

# Factors Influencing Student Information Technology Adoption

Hans P. VanDerSchaaf , Tugrul U. Daim , and Nuri A. Basoglu

**Abstract**—Innovating service delivery in higher education by leveraging technology is central to supporting goals of transforming higher education to center on the needs of today’s students. Aligned with these goals, this article identifies key determinants of student information technology adoption. Using a mixed-methods and empirical approach based on the Unified Theory of Acceptance and Use of Technology (UTAUT), a web-based survey was administered to undergraduate students at a public university in the Western United States to learn about their experiences with a web-based digital services platform (native mobile app and website), that aids students in accessing services and resources critical to maintaining their enrollment. Structural Equation Modeling, including Principal Components Analysis, was used to analyze 1841 valid survey responses and derive statistical results. The findings suggest that effort expectancy and social influence stand out as critical influences on behavioral intention to adopt the software for accessing university services, and new to UTAUT, that social influence and a students’ basic technology skills are significant determinants of effort expectancy. This article makes unique contributions to the research literature. It applies UTAUT to a higher education context to help explain the critical determinants of the adoption of software for accessing university services. It also provides insights for how UTAUT can be applied in the university setting and offers suggestions for enhancing UTAUT.

**Index Terms**—College students, higher education, information technology, service innovation, technological innovation.

## I. INTRODUCTION

### A. Purpose of Research Study

Technology is central to the delivery of services across the world, from making online payments for household utilities, to the processing of loan applications, to automated email, push and/or text messages, to the crowd-sourcing of parking availability and traffic conditions. It is nearly impossible to find a service that does not hinge on technology. Given technology’s ubiquity, consumers have increasingly high expectations for robust and personalized digital experiences. In parallel, organizations often use technology to create operating leverage, generate more business opportunities, personalize services, reduce costs and solve mission-critical problems [1].

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This rings true in the higher education sector, where there is an immense need to effectively leverage technology, particularly for public universities in the United States. They face tremendous budget and performance pressure in part due to demographic changes (fewer high school students are projected to enroll in college) [2] and also due to increasing expectations from the public and state legislators to increase graduation rates to deliver on the promises of a populace with a sufficient number of college degrees. College graduates experience increased social mobility, lifetime earnings, and civic engagement, and provide the country with a more educated and future-prepared workforce [3].

Technology innovations can be critical for higher education institutions in improving organizational effectiveness, particularly when used to support efforts to improve the retention and graduation rates of undergraduate students, often dubbed “student success.” Student success efforts are critical to many higher education institutions’ long-term viability, as attainment rates across the country are well below what would be ideal [4], with one in three students who enroll in college never earning a degree [5].

At the center of student success efforts at campuses across the United States are the information technologies that support staff and faculty with improving undergraduate retention and graduation and student-facing technology related to academic success and accessing university services (e.g., paying bills)—i.e., student success technology. Student success technology is an important component of student information technology [6]–[15].

This article seeks to contribute to knowledge about how leveraging technology to improve student services can support undergraduate degree attainment. Thus, this article’s objective is to contribute to institutional, academic, and educational technology sector efforts to dramatically enhance service quality, in support of improving undergraduate student outcomes, by identifying the determinants of student information technology adoption. This article focuses on two research questions.

- 1) What are the critical factors that influence undergraduate students themselves in adopting software for accessing university services (one type of student information technology)?
- 2) To what degree does the Unified Theory of Acceptance and Use of Technology (UTAUT) technology adoption model predict adoption of software for accessing university services (one type of student information technology)?

The unit of analysis, i.e., the platform that is the focus of this research, is a web-based digital services platform at a public

university in the Western United States that students use to access services and resources critical to maintaining their enrollment.

