DETERMINING THE INFLUENCE OF LEARNER CHARACTERISTICS ON ONLINE COURSE SUCCESS FOR UNDERSERVED STUDENTS IN HIGHER EDUCATION

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ABSTRACT

This study uses a logistic regression model to analyze survey data (n = 341) and predict factors influencing online course success for underserved and academically at-risk undergraduate students at a small, broad access, four-year, public Midwestern university. Three blocks of predictor variables, demographic (first generation, low income, minority status), educational (academic level, prior online experience, online vs. face-to-face major, transfer status, college cumulative GPA), and personal characteristics (self-regulation, Technological Efficacy), were used to explain student success in online courses. Low income, although initially significant, was not a significant predictor in the final model. College cumulative GPA remained a statistically significant predictor of online course success in every block of the regression analysis. Prior online experience and self-regulation were not significant predictors, although the overall model was significant. Controlling for all explanatory variables, college cumulative GPA and Technological Efficacy were found to be the most significant predictors of online course success in the final model. With increasing prevalence and popularity of online courses, it is crucial for universities catering to a larger proportion of underserved and academically at-risk students to identify the specific learner characteristics that lead to successful online course completion.

Keywords: *Underserved, minority, at-risk, online learning, GPA, technological efficacy, self-regulation, disadvantaged students*

INTRODUCTION

The global pandemic has fundamentally transformed the way teaching and learning is delivered and has brought a new spotlight on online learning. Prior to the pandemic, institutional desire to increase access and successful progression through higher education programs spearheaded the growth of postsecondary online education (Bragg et al., 2006; Jaggars & Bailey, 2010; Mead et al., 2020; Xu & Jaggars, 2013). This has been welcomed by both traditional and nontraditional students who need the convenience and flexibility of online learning to further their educational aspirations while honoring work and family responsibilities (Harris & Martin, 2012; Magda & Aslanian, 2018).

Consequently, online learning has grown steadily with increases in both the number of college students enrolled in at least one online course and the proportion of all enrolled students studying online (Allen et al., 2016; Cohen & Baruth 2017;

Ginder et al., 2017). According to Department of Education data, out of 19.6 million students in the fall of 2019 (the semester before the pandemic), 7.3 million (37.2%) students took online courses (Hussar et al., 2020). The onset of COVID-19 in March 2020, however, completely altered the postsecondary educational landscape when campuses physically closed and transitioned into fully online instruction. College students experienced shifts in their living and learning contexts that were both unanticipated and unprecedented. With the pandemic now in its third year, online learning has become a permanent fixture of higher education, thereby necessitating the need to explore the determinants of online success, especially for underserved students who have been the hardest hit by the pandemic (Rodríguez-Planas, 2022).

A primary assumption underpinning the increase in online course offerings is that they increase educational access, presumably for those who are traditionally underserved, such as low-income, rural or inner-city, first generation, or minority students (Allen & Seaman, 2008; Bailey et al., 2018; Bragg et al., 2006; Mead et al., 2020; Parsad & Lewis, 2008; Protopsaltis & Baum, 2019). However, despite significant increases in access, success rates among underserved students in online courses remain low (Bettinger & Loeb, 2017; Chatman et al., 2019; Xu & Jaggars, 2013). Student performance in online courses is generally weaker than in face-to-face (f2f) classes (Bettinger & Loeb, 2017; Hachey et al., 2012; Lehman & Conceicao, 2014; Moore & Kearsley, 2012). This is especially applicable to students coming from first generation, low-income, or minority populations (Hart et al., 2018; Mead et al., 2020; Xu & Jaggars, 2011, 2013).

This disparity is particularly troublesome given that a rising share of students entering minimally selective and open admission postsecondary institutions come from minority and low-income backgrounds (Fry & Cilluffo, 2019), and that these students are also more likely to enroll in online courses (Radford et al., 2015).

Since the outbreak of the COVID-19 pandemic, a vast majority of students are taking at least some, if not all of their courses, online. While a 2009 U.S. Department of Education meta-analysis (Means et al., 2009) found that students in online and f2f courses had comparable outcomes, subsequent research has found that online learning can have deleterious effects for students who are either academically at-risk or come from underserved backgrounds (Bettinger & Loeb, 2017; Jaggars & Bailey, 2010). Disparities in underlying health conditions, access to and quality of health care, and living and work conditions led minority communities to be disproportionately affected by COVID-19 (Webb Hooper et al., 2020). There is mounting evidence to suggest that students from such communities are especially vulnerable in the online format in light of the widespread campus closures and subsequent move to online instruction (Aucejo et al., 2020; Quach & Chen, 2021; Rodríguez-Planas, 2022). As online learning becomes more of a standard fixture in today's postsecondary educational landscape, an increased focus on learner characteristics that predict online course success is needed in order to address existing achievement gaps.

PURPOSE

While there is considerable research on underserved students' outcomes in online courses in community college settings (Bragg et al., 2006; Chatman et.al., 2019; Hart et al., 2018; Xu & Jaggars, 2011, 2013) there is not enough research investigating learner characteristics influencing online course success among underserved and academically at-risk students in four-year public college settings, especially at nonselective institutions that serve a higher proportion of underserved and academically at-risk students. Several prior studies examined the success outcomes of randomly assigned students to an online or in-person section of one course and reported negative effects on student test scores for online students (Alpert et al., 2016; Figlio et al., 2013; Joyce et al., 2015) or, null results (Bowen et al., 2014). These studies are well acknowledged but each examines only a single course in economics or statistics, and the focus is on college students at relatively selective public four-year institutions. This study examines success rates from more than 165 online courses at a broad access four-year state university that is the most diverse institution in the state system. Consequently, the institution serves a disproportionately higher number of underserved and academically at-risk students, a population that is growing in higher education and whose success is important if the goal of educational equity is to be attained. There is a need for more evidence about factors that lead to online course success for the above-mentioned demographics as this can provide higher education leaders and stakeholders with the information needed to improve underserved students' chances of success in the online environment, and, thereby, help narrow the achievement gap.

This study aims to extend the current literature by examining how demographic, educational, and personal characteristics interact to influence academic performance in the online environment. While many studies have demonstrated the influence of one or more of the aforementioned variables' effect on academic performance in online courses, this research is unique because it uses a logistic regression approach to tease out the singular impact of an individual explanatory variable's role in predicting academic success in an online environment. Based on previous empirical evidence, this study tries to discern the odds of success in online courses for underserved and at-risk students in the presence of more than one explanatory variable.

This study is pertinent as it further extends the literature by investigating the impact of demographic, educational, and personal variables on the likelihood of online course success of a diverse group of college students. Such students may be of white or minority status, but they may also possess other characteristics such as lower economic status, first generation college status, and academic underpreparedness, all of which, stand-alone or in combination, may predispose them to underachievement, thereby classifying them as underserved and/or academically at-risk (Zielezinski & Darling-Hammond, 2016). Using a logistic regression analysis, this study develops a model to examine how well learner characteristics such as demographic (first generation, low income, minority status), educational (academic level, online program major, transfer status, college cumulative GPA, prior online experience), and personal (self-regulation, Technological Efficacy) predict online course success and determine which characteristics are most significant in explaining online course success for underserved and academically at-risk students.

SIGNIFICANCE

Given the increased incidence of online learning, determining the key factors influencing course performance in an online environment for underserved and academically at-risk students can be used to guide and inform subsequent actions vital to bridging any educational equity gaps that exist across disadvantaged student groups (Cahalan & Perna, 2015; Kena et al., 2016; Protopsaltis & Baum, 2019). Course persistence and completion are particularly important for less selective open-enrollment institutions where a large proportion of students are low income, work long hours, or have dependents, and where few can readily afford the resources required to retake courses they did not successfully complete the first time (Adelman, 2005; Morest & Bailey, 2006; Planty et al., 2009). Consequently, these students, who are most likely to enroll in online courses and are also the group that the postsecondary system is most challenged to serve well, end up suffering most from unsuccessful attempts. This study extends the conversation on factors that predict online course success for disadvantaged student groups, and, therefore, can help inform policy and practices that might lead to greater equity in educational outcomes.

LITERATURE REVIEW

Demographic and Educational Characteristics

Underserved populations refer to a broad group of learners who may possess one or more of several at-risk characteristics such as belonging to lower economic status, first generation college attendees, minorities, testing into remedial courses (academically unprepared), undercredited (not full-time status), and not on track to graduate (Zielezinski & Darling-Hammond, 2016). Other studies have included transfer students in this category as well (Finley & McNair, 2013). Additionally, in the context of educational inequities, underserved students have been identified as those that lack access to high-quality educational and career planning opportunities and resources (Moore et al., 2018).

In this study, the word underserved is used to describe disadvantaged students—either low income, and/or first generation, and/or minority students, and/or academically at-risk students where academically at-risk refers to, singly or in combination, academically underprepared and undercredited. First generation is defined as students whose parents' education is high school or less. Low income is synonymously used with Pell Grant eligibility. Minority students are those who identified their race/ethnicity as anything other than white. Undercredited refers to students who carry an academic course load of less than 12 credit hours per semester. Academically underprepared refers to students who enter college needing remedial coursework.

