeks are caused by just trying to understand how to navigate a new course, it can guide researchers to exclude periods when clicks are not expected to be driven by motivation. Such work will be important for understanding how click data must be handled in order to parse out the difference between clicks that signal motivated behavior and clicks that don’t.

Conclusion

The science of targeted psychological interventions has shown a great amount of promise in improving students’ performance and closing achievement gaps, but increased scrutiny over for whom and under what circumstances these findings will work puts additional pressure on researchers in this field to describe a clear theoretical picture of how improving motivational beliefs can improve course performance. With the growth of online courses and the availability of click data, new opportunities have emerged to strengthen motivational theories by providing insight into the behavioral processes that may be linking motivational beliefs and performance outcomes. We provide insight into the types of click behaviors (specifically, spaced study behavior) that are associated with both motivational beliefs and performance in our sample and make recommendations for how future studies can ensure they generate relevant click measures of their own. More work should certainly be done to identify the role of self-regulation in these processes and the directionality between motivational beliefs and behavioral engagement in the course, but the tools to do so are more available than ever.

GENERAL DISCUSSION

The number of online courses are rapidly increasing in higher education despite concerns about their quality. Although online courses may offer students access to courses that they would have otherwise been unable to take, data from Study 1 (Modality Motivation) shows that many students who choose to take courses online could also be taking these courses in-person. Students opt into the OL version of courses despite their assertion that their goals and values for the course are largely similar to those of their F2F peers, yet still struggle to achieve as much as their F2F peers. Although the ideal situation for practitioners would be to work on identifying which students will thrive in either OL or F2F course formats, the data I provide reinforce the reality that students who take courses online perform worse, on average, than their F2F peers despite similar goals for achievement. Regardless of whether this is purely a function of selection effects (i.e., lower positive value for the course; higher cost and competing responsibilities), or that the OL course experience is simply inferior, comparisons of OL students' experiences with those of their F2F peers continue to demonstrate that the OL course experience must improve.

Motivational approaches to improving the online course experience

Although motivational processes are critical for understanding students' choices and performance, they are still understudied in the context of online courses. In these studies, I shed light on the role of motivation both in students' selection into online courses as well as their behaviors once they are in their online courses. Study 1 demonstrates that students' value for a course is indeed associated with students' decisions to select into online courses. Study 2 demonstrates that once this choice is made, the asynchronous nature of online courses creates barriers to developing a sense of belonging, which students admitted impacted their willingness to seek interactions with classmates or teachers. As seen in Study 1, the students who showed less motivation for the course and spent less time working in study groups were the ones who performed worse than their F2F peers. Given this fact, it should be especially troubling that the nature of online courses creates doubt in students' minds as to their classmates' and instructor's openness to being approached for help. Finally, Study 3 showed not only that students' interest in their courses is associated with better course grades, but also how this interest may be driving behavioral processes that produce better grades.

By taking a motivational approach, I was able to illuminate the processes by which OL students may find themselves underperforming and suggest effective ways to solve motivational issues unique to online courses. Study 1 showed that students who select into OL courses do so for different reasons, which in turn may result in different reasons for underperformance. Whereas some students select into OL courses because they have more competing responsibilities, greater opportunity cost, and may have less time to engage in study groups as a result, other students select into OL courses because they see less value in the course. Both groups underperform relative to their F2F peers, but we can now see that a one-size fits-all approach to helping students is unlikely to be as effective as providing different students overcome their respective challenges.

Recommendations for helping students with motivational were clearest when analyzing students' qualitative accounts of barriers to belonging in online courses. Although asynchronous online courses have fewer interpersonal interactions by their very nature, students described that the inability to see other students compounded the issue, creating additional uncertainty about whether reaching out to students or teachers would be welcome. But students were quick to mention changes that could remedy motivational issues specific to online courses. Sharing personal information through discussion activities, adding synchronous elements to the course, and encouraging the instructors to explicitly signal openness to their students' questions were relatively simple options that students suggested could make an important difference in their motivation to engage with peers and teachers in online courses.