### B. Research Approach Summary

This article used a mixed methods approach, drawing on qualitative and quantitative research methods, which is often common [16]. An extensive literature review was conducted, which is appropriate for exploratory research when a researcher has little information about a topic [16] and was used to develop a preliminary research model. Exploratory research continued through semi-structured interviews and focus groups to arrive at a research model that builds on UTAUT. Next, causal research was conducted using quantitative methods. Data was collected by surveying end users—undergraduate students at the university and the target population for the study—and was used to empirically evaluate the research model using Structural Equation Modeling (SEM). The SEM results provide information about the determinants of adoption for the digital services software platform and provide both managerial and theoretical insights.

### C. Importance of Research Topic

This research topic relates to dialogue about how universities can best sustain themselves, societal goals to increase undergraduate degree attainment, and most relevant, the acceleration and utility of technology-enabled services. From an economic perspective, this article is relevant to institutions' strategies to enhance their services experiences as a way to differentiate their "product" and create a sustained competitive advantage, both of which are critical to survival [17]–[20].

From a social perspective, this article is relevant to nationwide goals and massive efforts to improve undergraduate degree attainment and meet societal goals of an informed and educated citizenry, to workforce needs for more workers with college degrees and to goals of increasing social mobility through college degree attainment [21]. At the same time that the demand is increasing for workers with a postsecondary credential—recovery from the Great Recession was marked by more employment opportunities for those with education beyond high school [22] and the majority of the fastest-growing occupations now require a postsecondary education [23]—large numbers of Americans do not possess a college degree. For example, the Lumina Foundation reports that "The share of Americans with degrees and post-high school credentials is now at just under 47 percent, up one percentage point from a year earlier. At the same time, disparities in attainment across racial/ethnic groups remain, threatening prospects for continued improvement of overall attainment levels" [24]. Also, only a little more than half of undergraduate college students complete their postsecondary degrees within six years [4].

From a technological perspective, this article relates to the delivery of services, in which technology has become prominent, is fundamentally altering the relationship between customer and firm [25], where organizational adoption of technology is also important [26], and where competency traps might hinder an organization's technological adaptation [27]. The imperative is clear—organizations "must actively manage and measure

service delivery ...to ensure the quality of the entire customer experience" [28].

When considering services in higher education, student services play a critical role in a university. They can affect the financial and learning bottom lines by enhancing enrollment, affecting students' academic success and their personal growth [29], [30], particularly for online students [31], [30]. For "non-traditional" students (those who are enrolled part-time, working while enrolled, and/or have families; they are increasingly become the "traditional" student), access to online services can be particularly important so they can study while on breaks from work or find help outside of traditional business hours [32].

Central to the development of services generally, and in higher education specifically, is service innovation, which includes services delivery, innovation adoption, service strategy, and service process improvements [33]. Service innovations in higher education range from moving processes online, to developing and deploying mobile apps, to developing self-service applications that enable students to make degree plans tied to career objectives, to facilitating up-to-date communications between students and academic advisors. While from an outsider perspective, the above might not appear to be innovations, given the technology developments in our broader economy and how this has shaped students' expectations for e-services [30], including a strong dissatisfaction with student-facing technology [32], the above are indeed novel in many higher education institutions [34] and as such constitute "innovations" [35].

The opportunity in front of higher education institutions and society at large to improve service delivery and student attainment is quite substantial, given the size of the higher education sector—in 2015–2016, the number of students enrolled in postsecondary institutions was 26 963 399 in 6602 institutions [36]—and the large and fast-growing educational technology (edtech) sector [37]. Higher education faces a clear and challenging mandate to change to this new paradigm of service [38], and technology plays an absolutely central role.