Jaggars and Xu (2010) analyzed data on nearly 24,000 students in 23 institutions in the Virginia Community College system (VCCS) to conclude that students had a greater likelihood of failing or withdrawing from online courses than from f2f courses. Underprepared students (those who scored below college-ready standards on VCCS placement exams) performed more poorly overall while online students who were also categorized as underprepared performed most poorly. Similar conclusions emerged from a Washington State Community College System study (Xu & Jaggars, 2011). This study analyzed data from more than 51,000 students in 34 community and technical colleges and found that students enrolled in online courses were significantly more likely to withdraw or fail than those who took traditional f2f courses. The gap in online course completion narrowed significantly as students gained more experience with online courses. All types of students in the study performed worse in online courses, but African American students and those with lower prior GPAs had particular difficulty adjusting to online learning. Another study (Xu & Jaggars, 2013) of 125,218 course enrollments among 18,567 students in Washington state found that online course persistence rate was 91% compared to 94% in f2f courses. The GPA gap was 11% (2.54 vs. 2.65). Minority status, students eligible for need based aid, and those from lower socioeconomic status (SES) had significantly lower success rates in online courses.

Kaupp (2012) found that in California community colleges, students enrolled in online classes had, in the aggregate, lower completion rates and lower success rates than their peers in f2f classes. Online instruction significantly increased the achievement gap between white and Latinx students. Relative to the performance of each group in f2f sections of the same classes, the gap between white and Latinx students increased in online courses with the latter group experiencing worse outcomes, with large differences noted with respect to success rates, grades, and withdrawal rates.

Johnson and Cuellar Mejia (2014) found that students at California community colleges were less likely to complete online courses, and when they completed them, were less likely to obtain a passing grade. This result was consistent across all groups of students, many fields of study, and most colleges in the system, and persisted over a 10-year period.

Controlling for college cumulative GPA and other institutional factors, the study found that online course success rates were between 11 and 14 percentage points lower than success rates in f2f courses. Of particular note, gaps across racial/ethnic groups were larger in online courses. The authors found that African Americans, Latinxs, and students with lower levels of academic skill were all likely to perform markedly worse in online courses than in classroom courses.

In a study where students in a large introductory microeconomics course at a major research university were randomly assigned to either f2f lectures or watching the same lectures in an internet setting, Figlio et al. (2013) found that students with low GPAs had more difficulty adapting to the online context and their performance suffered. The results were particularly strong for Hispanic students and lower-achieving students. In another study (Mead et al., 2020) spanning 10,000+ course enrollments, the authors examined student demographics and course grades in a fully online biology degree program versus its equivalent in-person degree program at the same university. The comparison revealed that students who were Pell eligible, African American, Latinx, Native American, and Pacific Islander were each associated with lower course grades in online courses. The authors reported that students who were both low-income (Pell eligible) and minority status received lower course grades compared to their non low-income and white counterparts, whereas first generation students received lower grades in both online and f2f courses. Hart et al.'s (2018) study of over 3 million students in the California community college system found that students in online sections had significantly lower completion rates, significantly lower rates of successful course completion (with an A, B, C, or Pass grade), and significantly lower rates of obtaining grades of A or B compared to students in f2f courses. Results from the study showed that when broken down by race/ethnicity, the patterns of course completion and passing were strikingly similar, with minority students faring worse in the online medium.

In a study of cognitive engagement in online learning at the postbaccalaureate level (n = 121), Richardson and Newby (2006) found prior online learning experience to be significantly associated with students taking more responsibility for their own learning. Students who had taken more online courses utilized deep learning strategy and were more engaged and more self-directed, which led to success in the online environment. Bradley et al. (2017) reported that successful online course completion is likely explained by the mastery experience:

> Students who were successful in their online courses have evidence that they have what it takes to succeed. On the other hand, students who do not have mastery experiences in their online courses, that is, students who either were not successful in their online courses or have no prior experience in taking online courses, are less likely to feel that they possess the necessary capabilities to do well. (p. 526)

Based on an analysis of institutional data from a large representative community college (enrollment of 15,000+), Hachey et al. (2013) reported that prior online experience was a significant predictor of future online success, with students who had never taken a course online much more likely to withdraw or fail than students who have had successful prior online course experiences. The study found that students who had never taken a course online were much more likely to withdraw or fail than students who had successful prior online course experiences, and that students who had failed or dropped out of even one online course did significantly worse in future online courses than students with no prior online experiences. The authors reported that this effect persisted even when controlling for GPA. In another study of 149 minority students at a large Southeastern U.S. university, students' academic performance was significantly correlated with the number of online courses taken (Yeboah & Smith, 2016). The aforementioned studies confirm that underserved and academically at-risk students are likely to have lower success outcomes from online courses.

However, these findings are not limited to public institutions alone. Bettinger et al. (2017) reported similar results based on a large study conducted at a for-profit university with an undergraduate enrollment of more than 2,300,000 students, and with a high proportion of African American and Hispanic students. The study examined enrollment spanning 168,000 sections in more than 750 different courses and found that after controlling for the same syllabus, instructors, requirements, and assessments, students in online sections had consistently worse outcomes. They earned lower grades in the courses and had lower grades the following term, particularly in the same subject area or for subsequent courses for which the course in question was a prerequisite. Students were about nine percentage points less likely to remain enrolled the semester after taking an online course than after taking a similar course in an f2f setting. The authors found that performance in online courses was worse for students with lower prior GPAs.

The forced shift to online learning due to COVID-19 has been a challenging endeavor for students. Prepandemic research, discussed earlier, indicates that the negative effects of online course taking are far stronger for students coming from underserved backgrounds. Although the long-term impact of the pandemic on student achievement is an emerging phenomenon, an early study (Aucejo et al., 2020) of 1,500 undergraduate students at a large public institution reported that COVID-19 nearly doubled the gap between higher and lower income students' expected GPA. The gap in GPA attributable to income increased from 0.052 to 0.098 on a 4-point scale. The study reported that poorer outcomes in online courses tend to impact students' academic performance in future courses as well as increase the likelihood of such students dropping out of college altogether.

After March 2020, many institutions adopted a flexible grading policy, allowing students to opt for a pass/fail option rather than a letter grade. Rodríguez-Planas (2022) surveyed 2,817 students at a large urban institution in the summer of 2020 and reported that the flexible grading system worked favorably for lower income students. Evaluated on the basis of cumulative GPA at the end of the Fall 2019 semester, lower income students who were in the bottom quartile outperformed their higher income peers by 9% in the Spring 2020 semester. The lower income students were 35% more likely to exercise the pass/fail option and in the absence of the flexible grading policy, these students would have seen their GPA decrease by 5% relative to their prepandemic GPA. The study reported suggestive evidence of lower-income students experiencing greater challenges with online learning, reporting a higher use of incompletes than their higher-income peers and expressing heightened concerns about maintaining merit-based financial aid.

Self-Regulated Learning

With the increased focus on online learning, and such learning characterized by a greater degree of autonomy, self-regulation becomes a critical factor for academic success in such an environment (Barnard et al., 2009). Zimmerman (2013) defined Self-Regulated Learning (SRL) to be a self-directed process in which students set their own learning goals while monitoring, controlling, and regulating their behavior, motivation, and cognition. The author described SRL as a cyclical process in that the self-feedback from prior performance helps students adjust their future actions. According to the triadic loop of self-regulation, it is divided into behavioral, environmental, and covert self-regulation. Bradley et al. (2017) reported that positive self-regulatory behaviors can be used as reliable predictors of academic success in the online setting. There is evidence that students with greater self-regulating behavior do better in online courses (Hiltz & Shea, 2005).

In a study of 815 community college students in Southeastern United States, time and effort regulation were significantly related to grade performance in the online classroom (Puzziferro, 2008). Literature reports a significant positive correlation between self-regulation and academic performance with self-regulation predicting online success at a higher rate for first generation students (Naumann et al., 2003; Thibodeaux et al., 2017). Pintrich and Garcia (1991) defined time and study environment as the scheduling, planning, and budgeting of study time as well as regulation of the general study environment. Effort regulation was defined by the authors as the management of academic tasks that reflected the level of commitment students maintained when faced with obstacles and difficulties. The authors noted that when compared to students who received lower grades or withdrew from online courses, students who received higher grades in the online course were more likely to efficiently plan, schedule, and manage their study time. Students who withdrew demonstrated a lower ability to regulate and manage effort than students who received A, B, or C grades.

