Always Something There to Remind Me: The Role of Nudging in Assignment Submission

Carolyn Anne Bancroft Andrews

Brigham Young University

Follow this and additional works at: https://scholarsarchive.byu.edu/etd

Part of the Education Commons

BYU ScholarsArchive Citation
https://scholarsarchive.byu.edu/etd/8967

This Dissertation is brought to you for free and open access by BYU ScholarsArchive. It has been accepted for inclusion in Theses and Dissertations by an authorized administrator of BYU ScholarsArchive. For more information, please contact ellen_amatangelo@byu.edu.
Always Something There to Remind Me: The Role of Nudging in Assignment Submission

Carolyn Anne Bancroft Andrews

A dissertation submitted to the faculty of Brigham Young University in partial fulfillment of the requirements for the degree of Doctor of Philosophy

Heather M. Leary, Chair
Ross A. Larsen
Royce M. Kimmons
Benjamin A. Motz

Department of Instructional Psychology and Technology
Brigham Young University

Copyright © 2020 Carolyn Anne Bancroft Andrews
All Rights Reserved
Always Something There to Remind Me: The Role of Nudging in Assignment Submission

Carolyn Anne Bancroft Andrews
Department of Instructional Psychology and Technology, BYU
Doctor of Philosophy

Online learning continues to widen in popularity by providing greater access and flexibility in time and location the learning occurs. There is a shift in the profile of a traditional college student. Almost half of the students who are enrolled in online classes are 24 or older and tend to carry increased time constraints due to external factors such as employment and family responsibilities. Student retention remains a concern for institutions. Many students lack the skills necessary to be successful in the online platform. Research reports self-regulation learning skills are essential. Providing reminders for an upcoming assignment may give needed scaffolding. Intervention research is sparse in this domain.

This dissertation is written in a three journal article format. Article 1 is a systematic review of the literature focused on the use of auto-reminders or nudges as an intervention in higher education. This review employed systematic criteria to allow rigorous analysis, critique, and synthesis of related literature search. The search strategy focused on auto-reminder interventions in online classes. Keywords were searched in each of the databases (n = 3) ERIC, PsychINFO, and Scopus. Articles (n = 291) were added to Zotero. Three themes emerged. Health (n = 3), procrastination (n = 2), and motivation (n = 4) for a total of 9 articles. Findings reveal that the health field is successful in nudging their patients into better health practices; however, published research in the education field is lacking. Building on findings from Article 1, Article 2 sought to address nudging in the education field. Instructors volunteered to use a nudging app to remind students of upcoming assignments in their courses (n = 158). Enrolled students were invited to download a mobile app. This study attempted to create a profile of students who used the app. Findings reveal that students who used the app were more likely to be Asian and International and had higher scores on college entrance exams. App users had slightly lower prior GPAs, despite having earned significantly more credits in college at the time of the study. Building on Article 2, Article 3 explored the behavioral interaction with app users tapping (n = 443) and not tapping (n = 1102) of push notifications. Findings reveal app users submit more assignments and have higher average assignment grades when they tap the notifications. Assignment weight is generally lower, and there is generally less time between the time the student submitted the assignment and the assignment deadline. When push notifications are not tapped, assignment weight is higher, and there is more time between submission and deadline. More research is needed to determine push notification behavior.

Keywords: self-regulation, nudge, online learning, intervention
ACKNOWLEDGMENTS

I would like to express my sincere gratitude to the many people who supported me throughout this incredible journey. First, to my chair, Dr. Heather Leary, who has been an incredible mentor, cheerleader, and cherished friend. Her patience and encouragement have kept me on track to the finish line. I would like to thank three of the most exceptional committee members. Dr. Royce Kimmons has guided me through a complicated writing process and has been a continual source of feedback. Dr. Ross Larsen has been an incredible mentor and friend. Ross is always willing to help me understand statistics and does so in a most respectful way. Dr. Ben Motz has encouraged me to keep learning and improving.

To my fellow graduate program friends, who love and support each other. Thank you for listening and being a voice of reason. I would also like to acknowledge the many BYU faculty I have learned from - whose compelling examples have inspired me to reach new heights. I am privileged to associate with the most exceptional faculty at Brigham Young University. I could not imagine being able to complete this journey without the support of my Brigham Young University, Division of Continuing Education family. From my deans to my co-workers. Their constant love, support, and encouragement have been immense. I have often considered how fortunate I am to be surrounded by such support. Thank you.

I am grateful for the student employees I have had the privilege to work with over the years. Their perseverance amidst challenges has inspired me. Their encouragement has been inspiring. My “work kids” will always have a special place in my heart. I have been unbelievably blessed by the love and support of my family. I don’t even know where to start. I am speechless. To my parents, who have always believed their children could do anything. Their strong work ethic, constant service, love for God, and value for lifelong learning encourages me to develop
my talents and to be a better servant of God. To my seven siblings, they are pure gold. They will never know just how much their support and encouragement has meant to me. I have felt it from each one of them. I have profound gratitude for my husband, Tom, who just keeps on keeping on as we navigate this life together with our five beloved children. His behind-the-scene support has been incredible. He has kept juggling multiple responsibilities to support me in this endeavor. To my five kids who have been patient with a mom who has had more homework than they could imagine. Thank you for your sacrifice. Remember, education is worth the sacrifice. Go for it!

I would like to acknowledge a grandfather who believed in me so much that he would frequently tell me to continue to earn a Ph.D. Countless times. I would say to him I would not. Almost two decades later, I stand corrected. Thank you, Grandpa Prior.

Finally, I express my gratitude to God. I am grateful to have been blessed with a thirst for knowledge and the strength to persevere. I am humbled to have had earthly and heavenly angels sent, from a loving Heavenly Father, to buoy me in the most challenging times.
TABLE OF CONTENTS

TITLE PAGE ................................................................................................................................... i

ABSTRACT .................................................................................................................................... ii

ACKNOWLEDGMENTS ............................................................................................................. iii

TABLE OF CONTENTS ................................................................................................................ v

LIST OF TABLES ......................................................................................................................... ix

LIST OF FIGURES ........................................................................................................................ x

DESCRIPTION OF RESEARCH AGENDA AND STRUCTURE OF DISSERTATION ........ xi

Article 1: Literature Review ................................................................................................... xi

Article 2: Research on Characteristics of Students Who Opt-In for Nudging App ............... xii

Article 3: Research on Student Response to Nudges............................................................ xii

ARTICLE 1: Auto-Reminder Support for Online Learners: A Systematic Literature Review..... 1

Abstract ........................................................................................................................................... 2

Introduction ..................................................................................................................................... 3

Literature Review ........................................................................................................................ 4

Characteristics of Online Learners ......................................................................................... 4

Readiness for Online Learning ................................................................................................. 6

Self-Regulated Learning ........................................................................................................... 8

Learner Support ........................................................................................................................ 9

Nudge ........................................................................................................................................ 9

Domains .................................................................................................................................. 11

Persuasive Technologies ......................................................................................................... 12

Mobile Application Usage .................................................................................................... 12
LIST OF TABLES

Article 1

   Table 1  Auto-Reminder Support for Online Learners Keyword Search .................. 16
   Table 2  Inclusion Criteria ....................................................................................... 17
   Table 3  Definitions of Grey Literature and Published Study .................................. 18
   Table 4  Exclusion Criteria ....................................................................................... 19
   Table 5  Research Categories for “Auto-Reminder Support” .................................. 21

Article 2

   Table 1  Socio-Demographic Characteristics of Boost Users and No Boost Users .... 49
   Table 2  Academic Performance of Boost Users and No Boost Users .................. 50

Article 3

   Table 1  Student Response to BoostApp Push Notifications ................................. 75
LIST OF FIGURES

Article 1

Figure 1. Flow diagram of papers included in the review............................................. 20

Article 3

Figure 1. Representation showing an assignment push notification. ............................... 72
DESCRIPTION OF RESEARCH AGENDA AND STRUCTURE OF DISSERTATION

This dissertation, *Always Something There to Remind Me: The Role of Nudging in Assignment Submission*, is written in a multi-article format. This format reflects traditional dissertation requirements for submission to the university and conforms with journal publication content, length, and formatting requirements. References used for each article are at the end of that section. The appendix contains the Institutional Review Board (IRB) permission to analyze Indiana University's institutional de-identified aggregate data obtained through passive data collection.

In the first section of this manuscript, I provide an introduction and rationale for the dissertation. This dissertation includes three journal-ready articles: first, a systematic literature review, followed by two research studies as briefly described below.

**Article 1: Literature Review**

In the first section, I provide a systematic literature review, which synthesizes research findings related to the use of auto-reminders as an intervention. It considers literature published between 2008 and 2019 focused on auto-reminder interventions in online classes. The search criteria included keywords associated with delivery mode, interventions, and communication methods. In all, there were nine articles included. Auto-reminders or nudges have been very successful in the medical field, with few studies published from higher education. Contributions from the medical field have broad applicability. I propose that higher education focuses on publishing intervention research. This article will be submitted for publication and is formatted to meet the journal's requirements. I believe this paper will make a unique contribution to educational support services because it is the first systematic literature review that focuses explicitly on the use of auto-reminders as a form of a nudge.
Article 2: Research on Characteristics of Students Who Opt-In for Nudging App

In the second section, I provide the empirical research article, *Investigation of Student Characteristics Who Opted In to Use Boost Mobile App as an Educational Support Service*. This study explored the characteristics of students who opted-in to use an automated student support mobile app and compared the characteristics of non-Boost users. Findings reveal that opt-ins are farther along in their studies and slightly lower performing than their peers who did not opt-in. A profile of Boost users will help university administration, student support services, and instructors make data-informed decisions on optimal use of Boost. This article has been submitted and is under review for publication and is formatted to meet the Journal of Teaching and Learning with Technology (JoTLT) requirements. I believe this paper will make a unique contribution to the field of educational support services as it is the first study to create a profile of students in higher education who opt-in to use a nudging tool.

Article 3: Research on Student Response to Nudges

In the third section, I include a second empirical research article, *Exploratory Study of Student Response to Boost App Push Notifications*, which synthesizes research findings related to the context around students tapping on the push notification reminder when an assignment deadline is approaching. Researchers tracked student (1) submission rate; (2) submission time; (3) assignment weight; and (4) percent score and compared whether students had tapped or not tapped push notification reminders. Analysis reveals Indiana University Boost mobile application users submit more assignments and have higher average assignment grades when they tap the notifications. Assignment weight on final grade was generally lower, and there was usually less time between the time the student submitted the assignment and the assignment deadline.
In contrast, when push notifications were not tapped, the weight of the assignment was higher. There was also more time between submission and the deadline. This article will be submitted for publication and is formatted to meet the journal's requirements. I believe this paper will make a unique contribution to the field of learning sciences because it is the first study to explore student responses to push notifications as nudges to submit assignments.
ARTICLE 1:

Auto-Reminder Support for Online Learners:

A Systematic Literature Review

Carolyn Andrews

Brigham Young University
Abstract

A systematic literature review was conducted on auto-reminder support for online learners in higher education. Literature published between 2008 and 2019 focused on auto-reminder interventions in online classes were included. The search criteria included the terms. In all, there were nine articles included. Results for main outcomes auto-reminders or nudges have been very successful in the medical field, with few studies published from higher education. Contributions from the medical field have broad applicability. We propose that higher education focuses on publishing intervention research.

*Keywords*: self-regulation, nudge, online learning, intervention
Introduction

As the postsecondary online student growth rate has steadily increased, online education continues to widen in popularity. To put this into context, in 2016, an estimated 32 percent of students in higher education in the United States were enrolled in at least one distance education course equating to 6.3 million students, a growth rate of 5.7 percent since 2012 (McFarland, 2019). Interestingly, only 0.7% of all distance students are international, living outside of the United States (Seaman, Allen, & Seaman, 2018).

With steady growth, a majority of the online enrollments, approximately 68.9%, appear to be concentrated in public four-year institutions of higher education. This proportion is more significant than the number of online students within any other sector of higher education as private non-profit institutions enrolled 13.1% and private for-profit institutions enrolled 18% (Seaman et al., 2018). Means, Toyama, Murphy, Bakia, and Jones (2010), assert that this popularity is due to the potential for increased flexibility, particularly for non-traditional students. Increasingly, students are including a mix of online and in-person courses rather than entirely online or entirely in-person (Glazier, Hamann, Pollock, & Wilson, 2019).