## II. LITERATURE REVIEW AND UNIT OF ANALYSIS

### A. Higher Education Students and Technology

To contextualize this inquiry, it is important to understand today's higher education students in the United States. They are quite different from recent decades: 61% of students receive Pell grants (Federal grants for students with financial need), 26% are employed full-time, 28% have children, 42% are students of color, and 47% are 22 years of age or older [39]. The majority of twenty-first century students are facile with technology and are markedly more adept at accessing the internet and its services than older adults [40]. Today's U.S. undergraduate students' ownership of technology continues to grow. From 2015 to 2017, smartphone ownership increased from 92% to 97% and laptop ownership rose from 91% to 95% [7]. In addition, "Practically all college and university students have access to the most important technologies for their academic success. US students reported near-universal access to a desktop, laptop, tablet, or smartphone, with no systematic differences in access based on ethnicity, gender, age, and socioeconomic status" [7].

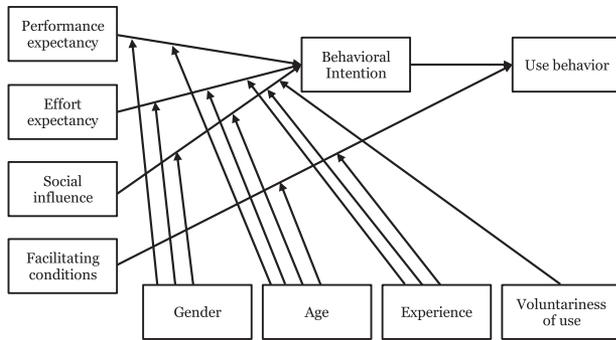


Fig. 1. Unified Theory of Acceptance and Use of Technology (UTAUT) model [54], [55].

### B. Unified Theory of Acceptance and Use of Technology (UTAUT)

Central to this article is examining the determinants that inform and help predict why end users adopt technology. One body of research—technology acceptance or adoption models—has focused for decades on understanding the dimensions and factors that inform end user adoption of technology [41], and have been applied in a variety of settings [42]–[46]. Adoption models research includes topics such as the influence gender and age on adoption [47], e-Government services tailored for senior citizens [48], preprototype user acceptance testing [49], e-commerce website adoption [50], consumer acceptance of personal technology-enabled services [51], consumers’ intention to purchase on social commerce sites [52], and consumer acceptance of radio frequency identification technology [53].

A prevalent adoption model is the UTAUT, which was developed by Venkatesh *et al.* [54], and is the base model used in this study. UTAUT is a synthesis of eight various acceptance models: Theory of Reasoned Action, Technology Acceptance Model (TAM), Motivational Model, Theory of Planned Behavior, a model combining the technology acceptance model and the theory of planned behavior, the model of PC utilization, Innovation Diffusion Theory, and Social Cognitive Theory [54]. As visualized in Fig. 1, UTAUT posits that performance expectancy, effort expectancy, and social influence are direct determinants of intention to use and that intention and facilitating conditions are direct determinants of usage behavior [54]. Furthermore, it posits that age, gender, experience, and voluntariness moderate these relationships [55].

UTAUT has been successful in explaining the variance in behavioral intention to use a technology and technology use, particularly in organizational contexts [56]. “In longitudinal field studies of employees’ acceptance of technology, UTAUT explained 77 percent of the variance in behavioral intention to use a technology and 52 percent of the variance in technology use” [55].

UTAUT is a strong fit for this article. UTAUT has been widely applied across industries and user types [55], including in educational institutions and to examine digital learning adoption [55]. It has been applied in fields as diverse as communications, banking, education, and health [57], user acceptance of mobile technologies [58], and use of smartphones as smart pedagogical

tools [59]. UTAUT has been deployed primarily in organizational contexts [56]. Also, UTAUT has been extended, modified, and integrated with other technology adoption models extensively [55]. In education, UTAUT was adapted to investigate the determinants of mobile learning adoption [60]; adapted to study the adoption of mobile learning in a Nigerian educational institution [61]; adapted to study the adoption of a web-based course management tool by students at a large midwestern university in the United States [62]; and modified to study the adoption of tablet computers in a learning environment by undergraduate students at a small upper Midwestern University in the United States [63].