In a study of 149 minority students at a major Southeastern university, qualitative analysis of responses indicated a lack of self-regulation skills such as time management and ability to complete assignments in a timely manner in online courses (Yeboah & Smith, 2016). The majority of students reported self-regulation of time and task to be the biggest challenge in obtaining a better grade. Approximately 83% of the minority students reported a lack of self-regulation skills such as time management related to submission of assignments, projects, and other requirements associated with timely course completion. These findings are consistent with the past research (Artino, 2007; Bothma & Moneith, 2004; King et al., 2000) that indicate that students in online environments need to deploy greater self-regulatory skills given that online learning is characterized by flexibility, additional demands on students, and greater emphasis on learner centeredness. In another study (Thibodeaux et al., 2017) of 589 first-semester undergraduates at a large, public, Mid-Atlantic university, the researchers analyzed contemporaneous associations between students' time use with self-regulation. The results indicated that academic time use (planned and actual academic hours) related to higher self-regulation and target GPA in the first and second semester. Bradley et al.'s (2017) study of 266 undergraduate students in a Southern university found strong correlations between self-regulatory skills and its influence on achievement in an online learning environment. The authors reported on how successful aspects of self-regulated learning such as goal setting and planning were positive predictors of metacognitive strategy, which in turn, influenced student self-regulatory behavior.

However, a study (Cazan, 2014) that investigated the relationship between SRL, academic achievement, and GPA amongst 80 undergraduate students enrolled in an online statistics course reported a weak positive correlation with academic achievement in the online environment even as the regression analysis demonstrated self-regulation to significantly predict grades at the end of the semester. Kitsantas et al. (2008) found self-regulation to not play a significant role in predicting academic achievement during the first or subsequent years of studies when analyzing student performance within the context of traditional learning environment at a large, public, Mid-Atlantic university (n = 198).

In a metanalysis of SRL and academic achievement, Broadbent and Poon (2015) reported on overall weak significant relationship between the variables. They analyzed 12 articles published between 2004 and 2014 that examined self-regulation as correlates of academic achievement in an online higher education setting. The authors concluded that although the contributors to achievement in traditional f2f settings appeared to generalize to online context, those effects seemed weaker and suggested that they may be less effective and that other, unexplored factors may be more important in online contexts.

The onset of the COVID-19 pandemic in March 2020 led to a shift of the learning setting to online for all students. This challenge necessitated adoption of active SRL strategies to cope with the situation. SRL strategies play a crucial role in academic success and cognitive, social, and adaptive functioning (Zimmerman, 2013). A diverse set of SRL strategies allow students to cope with various situations and social contexts more effectively (Schunk & Greene, 2018). Usher and Schunk (2017) reported that environment, with its different micro- and macro-level environmental factors and stressors, can have an impact on students' self-regulatory processes. From that perspective, the COVID-19 pandemic presented a specific environmental stressor that had an important impact on students' SRL (Juriševič et al., 2021). Quach and Chen (2021) reported that with students having to leave campus and move back home as a consequence of the pandemic, they were cooped up in small living spaces with parents, siblings, or other family members, which led to lack of adequate physical space or privacy for studying. Hamdan et al. (2021) reported overall low SRL scores during the pandemic induced period of emergency remote teaching (ERT) for a sample of 702 university students. Juriševič et al. (2021) reported that the most used academic self-regulation strategies during ERT were environment structuring (e.g., choosing a comfortable space without distractions) and goal setting (e.g., setting short- and long-term goals and standards). By contrast, task strategies (e.g., preparation of more detailed notes and questions, performing additional tasks) were the least used during ERT, as per the authors.

Technological Efficacy

Since the worldwide outbreak of COVID-19, digital technologies have taken center stage in dispensing education and this proliferation has important implications for the academic success of underserved and at-risk students. This is pertinent in light of existing literature that indicates that not all students have the necessary skills to fully take advantage of the broader access gained via online learning. A study (Buzzetto-Hollywood et al., 2018) of 2,800 undergraduate students enrolled in introductory and intermediate computer applications courses at a minority-serving institution found that students did not possess the necessary technological skills needed to succeed in college, and that there was a gap between students' level of skills and the computer skills necessary for academic success. The study found this gap to be more pronounced for minority students.

A meta-analysis of studies on academic outcomes in online courses by Protopsaltis and Baum (2019) underscored the importance of students' extensive exposure to technology contributing to greater adaptation and success in online learning. This was particularly true for underprepared and disadvantaged students who underperformed and, on average, experienced poor outcomes. The researchers concluded that gaps in educational attainment across socioeconomic groups were larger in online than in traditional coursework. A similar finding was reported in Yeboah and Smith's study (2016) where minority students' use of technology in online courses largely influenced their academic achievement. In a sample of 2,139 undergraduate and graduate students at another Southeastern U.S. university, Wang et al. (2013) reported a higher level of course achievement with higher levels of Technological Self-Efficacy, which included a general computer self-efficacy component and an online learning platform-related self-efficacy component. The results indicated that students with higher levels of Technological Self-Efficacy tend to receive better grades. They concluded that students who wanted to succeed in online learning should have confidence in general computer skills as well as in using online learning platforms.

These findings raise important concerns about whether such a gap between student ability and skills, as they pertain to use of technology, exists for postsecondary student populations. And, if so, whether such a gap, as it relates to impediments to student learning outcomes within an online learning environment, is likely to negate some or all of the gains in educational access that online course delivery seeks to accomplish. In light of the above, it may be surmised that an individual's ability to successfully navigate an online environment and leverage digital technologies for learning is linked with the person's abilities and skills as it relates to computers.

Technological Efficacy, then, refers to skills related to use of computer devices and skills related to use of the internet that, stand-alone or together, facilitate the use of technology for the purposes of learning (Banerjee, 2020).

Technological Self-Efficacy, on the other hand, is defined as a person's "perceptions of his or her ability to use computers in the accomplishment of a task," also known as computer self-efficacy (Compeau & Higgins, 1995, p. 191), and a person's "belief in one's capabilities to organize and execute courses of internet actions required to produce given attainments," also known as internet self-efficacy (Eastin & LaRose, 2000, p. 1).

In a study of nontraditional African American adult students' (n = 414) use of technologies and their perceptions towards it in technology-based environments at a Southern U.S. university, Kuo (2018) found that learners' levels of computer self-efficacy were a good predictor for both user attitude towards technology and computer anxiety.

Results also indicated that nontraditional minority students utilized basic software tools more frequently than the advanced ones, suggesting that many of them may lack the knowledge or skills for advanced technologies. Kuo and Belland (2019) found that learners with lower levels of computer self-efficacy exhibited anxiety related negative attitudes towards computers while learners with higher levels of computer self-efficacy exhibited positive attitudes towards computers. Results indicated that adult students showed a higher level of confidence in performing basic computer or software skills and internet browsing actions in comparison to advanced computer skills or internet tasks. Positive correlations were found between computer self-efficacy, internet self-efficacy, and academic self-efficacy. Both computer self-efficacy and internet self-efficacy were significant predictors of academic self-efficacy. Such a relationship between levels of computer self-efficacy and anxiety and attitude towards computers, as noted by Kuo and Belland (2019), appears to be reasonable given that negative emotions towards computers is likely to impact learners' confidence levels in performing computer related tasks. This comports with the Saadé and Kira's (2009) research on first-year undergraduate students at a Canadian university that found that (a) computer anxiety had a significant effect on perceived ease of use of a learning management system (LMS), (b) computer self-efficacy acted as a significant mediator in reducing the strength and significance of the impact of computer anxiety on perceived ease of use of an LMS, and (c) there was a strong and significant relationship between computer self-efficacy and computer anxiety.

A study (Bai, 2022) of 104 undergraduate students at a large public university found that when students were exposed to online learning, their technological confidence increased, they developed a more positive outlook, and they became more interested in technology, which led to higher levels of Technological Efficacy. In a study of undergraduate students enrolled in a communication course at a U.S. university, Eastin and LaRose (2000) found internet self-efficacy and internet use to be directly and significantly correlated as students were more likely to attempt and persist in behavior that they felt capable of performing. The study also found that internet self-efficacy directly influenced learner outcome expectancies, was positively correlated to internet usage, and was strongly influenced by prior experience. The authors surmised that positive assessment of internet self-efficacy directly influenced learners' outcome expectations, and such expectations, along with lower anxiety and/or higher confidence associated with higher levels of internet self-efficacy, promoted greater task persistence and influenced effort levels towards realizing such expectations. This, in turn, promoted greater use of technology, expanded technology related experience, and helped develop learner technology related skills, which then further bolstered internet self-efficacy, thereby completing a positive feedback loop. This assessment by Eastin and LaRose (2000) indicates that higher levels of Technological Self-Efficacy is likely to lead to higher levels of technology related skills or Technological Efficacy while lower levels of Technological Self-Efficacy is likely to lead to lower levels of Technological Efficacy.

The linkage between computer self-efficacy and online performance was also reported in a longitudinal study by Hauser et al. (2012) that examined the effect of computer self-efficacy, amongst other variables, on that of student performance. This study found that higher computer self-efficacy scores positively correlated to higher performance in online courses for undergraduate students at a midsized U.S. university. Kuo and Belland's study (2016) of African American working adult undergraduate students found a similar linkage between internet self-efficacy and performance. The study found higher internet self-efficacy to be significantly and positively correlated with learner-content interaction, learner-learner interaction, and learner-instructor interaction in an online learning environment, which in turn, was positively correlated with satisfaction in online courses. Higher levels of satisfaction, in turn, were correlated with better academic performance.