Finally, identifying behavioral correlates of motivation suggests how psychological interventions may be able to encourage students to improve their course performance. Study 3 was one of the first Expectancy-Value studies to measure behavioral processes that could mediate the relationship between motivation and performance outcomes. After identifying the large association between spaced studying behavior and students' final grade, we can work backwards to understand the most appropriate motivational levers for encouraging that behavior. The relationships between motivational constructs and click behaviors will improve as our click measures become more sophisticated and in contexts where students' pre-course motivation is better calibrated. For now, we still see that student's affective interest towards students' subject of study is predictive of this engagement, suggesting that fostering interest may be especially important for promoting study behavior that will lead to better grades.

New measures for new contexts

A critical theme running through each study is the need to construct contextually-relevant measures of motivation. In Study 1, it did not become clear that OL and F2F students differed in their values until students' reasons for selecting the OL course helped identify groups of students whose choice was likely related to lower positive value. Conversely, measures of cost were not especially informative because students' answers were likely conflated with their chosen course modality. Students' qualitative reasons again helped by signaling students for whom opportunity cost would be higher, and indeed led me to identify a group that spent larger amounts of time on non-academic activities at the expense of academic activities, ultimately receiving lower grades.

In both cases, our understanding of the motivational differences between OL and F2F students were enhanced by a measure that specifically targeted the role of motivation in students' self-selection between the modalities.

In no study was the importance of context-specific measures more apparent than Study 2, in which an accurate assessment of students' course-level belonging was crippled by students' misinterpretations of items adapted from a school-wide context. The initial goal of the study was to quantitatively test whether the OL course affected students' belonging differently than it did in the F2F course. Although it has become common practice to adapt sense of belonging scales for use in different contexts, a qualitative investigation showed several reasons why researchers who do so are likely to produce misleading results. The study ended with no quantitative comparisons, but a much clearer understanding of how belonging is conceptualized in online courses and how it should be measured so that it is contextually relevant.

Finally, Study 3 showed the importance of measuring motivation using items that contextualized by the same level as the outcomes we are trying to predict. Students' pre-survey levels of motivation did not seem to correlate strongly with their behaviors. This may have been because their pre-survey answers of more motivated students didn't incorporate an understanding of what motivated behavior in on online course would look like. Although these items were worded to be specific to the course, motivational measures that ask about specific tasks that students will be required to do during the course may be an important new avenue to explore when trying to understand how motivation is associated with course performance.

Overall, I believe that these studies reiterate the urgency with which improving online courses must be improved and contend that the motivational approach that I have taken illuminate more about both the issues present in OL courses as well as potential solutions for fixing them. The different motivational processes I have highlighted here and the individualized approaches that may be needed to improve the OL experience mirror the promise of OL courses themselves: that an understanding of individual differences can be combined with new technologies to drive the personalization of education. There is a long way to go, but continuing to study motivational processes will certainly help improve the exciting marriage between an appreciation of students' individual differences and educational technology.

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APPENDIX A: STUDY 1 - MODALITY MOTIVATION REASONS BY COURSE

Table A.1

Table A.1 Introductory Engineering - Reasons for Choosing OL and F2F Courses

Online (n = 57)				Face-to-face (n = 272)	
11% - Learn Pref	**54% - Univ. Constraints**	**26% - Need Flex**	**16% - Pref. Flex**	**4% - Univ. Constraint**	**88% - Learn. Pref**
4% - Peer Interaction	53% - F2F Full	23% - Course Conflict	16% - General	4% - F2F req. for future	44% - General
4% - Self-regulation		2% - Commute			20% - Self-regulation
4% - Prof. Interaction		2% - General			16% - Peer interaction
3% - General					10% - Prof. Interaction
					7% - Prof. Lecture
					3% - Dislike OL

