


URM and Non-URM Students in Online Courses: Student Perceptions and Adoption Intentions at a Hispanic Serving Institution

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ABSTRACT

Currently, the literature provides some coherent evidence of what underrepresented minority (URM) students perceive they need to be successful, as well as what researchers empirically find important for URM student success. However, while success factors overlap with adoption factors, online course adoption is also affected by several important non-success factors such as flexibility. Adoption patterns of URM students have not been coherently studied using a well-tested technology adoption model. This study applies an expanded unified theory of acceptance and use of technology (UTAUT) model to address these gaps. Among a sample of 1231 students, URM students perceived online classes to require more effort to achieve lower grades relative to non-underrepresented students. Second, a narrower set of factors predicts URM students' intention to take online courses in the future. Finally, contextually, URM students are 46% more likely to be employed, first-generation students, and have substantial family responsibilities than non-URM students.

KEYWORDS

Adoption Factors, Hispanic Serving Institution (HSI), Online Education, Underrepresented Minorities (URM), Unified Theory of Acceptance and Use of Technology (UTAUT)

INTRODUCTION

Online learning use in the U.S. had been increasing several percent a year for over a decade (Seaman, Allen, & Seaman, 2018; Zawacki-Richter & Naidu, 2016) prior to the COVID-19 pandemic, when health lockdowns moved most instruction online for intermittent periods of time (Dumont et al.,

DOI: 10.4018/IJAET.313436

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2021). While it is certain that online use will abate as health issues return to normal, there is little doubt that the long-term trajectory has bent upward because of increased student and faculty exposure to online courses, technology advances (i.e., videoconferencing & Web 2.0 tools), and increased institutional support. A primary goal of this study is to examine online course adoption patterns in a Hispanic-serving institution.

The U.S. Bureau of Labor Statistics (2021) reports a steady increase in the Hispanic population. Based upon projections about the growth of the Hispanic population, the U.S. Department of Labor (2021) predicts that Hispanics will be the dominating workforce accounting for 78% of the net gain in the U.S. labor market between 2020 and 2030. However, at the same time, the U.S. Department of Education (2021) reports that only 20.6% of Hispanics, 41.9% of Whites, and 28.3% of African American hold a bachelor's degree and higher. Even with these evident disparities, there has been limited research on the effect of online education at Hispanic-serving institutions (HSI).

Hispanics are reported to enroll in online courses at a lower rate compared to other students in a number of studies (Arbelo, Martin, & Frigerio, 2019; Koenhke, 2013; Linton et al., 2021). This trend suggests that concerns with social integration, online readiness, self-efficacy issues and course design, among other factors, may hinder their motivation to enroll in an online learning environment (Mese & Sevilen, 2021; Johnson & Galy, 2013; Markle, 2015; Wozniak, Pizzica, & Mahony, 2012). However, flexibility is among the top reasons Hispanic students enroll in online classes (Stewart et al., 2004; Grimes, 2002; Vielma & Brey, 2021) and low self-efficacy is among the most prevalent reasons for not taking online courses (Alhothali et al., 2022; Nur et al., 2022).

Student context—largely functioning as antecedent conditions to adoption factors—affect online learning differently as well. The focus in this study is racial and ethnic minority status where it has been shown to be important (Hamilton et al., 2018). Examples of context factors include family-related, school-related, and social factors. The three factors this study focuses on are family responsibilities, first-generation status, and employment status in an institution designed to serve underrepresented minority students (URM).

URM students are from groups who have been traditionally underrepresented in education, such as racial/ethnic minorities, first-generation college students, and students from lower socio-economic households. The majority of the URM students in the study sample were Hispanic and first-generation status.

Students' perceptions of their courses positively and negatively relate to academic performance, motivation, and engagement intention (Cohen & Baruth, 2017; Nur et al., 2022; Traynor-Nilsen, 2017; Wood, 2020). URM students frequently lack varied academic experiences as compared to non-URM students, contributing to students' deficit-based perceptions of online learning. This study will use a technology adoption model to explore the differences between URM and non-URM students' perceptions and adoption intentions.

The study seeks to explore the differences between URM and non-URM students in three areas: student perceptions of online courses, how perceptions relate to future online course intentions, and how student characteristics relate to these perceptions.

In sum, what do we know about URM and non-URM student differences (if any) related to their perceptions about factors that affect their online learning from an adoption perspective, the differences in the factors they actually emphasize in adoption, and related contextual factors? This requires the selection of a specific technology model.