The link between technology related efficacy and performance was also examined by Liu et al. (2007) in a meta-analysis of the determinants of online course dropout rates in a community college context. The authors noted that technology related efficacy, among other variables, was a key factor that influenced the decision to drop courses. The study found that the ability to use technology to achieve one's learning objectives was a significant factor influencing online success.

The development of such skills (Technological Efficacy) needed to accomplish tasks is influenced by the learner's level of Technological Self-Efficacy. Technological Self-Efficacy determines level of anxiety, confidence, task persistence and effort, usage of technology, technology related experience, and development of skills eventually leading to Technological Efficacy. Technological Efficacy, in turn, leads to an increase in Technological Self-Efficacy, thereby completing the learning reinforcement loop. As such, in the absence of tests examining actual levels of Technological Efficacy of a sample, self-assessment of technological skills or Technological Self-Efficacy is used to infer Technological Efficacy. In light of this, Technological Self-Efficacy is used as the appropriate construct for assessment of Technological Efficacy in a survey sample, in the absence of skills-based tests for the latter (Banerjee, 2020).

METHODOLOGY

Research Questions

The research questions we examined were:

RQ1) Are students with different demographic characteristics (first generation, low income, minority status) and educational characteristics (academic level, online program major, transfer status) equally likely to succeed in online courses?

RQ2) Can college cumulative GPA help explain students' success in online courses, while keeping the aforementioned demographic characteristics (first generation, low income, minority status) and educational variables (academic level, online program major, transfer status) constant?

RQ3) Can prior online experience help explain students' success in online courses, while keeping the demographic characteristics (first generation, low income, minority status), educational characteristics (academic level, online program major, transfer status), and college cumulative GPA constant?

RQ4) Can self-regulation help explain students' success in online courses, while keeping the demographic characteristics (first generation, low income, minority status), educational characteristics (academic level, online program major, transfer status), college cumulative GPA, and prior online experience constant?

RQ5) Can Technological Efficacy help explain students' success in online courses, while keeping the demographic characteristics (first generation, low income, minority status), educational characteristics (academic level, online program major, transfer status), college cumulative GPA, prior online experience, and self-regulation constant?

Design, Sample, and Data Collection

The study used a cross-sectional survey research design to investigate the research questions. A web survey assessing students' online learning experience was administered to undergraduate students at a small public Midwestern university. Email invitations to participate in the online survey were sent to the entire student body except for first-semester new and first-semester transfer students, thereby ensuring that the respondents had completed at least one semester at the institution—this was to ensure that the students had had the opportunity to complete at least one online course. In all, 535 undergraduate students completed the web survey. Among these respondents (n = 535), 341 students showed records of having taken online courses and were therefore included in the study. Course grades for the 341 survey respondents, spanning a total of 165 online courses, were obtained from the Office of Institutional Research and Assessment. In evaluating optimum sample size of an observational study, Austin and Steyerberg (2017) reported a minimum of 20 events per variable (EPV) to ensure predictive accuracy for a logistic regression. This study focuses on ten variables of interest, therefore requiring a minimum sample size of 200. The actual sample size of 341 exceeded this recommendation.

Procedures outlined by web survey experts to increase response rates, such as follow up contacts and incentives for survey completion, were employed. The initial survey link was sent via email to all 2,800 students during the 7th week of the semester. Weekly reminder emails were sent to those who had not completed the survey until the 14th week of the semester. Instructors were approached to announce the survey verbally in their f2f courses or in writing on their LMS home page. To increase response rate, the survey was incentivized. Students who completed the survey were placed in a draw to win Amazon gift cards. The survey response rate of 19.1% was in line with the typical esurvey response rate range of 20%-30% (Bosnjak & Tuten, 2001; Sheehan, 2001) and was consistent with general guidelines for quantitative research which deems a sample size of 10%-20% of a population as acceptable (Gay, 1996).

Instrumentation

An online course was defined in the survey as a course where 100% of the course content was delivered online. The survey included a section to assess self-regulation and a section to assess Technological Efficacy. A modified Motivation Strategy for Learning Questionnaire (modified MSLQ), and a Technological Efficacy Questionnaire (TEQ) were used in the current study along with student educational and demographic data obtained from the Office of Institutional Research and Assessment. Demographic characteristics covered students' gender, age, race/ethnicity, Pell Grant eligibility, income, transfer status, and first-generation college attendee status.

A slightly modified Pintrich and De Groot's (1990) self-regulation scale of the widely used Motivated Strategies for Learning Questionnaire (MSLQ) was used to assess self-regulation skills (Table 1). The original scale consisted of nine items but two items were added to fit the college student demographic and the 7-point Likert scale (1 = not at all true of me, 7 = very true of me) was shortened to a 5-point Likert Scale. Four of the eleven items were reverse coded (denoted by R in Table 1) to avoid response set bias. Because the MSLQ is designed to address motivation and self-regulation in a specific domain and context, the wording of the items of the self-regulation scale used in this study were slightly modified to address general academic tasks as opposed to performance in a specific context or domain (i.e., changing "in this class" to "in my classes"). Cronbach's alpha was 0.74 for the original scale and 0.78 for the modified scale, which can be considered reliable for perception related instruments (Wallen & Fraenkel, 2001).

Table 1.
Self-Regulation Scale

Items	Scale	Cronbach's alpha
a. I ask myself questions to make sure I know the material I have been studying.	1 = Strongly disagree 5 = Strongly agree (5-point Likert Scale)	0.78
b. When work is hard, I either give up or study only the easy parts (R).		
c. I work on practice exercises and answer end of chapter questions even when I don't have to.		
d. Even when study materials are dull and uninteresting, I keep working until I finish.		
e. Before I begin studying, I think about the things I will need to do to learn.		
f. I often find that I have been reading for class but don't know what it is all about (R).		
g I find that when the teacher is talking I think of other things and don't really listen to what is being said (R).		
h. When I am reading, I stop once in a while and go over what I have read.		
i. I work hard to get a good grade even when I do not like a class.		
j. I ask for help from a peer/study group/instructor when I face difficulty in understanding a course concept.		
k. I am easily distracted (R)		

The Technological Efficacy questionnaire (Table 2) was based on a scale that required students to self-assess their skills and degree of comfort with respect to basic technological skills (Technological Efficacy). Technological Efficacy was an eight-item measure on a 5-point Likert scale with 1 = strongly disagree to 5 = strongly agree. The eight items included perceptions of skillsets and preparedness related to using the computer and the internet and taking online courses. The items included perceived comfortability with tasks related to typing, saving, and organizing files in a computer; surfing the internet; finding internet resources and setting bookmarks; uploading and downloading files; installing software and changing configuration settings; navigating a learning management software; and two items on perceived confidence related to taking and completing online courses. The TEQ was developed based on a detailed literature review and in consultation with subject matter experts in the field of adult and distance education as well as faculty experienced in online teaching.

The Technological Efficacy questionnaire was loosely based on a review of three instruments: The computer self-efficacy (CSE) questionnaire used by Santoso et al. (2014), the internet self-efficacy questionnaire developed by Torkzadeh and Dyke (2001), and the internet self-efficacy scale used by Rodríguez Robles (2006). The 29 item CSE

Table 2.
Technological Efficacy Scale

Items	Scale	Cronbach's alpha
a. I felt comfortable typing, saving, and organizing files in a computer.	1 = Strongly disagree 5 = Strongly agree (5 point Likert Scale)	0.82
b. I felt comfortable surfing the internet.		
c. I felt comfortable finding internet resources (web search) and setting bookmarks.		
d. I felt comfortable uploading & downloading files.		
e. I felt comfortable installing software and changing configuration settings.		
f. I felt comfortable navigating a learning management software.		
g. I felt prepared to take an online course.		
h. I felt confident to complete an online course.		

questionnaire (Santoso et al., 2014) had three subsections on beginning skills (10 items), advanced skills (12 items), and file and software skills (seven items) with Cronbach's alpha scores of .93, .88, and .90, respectively. The internet self-efficacy questionnaire (Torkzadeh & Dyke, 2001) consisted of 17 items with three items representing confidence with browsing, another six items on encryption/decryption, and eight items on system manipulation. Cronbach's alpha reliability scores were .93, .98 and .94 for browsing, encryption/decryption, and system manipulation, respectively. Overall reliability for the 17-item scale was .96. The nine-item internet self-efficacy scale (Cronbach's alpha reliability score of .93) used by Rodríguez Robles (2006) consisted of student self-assessment of their abilities in browsing and navigating the internet (seven items) and self-assessment of their abilities in taking and completing an online course (two items).