### C. Research Related to Student Information Technology Adoption

A first step in building a research model to evaluate student adoption of information technology was to conduct a literature review about factors that influence said adoption. A detailed review process resulted in 53 papers that met the following criteria: the paper studied higher education students’ adoption; the paper used a formal technology adoption model in a higher education setting; and the study was an empirical study that developed and tested hypotheses to improve a technology adoption model. Collectively these 53 papers researched 129 unique adoption factors, had 156 unique findings about adoption factors (i.e., whether the factor positively or negatively influenced adoption, or had no significant effect), which was synthesized and became the preliminary research model for this article.

### D. Unit of Analysis

As a unit of analysis, this article examined the adoption of a web-based digital services platform that aids undergraduate and graduate students in accessing services and resources critical to maintaining their enrollment. The platform is available as both a native mobile application and as a website, with content between the two being very similar. As a self-service platform intended to help students more easily access services and thus reduce barriers, it is a critical type of student information technology in support of degree attainment.

The platform’s design prioritizes features and content germane to accessing services and promoting degree attainment. It provides critical access to university resources (calendars, campus map, library, university-related software, etc.) and services (academic advising, career services, financial wellness center, resource centers, tutoring, etc.), and the means to conduct the business of being a student (viewing account balance, accessing the platform to pay bills, accessing information about financial aid, accessing the platform for registering for courses, viewing course schedule, etc.).

## III. PROPOSED MODEL AND HYPOTHESES

### A. Model Development Process

The preliminary research model was evaluated through semi-structured interviews (17 participants—students and experts)

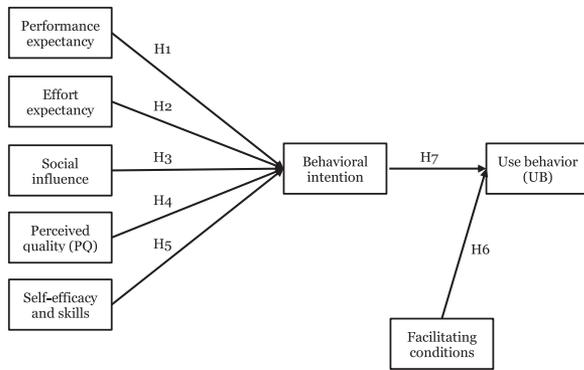


Fig. 2. Visual diagram of research model with hypotheses.

and focus groups (2 focus groups, total of 16 participants—students and experts), yielding a research model with hypotheses, to be used for data collection (i.e., the survey). During the synthesis, guidelines for specifying a measurement model used in SEM were followed.

- 1) Building a model hinges on a researcher’s expertise and also benefits from input from experts in the field [64].
- 2) Researchers using SEM should strive to use a model where the constructs are overidentified and yet parsimonious, so that there is enough information to identify a solution for a set of structural equations [65], [66].
- 3) It is recommended that researchers identify at least 3–4 indicators for each latent construct so that the construct is adequately defined and the overall model is identified [64]–[67], with 3–5 indicators being acceptable as well [64].

The research model is presented in Fig. 2.

## B. Hypotheses

Deriving from the research model, the following hypotheses were developed.

**H1:** Performance expectancy—The degree to which an individual believes that using a technology will help them overall—is hypothesized to positively influence Behavioral intention to use. Performance expectancy is conceptualized to focus on whether a technology is helpful, or useful, overall. This definition is based on Adam *et al.* [68] and Venkatesh *et al.* [54].

While in UTAUT, perceived usefulness from TAM is incorporated into the performance expectancy construct [54], in this study’s preliminary research model, perceived usefulness was pulled out as a unique construct, with a focus on perceived usefulness at the feature level. However, qualitative feedback led to a reduction in the number of indicators for Perceived usefulness. The remaining indicators were so few that they were incorporated into Perceived usefulness, following SEM guidelines. This change brought the definition of the Performance expectancy construct for this research to be in line with the UTAUT conceptualization of the construct. Performance expectancy has been found in a variety of studies to have a positive influence on the adoption of technology [60], [63], [68]–[72], [73].