Improving student retention rates has been an issue of concern to higher education for many years. With this virtual explosion, online learning has come under increased scrutiny. There has been considerable attention focused on students’ ability to succeed in online courses. Although many students are considered digital natives or “native speakers” of the “digital language of computers, video games, and the Internet” (Prensky, 2001, p. 1), this is not a guarantee for success. It may be taken for granted that today’s digital natives will harness the technology and be successful. Still, there are other critical success factors to consider, in addition to technological ability.
Attrition is a concern for all higher education systems. Online courses typically have a significantly higher attrition rate compared to in-person classes, potentially impacting retention and graduation rates (Jenkins, 2012). Despite concerns of attrition, in 2014, Allen, Seaman, and Seaman (2015) report that online education is part of the critical long-term strategy at 70% of higher education institutions. These institutions view online learning as a solution to issues with classroom space, increased educational costs, and an opportunity to allow for flexibility for students (Hart, Friedman, & Hill, 2015).

This explosion in online learning has encouraged students to take an active role in their learning (Ituma, 2011). However, many learners are unprepared for online work. The student experience in online classes differs from traditional in-person courses, and patterns of engagement seem to change between the two environments (Hullinger & Robinson, 2008). Otter et al. (2013) report that students in fully online classes felt more disconnected from their peers and instructors. Students felt more responsibility to be self-directed and sensed they received less help from their instructor. Students can also feel intimidated by the technological expectations of the online learning environment, particularly if they start without sufficient technical knowledge or support (Holley & Oliver, 2010; Perris & Zhang, 2004).

**Literature Review**

Significant research in online learning has focused on a range of topics pervasive to success in the online learning environment. Key topics are included in the following section.

**Characteristics of Online Learners**

Online classes provide greater access to higher education, particularly for students who balance family, work, and school responsibilities (Aslanian & Clinefelter, 2013; Brinkerhoff & Koroghlanian, 2007; Jaggars, 2014; Wyatt, 2005). Convenience is a major draw for diverse
populations of students with a wide range of needs that the traditional education model is unable to meet. This includes students juggling work and family responsibilities, and disadvantaged students, such as low-income, minority, and first-generation students. These students often have access, and resource constraints due to family commitments (Hiltz & Shea, 2005), work responsibilities (Dutton, Dutton, & Perry, 2002; Hiltz & Shea, 2005), financial limitations (Leasure, Davis, & Thievon, 2000), and geographical barriers (Dutton et al., 2002) compared to their non-disadvantaged peers. However, non-traditional students have always required flexibility. This flexibility was found in night classes, weekend seminars, and correspondence courses before the introduction of online classes (Cavanagh, 2012). Indeed, many students may be attracted to online classes for other reasons such as participating in extracurricular activities, employment opportunities, or to allow for a social life. Students seize the affordances an online education has to offer (Beqiri, Chase, & Bishka, 2010; Bocchi, Eastman, & Swift, 2004). However, availability and convenience do not translate to success as an online learner.

Increasingly, online students are enrolled in mix-modalities. Cavanagh (2012) explains that “even classically traditional students at classically traditional institutions” frequently require “nontraditional flexibility to meet their educational goals” (p. 216). It is noteworthy that the terms “traditional” and “non-traditional” are increasingly arbitrary with the ubiquity of online learning on college campuses.

The flexibility of online courses can be particularly beneficial for students who live with challenging cognitive disabilities including developmental (autism, ADHD, etc.), mental health (depression, anxiety, etc.) or acquired (brain injuries) disabilities that can be limiting to a student’s success in a traditional in-person classroom environment (Cinquin, Guitton, & Sauzeon, 2018). Introverted or more naturally reserved students are often hesitant to share ideas
in a face-to-face classroom setting. The social anonymity in online courses can encourage all
students to participate of their own volition and on their terms (Dzubinski, 2014; Hewitt, 2005),
and pre-course instructional activities (orientation for online learning prep course) can help
novice learners become acquainted with online learning expectations (Mykota & Duncan, 2007).

Online students enrolled at an institution of higher education are more likely to be 25 or
older, married with children, attending school part-time, and a full-time employee (Jaggers &
Xu, 2013; Ortagus, 2017; Nachazel, & Hannes, 2011). These students likely have academic
needs that differ from their traditional in-person counterparts, such as time and location
constraints.

Students who lack self-discipline or self-direction are characterized as dependent learners
and are at a higher risk of failing in online courses, leading to course withdrawal (Wintling,
2012). Lee and Choi (2011) found that characteristics such as age and gender do not directly
correlate with drop-out rates. Instead, academic background, skills, and relevant online
experience are more reliable indicators of a student’s readiness for learning and potential online
success.

Readiness for Online Learning

Various personal factors can influence student readiness for online learning. Readiness
or sometimes referred to as e-readiness, is defined as the measure of the degree to which a
community [student] may be eager and prepared to benefit from information and communication
technologies (ICT) (Dada, 2006). Readiness surveys are often used to determine whether a
student is at-risk for failing or dropping out. In 2002, a study concluded that 60% of institutions
used readiness surveys for their online students and that the six primary underlying constructs
examined were computer skills, time management, motivation, academic skills, online delivery,
and learning skills (Kerr, Rynearson, & Kerr, 2003). Another study concluded that student characteristics obtained by readiness surveys were better predictors of differential online rather than in-person performance (Samuels & Wladis, 2016).

The purpose of online readiness surveys is for students to self-assess competencies, where they may struggle particularly with the flexibility of an online environment, as opposed to in-person learning. However, a recent study concluded that online readiness surveys could discourage students from enrolling in online classes even if there was no increased risk of “poor outcomes online” (Samuels & Wladis, 2016). Ultimately, surveys are not a predictor of student success in an online environment. Institutions should use caution when using surveys and should help students know how to interpret the findings (Samuels & Wladis, 2016).

Regardless of whether a student is traditional or non-traditional, a key factor shaping the effectiveness of the online learning environment is the degree of the student’s readiness (Artino, 2009; Galy, Downey, & Johnson, 2011; Kruger-Ross & Waters, 2013). Identifying the skills required for successful online learning and adapting to this different way of learning can be challenging for students (Luyt, 2013; Mayes, Calhoun, Murray, & Zahid, 2011). The learners’ technical skills related to computers and the Internet (Peng, Tsai, & Wu, 2006), including perceptions and attitudes toward the Internet (Tsai, & Lin, 2001), cultural and language backgrounds (Luyt, 2013), and time management skills (Hill, 2002; Roper, 2007) are considered paramount for learners’ readiness to participate in online courses. Researchers have also noted that technical skills involving computers and the Internet are related to learners’ performance in Web-based learning environments (Peng et al., 2006).

Hung, Chou, Chen, and Own (2010) argued that there are five dimensions of readiness, including self-directed learning, motivation for learning, computer and Internet self-efficacy,
online communication self-efficacy, and learner control. Self-efficacy is the ability “to organize and execute the courses of action required to produce given attainments” (Bandura, 1997, p. 3). Internet self-efficacy includes not merely performing some “Internet-related tasks” such as “uploading or downloading files” but rather the ability to apply “higher-level skills such as troubleshooting problems” (Hung et al., 2010, p. 4).

Even though many students are not prepared to learn online, they are still enrolling in online courses. One potential indicator of readiness for online learning is a student’s ability to complete tasks on time. Not completing tasks on time is often attributed to academic procrastination, defined as intentionally delaying schoolwork that must be completed (Schraw, Wadkins, & Olafson, 2007). Balduf (2009) found that poor time management or academic procrastination contributed to academic underachievement. Results from Michinov, Brunot, Behoc, and Juhel’s (2011) study revealed that high-procrastinators’ desire to drop-out spiked earlier and more frequently throughout the semester than low-procrastinators. Self-regulated learning, which can increase a student’s ability to complete tasks on time, is essential for students enrolled in online classes and is critical to overall student success.

**Self-Regulated Learning**

Zimmerman and Schunk (1989) define self-regulation as a student’s “self-generated thoughts, feelings, and actions, which are systematically oriented toward attainment of their goals” (pg. 3). Self-regulated students are typically self-starters, displaying persistence on learning tasks, are confident and strategic in overcoming problems, and self-reactive to task performance outcomes (Zimmerman & Schunk, 1994).

Indeed, self-regulated learning requires the learner’s active effort in monitoring their study habits (Bjork, Dunlosky, & Kornell, 2013; Fernandez & Jamet, 2016). Pintrich (2000)
defined self-regulated learning as “an active, constructive process whereby learners set goals for their learning and then attempt to monitor, regulate, and control their cognition, motivation, and behavior, guided and constrained by their goals and the contextual features in the environment” (Pintrich, 2000, p. 453). Learners who lack these skills often need support until these skills are well-developed.

**Learner Support**

Learner support is grounded in Vygotsky’s sociocultural theory and the related principle of the zone of proximal development (Eun, 2019; McLoughlin & Marshall, 2000). The zone of proximal development (ZPD) has been defined as "the distance between the actual developmental level as determined by independent problem solving and the level of potential development as determined through problem-solving under adult guidance, or in collaboration with more capable peers" (Vygotsky, 1978, p. 86). Vygotskian theory asserts that with appropriate assistance or skillful tutoring, a student can achieve a specific task. This scaffolding supports the student as they develop through the ZPD. Support gradually fades until it is no longer necessary, and the student is self-sufficient. This theory provides a foundation for how technology can be seen as a skillful tutor to nudge students’ behavior.

**Nudge**

While studies concur that autonomy is necessary for self-regulation, there are ways to nudge students in the right direction while not compromising their independence. Borrowing from public policy research, there has been significant success with various applications of nudges. Notably, the most prominent of successes is the use of defaults to increase enrollment in defined contribution retirement savings plans (Madrian & Shea, 2001).
Rooted in behavioral economics, Nudge theory (Thaler & Sunstein, 2008) argues that positive reinforcement and indirect suggestions can influence behavior in significantly impactful ways. Thaler and Sunstein (2008) define a nudge as “any aspect of the choice architecture that alters people’s behavior in a predictable way without forbidding any options or significantly changing their economic incentives. To count as a mere nudge, the intervention must be easy and cheap to avoid” (p. 6). Central to Nudge theory is choice architecture; how options are presented matters.

Coined by Thaler and Sunstein (2008), choice architecture refers to influencing choice by “organizing the context in which people make decisions” (Thaler, Sunstein, & Balz, 2013 p. 428). In this way, change is enabled by designing choices that encourage better choice-making. Hausman and Welch (2010), noted that “nudges are ways of influencing choice without limiting the choice set or making alternatives appreciably more costly in terms of time, trouble, social sanctions, and so forth. They are called for because of flaws in individual decision-making, and they work by making use of those flaws” (p.126). Influencing choice-making is one of the functions of choice architecture. However, individual choice preferences are not always in alignment with socially optimal outcomes.

Changing how an individual evaluates the costs and benefits of different choice outcomes is another function of choice architecture. Madrian (2014) identified several behavioral economic tools a choice architect can use. Such applications include the use of reference points, framing, gain/loss, ordering effects, structural presentation, and social comparison. These same principles have been applied in other domains such as marketing and healthcare.
Domains

Nudges are present in many fields but are often different in form and can be seen in various applications such as email, fliers, mailers, text messages, push notifications, ads on TV, radio, and Spotify. Certain domains have leveraged nudges, such as healthcare. For example, many medical offices send Short Message Service (SMS) messaging to remind patients of upcoming appointments. Pharmacies send SMS and phone call alerts when a prescription is available for a refill. Consumers respond to the messaging with a confirmation or decline. Technology like FitBit aimed to increase steps, an Apple Watch nudges to get up and move, apps used to track the amount of water consumed are rooted in behavioral science and technology. Even SMS technology is enhancing medical educational interventions. The impact from these nudges ranges from high stakes (life and death) to low (brand of cereal to buy or tracking the daily amount of water consumption). Studies indicate that interactive computing could change consumers’ attitudes and behavior concerning their healthcare management, as this could reach a wider audience.