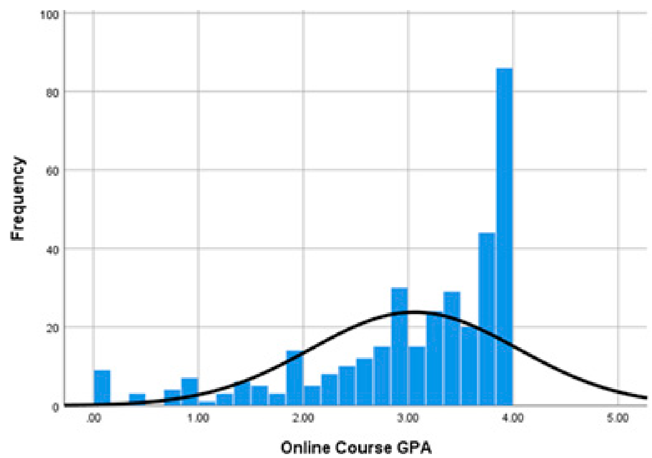
Cronbach's alpha reliability coefficient for the Technological Efficacy questionnaire used in this survey was .82 and can be considered reliable for perception related instruments (Wallen & Fraenkel, 2001). Construct validity for the entire questionnaire including TEQ was established by pilot testing the instrument on a small sample (n = 50) at our institution. According to Creswell (2008), content validity is typically established by researchers having a panel of judges or experts identify whether survey questions are valid. Content validity for the entire questionnaire was established as the instruments were developed based on a review of the relevant literature and in consultation with faculty experienced in online teaching and subject matter experts in the field of adult and distance education in the institution's Teaching and Learning Center.

Variables and Logistic Regression Analysis

We used logistic regression procedure because of the binary nature of the dependent variable (successful or not). Our goal was to determine the impact of each explanatory variable on the odds ratio of the observed event of interest—academic success in an online environment. The main advantage of using logistic regression is that it avoids confounding effects by analyzing the association of all variables together (Sperandei, 2014).

We exported the survey data to SPSS 26.0 to run descriptive and inferential statistics. The dependent variable was "online course success" and was operationalized as grade performance and completion. For the dependent variable, students' average GPA of previous online courses were used; however, due to the fact that online course GPA were severely skewed (mean = 3.06, SD = 0.987), we used B− (GPA = 2.67) as a benchmark to categorize students into two groups pertaining to their online course performance: success group (B− and above) or at-risk group (C+ and below). This dichotomous variable was used as the indicator of students' online course performance and dependent variables in this study (see Figure 1).

Figure 1.
Online Course Grade Distribution



Independent variables included in this study were students' demographic characteristics (e.g., first generation status, low-income status, minority status), educational characteristics (e.g., academic level, transfer status, online program major, cumulative college GPA, prior online learning experience), and personal characteristics (self-regulation, Technological Efficacy). The following variables are coded as categorical: minority status, first generation status, low-income status, academic level, online program major, and transfer status. Minority status was coded as 1, while nonminority status was coded as 0. The same coding rule was applied to first generation status, transfer status, and online program major, with 1 representing those belonging to the featured groups and 0 representing those who did not belong. For academic level, there are 4 levels: freshman, sophomore, junior, and senior. Other independent variables, namely, cumulative college GPA, prior online experience, self-regulation, and Technological Efficacy, were treated as continuous variables. Prior online experience was indicated as the number of all their previous online courses taken. Self-regulation and Technological Efficacy were both the composite scores based on the instrument.

We adopted a binomial logistic regression as data analysis method in this study to ascertain the effects of various independent variables on the likelihood of success in online courses. In order to investigate the unique impact of independent variables (students' demographic and socioeconomic features, overall academic achievement, prior online class experience, self-regulation, and Technological Efficacy) on the dependent variable (students' online class performance), the independent variables were entered into regression model in different blocks (see Table 3).

Table 3.
Logistic Regression Model (N=341)

	Independent Variables	Variable Classification	Variable Type	Block
1	First Generation	Demographic	Categorical	1
2	Low Income	Demographic	Categorical	1
3	Minority Status	Demographic	Categorical	1
4	Academic Level	Educational	Categorical	1
5	Online Program Major	Educational	Categorical	1
6	Transfer Status	Educational	Categorical	1
7	College Cumulative GPA	Educational	Continuous	2
8	Prior Online Experience	Educational	Continuous	3
9	Self-Regulation	Personal	Continuous	4
10	Technological Efficacy	Personal	Continuous	5
	Dependent Variable			
	Online Course Success		Categorical	

The first block included variables pertaining to online program major, transfer status, minority status, first-generation status, low-income status, and academic level. Variables of interest were sequentially entered in the model as individual blocks such that the second block contained student cumulative college GPA, and was then followed by the third block (prior online experience), followed by the fourth block (self-regulation), and then the fifth and final block (Technological Efficacy). The change in omnibus test of model coefficients, pseudo R square, and overall percentage of correctness from these five blocks and models were compared to determine whether the predictor variable was meaningful to the model.

Sample Demographics

The sample included 81 males (23.8%) and 260 females (76.2%), who ranged in age from 19 to 59 years at the time of the survey. The majority of the sample were white (69.2%), followed by Hispanic/Latinx (15.2%), African American (5.3%), and Asian (4.1%). The average age was 25.3 (SD = 8.10). Table 4 presents descriptive statistics of respondent characteristics.

Table 4.
Frequencies and Descriptive Statistics of Participants (N=341)

Characteristics	Categories	N	%
Online Course Performance	Success	254	74.5
	At Risk	87	25.5
Gender	Female	260	76.2
	Male	81	23.8
Race/Ethnicity	White	236	69.2
	African American	18	5.3
	Asian	14	4.1
	Hispanic/Latinx	52	15.2
	Native American	1	0.3
	Native Hawaiian/ Pacific Islander	1	0.3
	Multiracial	15	4.4
	Unknown	4	1.2
Employment	Don't work	41	12.1
	1–10 hours/week	49	14.4
	11–20 hours/week	88	25.9
	21–30 hours/week	71	20.9
	31–40 hours/week	51	15.0
	More than 40 hours/week	40	11.8
Academic Level	Freshman	8	2.3

	Sophomore	52	15.2
	Junior	94	27.6
	Senior	187	54.8
Transfer Status	Non-Transfer Student	178	52.2
	Transfer Student	163	47.8
Underrepresented Minority Student (URM)	Non-URM	250	73.3
	URM	91	26.7
First Generation Student	Non-FGEN	134	39.3
	FGEN	207	60.7
Income Level	Not Low Income	184	54.0
	Low Income	157	46.0
Online Program major	Not Online Program Major	315	92.4
	Online Program Major	26	7.6
Continuous Variables	Mean		SD
Age	25.3		8.10
Cumulative GPA	3.19		0.53
Prior online course number	4.13		4.25
Self-regulation	3.45		0.57
Technological Efficacy	4.21		0.61

The gender skews in survey responses is a function of the self-reporting nature of the study. The study focuses on underserved and underrepresented minority students. In an extensive review of the literature to identify the independent variables that could impact the students' success in online courses, gender was not identified as an underserved characteristic. However, in light of the higher representation of females in the survey sample, we performed a chi-square test of significance to evaluate the association between gender and success in online courses. The results indicated no significant association between gender and success in online courses ($\chi 2 = 0.1$, df = 2, p = 0.951).

Therefore, gender did not affect the outcome variable.

RESULTS

Assumption Testing

For a binomial logistic regression to be valid, linearity assumption and data screening was performed. Linearity of the continuous variables with respect to the logit of the dependent variable was assessed via the Box and Tidwell (1962) procedure. Interaction terms between the continuous independent variables and their natural log transformation were entered in the model to test the linearity. If the interaction term is statistically significant, the original continuous independent variables are not linearly related to the logit of the dependent variable. A Bonferroni correction was applied using all ten independent variables in the model resulting in a statistical significance level adjusted to .005 (Tabachnick & Fidell, 2014). The results revealed that there is a linear relationship between the continuous independent variables and the logit of the online course performance: interaction terms for cumulative GPA, $B = 5.23$, $Wald(1) = 1.50$, $p > .005$; interaction terms for prior online experience, $B = -.05$, $Wald(1) = .35$, $p > .005$; interaction terms for self-regulation, $B = 4.82$, $Wald(1) = 2.41$, $p > .005$; and interaction terms for Technological Efficacy, $B = -1.28$, $Wald(1) = .29$, $p > .005$. There were eight data points that had standardized residual greater than two standard deviations; however, they were deemed as genuine responses and were kept in the analysis. The correlation coefficient matrix was also inspected, there were no concerns related to multicollinearity.

Null model

The beginning block assesses a null model without any explanatory variable but a constant so that each student has the same chance of succeeding in an online course. There were 254 students whose online course GPA was B− and above, while 87 students scored lower than B−. The overall correctness of the baseline model showed that 74.5% of students were correctly classified if they were all predicted as succeeding in online courses.

Block One

The research question being examined is as follows:

> R1) Are students with different demographic characteristics (first generation, low income, minority status)

and educational characteristics (academic level, online program major, transfer status) equally likely to succeed in online courses?

Block one of the model shows the influence of the independent variables on student success in online courses after accounting for the conjoint effect of first generation, low income, minority, online program major, transfer status, and academic level. According to the omnibus tests of model coefficients, the inclusion of this block of demographic and educational variables is a significant improvement to the null model, $\chi^2 = 15.60$, $p < .05$. Only 6.6% of the variation in success of online courses can be explained by these demographic variables conjointly (Nagelkerke $R^2 = .066$). The result of Hosmer and Lemeshow Test for block one showed that this model fitted the data well ($\chi^2 = 10.28$, $p > .05$).