Table A.2

Table A.2 Advanced Anatomy - Reasons for Choosing OL and F2F Courses

Online (n = 61)				Face-to-face (n = 71)	
20% - Learn Pref	**0% - Univ. Constraints**	**28% - Need Flex**	**67% - Pref. Flex**	**15% - Univ. Constraint**	**87% - Learn. Pref**
8% - Pace Control		11% - Employment	34% - Commute	15% - F2F req. for future	35% - Self-regulation
7% - Self-regulation		11% - Commute	26% - General		30% - Prof. Interaction
3% - General		5% - General	7% - Employment		20% - Peer interaction
2% - Peer Interaction		3% - Course Conflict	3% - Family		14% - General
					10% - Prof. Lecture
					10% - Dislike OL

Table A.3

Table A.3 Introductory Chemistry - Reasons for Choosing OL and F2F Courses

Online (*n* = 126)				Face-to-face (*n* = 157)	
24% - Learn Pref	**21% - Univ. Constraints**	**23% - Need Flex**	**36% - Pref. Flex**	**1% - Univ. Constraint**	**97% - Learn. Pref**
8% - Pace Control	21% - F2F Full	13% - General	29% - General	1% - F2F req. for future	42% - General
8% - Self-regulation		8% - Course Conflict	5% - Commute		29% - Self-regulation
8% - General		1% - Employment	2% - Employment		15% - Prof. Lecture
1% - Dislike OL		1% - Family			9% - Prof. Interaction
1% - Peer Interaction					6% - Peer interaction
					6% - Dislike OL
					3% - Pace Control

Table A.4

Table A.4 Coding Scheme for Reasons for Choosing OL and F2F Courses

Main Themes	Subcategories	Definition	Key words/phrases	Sample Quote
Need Flexibility		Any answer that specifies a reason for why the flexibility is needed	"can't" ; "need" ; "interfered"	"I am unable to come to campus on the days the face-to-face class was offered."
	Employment	Work commitment is unchangeable, so can't take class in-person	"work" ; "conflict"	"Because I work full time during the week and would not be available to attend the in-person class due to my work schedule"
	Long Commute	Unreasonably far from campus to travel consistently	"far-away place"	"I live in San Diego and commuting to Irvine is too difficult."

	Course Schedule	A different course is taught at the same time as this course's in-person lecture	"same time" ; "conflict"	"Because the face-to-face one conflicts with the other course I am taking."
	Family	Family obligation completely prohibits taking course in-person	"family" ; "kids"	"I have to be home during the day to take care of my family."
Prefer Flexibility		Any answer about flexibility that indicates preference, but not necessarily need	"prefer" ; "like" ; "convenient"	"I decided to take online course because my time will be more flexible."
	Employment	Work commitment makes flexibility helpful for planning schedule	"work"	"I have work obligations, so it would be easier for me scheduling wise to have more freedom for when to take class."
	Long commute	The drive to campus could be made on a daily basis, but prefer avoiding it	"would rather not"	"I live 1.5 hours away from the school and would rather take it online than drive back and forth to come to class."
	Family	Desire to spend time with family/ better fulfill family obligations	"family"	"It is summer vacation and I was hoping online would make my schedule a little more flexible so that I could spend more time with my family."
Learning Preferences		Any answer that indicates they think this course will be better for their learning	"better"	"I like online classes better than in class."
	Dislike	If the student is choosing this course because of an unspecified *dislike* of the other course	"hated" ; "bad experience"	"The last time I took a science class online, it didn't end well. Face to face works better for me."
	Self-regulation	Concern that they will be less able to stay motivated or complete requirements in the other course modality	"distractions" ; "engagement"; "management"	"I don't feel that I can concentrate in the [other] version of the class." "More engaging."
	Pacing	Student prefers the pacing/ spread of lecture material, either for being spaced out (OL) or for being all at once (F2F)	"own pace" ; "space it out"	"I tend to do a little better in environments where I have the freedom to teach myself and move at a slower or faster pace."