Education policy researchers capitalized on behavioral economic nudging literature and utilized similar practices their campaign on college access. In their most recent working paper, Page, Sacerdote, Goldricks-Rab, and Castleman (2019) aimed to increase the number of Free Application for Federal Student Aid (FAFSA) and college persistence. However, results from this study were not promising despite the rising costs of college and marginalized students attending college without financial aid they would otherwise qualify. Education policy researchers should investigate conditions where at-scale nudging may be successful at improving student outcomes.
**Persuasive Technologies**

How information is presented, as a nudge, is an important consideration. We live in an age inundated with the use of persuasive technologies. The World Wide Web, smartphones, and other technologically advanced systems generate opportunities for nudges. Persuasive technology is defined as “interactive information technology designed for changing users’ attitudes or behavior” (Fogg, 2003). Interactive information technology can be a computing system, device, or application. Fundamental to attitudinal change is persuasion. Social psychologists suggest that a person’s behavior is determined by their intention to perform the behavior and that this intention is, in turn, a function of their attitude toward the behavior and subjective norms (Fishbein & Ajzen, 1975). Persuasion is human communication designed to influence attitudes or behavior.

**Mobile Application Usage**

With over 3.2 billion smartphone users worldwide (Richter, 2015), mobile application usage is exploding. Based on Gallup report data (2015), 81% of U.S. smartphone users keep their device close by “almost all the time during waking hours” (Newport, 2015). Seventy-two percent of the respondents reportedly check their smartphone at least once an hour, most of them several times. Twenty-two percent of 18- to 29-year-olds glimpse at their phone every few minutes, and another 51% do so several times an hour (Richter, 2015).

Armstrong (2019) reported findings by AudienceProject stating the most significant percentage of U.S. smartphone users say social media/chat apps take 49% of their screen time, followed by browser apps (42%), email apps (36%), games (26%) and music/radio (25%). Respondents were able to name up to three app types, which they spend most of their time on.
In a separate study, dscout research team (Winnick & Zolna, 2016) conducted a social interaction usage study using a smartphone app that captured every “touch” interaction (swipe, tap, type, and click) in real-time. Data revealed the average user taps, swipes, or clicks on their phone 2,617 times a day. That number doubled with the most substantial users to 5,427 touches a day. Smartphone screen time was 2.42 hours for the average user and 3.75 hours for the heavier user.

With reported usage like this, it is not surprising that technology platforms have given rise to a gig economy; mobile tech has significantly contributed. The impact of mobile applications to inform, educate, and persuade consumers should not be underestimated.

**Key Terminology**

As the landscape of online learning continues to evolve at rapid rates, there is little consensus on common definitions and terminologies. This lack of consistency of key conceptual terms is a cause of confusion among those who are not familiar with the history of the field and conceptual evolution (Moore, 2013, p.50). Guri-Rosenelt (2009) argues for the importance of clarifying terminology, particularly in educational technology, to avoid “The Tower of Babel Syndrome” often caused by using generic terms that lead to confusion (p.1). Due to the vast terminologies used for online learning, there are many definitions of online learning. Sometimes it is defined vaguely as learning and/or teaching in any form that takes place via a computer network (Kearsley, 1998). Ko and Rossen (2001) define online learning in very general terms, as the act of conducting a course partially or totally through the Internet. Consequently, it is difficult to gain consensus for one generally agreed-upon definition beyond the underlying assumption that the student is at a distance. As a result of the lack of an agreed-upon definition, for the purpose of this paper, online learning is defined as:
The use of the Internet to access learning materials; to interact with the content, instructor, and other learners; and to obtain support during the learning process, in order to acquire knowledge, to construct personal meaning, and to grow from the learning experience. (Ally, 2004, p. 17)

Additionally, online is operationalized as 80% or more of content delivered online (Allen & Seaman, 2013).

Despite the lack of a commonly accepted definition, online learning remains one of the fastest-growing educational approaches and has become strategic in higher education. In 2016, close to 70 percent of institutions of higher education report that online learning is a significant part of their strategic plan, with 6.35 million students taking at least one online course (Seaman et al., 2018). U.S. Department of Education’s (Means, Toyama, Murphy, Bakia, & Jones, 2010) meta-analysis of evidence-based practices uncovered that the majority of studies came from medical fields.

**Problem Formulation**

With the rapid integration of online education at institutions of higher education, student demand for the flexibility offered, higher attrition rate, and in many cases, a lack of learner readiness for online courses demands appropriate attention to identify immediate support for students. Studies have identified a lack of learner readiness and suggested support, but few have adequately addressed it through the use of nudges, or auto-reminders. The use of auto-reminders as an intervention in higher education research is emerging and has not undergone a comprehensive review of the literature. This review is focused on peer-reviewed research using auto-reminders as an intervention.
Literature Search Methodology

Search Strategy

The methodology of this review was patterned after Johnson et al. (2019). This review employed systematic criteria to allow rigorous analysis, critique, and synthesis of related literature search. To establish a collection of articles to be analyzed and synthesized, relevant databases for retrieving publications were identified (n=3): ERIC, PsychINFO, and Scopus. The same search terms (see Table 1) were utilized in each database and include manuscripts published from January 2008 through March 2019. The search strategy focused on finding articles that identified auto-reminder interventions in online classes. The search context was not restricted to systematic reviews or higher education interventions. All research on electronic database searching was eligible, including research outside higher education. The search process continued until the search did not reveal any new relevant articles. Keywords used were associated with delivery mode, interventions, and communication methods. The keywords used for the search are listed in Table 1.
Table 1

Auto-Reminder Support for Online Learners Keyword Search

<table>
<thead>
<tr>
<th>Subject</th>
<th>Keywords</th>
</tr>
</thead>
<tbody>
<tr>
<td>Delivery Mode</td>
<td>&quot;online course&quot; or &quot;distance learning&quot; or &quot;distance education&quot; or &quot;online class&quot;</td>
</tr>
<tr>
<td>AND</td>
<td>Intervention reminder or remediation or procrastination or intervention or prompt* or nudge or &quot;instructor feedback&quot; or &quot;teacher feedback&quot; or motivational</td>
</tr>
<tr>
<td>AND</td>
<td>Communication Method email or texting or &quot;text msg*&quot; or instant msg* or SMS or &quot;short msg* service&quot;</td>
</tr>
<tr>
<td>NOT</td>
<td>K-12 k-12 or &quot;elementary school&quot; or &quot;middle school&quot; or &quot;high school&quot; or &quot;secondary school&quot;</td>
</tr>
</tbody>
</table>

Limit applied after: English only; 2008-2019; scholarly (peer-reviewed)

Selection Process and Data Extraction

All stages of study selection, data extraction, and quality assessment were done independently by two reviews. Any disagreement during the selection, extraction, and assessment process were resolved by discussion and arriving at a consensus regarding eligibility. Only peer-reviewed published sources were considered to ensure the quality of the review. We considered a study ‘published’ when it appeared in a peer-reviewed journal.

Using the search string mentioned above, the initial search was performed per database. After the list was compiled, sources were downloaded to Zotero (George Mason University, 2006), and duplicate titles were removed. Articles went through three complete rounds of screening. First level screening involved reviewing journal titles and deciding whether they would be included or excluded. Included articles were coded with a “yes,” and excluded articles
were coded with a “no.” If it was not clear whether or not the article should be included, the article was coded as “maybe.”

To be included in the review, all searches were limited to publications that (a) were published in scholarly (peer-reviewed) journals, (b) published between January 2008-March 2019, (c) have no duplicates, (d) include full text, (e) include interventions using a reminder system, (f) studies pertaining to higher education, (g) written in the English language, (h) studies from any geographic location, (i) be original studies, and (j) include participants 18 years of age and older. The inclusion criteria are listed in Table 2.

Table 2
Inclusion Criteria

<table>
<thead>
<tr>
<th>Inclusion Criteria</th>
</tr>
</thead>
<tbody>
<tr>
<td>Types of Studies</td>
</tr>
<tr>
<td>• Published in scholarly journals</td>
</tr>
<tr>
<td>• Publication date January 2008 (inclusive)-March 2019</td>
</tr>
<tr>
<td>• No duplicates</td>
</tr>
<tr>
<td>• Include full text</td>
</tr>
<tr>
<td>• Interventions using a reminder system</td>
</tr>
<tr>
<td>• Studies in Higher Education</td>
</tr>
<tr>
<td>• English language</td>
</tr>
<tr>
<td>• Studies from any geographical location</td>
</tr>
<tr>
<td>• Original studies</td>
</tr>
<tr>
<td>Types of Participants</td>
</tr>
<tr>
<td>• Adults (&gt;18 yrs)</td>
</tr>
</tbody>
</table>

Secondary sources, or grey literature, were not considered in this review. The definitions of what constitutes a published study and grey literature are described in Table 3. Although it may be anticipated that systematic reviews that do not include grey literature study results are likely to over- or underestimate gaps in the literature, studies that are not published in
conventional journals and, therefore, are not indexed in electronic databases are likely not to be identified. As such, consideration of time, effort, and costs were taken. However, an extensive review was conducted at the beginning of this paper. Future research is needed to identify which reviews may benefit most from including grey literature.

Table 3

Definitions of Grey Literature and Published Study

<table>
<thead>
<tr>
<th>Term</th>
<th>Definition</th>
</tr>
</thead>
<tbody>
<tr>
<td>Grey literature</td>
<td>print or electronic information not controlled by commercial or academic publishers including non-indexed conference abstracts frequently published in journal collections, dissertations, press releases, government reports, policy documents, book chapters or data obtained from trial registers</td>
</tr>
<tr>
<td>Published study</td>
<td>published as a journal article (usually indexed in an electronic database)</td>
</tr>
</tbody>
</table>

In addition to grey literature, articles that were (a) written in non-English language, (b) published pre-2008, and (c) participants were K-12 were excluded from the review. Exclusion criteria are listed in Table 4.
Table 4

Exclusion Criteria

<table>
<thead>
<tr>
<th>Exclusion Criteria</th>
<th>Types of Studies</th>
<th>Types of Participants</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>● Non-English Language</td>
<td>● Children (&lt;18 yrs)</td>
</tr>
<tr>
<td></td>
<td>● Published pre-2008</td>
<td>● K-12</td>
</tr>
<tr>
<td></td>
<td>● Grey Literature/Not Published in a Peer-Reviewed Journal</td>
<td></td>
</tr>
</tbody>
</table>

Second-level screening involved reviewing the abstracts from the articles coded as “yes” or “maybe” during the first level screening. Article abstracts were screened and coded as “yes,” “no,” or “maybe.” Third-level screening involved reviewing the text of the article to determine inclusion. After this final round of review, articles included in the search, coded as “yes,” were saved, and excluded articles, coded as “no,” were removed.

The electronic database search strategies yielded 263 articles from EBSCO databases (ERIC and PsychINFO) and 28 articles from Scopus. Of these articles, 13 were duplicates, leaving a total of 278 articles to review. After the three levels of screenings, the remaining articles were excluded because they did not meet the inclusion criteria. Only nine articles remained for the review. Figure 1 depicts the search and selection process using a PRISMA flow diagram (Moher, Liberati, Tetzlaff, & Altman, 2009).
**Figure 1.** Flow diagram of papers included in the review.

**Characteristics of Included Research**

The remaining nine research articles were categorized and clustered into one of 3 sub-categories listed in Table 4. In brief, three research articles were related to health aspects, while two articles were based on procrastination, and four on motivation.
Table 5

Research Categories for “Auto-Reminder Support”

<table>
<thead>
<tr>
<th>Sub-category</th>
<th>Number of Articles</th>
</tr>
</thead>
<tbody>
<tr>
<td>Health</td>
<td>3</td>
</tr>
<tr>
<td>Procrastination</td>
<td>2</td>
</tr>
<tr>
<td>Motivation</td>
<td>4</td>
</tr>
</tbody>
</table>

After several visits with the specialist librarian on campus, developing and refining search strategies, and adapting them to different databases, every attempt was made to find all relevant research about auto-reminders in the literature. Due to the limited research available on this topic, there are very few studies included in this paper.

**Auto-Reminders Research**

**Health**

In total, three publications focused on using SMS, or text messaging, to extend disease control education for life-threatening diseases (Goodarzi, Ebrahimzadeh, Rabi, Saedipoor, & Jafarabadi, 2012; Lv et al., 2012; Zamansadeh, Zirak, Hemmati, & Parizad, 2017). The consequences of poor disease management often result in hospitalization. Guided management strategies through education have been proven to be effective (Goodarzi et al., 2012; Lv et al., 2012; Zamansadeh et al., 2017). Traditional interventions include visiting with a doctor or nurse to monitor disease and learn strategies to manage the disease. Despite preventative care and self-management strategies, many patients still lack the proper education to manage or control their disease (Lv et al., 2012). External barriers, including time and distance, often get in the way of receiving this critical assistance (Lv et al., 2012). Finding a more effective way to educate
patients is crucial for chronic, worldwide diseases. Harnessing technology is a cost-effective way to disseminate lifesaving information and removes barriers of time and space.