However, the correct classification rate was only 73.6%, which was not better than the null model. In this block, only income level was a significant explanatory variable: Those who are not in low-income group are 1.96 times more likely to succeed in online course than those in low-income group ($B = 0.67$, $Wald_{(1)} = 6.78$, $p < .05$). Results of variable coefficients in the equation of block one are presented in Table 5.

Block Two

The research question being examined is as follows:

R2) Can college cumulative GPA help explain students' success in online courses, while keeping the aforementioned demographic characteristics (first generation, low income, minority status) and educational variables (academic level, online program major, transfer status) constant?

College cumulative GPA was added to the model in block two. The inclusion of college cumulative GPA improved the model further. The second block is significantly different from the previous block ($\chi2 = 123.16$, $p < .05$), and the overall model is also statistically significant ($\chi2 = 138.75$, $p < .05$). The deviance (−2 Log likelihood) was greatly reduced from 371.72 in the previous model to 248.56. The variation in success of online courses were explained up to approximately 49.2% (Nagelkerke $R2 = .492$). The result of Hosmer and Lemeshow Test for block two also showed that this model fitted the data well ($\chi2 = 7.21$, $df = 8$, $p > .05$). The overall correct classification rate continued to increase up to 83%, compared to 73.6% in the previous model (block one). For variables of interest, college cumulative GPA is statistically significant ($B = 0.37$, $Wald(1) = 68.85$, $p < .05$).

Table 5.
Variables in the Equation of Block One (N=341)

	B	*SE*	*Wald*	*df*	*p*	Odds Ratio
Online Program Major	−0.03	0.54	0.00	1	0.95	0.97
Transfer Student	−0.22	0.28	0.64	1	0.42	0.80
Underrepresented Minority	0.37	0.29	1.64	1	0.20	1.44
First Generation	−0.37	0.27	1.87	1	0.17	0.69
Low Income	0.67	0.26	6.78	1	0.01*	1.96
Academic Level			2.87	3	0.41	
Freshman vs. Senior	−0.99	0.75	1.74	1	0.19	0.37
Sophomore vs. Senior	−0.33	0.38	0.75	1	0.39	0.72
Junior vs. Senior	−0.37	0.30	1.50	1	0.22	0.69
Constant	0.96	0.57	2.86	1	0.09	2.61

Note: *indicates significant results

All other variables being equal, for every 0.1 unit increase in college cumulative GPA, the odds of succeeding in online courses increases by 44.34% (i.e., Exp(0.367) = 1.4434).

Results of variable coefficients in the equation of block two are presented in Table 6.

Table 6.
Variables in the Equation of Block Two (N=341)

	B	*SE*	*Wald*	*df*	*p*	Odds Ratio
Online Program Major	0.04	0.70	0.00	1	0.95	1.04
Transfer Student	−0.15	0.34	0.20	1	0.65	0.86
Underrepresented Minority	0.32	0.37	0.76	1	0.39	0.73
First Generation	−0.45	0.34	1.73	1	0.19	0.64
Low Income	0.22	0.33	0.44	1	0.51	1.24
Academic Level			0.56	3	0.91	
Freshman vs. Senior	0.53	0.96	0.30	1	0.58	1.69
Sophomore vs. Senior	−0.06	0.50	0.01	1	0.91	0.94
Junior vs. Senior	−0.15	0.37	0.15	1	0.70	0.87
Cumulative GPA	3.67	0.44	68.85	1	0.00*	39.34
Constant	−9.63	1.44	44.85	1	0.00	0.00

Note: *indicates significant results

Block Three

The research question being examined is as follows:

> R3) Can prior online experience help explain students' success in online courses, while keeping the demographic characteristics (first generation, low income, minority status), educational characteristics (academic level, online program major, transfer status), and college cumulative GPA constant?

Prior online class experience was added to the model in block three. The inclusion of prior online experience to this block did not improve the model. This model is not significantly different from the previous block ($\chi^2 = 2.06$, $p > .05$), even though the overall model is still statistically significant ($\chi^2 = 140.81$, $p < .05$). The deviance (−2 Log likelihood) was slightly reduced from 248.56 in the previous model to 246.50. The variation in success of online courses were explained up to approximately 49.8% (Nagelkerke $R^2 = .498$), which was not different from the previous model. The result of Hosmer and Lemeshow Test for block three also showed that this model fitted the data well ($\chi^2 = 7.86$, $df = 8$, $p > .05$). The overall correct classification rate slightly increased to 84.8%; however, prior online class experience was not a significant predictor in this model ($B = -.06$, $Wald_{(1)} = 2.08$, $p > .05$). Results of variable coefficients in the equation of block three are presented in Table 7.

Table 7.
Variables in the Equation of Block Three (N=341)

	B	*SE*	*Wald*	*df*	*p*	Odds Ratio
Online Program Major	−0.44	0.77	0.33	1	0.57	0.64
Transfer Student	−0.13	0.34	0.15	1	0.70	0.88
Underrepresented Minority	−0.29	0.37	0.61	1	0.44	0.75
First Generation	−0.49	0.34	2.05	1	0.15	0.61
Low Income	0.21	0.33	0.40	1	0.53	1.23
Academic Level			0.99	3	0.80	
Freshman vs. Senior	0.38	0.96	0.16	1	0.69	1.47
Sophomore vs. Senior	−0.25	0.52	0.24	1	0.63	0.78
Junior vs. Senior	−0.30	0.39	0.58	1	0.45	0.74
Cumulative GPA	3.66	0.44	68.21	1	0.00*	38.91
Prior Online Class Number	−0.06	0.04	2.08	1	0.15	0.94
Constant	−8.81	1.53	33.37	1	0.00	0.00

Note: *indicates significant results

Block Four

The research question being examined is as follows:

> R4) Can self-regulation help explain students' success in online courses, while keeping the demographic characteristics (first generation, low income, minority status), educational characteristics (academic level, online program major,

transfer status), college cumulative GPA, and prior online experience constant?

Self-regulation was added to the model in block four. The inclusion of self-regulation in this block did not result in a model that was significantly different from the previous block ($\chi^2 = 1.42$, $p > .05$). However, the overall model is still statistically significant ($\chi^2 = 142.23$, $p < .05$). The deviance (−2 Log likelihood) was slightly reduced from 246.50 in the previous model to 245.08. The variation in success of online courses were explained up to approximately 50.2% (Nagelkerke $R^2 = .502$). The result of Hosmer and Lemeshow Test also showed that this model fitted the data well ($\chi^2 = 6.78$, $df = 8$, $p > .05$). The overall accuracy of classification was 84.2%; however, self-regulation was not a significant predictor in this model ($B = .37$, $Wald_{(1)} = 1.41$, $p > .05$). All other explanatory independent variables were not statistically significant predictors, except cumulative GPA. Results of variable coefficients in the equation of block four are presented in Table 8.

Table 8.
Variables in the Equation of Block Four (N=341)

	B	SE	Wald	df	p	Odds Ratio
Online Program Major	−0.40	0.76	0.28	1	0.60	0.67
Transfer Student	−0.08	0.35	0.06	1	0.81	0.92
Underrepresented Minority	−0.31	0.37	0.69	1	0.41	0.74
First Generation	−0.48	0.35	1.90	1	0.17	0.62
Low Income	0.20	0.33	0.39	1	0.54	1.23
Academic Level			1.04	3	0.79	
Freshman vs. Senior	0.51	0.97	0.28	1	0.60	1.67
Sophomore vs. Senior	−0.23	0.53	0.18	1	0.67	0.80
Junior vs. Senior	−0.27	0.39	0.48	1	0.49	0.76
Cumulative GPA	3.65	0.44	67.83	1	0.00*	38.56
Prior Online Class Number	−0.07	0.04	2.23	1	0.14	0.94
Self-regulation	0.37	0.32	1.41	1	0.24	1.45
Constant	−10.10	1.90	28.23	1	0.00	0.00

Note: *indicates significant results

Block Five

The research question being examined is as follows:

R5) Can Technological Efficacy help explain students' success in online courses, while keeping the demographic characteristics (first generation, low income, minority status), educational characteristics (academic level, online program major, transfer status), college cumulative GPA, prior online experience, and self-regulation constant?

Technological Efficacy was added to the model as block five. The inclusion of Technological Efficacy in this block improved the model. The fifth block is significantly different from the previous block ($\chi^2 = 4.96$, $p < .05$), and the overall model is also statistically significant ($\chi^2 = 147.19$, $p < .05$). The deviance (−2 Log likelihood) was greatly reduced from 245.08 in the previous model to 240.12. The variation in success of online courses were explained up to approximately 51.6% (Nagelkerke $R^2 = .516$). The result of Hosmer and Lemeshow Test also showed that this model fitted the data well ($\chi^2 = 8.14$, $df = 8$, $p > .05$). The overall accuracy of classification increased to 85.3%. The addition of Technological Efficacy improved the overall model.