LITERATURE REVIEW OF TECHNOLOGY ADOPTION AS RELATED TO ONLINE LEARNING

In this section, we briefly examine the literature that discusses factors relevant to student perceptions and technology adoption intentions. Where available, we introduce studies that focus on various URM students as a whole or as individual groups. The section starts with a review of a well-supported

technology adoption model. Next, it applies that technology adoption to the online learning context. Finally, we finish the section reviewing the context of URM students because our interest is not in controlling the differences between URM and non-URM students but in acknowledging their existence as antecedent factors even in an institution catering to URM students.

UTAUT: A WELL-SUPPORTED TECHNOLOGY ADOPTION MODEL

To date, no known study has compared the experiences of URM and non-URM students using a robust technology adoption model. The most common general models try to integrate elegance (the least number of factors to explain the most) and high-level contextual factors. For example, the second Technology Adoption Model (Venkatesh & Davis, 2000) had seven independent and three moderating variables. The Unified Theory of Acceptance and Use of Technology or UTAUT (Venkatesh et al., 2003) was simpler, with four independent variables, and four moderating variables and is the most cited because of its relative simplicity. Finally, a fully articulated model called the Technology Acceptance Model 3 or TAM3, included 11 independent variables and five moderating variables (Venkatesh & Bala, 2008). Of the many field studies in education that have used these models, customization is common (Abdullah & Ward, 2016).

The discussion is framed using factors chosen based on an extensive review of the technology adoption literature. Performance expectancy is how well the technology is thought to work before adoption, or how well it is thought it will work after initial exposure. Because of the importance of this factor, it can be broken down into performance in learning achievement and performance relative to the grades students expect. A third factor is the amount of effort expected to adopt and subsequently use a technology.

A fourth factor is the set of facilitating conditions that support the adoption and use of the technology such as training. A fifth factor is the degree to which a potential user experiences social influence from others to use a technology, such as friends or co-workers. A sixth factor is the level of voluntariness, which moderates social influence. As involuntariness increases, social influence decreases as was the case in the COVID-19 pandemic (Chakraborty et al., 2021).

A seventh factor is the flexibility that the technology allows. Frequently technology adoption is about replacing one physical technology with another and thus the flexibility offered by one technology over another is minimal. In the case of traditional and online learning, however, one technology is the physical classroom, and the other technology is mediated by the Internet. The eighth factor is the enjoyment or “hedonic motivation” that using the technology affords. What is the intrinsic satisfaction of using online learning compared to a traditional course modality?

Applying the UTAUT Model to Online Learning

This section reviews eight factors that typically affect adoption patterns.

Performance. It is well recognized that online learning outcomes are comparable to traditional courses teaching quality and student characteristics are equivalent (Bernard et al., 2004; Nguyen, 2015; Garratt-Reed, Roberts, & Heritage, 2016). However other researchers have suggested they are not equivalent. For example, students tend to perform best in online courses when they are high in self-efficacy, self-regulation, good at time management, have taken online courses in the past, and have a good record of academic achievement (Alquarish, 2016; Kuo et al., 2013; Paechter, Maier & Macher, 2010; Song et al., 2004; Hachey, Wladis, & Conwary, 2014; Wladis, Hachey, & Conway, 2015). Johnson (2013) supporting research, found that factors in a minority-serving institution that made the most difference were time management, the ability to work independently, and self-efficacy. In addition, Atuahene (2021) found a correlation between the success rates of minority male students based on the amount of time spent on academic work each week.

Numerous studies have indicated that lower academically prepared students of any ethnicity and gender do poorly—and get poorer grades—in online settings (Mather & Sarkans, 2018; Baum

& McPherson, 2019; Garratt-Reed et al., 2016; Xu & Jaggars, 2014). Moreover, studies examining underrepresented minorities not only support these findings (Richardson, 2018; Whitcomb, Cwik & Singh, 2021) but suggest that sometimes the online environment exacerbates the performance gap (Angiello, 2002; Kaupp, 2012).

Effort. Regardless of ethnicity or gender, most students find effort to be an important consideration in taking online classes (Tung & Chang, 2008; Park, 2009; Abbad, Morris & Nahlik, 2009) and for online courses to take more effort (Otter et al., 2013; Van Wart et al., 2020, Venable, 2020). Several studies have found that successful minority students tend to focus on taking less complicated and demanding classes online while taking challenging courses in a face-to-face mode (Jaggars, 2014; Salvo, Shelton, & Welch, 2019). However, one study found that students with lower academic preparation and lower socioeconomic status were more likely to take online courses (Wladis et al., 2015).