Health studies in this review centered around the perceived control of asthma (Lv et al., 2012), and diabetes control (Goodarzi et al., 2012; Zamansadeh et al., 2017). All three studies conducted randomized controlled trials. In each of the studies, pushing information through a distance education model was found to have a significant effect on patients controlling diseases. SMS was significantly helpful in the dissemination of critical preventative care strategies (Goodarzi et al., 2012; Lv et al., 2012; Zamansadeh et al., 2017). Patients who received SMS messaging had higher perceptions of control, quality of life (Lv et al., 2012), increased knowledge, attitude, practice and self-efficacy (Goodarzi et al., 2012), and a significant effect on patient self-empowerment, critical in chronic disease management (Zamansadeh et al., 2017).

**Procrastination**

Two publications included in the final review focused on the impact of auto-reminders on procrastination in courses. Davis and Abbitt (2013) examined the utility and feasibility of implementing an intervention based on SMS technology to send frequent reminders to students' mobile phones to reduce academic procrastination. Similarly, Baker, Brent, and Thomas (2016) investigated the efficacy of a scheduled Nudge sent by email aimed at instilling successful time management strategies since time management skills are crucial for success in online, asynchronous learning environments.

Interventions included increasingly “annoying” SMS reminders sent to students delaying the completion of a quiz that would stop when the quiz was completed (Davis & Abbitt, 2013) or weekly auto-reminders about the course requirements and approximate time commitment to complete the content (Baker et al., 2016).
Overall, the results using SMS or email were not promising. Davis and Abbitt (2013) found some evidence that reminders sent via SMS technology may affect academic procrastination and performance. Baker et al. (2016) concluded that the design of behavioral nudges should be sensitive to a possible negative interpretation of a nudge by differing demographics. They acknowledged that many students do not attend to their email accounts.

**Motivation**

Four publications that appear to center around creating messaging to increase motivation were included. Some articles focused on the methodology of the messaging while others looked at the technology to send the messaging. The articles focused on challenges of retention in distance education courses and improving those challenges by increasing motivational support (Huett, Kalinowski, Moller, & Huett, 2008; Inkelaar & Simpson, 2015; Robb & Sutton, 2014; Rooyen & Wessels, 2015). The use of mobile technologies for academic support is an efficient way to engage students and to help form connections through didactic conversations (Rooyen & Wessels, 2015). Motivation emails accounted for a 2.3% increase in student retention (Inkelaar & Simpson, 2015); however, studies concur that motivational emails are unlikely to be the only cause of student retention. Adding to other retention efforts, emails may be more effective (Huett et al., 2008; Inkelaar & Simpson, 2015; Robb & Sutton, 2014), by creating a sense of community (Huett et al., 2008; Rooyen & Wessels, 2015), increased course completion (Robb & Sutton, 2014; Rooyen & Wessels, 2015), and relevant by nudging and priming students (Inkelaar & Simpson, 2015). Rooyen and Wessels (2015) conclude that regular mobile interaction keeps students motivated, provides immediate support, creates a sense of emotional involvement, and motivation to persist.
Conclusion

This systematic literature review sought to inform the development of the evidence base for intervention strategies by comprehensively synthesizing the body of research on the impact of the use of auto-reminders or nudges in higher education. The critical review of these studies enables us to discriminate between the studies in terms of quality and informs our recommendations for search strategies and research design for future evaluations of the interventions with most evidence of promise. Despite the lack of peer-reviewed scholarly studies on auto-reminders in higher education, it is evident that auto-reminders have been influential in other domains. This signifies an untapped area of online learning with great potential. Auto-reminders may be the future of retention efforts and a way by which colleges can help their students succeed. The rapid increase in online class enrollment signifies that online learning is here for the foreseeable future (Allen, Seaman, Poulin, & Straut, 2016).

Limitations

These findings have some limitations. First, this systematic review did not include grey literature. Concerns have been raised regarding the methodological and reporting quality in unpublished studies because grey or unpublished literature is often not peer-reviewed. Further, there may be a tendency in research to publish the most exciting and positive results more rapidly, and negative ones less quickly, if at all. Secondly, while there is no doubt that studies that have positive outcomes are subsequently published as full-length journal articles more often than studies with adverse effects, intervention research is often conducted by practitioners and administrators who do not always have a responsibility to publish. Lack of time may be a significant reason for the non-publication of research, independent of the direction of results.
Implications for Further Research

As administrators and practitioners across the higher education landscape seek to support students, over the last 25 years, intervention research in education has continued on a downward trend (Robinson, Levin, Thomas, Pituch, & Vaughn, 2007). Since much of higher education intervention work is conducted by administrators, time constraints, no formal requirement to publish, and less than ideal data collection technology infrastructure may hinder administrators from developing and publishing adequate intervention measures. Peer-reviewed research, including systematic reviews, should form the cornerstone of practical guidelines. Perhaps with a rising interest in educational interventions rooted in principles of behavioral science, many will answer the call to develop a long-term vision (Bradon, 2019) to consider partnerships with other disciplines (Reid & Schmidt, 2018) and close the academic-practice gap (Rynes & Bartunek, 2017) by using a design-based research collaborative approach (Ford, McNally, & Ford, 2017).
References


George Mason University (2006). Zotero (5.0) [A software tool to help you collect, organize, cite, and share your research sources (JavaScript)]. Fairfax County, VA: Center for History and New Media.


Conference on Mobile and Contextual Learning, Venice, Italy.

https://doi.org/10.1007/978-3-319-25684-9_14


ARTICLE 2:

Investigation of Student Characteristics Who Opted In to Use Boost Mobile App

as an Educational Support Service

Carolyn Bancroft Andrews

Benjamin A. Motz

Jamie G. Israel

Heather Leary
Abstract

This exploratory study aimed to investigate the characteristics of students who opted-in to use Boost, an automated student support mobile app, and compare characteristics of non-Boost users. Boost is a mobile app that integrates with the Learning Management System (Canvas) and provides support services aimed at improving student behavior and success. At the start of the Spring 2019 semester at Indiana University, instructors were invited to opt-in for Boost to be available to their classes. Instructors who opted-in invited their students to use Boost. Our multivariate analysis of variance (MANOVA) compared those who opted-in for automated support with those who did not (n=158 courses). Findings reveal that opt-ins are farther along in their studies and slightly lower performing than their peers who did not opt-in. A profile of Boost users will help university administration, student support services, and instructors make data-informed decisions on optimal use of Boost.

Keywords: educational technology; learning analytics, self-regulated learning; online learning
Introduction

With reports of the associated staggering costs in terms of tuition, books, and living expenses, student attrition is an increasing concern for institutes of higher education in the U.S. Compounding the rising costs of higher education, are reports that overall, fewer than 60% of students are graduating with a two- or four-year degree in six years (Shapiro et al., 2018) and almost 700,000 (30%) of approximately 2.2 million post-secondary students will discontinue their studies prior to graduation (Shapiro et al., 2018). By 2028, undergraduate enrollment is projected to reach 17.2 million students (McFarland et al., 2019). More than ever, colleges and universities are searching for efficient ways to support their students.

Increasingly, students are balancing family, work, and school responsibilities (Aslanian & Clinefelter, 2013; Brinkerhoff & Koroghlanian, 2007; Jaggars, 2014; Wyatt, 2005), and some students lack self-regulated skills necessary to succeed, such as setting goals and monitoring and reflecting on cognition, motivation, and behavior to meet those goals (Pintrich, 2000). Self-regulation is not an inherent skill that every student possesses. There is a growing body of research that highlights the importance of students' use of self-regulated learning strategies in their academic achievement (Zimmerman, 1990).

Although there is a wealth of research on self-regulated learning strategies, few studies focus on the use of technology for auto-reminders, or nudges, which may potentially be beneficial to bridge this skill gap for a high proportion of unprepared students who have a lot of work to manage. Short Message Service (SMS) and email technologies have been utilized in studies as cellphones are already in the hands of more than five billion people, making them commonplace. SMS messaging has been successfully implemented in other disciplines, most notably in the healthcare field. For example, studies have shown improvement in critical care
management in patients with asthma and diabetes who received guided management strategies through education via SMS (Goodarzi, Ebrahimzadeh, Rabi, Saedipoor, & Jafarabadi, 2012; Lv et al., 2012; Zamansadeh, Zirak, Hemmati, & Parizad, 2017). Healthcare is arguably more advanced in the way technology is implemented for use in interventions; it does provide an ideal touchstone for studies in Higher Education.

**Literature Review and Research Questions**

Given the rapid pace of technological advancement and that online education is one of the fastest-growing segments of higher education in the U.S. (Kelly-Reid, & Mann, 2019; Seaman, Allen, & Seaman, 2018), the terms “traditional” and “non-traditional” are increasingly arbitrary as students blur the lines between being on-campus and enrolled in online courses.

Most often, the age of a student has been a defining characteristic of traditional and nontraditional students (Bean & Metzner, 1985). Traditional post-secondary students are commonly referred to as recent high school graduates, between 18 and 23 years of age when first enrolled (Chartrand, 1990, 1992; Jinkens, 2009), and from medium-high socioeconomic status families (Bradley, Noonan, Nugent, & Scales, 2008; Choy, 2002).

On the other hand, nontraditional students are those students who are 24 years of age and older (Chartrand, 1990, 1992; Jinkens, 2009). Online students enrolled at an institution of higher education are more likely to be 25 or older, married with children, attending school part-time, and to be a full-time employee (Campbell & Wescott, 2019; Jaggers & Xu, 2013) have academic needs that differ from their traditional face-to-face counterparts such as time and location constraints.

Nontraditional students are perceived as having considerable barriers to higher education. The convenience of online classes provides greater access to higher education, particularly for
students who balance family, work, and school responsibilities. This also includes disadvantaged students, such as low-income, minority, and first-generation college students. These students often have access, and resource constraints due to family commitments (Hiltz & Shea, 2005), work responsibilities (Dutton, Dutton, & Perry, 2002; Hiltz & Shea, 2005), financial limitations (Leasure, Davis, & Thievon, 2000), and geographical barriers (Dutton et al., 2002) compared to their non-disadvantaged peers. Clearly, non-traditional students have always required flexibility, and before online classes, this included night classes, weekend seminars, and correspondence courses (Cavanagh, 2012). However, many students may be attracted to online classes for other reasons, such as participating in intercollegiate athletics or to allow for a social life. Students seize the affordances an online education has to offer (Beqiri, Chase, & Bishka, 2010; Bocchi, Eastman, & Swift, 2004). However, availability and convenience do not translate to success as an online learner.

**Self-Regulated Learning**


One of the widely cited SRL models developed over the last two decades proposed by Zimmerman (1998, 2002) describes SRL as a student’s “self-generated thoughts, feelings, and actions that are planned and cyclically adapted to the attainment of personal goals” (Zimmerman, 2000, p. 14). These self-generated thoughts occur throughout a three-phase sequenced routine:
(1) forethought, (2) performance or volitional control, and (3) self-reflection. Within each of the three phases, research has identified two major subcategories (Zimmerman, 1986).

In the forethought phase, learners plan and set goals. A major subcategory is task analysis and consists of goal setting and strategic planning. The second subcategory, self-motivation beliefs, includes self-efficacy, outcome expectations, intrinsic interest value, and learning goal orientation. Novices to the forethought phase are found to be reactive learners. Due to a lack of goal setting, these learners compare their performance to the learning of other students (Zimmerman, 1986).

Performance or volitional control, or second phase processes, fall into two major classes or subcategories. The first subcategory is self-control. It consists of imagery, self-instruction, attention focusing, and task strategies. Self-observation, the second subcategory, includes self-recording and self-experimentation. In this second phase, learners use strategies and monitor performance. Experts in this domain agree that self-monitoring is the crucial element for successful SRL (Corno, 1986; Corno & Mandinach, 1983; Mace & Kratochwill, 1988; Nelson, 1977; Schunk, 1989; Shapiro, 1984).