Professor Interaction	Student likes to interact with or ask questions to professor in person	"active learning" ; "relationship" ; "ask"	"The professor is more accessible and I can ask him questions then and there is something in the material doesn't make sense."
Professor Lecture	Student likes to receive lecture while sitting in a classroom	"verbal" ; "lecture" ; "sit"	"It is easier for me to learn when a professor is lecturing. Verbal lectures help me remember the information more."
Peers	Student likes to interact or be around other students	"peers" ; "classmates"	"When a class is offered in-person there are more opportunities to form study groups with other classmates."
University Constraint	Student mentions a restriction imposed by the university		
F2F full	OL student says spots were full in the F2F course	"full"	"There was no more available spots for her face-to-face course."
Need F2F for higher degree	OL is not accepted for student's future program	"doesn't accept OL"	"Most med school and graduate schools require this course to be taken face to face."
Unclassified	Responses that do not qualify for above themes		
Unsure	When response is too short to be sure about classifying response		"Better."
Unaware	They admit they didn't know the other course was an option	"unaware" ; "didn't know"	"I did not know there was an online course."

APPENDIX B: STUDY 2 - QUALITATIVE CODING SCHEME AND RESULTS

Table B.1

Table B.1 Coding Scheme for Interviews

Codes	**Definition**	**Example**
Belonging attributes (a priori codes)		
acceptance	process of being received as adequate or suitable	"I could be myself"
respect/ care	action based on recognition of others' needs	"people in the group are loyal and care for me"
valued involvement	appreciation expressed by others for something one has offered	"People care whether I'm there or not"
"fit"	perception that one's context is well-suited for his or her own attributes	"I have a lot in common with this group"
Interpersonal interactions		
Common experience	Similarities perceived between one and others based on past experiences	"I really connected with these people and I can relate to them so well"
Interest-driven discussion	dialogue not centered on course content	"She talked to us a lot about her, like her family, kids, and their accomplishments"
Content-driven discussion	dialogue centered on course content	"People actually discuss what the TA's talking about"
Visibility of others	ability to see others/ otherwise sense their presence	"she's not physically there…so it's harder"
Other experiences		
Ability level	Process of judging how strong one's ability is	"my sense of belonging came more from knowing that I was supposed to be taking the class in general"
Ability demonstration	Showing one's ability in front of others in the class	"I have the right answer and I can explain it clearly, so I feel like I'm being utilized"

Table B.2

Table B.2 General Context: Case Dynamics Matrix Describing Belonging and its Antecedents

Type of interaction	Interacting with	Supports/ diminishes	Association with belonging	Sample Quote
Common experience	Peers	Supports	Acceptance "Fit" Valued involvement	"We share a lot of the same interests, we have a lot of the same goals…and we get more familiar and more comfortable with each other" (P1) "I really connected with these people and I can relate to them so well, and I just felt like we could be really really good friends for potentially a long time" (P4) "I like cartoons and video games. If I find somebody else that likes cartoons like me, I feel like I would fit in" (P6) "I felt a sense of belonging, a lot of communication, like they just accepted me. I was friends with everyone. I knew everyone personally" (P10) "So I guess having to see each other and having to interact with each other and work together to that extent to get the job done made me feel like I was part of their group"(P12) "It's like we're each fingers and if you put us together we make a fist/rock because we do everything together" (P14)
Interest-driven discussion	Peers	Supports	Acceptance Valued involvement	"Hanging out with like Intervarsity people, it was really fun and they're pretty open and like, accepting" (P2) "I'm in the robotics club there. Everybody else contributes and what I say matters" (P3) "I felt like other clubs weren't as friendly, more clique-y, less open, and the one I liked was less exclusive…I felt so welcomed and accepted" (P7) "It's like they care about you being there. It's not like you're this random person and a benchwarmer. That's where I feel like I belong because it's like they want me to be there" (P13)

Table B.3

Table B.3 F2F Classroom Context: Case Dynamics Matrix Describing Belonging and its Antecedents