Facilitating conditions. In the past, providing conditions that facilitate the mastery and use of online learning was a substantial factor (e.g., Abbad, et al., 2009; Jung, 2011). However, facilitating conditions seem to have declined in importance as students become more proficient and resources have become more robust (Ni et al., 2021). However, Martin's (2018) study of 12 facilitation strategies with four constructs (instructor presence, instructor connection, engagement, and learning) found instructors' timely response to questions and instructors' timely feedback on assignments as significant factors for success and students' interest in taking another online course.

Social influence. Seeing others use technology and hearing their advice is vital in the initial stages of technology adoption when the initial adoption decision is made, but rapidly decreases as a factor after initial exposure and initial start-up effort has been completed (Venkatesh et al., 2003). Furthermore, network and social influence are likely to have reduced this factor because of the mass emergency move to online teaching. The degree of *voluntariness* tends to be inversely correlated with social influence. Voluntariness shifted in the pandemic from taking face-to-face or online courses, to taking online or no courses. Thus, voluntariness will remain an issue if substantially diminished.

Flexibility. Convenience and flexibility are significant drivers of online course adoption (Paechter, Maier, & Macher, 2010; Venable, 2020; Mather & Surbaks, 2018). In addition, because of scheduling needs for work or family responsibilities, minority students often resort to online courses in greater numbers (Wladis et al., 2015).

Hedonic motivation. Another factor of significance is called *hedonic motivation*, or the degree of satisfaction derived from using the technology. Perceptions of satisfaction with courses themselves are frequently equivalent when students take online courses voluntarily, there is a good fit (Ni/MPA), and flexibility and convenience are factored in. One study found that conscientious students tended to be more satisfied (Cohen & Baruth, 2017). Typically, student perceptions of online courses are slightly lower than face-to-face courses (Lowenthal, Bauer, & Chen, 2015). Researchers have found this is due to less engagement (Johnson & Galy, 2013), ineffective instruction (Zhang et al., 2021), or students' sense that they are teaching themselves (Otter et al., 2013).

Aspects of online education that can reduce hedonic motivation include feelings of isolation, lack of interaction leading to boredom, and computer fatigue (e.g., Stephan, Markus, & Gläser-Zikuda, 2019; Otter et al., 2013; Chakraborty et al., 2020). Two factors that increase hedonic motivation are the quality of teaching, especially lectures and labs, and techniques that enhance engagement and rapid feedback (Kehrwald, 2008; Garratt-Reed et al., 2016; Traynor-Nilsen, 2017). In addition, enhancing student engagement has been targeted as particularly important for minority students (Traynor-Nilsen, 2017).

Contextual Factors

For Hispanic students, the literature suggests that many prefer to interact with one another and engage in discussions relevant to their current lives, work, or community (Chávez, Ke, & Herrera, 2012). Additionally, previous studies found the most effective and influential factors for Hispanic student

success were related to cultural constructs and relational structures. Such cultural construct factors are mentorship, relationships, and support programs (Ainsa & Olivarez, 2017; Gurantz, Hurwitz, & Smith, 2017); interactive discussions (Osuna-Acedo, Marta-Lazo & Frau-Meigs, 2018); teachers' motivation and support (Wood, 2020); and relevance to their own lives, work, or community (Chávez et al., 2012). In addition, other relational factors linked to Hispanic online education success were self-confidence, time management, technology skills, course structure, instructional materials sequencing, and independent learning ability (Johnson & Galy, 2013; Shapiro et al., 2020).

Hispanic students benefit from interactions that fit underlying cultural constructs where they are allowed to engage in discussions after having an opportunity to interact with the material (Chávez et al., 2012). Instructors need to be aware of how these interactions and rules of engagement promote a safe and equitable environment (de la Garza, Sancho-Vinuesa, Gómez, & Zermeño, 2018). In addition, first-generation students benefit from instructional support related to funds of knowledge, scheduling assignments, restructuring assessments and times, reminders, and assignment due dates are essential for students' success (Arbelo-Marrero & Milacci, 2016; Acevedo, 2018).

A recent study regarding the performance of Hispanic students at a HSI suggests that there is a need to explore the value that the students place on adopting online courses (Cottrell, 2021). In addition, it is essential to note that self-perceptions can also influence the performance of students regarding grades or learning (Johnson & Galy, 2013). Finally, the literature also suggests that Hispanic students face disproportionate challenges that could affect their expectations for success (Barber et al., 2021).