In this final phase, processes are focused on self-reflection, where learners reflect and adapt. The first of two subcategories is self-judgment. Self-judgement consists of self-evaluation and causal attribution. Self-reaction, the second major subcategory, consists of self-satisfaction, affect, adaptive and defensive.

Students who have stronger self-regulated learning skills are typically self-starters, displaying persistence on learning tasks, are confident and strategic in overcoming problems, and self-reactive to task performance outcomes (Zimmerman & Schunk, 1994). Indeed, SRL requires the learner’s active effort in monitoring their study habits (Bjork, Dunlosky, & Kornell, 2013;
Fernandez & Jamet, 2016). Studies have emphasized that SRL is not a fixed trait, rather a skill that can be developed and refined through instruction, role models, experience, and practice by applying self-regulated learning strategies (Schunk, 2005; Zimmerman, Schunk, & DiBenedetto, 2015).

Learning Analytics

Learners with underdeveloped SRL skills benefit from support to improve their ability to self-regulate their learning. However, researchers have shown that even skillful learners manifest deficiencies in their SRL skills (Pressley & Ghatala, 1988, 1990; Pressley, Ghatala, Woloshyn, & Pirie, 1990) and benefit from support. Increasingly, learning analytics (LA) and learning analytic dashboards (LAD) are used as an intervention to provide support to all students (Kennedy et al., 2014). The intent of LAD’s is to provide near real-time feedback to the student and other stakeholders (Few, 2006). Recently, researchers at The University of Iowa revealed that students who frequently monitored their LAD had significantly higher grades on assignments and tests than students who did not (Van Horne, Curran, Smith, Miller, & Larsen, 2018). However, in their literature review, Bodily and Verbert (2017) assert that minimal research has addressed the way students are using LAD’s and how to increase student use. More research is needed on the perceived and actual effects of LAD’s on student behavior, achievement, and skills (p.19).

Research Question

There is limited research on the types of students who opt-in for support services. The purpose of this research study was to investigate the characteristics of students who opted-in to use Boost, an automated student support mobile app, and compare with the characteristics of their non-Boost using classmates (Indiana University, 2018). Developing an understanding of students who opt-in to use the Boost app will help instructors and administrators as they work...
together to improve student support services. Aggregate properties of Boost users were used to answer the research question: What are the characteristics of students who opt-in to receive automated support, compared with those who do not opt-in?

**Method**

**Participants**

At the start of the Spring 2019 semester at Indiana University, instructors were invited to participate in a research study using a smartphone app developed by Indiana University designed to help students keep track of their schoolwork in the learning management system (LMS). This no-cost app named “Boost” was downloadable from the iOS and Android App Stores. From the mobile app, students authenticate to the learning management system, and select individual course(s) to receive reminders via push notifications to be sent about their course work. During this Spring 2019 semester, only courses taught by instructors who had explicitly opted-in to have Boost available would be operational within the app. Invitations to participate were sent via various university listservs, including teaching centers, learning technology units, and a global announcement via the learning management system. Instructors were eligible to participate if they were teaching a for-credit course with an active, published course on the Canvas LMS (Coates, 2008).

Instructors of 738 courses with published Canvas sites opted-in to have Boost available to their students, with an average enrollment of 40.5 students in each course. Courses, where fewer than two students signed-up for Boost, or fewer than two students did not sign-up for Boost during the Spring 2019 semester, were excluded from further analysis (which filtered a large number of low-enrollment courses), leaving a final sample of 158 courses, with an average enrollment of 47.1 students.
All analyses in this study are performed at the course-level, contrasting the aggregate properties of students who volunteered to use Boost (who downloaded, installed, and logged-in to Boost during the Spring 2019 semester) from the aggregate properties of students who did not volunteer to use Boost. Least-squares weighting was used to account for different enrollment sizes in these aggregate summaries at the course-level (see Data Analysis, below).

Procedures

Instructors who opted-in to have Boost available to their students were provided with a verbal script and an email template to invite students to download the Boost mobile app, both of which were approved by the Indiana University Institutional Review Board (IRB). Up to three additional IRB-approved invitation, emails were sent from boost@iu.edu; filtering students who had already signed up, and containing instructions on how to access the mobile app. All students completed their course in a usual fashion, according to instructor and discipline, but were allowed to use the app if they desired (no incentives were provided, other than the possibility that Boost might help them avoid missing deadlines). After downloading the app, students authenticated via a single sign-on service to connect with the university’s instance of Canvas and to consent to participate in this research and have their data analyzed. Upon providing consent, students then configured the app by configuring the kinds of push notifications they would receive in the app. However, students who did not use Boost provided no such consent, which is why all analyses in this study are performed at the aggregate course-level, rather than at the individual student-level.

Data Collection

Data that already existed in institutional databases were retrieved from various data sources, primarily the student information system and Canvas data warehouse. No individually-
identifiable data was returned in the database queries for comparing notification tool users to their peers; only aggregate class-level means and percentages were analyzed for Boost and non-Boost users. The class itself was de-identified in the analysis dataset (no section numbers, course numbers, or campus information is included) to eliminate the possibility of deductive disclosure of student information. No student was identifiable in the data under analysis for this contrast, nor was the study data able to be mapped back onto individual students.

Data Analysis

To investigate each research question, course level aggregate data from Indiana University were consolidated and analyzed using IBM SPSS statistical software (IBM, 2019). Data were analyzed using a between-subjects study design approach (Charness, Gneezy, & Kuhn, 2012) wherein a generalized linear model (GLM) was selected as it is traditionally the primary method used for the analysis of count data (McCullagh & Nelder, 1989; Wood, 2006). Multivariate analysis of variance (MANOVA) was used in the data analysis as it is an accepted test suited to investigate between-group differences (Field, 2013). Researchers applied weighted least squares regression to make the distribution of the number of students in the data approximate the distribution of the number of students in the population from which the sample was drawn. Weights are a function of observed independent variables included in the model.

Data analysis began by determining Wilks’ Lambda criterion (Wilks, 1932). A one-way MANOVA was calculated examining the effect of Boost (use or no use) on average age, percent undergraduate, percent female, percent married, percent instate, percent international, percent first-generation, percent White, percent Asian, percent underrepresented and percent multiracial variables. Lambda was not significant, \( \lambda(11, 304) = .965, p > .05 \), suggesting that these
demographic and academic history variables account for a relatively small percentage of variance in whether students opt-in to auto-reminders, as expected from SRL theory.

Quantitative data were analyzed both descriptively and inferentially. Descriptive statistics were used to describe the basic features of the data. In this study, MANOVA was used to investigate the characteristics of Boost users with non Boost users.

**Results**

**Descriptive Analysis**

Descriptive statistics for study variables were found using means and SDs for continuous variables, and for percentages observed in each course. A total of 158 courses met the criteria for inclusion in this study (instructor opt-in, published Canvas site, at least 2 Boost-users and non-users), with an average enrollment of 47.1 students. Across these courses, an average of 6.3 students volunteered to use Boost (13.3%). Having two levels of an independent variable (Boost, or No Boost), the aggregate demographic values and percentages are analyzed as dependent variables in a linear model, weighted by the number of students comprising each observation at the course-level.

**Socio-Demographic Characteristics of Boost Users**

Descriptive statistics for each of the socio-demographic study variables are presented in Table 1. Results showed the percent of Boost users who were White was lower than the percent of non-Boost users who were White, $F(1, 314) = 7.516, p < .05$. This was largely driven by a significantly higher percentage of Asian students using Boost, $F(1, 314) = 5.635, p < .05$, many of whom also contribute to a significantly higher percentage of international students using Boost, $F(1, 314) = 4.201, p < .05$. The demographic profile of students who opted-in to use Boost skews largely in the direction of minority students, but who are not considered underrepresented.
<table>
<thead>
<tr>
<th>Characteristics</th>
<th>Boost - M(SD)</th>
<th>No Boost - M(SD)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean Number of Students</td>
<td>6.3</td>
<td>40.8</td>
</tr>
<tr>
<td>Mean Age</td>
<td>20.6 (6.7)</td>
<td>20.7 (11.3)</td>
</tr>
<tr>
<td><strong>Gender</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Percent Female</td>
<td>48.0% (0.8)</td>
<td>54.6% (1.4)</td>
</tr>
<tr>
<td><strong>Marital Status</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Married</td>
<td>0.7% (0.1)</td>
<td>0.6% (0.2)</td>
</tr>
<tr>
<td><strong>Ethnicity</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>White</td>
<td>73.0%**(0.5)</td>
<td>78.8% (0.7)</td>
</tr>
<tr>
<td>Asian</td>
<td>21.3%**(0.5)</td>
<td>16.1% (0.8)</td>
</tr>
<tr>
<td>Under-represented</td>
<td>14.8% (0.4)</td>
<td>15.5% (0.5)</td>
</tr>
<tr>
<td>Multiracial</td>
<td>4.7% (0.2)</td>
<td>4.9% (0.2)</td>
</tr>
<tr>
<td><strong>Post-Secondary Level</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Undergraduate</td>
<td>95.5% (0.5)</td>
<td>95.8% (1.3)</td>
</tr>
<tr>
<td><strong>Residency</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Instate</td>
<td>64.4% (0.6)</td>
<td>67.3% (1.2)</td>
</tr>
<tr>
<td>International</td>
<td>8.5%** (0.3)</td>
<td>5.6% (0.5)</td>
</tr>
<tr>
<td><strong>Student Status</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1st Generation</td>
<td>11.2% (0.3)</td>
<td>12.3% (0.4)</td>
</tr>
</tbody>
</table>

**p<.05 differences between groups
Descriptive statistics for each of the study variables related to educational background are presented in Table 2. There was a significant difference between average credits taken in Boost users and average credits earned in those who did not use Boost, $F(1, 314) = 3.794, p<.05$, and similarly, the Boost users had more credits than those who did not use Boost, $F(1, 314) = 3.840, p<.05$. SAT scores (which were imputed in the case of students who entered college with alternative test scores such as the ACT) were higher among Boost users than those who did not use Boost, $F(1,314) = 5.016, p<0.05$, despite a directional trend for Boost users to have slightly lower prior grade-point averages (GPAs) than those who do not use Boost, $F(1,314) = 3.598, p=0.059$.

Table 2

<table>
<thead>
<tr>
<th>Academic</th>
<th>Boost</th>
<th>No Boost</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>M(SD)</td>
<td>M(SD)</td>
</tr>
<tr>
<td>Course Grade</td>
<td>3.4 (1.2)</td>
<td>3.4 (2.2)</td>
</tr>
<tr>
<td>Credits Taken</td>
<td>14.8** (4.0)</td>
<td>14.3 (7.2)</td>
</tr>
<tr>
<td>Credits Passed</td>
<td>14.6** (4.2)</td>
<td>14.1 (7.2)</td>
</tr>
<tr>
<td>Prior GPA</td>
<td>2.4 (1.4)</td>
<td>2.6 (2.9)</td>
</tr>
<tr>
<td>SAT Score</td>
<td>1251.2** (294.6)</td>
<td>1217.7 (538.4)</td>
</tr>
</tbody>
</table>

**$p<.05$ differences between groups

Discussion

The purpose of this study was to investigate the socio-demographic characteristics and academic performance of students who opted to use the Boost app with those who opted out and their differences. In total, the students who opted to use Boost were more likely to be Asian and
international and had higher scores on college entrance exams than their classmates who opted not to use Boost. However, students who used the app did not show signs of outperforming their peers who did not use the app; if anything, there was a trend that Boost users had slightly lower prior GPAs than non-Boost users, despite having earned significantly more credits in college at the time of the study. It would seem that, in this study, students who volunteered to receive automated reminders were those who had traditionally outperformed their peers, but after experience in college without such performance, had realized that they could benefit from automated support.

A critical component of academic success is self-regulated learning (Broadbent & Poon, 2015) and requires forethought, performance, and self-reflection (Zimmerman & Schunk, 1989). In 2019, the Boost app was a new tool on campus that was only available to a subset of the university. Recruitment came from select faculty who agreed to invite their students to participate. This was also a new tool for the faculty. Other than the faculty recruitment of students in their class, students received three email reminders inviting them to participate. Students were ultimately left to decide if they would download the Boost app and how they would implement it. Based on results from this study, students who ignored or decided against using the app had earned fewer college credits than their counterparts who chose to use the app. Arnold & Pistilli (2012) assert that students early in their college career are not often aware of the behaviors or necessary actions to take to be successful.