For explanatory variables, most independent variables were not statistically significant predictors. The previously significant difference between low-income and not low-income groups is no longer significant ($B = 0.18$, $Wald_{(1)} = 0.29$, $p > .05$). However, students' college cumulative GPA is still statistically significant ($B = 3.84$, $Wald_{(1)} = 65.94$, $p < .05$). This means that for every 0.1 unit increase in college cumulative GPA, the odds of succeeding in online courses increases by 46.8% (i.e., Exp(0.384) = 1.468). For variables of interest, Technological Efficacy is statistically significant ($B = .67$, $Wald_{(1)} = 4.89$, $p < .05$). Therefore, holding other variables in the model constant, for every 1 unit increase in Technological Efficacy, the odds of succeeding in online courses increases by 96% (i.e., Exp(0. 67) = 1.96; Odds ratio of 1.96). Results of variable coefficients in the equation of block five are presented in Table 9.

Table 9.
Variables in the Equation of Block Five (N=341)

	B	*SE*	*Wald*	*df*	*p*	Odds Ratio
Online Program Major	−0.80	0.79	1.04	1	0.31	0.45
Transfer Student	−0.05	0.35	0.02	1	0.90	0.96
Underrepresented Minority	−0.37	0.38	0.95	1	0.33	0.69
First Generation	−0.38	0.35	1.19	1	0.28	0.68
Low Income	0.18	0.33	0.29	1	0.59	1.20
Academic Level			0.51	3	0.92	
Freshman vs. Senior	0.32	0.99	0.10	1	0.75	1.37
Sophomore vs. Senior	−0.13	0.54	0.06	1	0.81	0.88
Junior vs. Senior	−0.22	0.40	0.30	1	0.58	0.80
Cumulative GPA	3.84	0.47	65.94	1	.00*	46.51
Prior Online Class Number	−0.09	0.05	3.63	1	0.06	0.92
Self-regulation	0.17	0.33	0.27	1	0.61	1.19
Technological Efficacy	0.67	0.30	4.89	1	0.03*	1.96
Constant	−12.35	2.23	30.75	1	0.00	0.00

Note: *indicates significant results

DISCUSSION AND RECOMMENDATIONS

Using a logistic regression approach, this study examined the effects of demographic, educational, and personal characteristics on the likelihood of online course success for a group of underserved and academically at-risk students at a small, Midwestern, four-year broad access public institution that serves a disproportionately higher number of disadvantaged students. Among demographic characteristics entered in the first block, low income was the only significant explanatory variable in predicting online success, with those not in low-income group being more likely to succeed. This finding is consistent with past research (Mead et al., 2020; Xu & Jaggars, 2011, 2013) that found Pell eligible students associated with lower course grades in online courses. A recent study (Aucejo et al., 2020) indicates that this also holds true in a pandemic influenced educational landscape with lower income students facing greater challenges with maintaining their grades and GPA, or even completing a course in an online environment. However, Rodríguez-Planas (2022) found that low-income and Pell eligible students fared better in a pandemic induced flexible grading policy scenario, suggesting that there is room for the application of innovative pedagogy to ameliorate the struggles of disadvantaged students and improve learning outcomes in the online environment.

Unlike other studies (Figlio et al., 2013; Hart et al., 2018; Johnson & Cuellar Mejia, 2014; Kaupp, 2012; Mead et al., 2020; Xu & Jaggars, 2011, 2013), first-generation status and minority status were found to be not significant. This could be because of the homogenous nature of the sample in terms of its underserved and at-risk characteristics. A more demographically diverse sample could have allowed for more diversity in findings and possibly different levels of group differences.

Among educational characteristics, academic level, online program major, or transfer status were not significant predictors. However, when college cumulative GPA was introduced in the model in the second block, controlling for demographic variables (first generation, low income, minority status) and educational variables (academic level, online program major, transfer status), it was significant and remained a significant predictor in subsequent blocks. This finding is consistent with previous research (Bettinger et al., 2017; Figlio et al., 2013; Xu & Jaggars, 2011, 2013). Since online learning is an important strategy to improve course access and flexibility in higher education, and it also offers disadvantaged students the opportunity to pursue college while being employed and/or tending to competing responsibilities (Allen & Seaman, 2010; Jaggars & Bailey, 2010), it remains an appealing option, especially for this population. However, given that college cumulative GPA is a significant predictor of online success, underprepared students with weak academic backgrounds, the very cohort that is more likely to avail themselves of online learning, are likely to be the ones who will be especially vulnerable to failure and dropping out. This, therefore, elevates the importance of addressing this issue if online learning is to fulfil its objective of reducing achievement gaps in higher education.

Prior online experience, introduced in the third block, was not a significant predictor of online course success. However, introduction of this variable resulted in a modest improvement in the model, and the overall model remained significant. While prior online experience was found not to be a significant predictor, this might be attributable to the fact that approximately three-fourths of the survey respondents had successful prior online experiences (Table 4). Despite the inconclusive results, existing research on this provides information that might be leveraged to inform future policy. Xu and Jaggars' study (2011) found that the online course completion gap narrowed significantly as students gained more experience with online courses, a finding that was consistent with Hachey et al. (2013) who reported prior online experience to be a significant predictor of future online success with students who had never taken an online course to be more likely to withdraw or fail than students who had successful prior online experiences. In their study, controlling for GPA, students who had failed or dropped out of even one online course did significantly worse in future online courses than students with no prior online experiences, thereby suggesting that successful prior online experiences were likely to lead to future online success while unsuccessful prior online experiences were likely to lead to worse future online outcomes. The importance of prior online experience, as noted above (Xu & Jaggars, 2011; Hachey et al., 2013), parallels Bradley et al.'s study (2017), which reported that mastery experience from prior online course(s) was likely to positively influence future online course grades.

The results from the current study indicate that institutional and instructor-based remedial measures geared towards improving online learning outcomes of at-risk students could be targeted at students with lower GPAs. Additionally, based on existing research, such remedial measures may also be targeted towards students with no prior online experience or unsuccessful prior online experience. This is consistent with recommendations outlined by Hachey et al. (2013) that state that initiatives should focus on students with no prior online experience and GPAs at the lower end of the spectrum and on students (regardless of GPA) who have had a prior unsuccessful experience in an online course. The authors also suggest that community colleges should develop e-advising programs that identify and provide focused support for students taking their first online course, and this recommendation would appear to be applicable for open enrollment, four-year institutions serving at-risk student populations. Institutional data can be utilized to focus on underserved and at-risk groups' online success outcomes and design data driven interventions that are geared towards improving such outcomes. Policies and resource allocations based on such investigation will be likely to improve the chances of reaching the goal of online success for the most vulnerable groups in higher education.

Self-regulation, introduced in the fourth block, was not a significant predictor of online course success either. While the overall model did not improve, it remained significant. The inconclusive nature of the findings is consistent with some prior research that reported weak correlation between self-regulation and academic performance (Broadbent & Poon, 2015; Cazan, 2014) or no correlation at all (Kitsantas et al., 2008). It is possible that the inconclusive results from the fourth block with respect to self-regulation being a significant predictor might be attributable to the fact that ~75% of the survey respondents in this study had completed online courses successfully (Table 4), and, therefore, possibly possessed adequate self-regulation skills that enabled them to succeed in the first place. However, several other studies did report significant positive correlation between self-regulation and academic performance (Bradley et al., 2017; Naumann et al., 2003; Puzziferro, 2008; Thibodeaux et al., 2017; Yeboah & Smith, 2016), which suggests that considering measures that might aid self-regulation in students can be a worthwhile endeavor with an eye to reducing academic achievement gaps in an online learning environment.

Disadvantaged students come to college with competing priorities. The ubiquity of online education as a consequence of COVID-19 pandemic exacerbated their already challenged life situations. Many underserved students had to take on additional responsibilities in order to take care of ailing family members during the pandemic, and in response to financial instability arising from pandemic related job losses, which together, put additional strain on students' time and schedule. Furthermore, students had to deal with cramped and shared living quarters on account of campus closures, which led to a lack of adequate physical space or privacy for studying (Quach & Chen, 2021). Juriševič et al. (2021) indicated that students, in coping with the pandemic induced switch to online learning, did not prioritize task strategies even as they targeted goal setting strategies and environment structuring.

While teachers in f2f classrooms provide students with on-the-spot guidance and feedback, in online learning, the students are not exposed to that level of supervision and direction. The online environment also precludes the instructor from assessing student needs from facial cues or nonattendance. As a result, online learners must take greater responsibility for the management and control of their own academic progress. As there could be differing levels of self-regulatory behavior, online instructors could use short survey tools to gauge such beliefs and behaviors early on in the semester and provide individualized feedback to steer students towards appropriate resources. Providing developmentally appropriate scaffolding (first year vs. senior) will also ensure that online learners are appropriately encouraged and guided towards greater inculcation of self-direction and autonomy. Knowledge about self-regulation processes can enable students to maximize their college career paths while allowing universities to implement better intervention programs to encourage struggling students to persist and complete their education (Kitsantas et al., 2008).