Interpersonal interaction	Interacting with	Supports/ diminishes	Association with belonging	Sample Quote
Interest-driven discussion	Instructor	Supports	Respect/care "Fit"	"When our labs would finish early…[the instructor] would talk to us. She wouldn't just go on her phone; she would interact with her students."(P1) "Her words of advice that she'd give us were very meaningful to me. She talked to us a lot about her, like her family, kids, and their accomplishments. I can kind of relate to that. I understand what she was saying." (P9) "[The teacher] didn't really reprimand us for doing something wrong. In her eyes, there was nothing you could do wrong. You were only wrong if you didn't ask a question. So she definitely encouraged thinking outside of the box" (P11) "If someone missed a day, the teacher would ask what happened. She would definitely care, and you feel like you're not just another student there. You're important and you're loved" (P13)
Content-driven discussion	Peers	Supports	Valued involvement	"If people actually…actually discuss what the TA's talking about…where everyone's, like, sharing ideas" (P2)
Common experience	Peers	Supports	"Fit"	"They started talking about how closely they are tied with education and how it really matters to them. The same thing is applied in my culture" (P3)
Common experience	Peers	Supports	"Fit"	"Just having a lot of friends around me that are going through the same stuff, I'm motivated to actually do like well, and I felt really good, knowing that there is so many people on the same boat as me" (P10) "They're taking those courses because they want to go to graduate school and that aligns with what I want to do too, so in that sense I feel like I belong" (P15)
Ability demonstration	Instructor or Peers	Supports	Valued involvement	"She would have me demonstrate stuff when we would be learning how to cook something…people care about what you could offer" (P4) "What makes me feel like I belong in a group setting is if I have the right answer and I can explain it clearly, so I feel like I'm being utilized" (P6) "Anytime we would do an assignment, and there was a hard question that no one understood, the teacher would call on me and ask if I knew it. If the teacher had that expectation from me, it made me feel like I'm doing well and I belong here" (P8)
Ability level	Peers	Diminishes	Valued Involvement	"When I'm in science classes that are more competitive, it's tough. They're curved, so it doesn't foster a lot of growth and friendships" (P7)

Table B.4

Table B.4 OL Classroom Context: Case Dynamics Matrix Describing Belonging and its Antecedents

Interpersonal interaction	Interacting with	Supports/ diminishes	Association with belonging	Sample Quotes
(Lack of) visibility of others	instructor	Diminishes	Acceptance Valued involvement Respect/care	"You can't feel comfortable enough to ask them a question if you don't really see them ever and you don't know how they'll react to your question" (P1) "The teacher has to deal with so many students, and she's not physically there…so it's harder for the instructor to discern how different people might be doing better" (P8) "The teacher gave the impression that she was very busy and doesn't have time for questions because she would say we're college students and could figure it out" (P11) (P2)
Content-driven conversation	Peers	Supports	Valued involvement	"If there was extra credit or part of the assignment was you had to cooperate or collaborate with other students on group quizzes or projects, that really creates comradery" (P6) "If you have a lot of team projects and projects where students get to know one another, that will encourage students to help each other and care about the other student's success" (P13)
(Lack of) visibility of others	Peers	Diminishes	"Fit" Valued involvement Acceptance	"I really like surrounding myself with people who want to learn what I'm learning, where I can actually look at someone" (P3) "I feel like it's easier to make connections and friends in lecture, in a physical lecture hall, rather than online" (P4) "When you don't know anything but someone's name, it's kind of hard to assume like are they outgoing, would they even answer if I asked them any questions?"(P10) "I don't think it's necessarily what we would talk about because you can talk about the same things online so it wouldn't be that. I think it would be more about seeing the other person's emotions and reactions to what you say" (P15)
Ability level	None	Supports	"Fit"	"Knowing more about the subject ... you actually know what you're doing, so that will make you feel like you belong into that class. Rather than like you trying to learn like a whole new kind of thing" (P16) "Like I would say my belonging, my sense of belonging came more from knowing that I was supposed to be taking the class in general. It wasn't from like people interactions, like how I was talking about earlier" (P21)

Common experience	Peers	Supports	Valued involvement	"What brings people together the most is a common enemy I guess, so it would be something super-duper hard where you all have to figure out then you probably see a lot more activities" (P5).