Research Questions

To fill the gaps of understanding about differences between URM and non-URM students, we proposed three research questions:

Research Question 1 [RQ1]: How do URM and non-URM students differ in their perceptions of online courses?

Research Question 2 [RQ2]: Do online course perceptions predict future intentions differently for URM and non-URM students?

Research Question 3 [RQ3]: Are URM/non-URM differences exacerbated by other student characteristics?

METHOD

The study was conducted in Spring 2021 at a large public minority-serving institution in the Southwestern United States. The survey was distributed during the first nine weeks of the semester, which was the university's third term of emergency remote instruction. The study was conducted with Institutional Review Board approval and informed consent from all participants.

Participants

Students were primarily recruited through their instructors, who were asked to distribute the survey to their classes. Students either received extra credit for their participation or participated as volunteers. A subset of the sample (10.4%) was recruited from a research participation pool in the psychology department.

After quality checks, the final sample size was $N = 1231$ students. A total of 1326 participants responded to the question "What is your race/ethnicity?" but 92 responses were excluded due to missing multiple attention checks, invalid response patterns, or duplicate submissions from the same student. Three additional responses were excluded for stating that their racial or ethnic identity was not listed, without specifying a write-in option.

The demographic composition of the sample is shown in Table 1. Consistent with the student body at large, the sample was majority Hispanic. Following the university's categorization, 69.8% of the sample was designated URM ($n = 859$; Hispanic/Latino/Latina, Black/African American, Native American, and multi-ethnic combinations of these categories) and 30.2% was non-URM ($n = 372$; White/Caucasian, Asian/Pacific Islander¹, Middle Eastern/Indian, and multi-ethnic combinations of these categories). On average, URM students were two years younger than non-URM students ($M_s = 25.7$ and 27.8 years), $t(1226) = -4.14$, $p < .001$, $d = .26$. We explored the impact of adding age to the multiple regression models. However, including age did not substantially change the pattern of results or amount of explained variance.

Students represented a wide variety of academic disciplines. They reported majors within the colleges of business (35.2%), natural sciences (30.7%), social and behavioral sciences (18.3%), education (9.5%), and liberal arts (5.6%). Most students had taken an online or hybrid course before the university switched to mandatory virtual instruction: 59.4% had previous experience in online/hybrid courses, whereas 39.2% did not. Previous online course experience did not differ between URM and non-URM students ($\chi^2(1) = 0.02$, $p = .90$). On average, students were taking 4.6 courses when the study was conducted (median = 5.0, $SD = 1.2$).

Measures

The survey included three major sections: 1) Academic history, which included students' major, previous number of online courses, and current course load; 2) Perceptions of online courses (UTAUT variables); and 3) Demographic information.

UTAUT variables were measured using a questionnaire that was pilot-tested and refined in a separate sample of participants. All items were measured on 5-point scales from (1) Strongly disagree to (5) Strongly agree, with a neutral midpoint (3). Internal consistency reliabilities were high across all scales, average Cronbach's $\alpha = .86$ (range = .754 to .940).

Performance expectancy was measured using five learning-based items ("I understand the material well in online classes") and four grade-based items ("I worry that online classes lower my GPA" [reverse-coded]). The remaining variables were measured using six items for effort expectancy ("Online classes require more effort than in-person classes")², six items for facilitating conditions ("There is help available to students taking online classes"), six items for social influence ("Many of my friends take online classes"), six items for voluntariness ("I get to choose whether my classes are online or not"), five items for flexibility ("The flexibility of online classes is important to me"), 6 items for hedonic motivation ("Taking online classes can be fun"), and five items for future intentions to take online ("I plan to take online classes in the future").

The order of presentation for UTAUT variables was randomized across participants, except for future intentions being presented last. Participants were instructed to "Reflect on your current view of online courses, now that [university] has switched to virtual instruction." For future intentions, participants were asked to report their intentions to continue taking online courses once the university returns to normal instruction.