Further, based upon anticipated performance, there is evidence that lowest-performing students are often the most inaccurate at predicting their prospective academic performance (Kruger & Dunning, 1999). There is reason to believe that students who need additional help are those who pass it up. Academic advisement centers and faculty can recommend students
download Boost, particularly at-risk and lower-achieving students. However, students who are vulnerable about their knowledge or ability are also less likely to seek help (Karabenick & Knapp, 1991). Providing a non-threatening environment to set up Boost may increase the usage, particularly for at-risk, 1st generation, and underrepresented populations.

Results from the study indicated that Boost users had taken and passed more credits than those who chose not to participate. It could be argued that students who opted to use Boost had a better understanding of challenges keeping on top of their homework and understood the behaviors and actions necessary to be successful. It is also possible that this subset of students from our study possess characteristics of self-regulated learning study behaviors and were in what is termed by Zimmerman (1986) as the forethought phase, where learners strategically plan and set learning goals. However, the current study did not collect any self-report data to support this hypothesis.

The profile of Boost users had a significantly higher percentage of Asian and International students than the students who did not use Boost. East Asian students in the United States typically suffer from a “model minority” stereotype -- where they are viewed as hard-working and academically-gifted (Wong, Nagasawa, & Lin, 1998). Social pressure from perceptions of this stereotype may lead Asian students to become particularly sensitive to identity threats in both traditional and online classes (Lagier, 2003; Wang, 2007). Language barriers may also exacerbate these challenges, such that when their academic performance dips, Asian students may have more difficulty seeking out assistance (Yeboah & Smith, 2016). For these students, Boost may provide uniquely beneficial, non-threatening, automated support for helping them stay on top of their coursework.
However, other demographic groups could also clearly benefit from automated support, and the current results suggest that institutions may need to invest extra efforts to get tools such as Boost into the hands of underrepresented minorities, non-traditional students, or incoming freshmen (for example, among others). In contrast to East Asian students who may adopt Boost due to massive social pressure toward academic achievement, other segments of the student population may need to be convinced of the challenges of academic workload, and the necessity of additional support. This need to be convinced is at the heart of the difficulties faced when training college learners to adopt SRL strategies and skills, helping students to reach the *forethought phase* before they experience academic challenges that are difficult to overcome.

This study was not without its limitations. By design, this study had a small sample size (only open to those instructors who opted-in), a limited student population (only one university), and one-semester duration of the study, which are all limiting factors to generalizability. While our aggregate course-level data provides useful information for general understanding, understanding of the individual-level will offer more insight into specific research questions. Nonetheless, this generalized understanding lays essential groundwork for future work that seeks to support student success through mobile applications interventions employing learning analytics.

Our research goal focused on better understanding the characteristics of students who opted-in and who opted-out of Boost, and characteristics of students who used the Boost app differ from their classmates who did not. To further this research, we propose to explore the context around student behaviors with Boost. Specifically, students push notification tapping behaviors. For example, what types of notifications are they more likely to tap on, how often students tape on the notifications, is there a specific point in the semester they are more likely to
tap on notifications, and what the assignment submission rates were compared between tapped and non-tapped notifications. Further, it would be useful to understand students’ self-regulation study behaviors, why they opted in to use Boost, and if they perceive Boost as useful.

**Conclusion**

Learning analytics as support for student self-regulated study behaviors is a rapidly evolving research domain in student success scholarship. With the continued growth of online learning, a growing concern for the rising costs in higher education, and student retention efforts, this research has a critical application to the higher education landscape. Educational intervention research can influence and impact student success. Real-time automated services to support student self-regulated learning behaviors and academic achievement. More research is needed in this area.
References


Campbell, T., & Wescott, J. (2019). *Profile of undergraduate students: attendance, distance and remedial education, degree program and field of study, demographics, financial aid, financial


IBM (2019). IBM SPSS statistical software (version 26.0). [IBM SPSS Statistics software is the world’s leading statistical software used to solve business and research problems by means of ad-hoc analysis, hypothesis testing, and predictive analytics]. Armonk, NY: IBM.

Indiana University (2018). Boost [Boost is a mobile app for Android and iOS that aggregates information about student schoolwork and uses it to deliver timely, personalized, automated notifications]. Bloomington, IN: eLearning Design and Services


ARTICLE 3:

Exploratory Study of Student Response to Boost App Push Notifications

Carolyn Andrews

Brigham Young University
Abstract
This paper explored the context around students tapping on the push notification. One thousand three hundred thirty-five student volunteers downloaded the Indiana University Boost mobile application and set the app to send them reminders before assignment deadlines. Researchers tracked student (1) submission rate; (2) submission time; (3) assignment weight; and (4) percent score and compared whether students had tapped or not tapped push notification reminders. The analysis revealed IU Boost app users submit more assignments and have higher average assignment grades when they tap the notifications. Assignment weight on final grade was generally lower, and there was generally less time between the time the student submitted the assignment and the assignment deadline. In contrast, when push notifications were not tapped, the trend seemed to be that the weight of the assignment was higher, and there was more time between submission and deadline.

*Keywords:* push notification reminder, intervention, nudge theory
1.1 Introduction

With the trajectory of increasing undergraduate enrollments in higher education in the United States by 2027 (McFarland, 2019, p. 158), while at the same time online learning has become commonplace in the 21st century higher education landscape, and current reports indicate almost eight million (39%) of approximately 20.5 million university students will discontinue their studies before graduation (Shapiro, Dundar, Wakhungu, Yuan, & Hwang, 2017), efforts to increase student retention are paramount. Increasingly, institutions of higher education are prioritizing interventions aimed at student retention.

Studies on student retention are closely tied to self-regulated learning (SRL) and student engagement literature. SRL is broadly defined as the extent students are engaged in the learning process motivationally, metacognitively, and cognitively (Zimmerman, 1989). Student engagement and SRL are often used interchangeably in educational literature. This is due to the shared focus of understanding students’ academic functioning and performance using terminology and concepts central to both included in their definitions (Wolters & Taylor, 2012). SRL has been linked to outcomes such as persistence, completion, and student grade (Bigatti & Svanum, 2009; Hullinger & Robinson, 2008; Kuh, Cruce, Shoup, Kinzie, & Gonyea, 2008). It is considered to be a malleable state and can be shaped, suggesting that intervention can lead to improvement (Kahu, 2011). More than attending or performing academically; engaged students put forth an effort, persist, self-regulate their behavior toward goals, challenge themselves to exceed, and enjoy challenges and learning (Christenson et al., 2008; Klem & Connell, 2004; Stipeck & Cohen and the Institute of Medicine [NRC and IoM], 2004). Results from Christenson et al. (2008) underscored the need for sustained interventions to improve indicators of academic
(e.g., credits earned, homework completion) and behavioral (attendance, ratings of social skills) engagement.

Borrowing successes from public policy (Madrian & Shea, 2001) and healthcare (Davenport, Guszcza, & Swartz, 2018) domains, proactive behavioral interventions can inform educational intervention. Additionally, operationalizing what student engagement looks like in a digital context while drawing on the research of learning analytics will assist in developing an education intervention research framework in automated behavioral interventions (such as nudging) aimed at improving SRL.

1.2 Literature Review and Research Questions

1.2.1 Operationalizing Student Engagement

With the growth of online learning and the prevalence of web-based learning management systems (LMSs), student engagement can be operationalized in terms of actual behavior such as collaboration in discussion forums, graded assignments, and quizzes. This type of active learning can be measured by LMS web log data (Motz, Quick, Schroeder, Zook, & Gunkel, 2019).

1.2.2 Behavioral Interventions

While studies concur that autonomy is necessary for self-regulation and SRL, proponents agree there are ways to nudge students while not compromising their independence. Using public policy research, there has been significant evidence of success with various applications of nudges. Notably, the most prominent of achievements is the use of defaults to increase enrollment in defined contribution retirement savings plans (Madrian & Shea, 2001). Motz, Mallon, and Quick (under review) suggest that a broad goal of education is to promote
behavioral change, and the application of principles of behavioral economics can encourage positive outcomes.

1.2.2.1 Nudge Theory Popularized by economist Thaler and legal scholar Sunstein (2008), the behavioral economics concept of ‘nudging’ is the culmination of the interdisciplinary work of psychologists Kahneman and Tversky (1979). As a discipline, Nudge Theory falls broadly within public policy and applied to policy issues ranging from the environment to discrimination to public health (Shafir, 2012, pp. 245, 475). Criticized for its operational fuzziness, this interdisciplinary nature has made it challenging to define Nudge Theory (Marteau, 2011, p. 228). Succumbing to short-term impulses at the expense of long-term goals is not always aligned with intention; the discrepancy between an individual's intentions, values or attitudes, and their actions or behavior is known in different bodies of literature as the ‘intention-behavior gap’ (Godin, Connor, & Sheeran, 2005), the ‘value-action gap’ (Blake, 1999) or ‘attitude-action gap’ (Mairesse, Macharis, Lebeau, & Turcksin, 2012). Disruption of motivation or willpower has been attributed to this gap (Kahneman, 2011, pps. 49-50).

1.2.2.3 Disruption of motivation can be explained through the Biases and Heuristics work of Kahneman and Tversky, particularly portrayed in Kahneman’s *Thinking, Fast and Slow* (2011), and is rooted in Dual Process Theory (DPT) which differ in detail but conceptually the same; humans employ two modes of thinking. DPT provides an architecture for how the human brain resolves the conflict between dual systems (Evans & Stanovich, 2013). These dual systems are referred to in the literature as System 1 and System 2. Equally valuable, each system serves a very different purpose. System 1, intuition or automatic thinking, is characterized as uncontrolled, effortless, associative, fast, unconscious, and skilled. Whereas System 2, reasoning or reflective thinking, is described as controlled, effortful, deductive, slow, self-aware, and rule-
following (Evans & Stanovich, 2013; Kahneman, 2011; Stanovich, 1999). Kahneman (2003) claimed System 1 (automatic) was based on formed habits and, thus, difficult to change and subject to conscious judgments and attitudes. System 2 (reasoning) was slower and much more volatile. While System 1 operates on its own, System 2 operates on assumptions and context provided by System 1 thinking. In that we have the proclivity to conserve effort, System 2 only comes into action when System 1 becomes overwhelmed by the situation.

With the majority of our daily decisions are handled by System 1, we apply heuristics. Heuristics are simple processing rules or techniques that act as mental shortcuts or rules of thumb that simplify decision making. Accordingly, Nudges are aimed at influencing System 1 thinking, which impacts actions and behaviors.

1.2.2.4 Choice Architecture  Fundamental to action or behavior is decision-making from the choices available. Nudge theory attempts to improve understanding and management of the heuristic influences on behavior, central to changing people. Nudge theory argues that positive reinforcement and indirect suggestions can influence behavior in significantly impactful ways. Thaler and Sunstein (2008) define a nudge as “any aspect of the choice architecture that alters people’s behavior in a predictable way without forbidding any options or significantly changing their economic incentives. To count as a mere nudge, the intervention must be easy and cheap to avoid” (p.6). Central to Nudge theory is choice architecture; how options are presented, matters.

Coined by Thaler and Sunstein (2008), choice architecture refers to influencing choice by “organizing the context in which people make decisions” (Thaler, Sunstein, & Balz, 2013, p. 428). In this way, change is enabled by designing choices that encourage better choice-making. Influencing choice-making is one of the functions of choice architecture. However, individual choice preferences are not always in alignment with socially optimal outcomes.
Changing how an individual evaluates the costs and benefits of different choice outcomes is a function of choice architecture. Madrian (2014) identified several behavioral economic tools a choice architect can use. In addition to (1) changing the default, (2) requiring an active choice, and (3) simplifying foundational to Thaler and Sunstein (2008), other tools include the use of framing a reference point (see Kahneman & Tversky, 1984; Kahneman & Tversky, 1979), gain/loss incentives (for example, student receive loss/gain from performance in the form of loss of or additional credit or benefit), ordering effects (for example, changing the order information appears; structural presentation), and social comparison (for example, individual performance in reference to others).

1.2.3 Learning Analytics

In higher education, LA literature, using student data to optimize the teaching and learning environments through the use of performance dashboards and other educational technologies abound in the research. LA is commonly defined as “the measurement, collection, analysis, and reporting of data about learners and their contexts, for purposes of understanding and optimising learning and the environments in which it occurs” (Long & Siemens, 2011, p. 34). This research centers on the learning process by understanding students' learning behavior and enhancing the effectiveness of learner support.