Table B.5

Table B.5 Results of Cognitive Interviewing of PSSM in an Online College Course

1	**"I feel like a real part of this class"**		Conclusion
	Issues with comprehension of item	Students have different criteria for what being a part of a something means (presence, participation, achievement)	
	Information retrieved	Participation, interacting with teacher and classmates, more visual/ real-time discussion (3 times)	
	Context affecting interpretation	Notions of presence and participation can be different between OL courses and school-wide	Question is okay. Some minor general and context-specific issues affecting interpretation.
	Context affecting judgment	Rarely seeing instructor or peers degrades this. Discussion boards may play a larger role	
2	**"People in this class notice when I'm good at something"**		Conclusion
	Issues with comprehension of item	none	
	Information retrieved	Demonstrating ability during in-person tests and discussion board activities	
	Context affecting interpretation	Lack of interactions with classmates leads students to question whether "people" includes teachers and TAs as well	Question is okay. Some minor general and context-specific issues affecting interpretation.
	Context affecting judgment	Few opportunities to demonstrate performance to others reduces students' endorsement	
3	**"It is hard for people like me to be accepted in this class"**		Conclusion
	Issues with comprehension of item	Salience of peers and teachers differs between students. Acceptance not meaningful when coming from a figure presumably required to accept you (e.g., teachers). "People like me" can be interpreted as referring to gender or ethnicity	Question is okay. Some minor general and context-specific issues affecting interpretation.
	Information retrieved	Whether students and teachers are nice when you talk during discussion	

	Context affecting interpretation	none	
	Context affecting judgment	Anonymity limits opportunities of others to ostracize as well as opportunities to show acceptance. "People can't see my face"	
4	**"Other students in this class take my opinions seriously"**		Conclusion
	Issues with comprehension of item	none	
	Information retrieved	How other students react when you speak in class	
	Context affecting interpretation	Inability to see others' reactions limits ability to answer this question accurately.	Students' answers are admittedly based on little information
	Context affecting judgment	How other students react when you speak in class	
5	**"The instructor of this class is interested in me"**		Conclusion
	Issues with comprehension of item	none	Students' accuracy is diminished by conflation of experience with personal differences in seeking interactions with teacher
	Information retrieved	Quality of interactions with instructor	
	Context affecting interpretation	Interactions with instructor are crucial for answering this item, but OL courses do not require interactions. Students admit "I am not the type of person who goes to office hours"	
	Context affecting judgment	Lack of interactions with instructor degrades endorsement of this item	
6	**"Sometimes I feel as if I don't belong in this class"**		Conclusion
	Issues with comprehension of item	Disagreement over whether performance is an indicator of belonging	
	Information retrieved	Performance in class. Are group members taking what you say seriously? Is instructor responsive to you?	Students' answers may conflate academic and social belonging in classroom context more so than school-wide context
	Context affecting interpretation	Being in a class with prerequisites is a sign of belonging. "This seems like a question for middle school." Inability to see others makes it hard to judge fit relative to how others fit	
	Context affecting judgment	none	
7	**"I can talk to the instructor of this class if I have a problem"**		Conclusion
	Issues with comprehension of item	none	Question is okay. Some minor general and

	Information retrieved	Instructor effort to reach out to students or how instructor responds to students' questions	context-specific issues affecting interpretation.
	Context affecting interpretation	Disagreement over whether teaching assistants count as instructors	
	Context affecting judgment	Lack of regular scheduled interactions with instructor may lead to perception that teacher doesn't care and/or doesn't have time for students	
8	**"People in this class are friendly to me"**		<u>Conclusion</u>
	Issues with comprehension of item	none	
	Information retrieved	Do students respond to each other in discussions/ discussion boards more or less friendly than they do to others	
	Context affecting interpretation	Students are less likely to look to make friends in OL courses, leaving them uncertain about expectations for what constitutes friendly treatment	Question is okay. Some minor general and context-specific issues affecting interpretation.
	Context affecting judgment	There are few opportunities for students to be either mean or friendly	
9	**"The instructor of this class is/are not interested in people like me"**		<u>Conclusion</u>
	Issues with comprehension of item	"People like me" can be interpreted as referring to gender or ethnicity	
	Information retrieved	Does instructor treat student differently from others	
	Context affecting interpretation	Students do not observe instructor communication with other students, limiting students' ability to answer this question. Item may be skipped if there are no relevant experiences.	Students' accuracy is diminished by lack of information about how instructor interacts with other students
	Context affecting judgment	Students cannot really observe discrimination or differential treatment even if it is happening, leading most to reject this statement.	
10	**"I am included in lots of activities in this class"**		<u>Conclusion</u>
	Issues with comprehension of item	Hard to define what an activity is	
	Information retrieved	Considering the number of activities available, are you included as much as others. Item may be skipped if there are no activities	Students' accuracy is diminished by lack of information about how instructor interacts with other students
	Context affecting interpretation	OL courses often have few, if any collaborative activities. High response may come because students simply don't feel excluded.	