RESULTS

Item-level responses were examined descriptively to gain a general understanding of student perceptions of online courses. All items were measured on 1-to-5 scales. On average, students believed that they could be successful in online classes ($M = 4.15$). However, they felt that online classes force students to learn on their own ($M = 4.01$) and require more effort than in-person classes ($M = 3.81$). Students' view of learning outcomes in online classes were more moderate, as they rated most learning-based performance items close to the midpoint ($M_s = 3.23$ to 3.40). The flexibility of online classes is important to students ($M = 4.22$), and the online format is seen as more convenient than in-person classes ($M = 3.88$). While students felt online classes could be somewhat fun ($M = 3.52$),

they are less enjoyable than in-person classes ($M = 2.31$) and it is hard to stay engaged ($M = 2.38$). Overall, these impressions of online courses are consistent with what has been reported elsewhere as noted in the literature review above.

Group Differences: RQ1

Table 2 reports means and standard deviations for the key variables of interest. To test the first research question, a multivariate analysis of variance was conducted with URM status as the between-subjects factor. All scale scores were calculated by averaging the items corresponding to each scale. The following scales were entered as dependent variables: learning-based performance expectancy, grade-based performance expectancy, effort expectancy, facilitating conditions, social influence, voluntariness, flexibility, hedonic motivation, and future intentions. Overall, perceptions of online courses differed significantly between URM and non-URM students, $F(9, 1220) = 3.98, p < .001$, partial $\eta^2 = .029$.

Specifically, URM students had lower expectations of grade-based performance compared to non-URM students, $F(1, 1228) = 7.30, p = .007, \eta_p^2 = .006$. Consistent with this result, URM students report significantly lower GPAs ($M = 3.28$) than non-URM students ($M = 3.44$), $t(1170) = -4.98, p < .001, d = 0.32$.

URM students also had higher expectations of effort in online courses compared to non-URM students, $F(1, 1228) = 23.36, p < .001, \eta_p^2 = .019$. Finally, URM students perceived slightly less social influence to take online courses, $F(1, 1228) = 4.38, p = .036, \eta_p^2 = .004$. No significant differences were observed between the groups on the remaining dependent variables.

Predictive Models: RQ2

To test the second research question, multiple regression analysis was used to predict future online course intentions from UTAUT factors. Separate models were conducted for URM and non-URM students. Regression results are reported in Table 3. The models explained a similar amount of variance: UTAUT factors explained 73.6% of the variance in future intentions for URM students ($R^2 = .736$). For non-URM students, UTAUT factors explained 75.1% of the variance in future intentions ($R^2 = .751$).

The relative importance of predictors differed between URM and non-URM students. For URM students, learning-based performance expectancy, flexibility, and hedonic motivation were significant predictors of future online course intentions ($ps < .001$). The same predictors were significant for non-URM students, but effort expectancy and facilitating conditions also predicted future intentions among this group ($ps < .04$). In both models, hedonic motivation was the strongest predictor, uniquely explaining 4.7 – 5.0% of the variance in future intentions ($sr^2s > .046$). Flexibility was the second-strongest predictor in both models, uniquely explaining 3.2% – 3.6% of the variance ($sr^2s > .032$).

Despite explaining a large amount of overall variance in future intentions (over 70%), the unique contributions of UTAUT factors are relatively small (none above 5%). Collinearity diagnostics did not indicate concerns with multicollinearity in the regression analyses (VIFs < 5). However, the UTAUT predictors are highly intercorrelated and appear to jointly explain much of the variance. To aid interpretation, bivariate correlation coefficients between each UTAUT factor and future intentions are also reported in Table 3. Grade-based performance expectancy and effort expectancy were not significant regression predictors for URM students. However, at the bivariate level both variables are related more strongly to future intentions for URM students than for non-URM students.

Additional Student Characteristics: RQ3

To examine the third research question, exploratory analyses were conducted using additional student characteristics. URM students were more likely to report first-generation status (76.4%) than non-URM students (44.6%), $\chi^2(1) = 116.89, p < .001$. URM students were more likely to be employed while attending college (66.1% of URM students employed; 57.0% of non-URM students employed), $\chi^2(1) = 9.24, p = .002$. URM students also reported heavier family responsibilities than non-URM students, with 81.8% of URM students and 70.7% of non-URM students reporting moderate to heavy family responsibilities (such as taking care of children or relatives, or other household duties), $\chi^2(4) = 21.05, p < .001$.

Taken together, 43.1% of URM students were first-generation, employed while attending college, and had substantial family duties. In contrast, only 23.1% of non-URM students were first-generation, employed, and had substantial family responsibilities. Exploratory analyses of variance were conducted to examine whether these characteristics exacerbate differences between URM and non-URM students. No notable patterns were found, but differences in these characteristics provide insight into the greater commitments and challenges that may be faced by URM students.