Increasingly, researchers are focusing on a wide variety of student activity indicators captured from the volumes of detailed activity logs recorded in a learning management system (LMSs). Evident in educational literature in LA and learning analytic dashboards (LADs), we can see the application of choice architecture principles. For example, prevalent tools carefully architectured into LMSs are what-if calculators, allowing students to see what their grade would be if they received a particular score on an upcoming assignment or if they chose not to submit it
at all. These grade calculators allow students to estimate the impact of individual grade gains and losses before they happen. Another example is the visualization of assignment or test score statistics aimed to inform students on how they did in reference to other students in their class.

From an institutional and administrative stance, an optimal outcome of LA practice includes improving student retention, through timely feedback, by providing support for informed decision-making, to increase student motivation and engagement, and to highlight the impact and effectiveness of LA interventions on student success and performance outcomes. In terms of student success and retention, current evidence suggests the potential efficacy of LA interventions. For example, LA has contributed to improved student retention, realizing between 11% (Cambruzzi, Rigo, & Barbosa, 2015) and 25% higher retention (Arnold & Pistilli, 2012) from pre- to post-intervention. Further, Jayaprakash, Moody, Eital, Regan, and Baron (2014) found a 6% increase in overall grades, while Arnold and Pistilli (2012) found 10% increases in top grades (As and Bs) (Arnold & Pistilli, 2012), and Fritz (2011) found a nearly twofold increase in the likelihood of students achieving C-grades or above. Access to LMS data provides the provision of personalized assistance to students with the ability to automate nudges, messaging, and reminders of upcoming assignments.

1.2.4 Purpose of Study

The purpose of this study is to assess the benefit of nudges (push notifications) by examining the context of student tapping behavior when they receive a reminder of an upcoming assignment. Specifically, (a) the tapping behavior of students who opted in to use the Boost mobile app, (b) the assignment submission rates compared between tapped notifications and not-tapped notifications, (c) the relationship between students’ time of submission and their
academic performance (average assignment grade), and (d) the comparison submission rates and weight of assignments (Indiana University, 2018).

1.3 Method

For this study, we used quantitative methods to answer the research questions. Next, we provide more detail about our sampling, data collection, and analysis methods.

1.3.1 Participants

At the start of the Spring 2019 semester at Indiana University (IU), instructors were invited to participate in a research study using a smartphone app developed by IU designed to help students keep track of their schoolwork in the learning management system (LMS). This no-cost app named “Boost” was downloadable from the iOS and Android App Stores. From the mobile app, students authenticate to the learning management system, and select individual course(s) to receive assignment deadline reminders via push notifications to be sent about their course work.

During this Spring 2019 semester, only students taught by instructors who had explicitly opted-in to have Boost available would be operational within the app. Invitations to participate were sent via various university listservs, including teaching centers, learning technology units, and a global announcement via the learning management system. Instructors were eligible to participate if they were (1) teaching a for-credit course, (2) with an active, published course on the Canvas LMS, (3) the course included an assignment deadline, (4) the assignment submission was through the LMS, and (5) the assignment point value was greater than zero (Coates, 2008).

Instructors of 738 courses with published Canvas sites opted-in to have Boost available to their students, with an average enrollment of 40.5 students in each course. A total of 1335 unique students are included, and all analyses in this study are performed at the student-level, aggregate
properties of students who volunteered to use Boost (who downloaded, installed, and logged-in to Boost during the Spring 2019 semester). Least-squares weighting was used to account for different assignment counts in the aggregate at the student-level (see Data Analysis, below).

1.3.2 Procedures

Instructors who opted-in to have IU Boost app available to their students were provided with a verbal script and an email template to invite students to download the Boost mobile app, both of which were approved by the Indiana University Institutional Review Board (IRB). Up to 3 additional IRB-approved invitation, emails were sent from boost@iu.edu; filtering students who had already signed up, and containing instructions on how to access the mobile app. All students completed their course in a typical fashion, according to instructor and discipline, but were given the opportunity to use the IU Boost app if they desired (no incentives were provided, other than the possibility that the app might help them avoid missing deadlines).

After downloading the app, students authenticated via a single sign-on service to connect with the university’s instance of Canvas and to consent to participate in this research and have their data analyzed. Upon providing consent, students then configured the app by configuring the kinds of push notifications they would receive in the app. A representation of the information displayed can be seen in Fig. 1. For example, students could select (1) due date reminders, with messaging indicating that an assignment due date was approaching; (2) instructor announcement notifications, indicating there was a new announcement posted; and (3) daily assignment digest, once a day messaging that listed all the assignments due within the following 24 hours. A fourth message, assignment submission confirmation, was not a choice on the menu, rather, randomly assigned to students. This push notification acknowledged receipt of an assignment submission in Canvas and included short praise or value-based statement. On a course-by-course basis,
students could set how long before a deadline a due date reminder should be deployed. The
default was 4 hours, customizable to 1-24 hours. Additionally, the IU Boost app could display a
student’s Canvas To Do list (see bottom-right button in Fig. 1), and students could opt-out of
receiving push notifications (by muting all courses).

1.3.3 Data Collection

To understand behavioral interaction with the IU Boost app, due date reminder push
notification (n = 1545) interactions were tracked. Each hour, an API call was made to the Canvas
data warehouse to retrieve upcoming assignment details for study participants. If an assignment
deadline was revealed within the notification window (1-24 hours), the app deployed a push
notification to IU Boost app users. The generic text of the due date reminder push notification
was, "The due date is approaching for one or more Canvas assignments." A notification could be
tapped or untapped. An untapped push notification could either be dismissed or left to expire.
Untapped notification (n = 1102) data from the mobile device were not reported to Boost.
However, the number of untapped notifications are easily discernible from the number of
reminders sent subtracted from the numbers of tapped notifications. Tapping on a notification
resulted in the Boost app opening to display more information about a notification. For each
tapped notification (n = 443), the mobile device reported to Boost and data were stored in the
Boost database. Students may have opted to receive other kinds of push notifications, but those
are not included in this analysis.
Student assignment data was recorded in Canvas, stored in the Canvas data warehouse, and study participants’ data was directly retrieved at the time of analysis. No individually-identifiable data was returned in the database queries for comparing notification tool use and course data. The assignments were de-identified in the analysis dataset (no course information, assignment names, or campus information is included) to eliminate the possibility of deductive disclosure of student information. No student was identifiable in the data under analysis, nor was the study data able to be mapped back onto individual students.

1.3.3 Measured Variables To examine the effect of assignment push notifications (tapped or untapped), we focused on the following dependent variables: (1) submission rate, percent of assignments that had a submission by the user, in which the user’s latest submission to the
assignment was before the deadline; (2) submission time, the average amount of time, in hours, minutes, and seconds between a student’s submission and the assignment’s submission deadline; (3) assignment weight, average weight of assignments as instituted by the instructor; and (4) percent score, average grade earned on the assignment.

1.3.4 Data Analysis

To investigate each research question, student-level aggregate data from Indiana University were consolidated and analyzed using IBM SPSS statistical software (version 26.0). Data were analyzed using a between-subjects study design approach (Charness, Gneezy, & Kuhn, 2012) wherein a generalized linear model (GLM) was selected and two-way factorial analysis of variance (ANOVA) was used in the data analysis. Weighted least squares regression was applied to make the distribution of the number of assignments in the data approximate the distribution of the number of assignments in the population from which the sample was drawn. Weights are a function of observed independent variables included in the model.

After examining diagnostic information (histograms, bivariate correlations, and scatter plots), we found the assumptions of linearity to be met and no outliers to be present. Missing data (n = 146) with one of the outcome variables, submission rate, was addressed. There was a 7.5% missingness, which is considered sufficiently low to ignore. Levene’s tests were carried out, and the assumptions were not met. Descriptive statistics were used to describe the basic features of the data. In this study, ANOVA was used to investigate the tapping behavior of students by examining the interaction effect of assignment reminders (tapped or untapped push notifications) on the submission rate, submission time, assignment weight, and average assignment grade.
1.4 Results

1.4.1 Descriptive Analysis

Descriptive statistics for study variables were found using means and SDs for continuous variables, and for percentages observed in each assignment. Having two levels of an independent variable (tapped notification, or non-tapped notification), the aggregate assignment values and percentages (submission rate, submission time, assignment weight, and average assignment grade) are analyzed as dependent variables in a linear model, weighted by the number of assignments comprising each observation at the student-level.

1.4.2 Student Response to Boost App Push Notifications

Descriptive statistics for each of the assignment variables are presented in Table 1. Results showed a significant main effect for submission rate ($F(1,1669) = 8.142, p < .05$) and for average assignment grades ($F(1,1667) = 5.563, p < .05$) for IU Boost app users who tapped on push notifications. When push notifications were not tapped, Boost users were less likely to submit by a coefficient of -4.664 and have a lower average assignment grade by a coefficient of -4.117. IU Boost app users submit more assignments and have higher average assignment grades when they tap the notifications. There was no significant effect found for submission time or weight of the assignment when IU Boost app users tapped on the push notifications.

When push notifications were not tapped, the weight of the assignment is higher ($M = 49.96, sd = 2.95$), and there is more time between submission and deadline ($M = 24:53, sd = 314:36$).
Table 1

*Student Response to BoostApp Push Notifications*

<table>
<thead>
<tr>
<th>Variables</th>
<th>Tapped M(SD)</th>
<th>Not Tapped M(SD)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Percent Score</td>
<td>82.52%** (34.68)</td>
<td>78.41% (63.76)</td>
</tr>
<tr>
<td>Submission Rate</td>
<td>89.97%** (32.55)</td>
<td>85.31% (59.72)</td>
</tr>
<tr>
<td>Assignment Weight</td>
<td>47.20 (1.28)</td>
<td>49.96 (2.95)</td>
</tr>
</tbody>
</table>

*Displayed as HH:MM:SS
**p<.05 differences between groups

1.5 Discussion

The purpose of this study was to explore the context around students tapping on the push notification. The analysis revealed some interesting differences between tapped and not tapped push notifications. For example, results revealed that IU Boost app users submit more assignments and have higher average assignment grades when they tap the notifications. Further, assignment weight is generally lower, and there is generally less time between the time the student submitted the assignment and the assignment deadline. In contrast, when push notifications are not tapped, the trend seems to be that the weight of the assignment is higher, and there is more time between submission and deadline. This appears to be consistent with the idea that perhaps IU Boost app users need to be reminded about the assignments that are not worth as much and that they are more likely to need to inquire about the content of a reminder for slightly lower weighted assignments.

It is accepted that having more lower-stakes assignments is a pedagogically sound teaching practice. Results from our study are generally consistent with previous literature in
terms of lower-weighted assignments. Research bears that low stake assignments promote engagement with course content (Stewart-Mailhiot, 2014). Our analysis revealed that study participants performed better and had a higher submission rate on lower weighted assignments, possibly an indication of engagement in their course.

One of the reported benefits of having more frequent lower-stakes assignments is to develop students for high stake assignments gradually. This gradual preparation is to improve performance in high stake assignments (Elbow, 1997). However, study participants did not show an improvement in their performance on the higher-stake assignments. There are some possible reasons. For example, studies have shown that a significant proportion of students report giving little effort to low-stakes assignments (Hoyt, 2001; Sundre & Kitsantas, 2004). If effort is an indicator of learning, students would not be prepared for higher-stakes assignments. Our analysis would support this research.

In a similar study conducted by a co-author from the current study, Motz et al. (under review), findings revealed when students received an assignment reminder; students were significantly more likely to submit their assignments and receive higher assignment scores. These findings imply the need for reminders and support the concept of just-in-time (JIT). The JIT concept is widely used within the field of instructional psychology and the learning sciences and has its roots in cognitive load theory. Its purpose is to provide the necessary information, JIT, to scaffold a novice learner (Merrienboer, Kirschner, & Kester, 2003). According to behavioral economic principles, individuals are typically inattentive to future essential actions, which can lead to a misallocation of resources and missed deadlines. Without a planned intervention, certainly competing demands are likely distracting students from what it is they needed to do. Encouraging a plan can assist individuals to reach their goals (Madrian, 2014).
1.5.1.1 Limitations One of the limitations of this study is that the research team did not have access to the course assignments. Assignment weights were set by individual instructors. Neither the number of assignments or whether an assignment was properly weighted could be verified. Likewise, as we did not have access to final grades, ultimately, we were not able to measure the cumulative impact of lower weighted assignments.