	Context affecting judgment	none	
11	**"In this class, I am treated with as much respect as other students"**		<u>Conclusion</u>
	Issues with comprehension of item	none	
	Information retrieved	Teacher considered more than peers. Whether teacher presents opportunities fairly or is disparaging relative to other students. How quickly students' questions are answered relative to those of other students	
	Context affecting interpretation	Peers not considered because peers do not interact. Lack of insight into how teacher treats other students leaves students with little information on which to make this decision	Students' answers are admittedly limited based on lack of information about how instructor interacts with other students
	Context affecting judgment	Lack of information to the contrary leads students to endorse item highly	
12	**"I feel very different from most other students in this class"**		<u>Conclusion</u>
	Issues with comprehension of item	none	Students' answers are admittedly limited based on lack of information about how they compare to other students
	Information retrieved	comparisons with peers	
	Context affecting interpretation	Most information available on which to compare is academic	
	Context affecting judgment	Lack of information to the contrary leads students to endorse item highly	
13	**"I can really be myself in this class"**		<u>Conclusion</u>
	Issues with comprehension of item	none	
	Information retrieved	Whether or not your peers accept you	
	Context affecting interpretation	Feeling that you can be yourself is endorsed not because you feel accepted by your peers, but rather because the nature of OL course gives peers few opportunities to show that they don't accept you	Question is interpreted differently in online contexts due to few interactions with peers.
	Context affecting judgment	Lack of interactions with classmates reduces fear of judgment from others	
14	**"The instructor in this class respects me"**		<u>Conclusion</u>

	Issues with comprehension of item	none	
	Information retrieved	Interactions with instructor	
	Context affecting interpretation	Whether norms of interactions in online courses change what it means to be respected. Students do not expect instructor to engage with them individually	Question is affected by context, changing the criteria that signals respect from the instructor
	Context affecting judgment	Lack of disrespect leads to high endorsement of this item, despite the absence of interactions signaling respect	
15	**"People in this class know I can do good work"**		Conclusion
	Issues with comprehension of item	none	
	Information retrieved	Whether students, instructors, and TAs have observed ability through test scores	
	Context affecting interpretation	Because only instructors and TAs can see performance, uncertainty whether answer should be based on instructor or classmate perceptions	Question is okay. Some minor general and context-specific issues affecting interpretation.
	Context affecting judgment	Lack of interactions with classmates reduces students' endorsement of this item	
16	**"I wish I were in a different class"**		Conclusion
	Issues with comprehension of item	none	
	Information retrieved	Desire to be in another version of this class due to time of the other class or modality of the other class	
	Context affecting interpretation	Interactions with classmates and teachers are actually not a consideration because there are so few interactions with classmates	Information retrieved is not relevant to sense of belonging in the class.
	Context affecting judgment	Students specifically in OL be more likely to endorse this because they often wanted to be in the F2F version, but it was full.	
17	**"I feel proud of belonging to this class"**		Conclusion
	Issues with comprehension of item	none	Students do not report feeling pride as an emotion associated with the classes they are in
	Information retrieved	Is this class perceived as special relative to other classes?	
	Context affecting interpretation	Students unsure of where pride in a class would come from. Having an outstanding teacher was suggested	