Given that 84.1% of the sample were undergraduates, we also explored the results when excluding graduate students. Graduate student experiences in online courses may be materially different from undergraduates, yet graduate students were not sufficiently sampled to compare across groups. Tables reporting the analyses using undergraduates only are available in the Appendix. The undergraduate multivariate ANOVA confirmed that grade-based performance expectancy and effort expectancy were the main differences in URM and non-URM student perceptions. However, learning-based performance expectancy also emerged as a significant difference. Specifically, URM undergraduates expected to learn less from online courses, relative to non-URM students, $F(1,1042) = 6.19, p = .025, \eta_p^2 = .005$. The undergraduate-only multiple regression analyses largely replicated the findings for RQ2. Flexibility, hedonic motivation, and grade-based performance expectancy were the strongest predictors of adoption intentions among both URM and non-URM undergraduates. The pattern of results for other predictors differed slightly, but the magnitudes remained small ($\beta_s \leq .06$ for URM students; $\beta_s \leq .10$ for non-URM).

DISCUSSION

Students in the sample were relatively positive about online learning, especially about learning achievement and flexibility, including noting that it *could* be fun. However, when compared to face-to-face learning, students were more negative, suggesting that the quality of teaching on average was not at the level to cope with the liabilities and maximize the opportunities of online teaching. This is understandable since high quality online teaching has many challenges to faculty (Dumont et al., 2021), many of which were exacerbated by the sudden, if temporary, shift to the online mode (Chakraborty et al., 2021).

Our first research question was about significant differences between URM and non-URM students in terms of how they currently view online learning. The groups did not differ in their perceptions of facilitating conditions, voluntariness, flexibility, or hedonic motivation. However, URM students believed that online courses required significantly more effort, while resulting in lower grade performance and—among undergraduates—less learning. This is a theme in minority studies (DeSante, 2013). What makes this finding even more noteworthy is that the sample is from a minority-serving institution. No matter whether these perceptions are based on weaker academic backgrounds, family and work demands, or even implicit racial bias in grading (Malouff & Thorsteinsson, 2016; Quinn, 2020), it suggests that URM students need more encouragement and support in being successful. Notably, URM and non-URM students reported equal interest in taking more online courses, despite URM students' more negative expectations toward grades and the effort required.

The second research question compared the relationships between online course perceptions and adoption intentions for URM versus non-URM students. The overall models performed very well, capturing 74% and 75% of the variance in adoption intentions. Although many factors overlapped, hedonic motivation and flexibility stood out as the most important factors for both groups. Since we know that students value flexibility highly, but have more reservations about the online experience, these two factors tend to counterbalance one another. Although a small contributor as an individual factor, learning performance was significant in both. While the contributions of effort expectancy and facilitating conditions were significant for non-URM students, they were not for URM students. This suggests that URM students may focus primarily on their personal impressions of the online learning experience, balanced with their need for flexibility.

The third research question relating to additional student characteristics is particularly interesting within the context of a minority-serving institution. URM students were somewhat more likely to work and have family responsibilities compared to non-URM students (by 9% and 11%, respectively) but far more likely to have first generation status (by 32%). This suggests that the environment at a minority-serving institution is still not level. URM students, in general, must contend with more nonacademic challenges than non-URM students.

LIMITATIONS

A number of limitations to the study are significant. Our study used multiple recruitment methods to obtain a large interdisciplinary sample. The sample comprised about 7% of the entire student body at this university. While this approach helped reach as many students as possible, it presents potential limitations. Students who volunteered to take the survey may have had different motivations or viewpoints on online courses than those who were incentivized with extra credit. We attempted to reduce response bias by emphasizing the confidential nature of the study. In addition, the authors did not recruit from their own courses and the study was taken online at students' convenience (i.e., not necessarily in the classroom or in the presence of instructors). These steps encouraged students to share their honest opinions about online classes, but there may still be unexamined influences on the responses. Further, while there was an interest in examining minority student perceptions and adoption patterns at a minority serving institution, such institutions will vary by racial and ethnic composition.