Participation was voluntary, which can introduce selection bias. Without demographic information, this sample could represent a highly motivated group and may not be representative and not generalizable. Additionally, we did not have a comparison (control) group; data from students who opted-out of IU Boost app could eliminate possible bias.

1.5.1.1 Call for action For decades, published intervention research has been on the decline despite the clarion call for increasing intervention and action published research (Blackwell, Trzesniewski, & Dweck, 2007; Hidi & Harackiewicz, 2000; Hsieh et al., 2005; Lazowski & Hulleman, 2016; Maehr & Meyer, 1997; Midgley & Edelin, 1998; Pintrich, 2003; Robinson, Levin, Thomas, Pituch, & Vaughn, 2007; Wentzel & Wigfield, 2007). There are a variety of reasons, including an increasing number of administrators designing and implementing interventions without the time or responsibility to publish. To bridge the gap between theory and practice, intervention researchers should work in tandem with practitioners, using a scientific iterative methodology known as design-based research (DBR). (See McKinney & Reeves (2018) for a full treatment of this approach.) Reporting on DBR raises awareness and shares meaning across the educational intervention landscape.
1.6 Conclusion

Findings in this article support important groundwork for automated educative nudges. With an app on their smartphone, students reliably benefit from just-in-time automated educative nudges (Motz et al., under review). Higher submission rates support the JIT notion or automated educative nudges, to provide the right type of support needed (an assignment reminder), promptly when needed (within hours of the deadline), and only when required (only if unsubmitted). Automated educative nudge research is promising for improving student engagement in courses and improving retention overall.
References


Indiana University (2018). Boost [Boost is a mobile app for Android and iOS that aggregates information about student schoolwork and uses it to deliver timely, personalized, automated notifications]. Bloomington, IN: eLearning Design and Services


https://doi.org/10.1207/s15326985ep3304_4

https://doi.org/10.1145/3303772.3303789


https://doi.org/10.1037/0022-0663.95.4.667


The projected number of enrollments in degree-granting postsecondary institutions follows a steady upward trend. By most accounts, this is applauded. Online education has increased access and flexibility, removing barriers that were once prohibitive to non-traditional students. However, retention rates are not as encouraging. Within a 6-year timeframe, roughly 60% of students complete a degree. The staggering cost of higher education is skyrocketing, and student loan debt is crippling. Those feeling the impact of student loans, the hardest are those who never graduated. Increasingly, institutions are coming under greater scrutiny, particularly those that receive government funding. Finding efficient ways to support students is imperative.

The balance of family, work, and school responsibilities are often overwhelming. Furthermore, some students lack the self-regulation necessary to succeed. For example, students may lack the ability to set appropriate goals, monitor their progress, and self-reflect on how they can adapt to meet their goals, essential skills found in students who direct their academic success. Completing tasks and timely submission of assignments are predictive of student success. The technology used for nudging students when assignment due dates are approaching may potentially bridge the gap for unprepared students.

Self-regulated learning (SRL) was used as a guiding framework. This research started with a systematic review of auto-reminder or nudging used as an intervention in higher education. We found there is a lack of peer-reviewed scholarly auto-reminder or nudge interventions in higher education studies. Auto-reminders have been powerful in other domains predominantly in the medical field, signifying an untapped area of online learning. My next two articles were quantitative research studies. We explored the characteristics of students who opted-in to use an educational support app.
Further, we studied the context of assignment deadline push notification tapping behavior. We found that students who opted in to use the mobile app were more likely to be Asian and International students. These students had higher scores on college entrance exams, earned significantly more college credit and had slightly lower prior GPA’s. These students tapped on push notifications of lower-weighted assignments. They had higher average assignment grades, more assignment submissions, and there was generally less time between the time the student submitted the assignment and the assignment deadline. Push notifications left untapped were generally those assignments with higher-weights. Students also had more time between the assignment submission and the deadline.

This dissertation has contributed to the field in a few significant ways. Perhaps one of the overarching contributions is in the call for research partnerships to attend to the lack of peer-reviewed intervention research. Interventions are typically overseen by administrators who often do not have a responsibility to publish in peer-reviewed journals. By forming partnerships to conduct educational design research, theoretical and practical knowledge will inform the field. These partnerships will contribute to an increase in peer-reviewed publications. The underlying motive for the call to increase publications is to involve more researchers in the iteration of these interventions and the replication of these studies. As interventions evolve and knowledge is shared, advances within and across contexts will lead to a more exceptional ability for generalizations.

This research was groundbreaking for the Boost mobile app. Overall findings from the two automated nudge studies seem to suggest that students who opted-in to receive push notifications have better-developed self-regulation skills than perhaps peers who opted out of using the Boost app. These app-adopters are the students who had traditionally outperformed
their peers. Still, after experience in college without continuing such performance, findings suggest these students had realized that they could benefit from automated support. However, we should be cautious in drawing definitive conclusions based on this one, preliminary study.

Future studies should include data on why students chose to opt-out from a tool geared for student success. In a world that offers a vast array of technology solutions, it seems reasonable that some students may already have their system that integrates more than just their schoolwork to assist in better overall planning. With the vast number of solutions, consumers can become overwhelmed by the sheer number of mobile applications and choose a minimalist approach.

If opening a push notification is an indication of utility, our findings seem to suggest students find more usefulness in nudges for assignments that do not have as much weight on the final grade. Moreover, they are more likely to inquire about the content of a reminder for slightly lower weighted assignments. However, without collecting contextual data on tapping behavior, it is challenging to state reasoning with confidence. It would be reasonable to believe that many students would be more attuned to higher-stakes assignments and not need a reminder. Further, since this was the first study Indiana University (IU) conducted with the brand-new Boost app, usage was limited by instructor invitation and subsequent adoption. Likewise, students were not familiar with the Boost app, like IU students are today. Data collected today may reveal quite a different set of findings. Replicating this study and comparing results is recommended.

To advance the research, a recommendation would be to administer a self-reported SRL instrument to participants and their non-participating peers. This would provide a more in-depth, more conclusive look at perceived SRL skills. Researchers would also be interested in gathering participants perceived value of the Boost app and suggestions for other types of push
notifications they perceive would be valuable, for example, messaging encouraging the participant to meet with their instructor, praise for a high score on an assignment or suggestions on how to improve on future assignments.

If conclusions drawn are accurately suggesting that students who opted-in to use the Boost app are higher self-regulated learners than their peers who opted out, how can students who lack self-regulated learning skills be encouraged to take advantage of the built-in scaffolding? For example, first-generation and underrepresented students were not significantly represented in the study despite having the same invitation to participate. How might practitioners and researchers approach the digital divide of historically marginalized students? It would seem that access is less of an issue with a prevalence for college students to own a smartphone. Further efforts to bridge the gap is the open access to the free app available for iOS or Android users. However, researchers need to address the digital literacy divide. There are a few suggestions that could assist in bridging this gap. As the Boost app is still being socialized on Indiana University campus, practitioners and researchers should look for ways to advertise the Boost app more broadly. This could include digital media campaigns targeting Indiana University students. Table tent ads can be placed in common eating areas. Posters and marquis messaging can call out the benefits at no cost. Where possible, including a QR code to the iOS and Android app stores and a link to the Boost app webpage.

Instructors may be encouraged to consider the promotion or even requirement of the app in their class. A quick intervention could be for instructors to send a personalized invitation to poorly performing students to download the app and instructions on how to use it. Further, a kiosk could be set up in a prominent area for students to get in-person help downloading and setting up the app. Other suggestions may include requiring all 1st-year and transfer students to
use the app to help them make a successful transition to college life. Offices geared to assist 1st generation and underrepresented students could also promote and set up the app as part of their mentorship.

While there are perhaps many more questions than answers derived from this research, future studies now have a foundation to start from and suggestions on possible next iterations. As researchers and practitioners work in partnership, intervention research will flourish, and marginalized student and retention efforts will have increased potential to benefit more than a single institution.
APPENDIX

IRB Approval

Research Not Subject to Human Subjects Regulation

 Protocol Number: 1906713895  Submission Type: Initial Protocol Application
 Title: Aggregate Comparisons of Institutional Data Regarding Canvas Notification Tool  Principal Investigator: Motz, Benjamin Alan
 Report Printed: 07/19/2019

- ID #25358: Provide a brief summary of the project in lay terms, including the source of the data.
  - Indiana University has recently created a smartphone app that helps students keep track of their schoolwork in Canvas. This app (hereinafter called the "Notification Tool") is freely available to IU students. They can download the app, connect it to Canvas, select their courses, and it will send helpful reminders and notifications about their coursework. In this way, some students will download the app, and other students will not. Moreover, any student using the Notification Tool may activate it for some courses, but may leave it inactive in other courses. The purpose of this study is to draw aggregate comparisons between these groups to answer the following questions: How do students who use the Notification Tool differ from their classmates who do not? How do students using the Notification Tool behave in courses where the notification tool is active, compared with courses where it is inactive?

  For this study we will have no contact with any subject. We only wish to analyze data that already exist in institutional databases, and that have been aggregated and deidentified. All study personnel already have legitimate educational interests in the data being extracted, because the current research is part of a larger institutional initiative, a collaboration between University Information Technology Services (UITS) and the Office of the Executive Vice Provost for University Academic Affairs (OVPUAA). This larger initiative involves examination of student behaviors from Canvas data in order to better understand how to support student success at Indiana University.

  The Notification Tool was created as an element for this larger initiative. IRB protocols for the pilots of the Notification Tool were approved (protocol nos: 19072586674, 1811284997, and 19032589880), but these protocols did not involve comparisons between the students who use the Notification Tool and those who do not, nor did these protocols involve comparisons between active and inactive courses among the Notification Tool's users. The current protocol aims to address these unanswered questions by (1) drawing aggregate comparisons of Notification Tool users and their peers, (2) drawing anonymized comparisons between the Notification tool users' behaviors in active and inactive courses.

  By "aggregate comparisons" (see (1) in the previous paragraph) we mean that no individually identifiable data will be returned in the database queries for comparing notification tool users to their peers — only aggregate class level means and percentages will be analyzed for notification tool users and non-users. The class itself will also be de-identified in the analysis dataset (no section numbers, course numbers, or campus information will be included). In situations where only one member of the class is using the notification tool, that class will be excluded from analysis. By "anonymized comparisons" (see (2) in the previous paragraph), we mean that no individually identifiable information will be returned in the database queries for comparing notification tool users' behaviors in active and inactive courses. No student will be identifiable in the data under analysis for this contrast, nor will the study data be able to be mapped back onto individual students.

- ID #25359: Choose the category of activities which will be conducted by the IU affiliated investigators.
  - Receipt and/or analysis of coded private information or biospecimens
  - Receipt and/or analysis of a limited data set
  - Receipt and/or analysis of fully deidentified data
  - Receipt and/or analysis of deidentified PHI
  - Data collection and/or analysis for internal monitoring and quality improvement purposes
  - Implementation of an accepted practice to improve the delivery or quality of care or services provided by a specific department or institution
  - Case report
  - Other

- ID #25361: Will the IU affiliated investigators have access to any information (i.e. any unique identifying number, character, or code) which would allow them to readily identify subjects? Identifiers include the following: • names, including initials • any geographic subdivision smaller than a state, including street address, city, county, precinct, zip codes (if the geographic unit of combining all the same address contains more than 20,000 people) • all elements of dates (except year) for dates directly related to an individual, including birth date, admission date, discharge date, date of death • ages over 89 (unless aggregated in a single category of age 89 or older) • telephone number • fax numbers • email addresses • social security numbers • medical record numbers • health plate beneficiary numbers • account numbers • certificate/license numbers • vehicle identifiers and serial numbers, including license plate numbers • device identifiers and
Research Not Subject to Human Subjects Regulation

serial numbers • web universal resource locators (URLs) • internet protocol (IP) address numbers • biometric identifiers, including finger and voice prints • full face photographic images and any comparable images

☐ No
☐ Yes. Your project includes identifiers. Please review the other options and/or contact the Human Subjects Office for assistance.

• ID #2125347: Choose how data will be collected.
   ☒ Use of data originally collected for a non research purpose
   ☐ Data collection through oral or written communications with individuals
   ☐ Other