	Context affecting judgment	none	
18	**"Other students in this class like me the way I am"**		Conclusion
	Issues with comprehension of item	none	
	Information retrieved	Negative reactions from classmates when posting to course page	Response may be based on a lack of negative experiences rather than presence of positive experiences
	Context affecting interpretation	Lack of interactions led to uncertainty over whether this item should be considered true if other simply don't care to notice each other	
	Context affecting judgment	Lack of negative experiences with others taken as a sign that other students do indeed like them the way they are	

APPENDIX C: STUDY 3 – SURVEY MEASURES

Table C.1

Table C.1 Table of Survey Measures used to Measure Course-level Expectancies and Values

		Cronbach's Alpha	
Item	**Response Scale**	**Pre-survey**	**Post-survey**
Perceived Competence		**0.89**	**0.93**
I am confident that I will do well in this course.	1=Not at all true -7=Very true		
I expect to get a good grade in this course.	1=Not at all true -7=Very true		
I believe that I can be successful in CHEM 1A.	1=Not at all true -7=Very true		
I expect to do well in CHEM 1A this quarter.	1=Not at all true -7=Very true		
Competence Valuation		**0.77**	**0.79**
It is important to me to do well in CHEM 1A.	1=Not at all true -7=Very true		
I want to do well in this course.	1=Not at all true -7=Very true		
Interest - Affective		**0.93**	**0.94**
I'm really looking forward to learning more about chemistry.	1=Not at all true -7=Very true		
To be honest, I just don't find chemistry interesting.*	1=Not at all true -7=Very true		
Chemistry fascinates me.	1=Not at all true -7=Very true		
I think the field of chemistry is very interesting.	1=Not at all true -7=Very true		
I'm excited about chemistry.	1=Not at all true -7=Very true		
I enjoy learning about chemistry.	1=Not at all true -7=Very true		
Interest - Behavioral		**0.81**	**0.84**
I like to read about chemistry topics in my spare time.	1=Not at all true -7=Very true		
I enjoy figuring out answers to chemistry problems.	1=Not at all true -7=Very true		
I enjoy explaining chemistry ideas that I learn about to my friends.	1=Not at all true -7=Very true		
If I had plenty of time, I would take a chemistry class outside of my major requirements just for fun.	1=Not at all true -7=Very true		

Note. * Item was reverse coded.

Table C.1 (Continued)

Table of Survey Measures used to Measure Course-level Expectancies and Values

		Cronbach's Alpha	
Item	**Response Scale**	**Pre-survey**	**Post-survey**
Attainment Value		**0.88**	**0.92**
The study of chemistry is personally meaningful to me.	1=Not at all true -7=Very true		
The study of chemistry is personally important to me.	1=Not at all true -7=Very true		
Learning about chemistry will help me become the person I want to be.	1=Not at all true -7=Very true		
Learning about chemistry is relevant to how I see myself in the future.	1=Not at all true -7=Very true		
Utility Value		**0.81**	**0.84**
Chemistry can be useful in my everyday life.	1=Not at all true -7=Very true		
I think what we are learning in this course is important.	1=Not at all true -7=Very true		
I think the material we study in CHEM 1A is useful for everyone to know.	1=Not at all true -7=Very true		
CHEM 1A is important to my future.	1=Not at all true -7=Very true		
Prosocial Utility Values		**0.81**	**0.89**
Chemistry can be useful for helping others.	1=Not at all true -7=Very true		
Chemistry can be useful for promoting human health and well-being.	1=Not at all true -7=Very true		
Chemistry can be useful for finding solutions to problems people face in their everyday lives.	1=Not at all true -7=Very true		
Behavioral Intentions		**0.91**	**0.94**
Do you plan to obtain a degree or certificate in the chemical and health sciences?	1=Definitely will not - 7=Definitely will		
Do you plan to pursue a career in the chemical and health sciences?	1=Definitely will not - 7=Definitely will		

Note. * Item was reverse coded.