CONCLUSION

Online education offers a variety of evolving opportunities and challenges. Students are favorable overall about online learning, more so than faculty, but tend to have reservations about aspects of the experience. This study focused on the differences between URM and non-URM students at a minority serving institution. The first question sought to find if there were any significant differences between URM and non-URM students in terms of how they currently view online learning. Results showed that the groups did not differ in their perceptions of facilitating conditions, voluntariness, flexibility, or hedonic motivation. However, URM students believed that online courses required significantly more effort, while resulting in lower grade performance and—among undergraduates—less learning. The second research question compared the relationships between online course perceptions and adoption intentions for the two groups and the findings actually showed that both groups consider flexibility and hedonic motivation as the most important factors. Results also suggested that URM students may focus primarily on their personal impressions of the online learning experience, balanced with their need for flexibility. This could very well be related to the disparities in the challenges the two groups face in relation to family responsibilities and first-generation status answered by the third question in this study. URM students were somewhat more likely to work and have family responsibilities compared to non-URM students (by 9% and 11% respectively) but far more likely to have first generation status (by 32%).

URM students have more challenges to deal with than non-URM students, and this could affect their belief that online learning requires more effort in return for poorer performance.

Future adoption intentions among URM and non-URM students were relatively similar

Future research could replicate these findings at different types of URM-serving and non-URM-serving institutions. In addition, more studies could focus on the supports that URM students perceive would be most helpful to increase their flexibility and opportunities to succeed.

COMPETING INTEREST STATEMENT

The authors of this publication declare there are no competing interests.

FUNDING AGENCY

This research received no specific grant from any funding agency in the public, commercial, or non-profit sectors. Funding for this research was covered by the authors of the article.

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ENDNOTES

- ¹ Pacific Islander is a URM category but was not assessed separately from Asian. However, less than 0.2% of students at the university identify as Native Hawaiian or other Pacific Islander, whereas Asian students make up over 5% of the student body. Consequently, the vast majority of students who identified as Asian/Pacific Islander would be of Asian descent.
- ² In many technology adoption studies, the factor of effort expectancy is defined as “ease of use,” such that *higher* effort expectancy reflects *lower* expectations of effort. In this study, this factor is scaled such that higher scores on effort expectancy reflect higher expectations of effort.

APPENDIX TABLES

Table 1. Demographic Composition of Sample

	Count	Percentage (Count / N = 1231)
Race / Ethnicity		
Hispanic/Latino/Latina	720	58.5%
White/Caucasian	230	18.7%
Asian/Pacific Islander	109	8.9%
Black/African American	48	3.9%
Middle Eastern/Indian	31	2.5%
Native American	4	0.3%
Multi-ethnic / Mixed	89	7.2%
Age (Average = 26.3; Median = 23)		
18 – 19	127	10.3%
20 – 24	597	48.5%
25 – 29	209	17.0%
30 – 34	115	9.3%
35 – 39	81	6.6%
40+	99	8.0%
Gender		
Female	756	61.4%
Male	472	38.3%
Not Listed (Non-Binary)	4	0.2%
Year		
Freshman	66	5.4%
Sophomore	111	9.0%
Junior	444	36.1%
Senior	413	33.5%
Graduate Student	196	15.9%
Residency Status		
In-State Resident	1183	96.1%
Out-of-State Resident	3	0.2%
International Student	45	3.7%
First Generation Status		
First Generation Student	822	66.8%
Not First Generation	408	33.1%

Table 2. Descriptive Statistics for UTAUT Scales by URM Status

	URM Students (n = 859)		Non-URM Students (n = 372)		MANOVA Sig.
	Mean	SD	Mean	SD	
Performance - Learning	3.28	(1.12)	3.39	(1.09)	.116
Performance - Grades	3.47	(1.03)	3.64	(0.93)	.007
Effort Expectancy	3.62	(0.83)	3.37	(0.81)	< .001
Facilitating Conditions	4.11	(0.86)	4.12	(0.82)	.896
Social Influence	3.63	(0.88)	3.74	(0.86)	.036
Voluntariness	2.55	(0.96)	2.49	(0.98)	.339
Flexibility	3.74	(0.89)	3.78	(0.92)	.447
Hedonic Motivation	2.79	(1.07)	2.88	(1.09)	.210
Future Intentions	3.35	(1.31)	3.42	(1.28)	.358

Note. MANOVA Sig. column shows *p*-values for the multivariate ANOVA comparison between URM and non-URM students. More detailed results and effect sizes are provided in the text.