Tangible steps such as having students take a self-regulation assessment as part of an online orientation module and communicating the results to the students, along with providing them with relevant self-regulation strategies, is likely to raise student awareness of the pitfalls of online learning and help them both identify and remedy the same. This can serve the dual purposes of familiarizing students with an unfamiliar learning management system as well as helping them be cognizant of the self-regulation necessary to be successful in college. Advisors should have conversations with students regarding how to plan and prioritize time for online classes. If students were to consider their schedules and allocate the hours necessary for online classes prior to enrollment, they might make better-informed decisions, thereby increasing their odds of success in an asynchronous online environment.

Instructors need to be mindful of the self-regulation challenges faced by students and design courses with a goal to mitigate some of the pitfalls arising due to a lack of proper self-regulatory skills or deprioritization thereof. Pedagogical frameworks that are centered around instructor presence and availability to monitor student progress would allow instructors to reach out promptly and help students correct course before it gets too late. Addressing self-regulation behaviors can also be accomplished through curriculum and course design. Having learning outcomes and tasks listed for every week and having consistent due dates for weekly assignments (for example, reflections due Saturdays before midnight, weekly quizzes due Sundays before midnight) as opposed to multiple scattered deadlines can help establish a regular schedule that would help students establish a rhythm, which in turn, could foster development of self-regulation skills.

Technological Efficacy was introduced in the model in the fifth block. Introduction of this variable resulted in a modest improvement in the model, and the model remained significant. Technological Efficacy was found to be a significant predictor of online course success. The finding that Technological Efficacy is significant in influencing online course outcomes has been supported by prior research that has shown that higher levels of Technological Efficacy is associated with better grades (Hauser et al., 2012; Kuo & Belland, 2016; Saadé & Kira, 2009; Wang et al., 2013) and lower drop out rates (Liu et al., 2007). Existing research on Technological Efficacy, as discussed earlier, has shown that developing technology related skills and competence is influenced by the learner's level of Technological Self-Efficacy, which in turn determines the learner's level of anxiety, confidence, task persistence and effort, usage of technology, technology related experience, and development of skills that eventually lead to Technological Efficacy. Therefore, the level of Technological Self-Efficacy determines Technological Efficacy, which in turn impacts Technological Self-Efficacy, leading to a learning reinforcement loop.

The finding that lower levels of Technological Efficacy adversely affect the academic achievement of the already at-risk student, along with the fact that Technological Efficacy is positively correlated with higher performance in the online classroom (Hauser et al., 2012; Kuo & Belland, 2016; Saadé & Kira, 2009; Wang et al., 2013), have important policy implications surrounding the question of how institutions can act to bring such students' skill levels up to par with the computer skillsets required for college success. Steps should be taken to make sure that at-risk students coming from underserved backgrounds possess the technology related skills needed to be successful in remote learning. Given that Liu et al.'s study (2007) reported technology related efficacy, among other variables, to be a key factor in influencing the decision to drop an online course, early identification of a lack of optimal Technological Efficacy skills among incoming students may be an important step towards developing preparedness initiatives at institutions serving a higher number of at-risk students. This should inform the deployment of targeted preassessment tools, computer application courses, or similar competencies integrated into first-year seminar courses as pathways to boost Technological Efficacy. This is echoed by Buzzetto-Hollywood et al. (2018), who recommended the introduction of an online simulated learning and assessment tool with an instant, automated feedback mechanism that aids remediation and thereby helps build the computer and information literacy skills of students. Furthermore, this type of assessment will allow institutional services and faculty to employ complementary classroom learning strategies.

Yeboah and Smith's study (2016) reported that minority students who received little or no support from online instructors with questions related to navigating the LMS, experienced academic challenges, which in turn, led to lower academic performance. Requiring some kind of LMS tutorial upfront to determine Technological Efficacy skills and suitability for online learning could also help mitigate such situations. Faculty need to be mindful that online students may need additional support compared to f2f students as underserved students may not always have the Technological Efficacy or access needed to succeed (Banerjee, 2020).

Given that disadvantaged students, especially in an online environment, may start with less than optimal skills related to Technological Efficacy, and this may negatively impact confidence, self-belief, and engagement, faculty need to consider a larger role in motivating and engaging students to ensure success and develop an online culture of support that will help students overcome Technological Efficacy related self-doubt. The general trend of increasing online courses at institutions of higher learning has been reinforced by pandemic induced realities that have threatened f2f learning, thereby leading to a greater number of courses being offered in online or hybrid mode. In light of this, the role of Technological Efficacy and its influence on academic success in an online environment has become more pronounced. Consequently, the need for effective interventions is paramount.

FUTURE DIRECTIONS

In addition to a paucity of research on predictors of underserved and at-risk students' college success in four-year institutions, existing research about this population tends to focus on quantitative data, which fails to represent a student voice. Therefore, suggestions for further study would be to seek out student perspectives regarding online courses to determine other factors that contribute to successful and unsuccessful online course experiences for underserved students. Since many public institutions have declared that online learning is "critical" to their long-term strategy and planning (Allen & Seamen, 2008), additional research in this dimension might help in discovering other determining variables that will help in achieving this goal. Future studies could also be guided by the many theoretical models of retention to incorporate academic factors, social factors, and other relevant factors to provide a comprehensive analysis of online course success for such student populations.

Self-regulation was not a significant predictor of online success in this study although the overall model was significant. The results might be different if either the multiple dimensions of self-regulation such as planning, monitoring, and regulating are examined individually, and/or if such an examination is done in a single course setting, as opposed to the self-regulation instrument being administered across a survey sample spanning many online courses, as was done in the current study.

LIMITATION

The results of this study should be considered within the context of the following limitations. This study was conducted on students attending a single institution whose student population exhibited underserved characteristics. It employed a quantitative research design with self-report survey measures and, therefore, the responses were limited to the honesty and accuracy with which respondents completed the questionnaire. Nevertheless, the study sample represented the institution's student body stratification well in major demographic areas as they relate to underserved characteristics, thus allowing for meaningful generalization.

CONCLUSION

This paper used a logistic regression method to investigate the individual effects of demographic, academic, and personal characteristics on online course success for underserved and at-risk student populations to identify significant predictors of course success in the online environment. This research is important as the growth in undergraduate enrollees in broad access four-year universities has mostly been fueled by an influx of students from economically disadvantaged and minority backgrounds (Fry & Cilluffo, 2019). Additionally, a large proportion of these students possess some form of at-risk characteristics making them academically vulnerable. Thus, online student success is a concern for broad access and minimally selective institutions of higher education. The students most likely to enroll in online courses, and those the postsecondary system is most challenged to serve well, might suffer most from this learning format. In other words, moving vulnerable students online might lead to the widening of attainment gaps instead of solving the seemingly intractable problem of unequal educational opportunity (Protopsaltis & Baum, 2019).

This study showed a consistently positive and significant relationship between college cumulative GPA and online course success underscoring the fact that at-risk and underserved students are more vulnerable in the online environment. The significant role of Technological Efficacy in predicting online course success among disadvantaged student populations speaks to the urgency of, and need for, timely actions to ameliorate the skills gap, if the goal of greater equity in educational outcomes is to be achieved. These findings are particularly relevant for broad access postsecondary institutions that cater to a higher proportion of underserved, minority, and academically underprepared student bodies. Although research has demonstrated the favorable impression students possess toward online education (Allen & Seaman, 2008), noncompletion and failure rates limit the potential benefits of online learning.

The results of this study add to the literature about predictors of student success in online courses and indicate important variables of interest that advisors, faculty, and administrators could focus on as they advise, teach, and create programs and services for online students. Being able to make predictive assertions about the likelihood of success or nonsuccess in online courses enhances the ability of advisors and administrators to build precourse assessments to identify specific, weighted characteristics (Puzziferro, 2008). These findings have implications for how instructors might facilitate online courses and how administrators could take into consideration Technological Efficacy related gaps in underserved and at-risk student groups to devise institutional interventions and formulate pedagogical approaches that would account for existing gaps in educational equity. Given the rapidly expanding landscape of online education, this will help ensure pathways to sustained student success in online courses.

Online learning remains an important strategy to improve course access and flexibility in higher education, and it is an especially appealing option to underserved students who face many challenges to completing a college education. The results of this study underscore the fact that as online education becomes the norm, students with weaker academic achievements or lower Technological Efficacy will continue to be at a disadvantage, and this is likely to disproportionately impact underserved and at-risk students who not only comprise a significant portion of the cohort that turns to online learning to fulfil their educational aspirations, but are also likely to be the ones with characteristics that lead them to be most negatively impacted. This is in addition to an ongoing pandemic that has added even more impediments to their already challenging path to a college education.

This research was conducted to advance the conversation about online education equity issues with the expectation that the dissemination of findings will help inform policy and practices that will hopefully lead to greater equity in educational outcomes of underserved and academically at-risk students in the online environment. At a time when COVID-19 has exposed the widening race and class divides in higher education, supporting underserved students to achieve their educational aspirations is more important than ever.

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