Table 3. UTAUT Factors Predicting Future Online Course Intentions by URM Status

.	B (SE)	β	t	p	sr ²	r
URM Students (R2 = .736)						
Performance - Learning	.189 (.04)	.163	4.43	<.001***	.006	.764
Performance - Grades	.057 (.04)	.045	1.59	.112	.001	.643
Effort Expectancy	.058 (.04)	.037	1.67	.096	.001	-.467
Facilitating Conditions	-.035 (.03)	-.023	-1.11	.270	.000	.376
Social Influence	.051 (.03)	.034	1.72	.085	.001	.065
Voluntariness	.054 (.03)	.039	1.83	.067	.001	.351
Flexibility	.423 (.04)	.289	10.17	<.001***	.032	.766
Hedonic Motivation	.548 (.04)	.450	12.64	<.001***	.050	.824
Non-URM Students (R2 = .751)						
Performance - Learning	.270 (.06)	.230	4.22	<.001***	.012	.770
Performance - Grades	-.017 (.06)	-.012	-0.29	.769	.000	.576
Effort Expectancy	.172 (.05)	.109	3.27	.001**	.007	-.408
Facilitating Conditions	-.102 (.05)	-.066	-2.11	.035*	.003	.348
Social Influence	.036 (.04)	.024	0.85	.398	.000	-.028
Voluntariness	.035 (.04)	.027	0.84	.404	.000	.441
Flexibility	.439 (.06)	.315	7.24	<.001***	.036	.771
Hedonic Motivation	.559 (.07)	.476	8.25	<.001***	.047	.827

Note. n = 858 for URM students; n = 372 for non-URM students. DV = Future intentions to take online courses. All predictors are mean-centered. r coefficients represent bivariate Pearson correlations between each predictor and the DV. All coefficients except social influence are significant at *p* < .001.

Table 4. Descriptive Statistics for UTAUT Scales by URM Status – Undergraduates Only

	URM Students (<i>n</i> = 790)		Non-URM Students (<i>n</i> = 254)		MANOVA Sig.
	Mean	SD	Mean	SD	
Performance - Learning	3.28	(1.12)	3.46	(1.08)	.025
Performance - Grades	3.47	(1.04)	3.67	(0.92)	.007
Effort Expectancy	3.61	(0.83)	3.35	(0.80)	< .001
Facilitating Conditions	4.11	(0.87)	4.13	(0.81)	.711
Social Influence	3.63	(0.88)	3.69	(0.86)	.294
Voluntariness	2.56	(0.96)	2.51	(0.99)	.491
Flexibility	3.76	(0.89)	3.83	(0.89)	.219
Hedonic Motivation	2.81	(1.07)	2.95	(1.08)	.062
Future Intentions	3.36	(1.29)	3.49	(1.27)	.161

Note. MANOVA Sig. column shows *p*-values for the multivariate ANOVA comparison between URM and non-URM students. More detailed results and effect sizes are provided in the text.

Table 5. UTAUT Factors Predicting Online Course Intentions by URM Status – Undergraduates Only

	B (SE)	β	<i>t</i>	<i>p</i>	<i>sr</i> ²
URM Students (<i>R</i>² = .733)					
Performance - Learning	.149 (.02)	.128	3.33	<.001***	.004
Performance - Grades	.080 (.04)	.064	2.15	.032*	.002
Effort Expectancy	.080 (.04)	.051	2.17	.031*	.002
Facilitating Conditions	-.042 (.03)	-.028	-1.32	.118	.001
Social Influence	.062 (.03)	.042	2.03	.043*	.001
Voluntariness	.066 (.03)	.049	2.19	.029*	.002
Flexibility	.429 (.04)	.296	9.98	<.001***	.034
Hedonic Motivation	.560 (.05)	.464	12.40	<.001***	.053
Non-URM Students (<i>R</i>² = .763)					
Performance - Learning	.247 (.08)	.211	3.20	.002**	.010
Performance - Grades	-.139 (.07)	-.101	-2.12	.035*	.004
Effort Expectancy	.129 (.06)	.081	2.13	.034*	.004
Facilitating Conditions	-.078 (.06)	-.050	-1.31	.193	.002
Social Influence	-.013 (.05)	-.009	-0.26	.796	.000
Voluntariness	.087 (.05)	.068	1.70	.090	.003
Flexibility	.466 (.07)	.329	6.32	<.001***	.039
Hedonic Motivation	.579 (.08)	.495	7.25	<.001***	.051

Note. *n* = 790 for URM students; *n* = 254 for non-URM students. DV = Future intentions to take online courses. All predictors are mean-centered. *** *p* < .001; ** *p* < .01; * *p* < .05.

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