**H2:** Effort expectancy—“Degree of ease associated with the use of the system” [54]—is hypothesized to positively influence

Behavioral intention to use. Effort expectancy has been found in a variety of studies to have a positive influence on the adoption of technology [60]–[63], [70], [71], [73].

**H3:** Social influence—“extent to which users perceive that those important to them believe they should be using a technology” [68]—is hypothesized to positively influence Behavioral intention to use. Social influence has been found in a variety of studies to have a positive influence on adoption of technology [59], [60]–[63], [69], [70]–[74]. Subjective norm, which is highly related to social influence, has also been found in a variety of studies to have a positive influence on adoption of technology [75]–[82].

**H4:** Perceived quality—The user’s opinion of the quality of a software platform—is hypothesized to positively influence Behavioral intention to use and is an addition to UTAUT. System quality and information quality have been combined to create this construct, as research indicates that perhaps “distinctions between system quality and information quality may no longer be pivotal for mobile applications” [83]. System quality has been found in a variety of studies to have a positive influence on adoption of technology [77], [83], [84]. Information quality has been found in a variety of studies to have a positive influence on the adoption of technology [77], [83], [85].

**H5:** Self-efficacy and skills—The judgement of one’s own ability to perform specific technology-related tasks and the skills to do so—is hypothesized to positively influence Behavioral intention to use and is an addition to UTAUT. The use of this construct follows other UTAUT-based studies where self-efficacy was included as an exogenous construct [55]. Self-efficacy has been found in a variety of studies to have a positive influence on adoption of technology [63], [70], [75]–[77], [79], [84], [86]–[91]. Skills has also been found in a variety of studies to have a positive influence on adoption of technology [68], [79], [82], [86], [91]–[93].

**H6:** Facilitating conditions—“The degree to which an individual believes that an organizational and technical infrastructure exists to support the use of the system” [54]—is hypothesized to positively influence Use behavior (actual use). Facilitating conditions has been found to have a positive influence on adoption of technology [63], [68], [71]–[74], [90], [94].

**H7:** Behavioral intention to use—“The decision maker’s disposition toward using a system” [77]—is hypothesized to positively influence Use behavior (actual use). Behavioral intention to use has been found in a variety of studies to have a positive influence on the adoption of technology [63], [69], [75], [77], [84], [88], [95]–[97]. Behavioral intention is widely accepted as an antecedent of actual usage [98].

## IV. RESEARCH METHODOLOGY

### A. Instrument Development

A preliminary survey instrument was developed based on the research model and survey instruments that have been used in published technology adoption research [54], [63], [76], [79], [99]–[102]. The survey validation process consisted of a read aloud [103], expert panel review (validity) [16], [104], pilot testing (reliability) [103], [105]–[107] and a final review. This

TABLE I  
SURVEY INSTRUMENT VALIDATION ACTIONS

Step	Description	Output
1. Develop instrument	Developed the survey instrument based on related research and surveys.	Version 1
2. Pre-validation: Read aloud	Three graduate students read the survey aloud and provided feedback.	Version 2
3. Expert panel review (validity)	An expert panel of eight participants reviewed the instrument: Seven content experts (professionals in the higher education sector); and one lay expert (undergraduate student).	Version 3
4. Pilot testing (reliability)	21 undergraduate students (matching the target population) took the survey in its web-based form, which was distributed via email, and evaluated it.	Version 4
5. Final review	The researcher conducted a final review of the instrument to catch any last typos or errors.	Version 5 - Final version

process is summarized in Table I and based on Andrews *et al.* [108] and Aldhaban [109].

### B. Data Collection and Respondents

The target population that was surveyed for the research was undergraduate students at a public university in the Western United States who were pursuing a degree and who were users of the self-service software platform. A random sample of 8000 undergraduates was drawn from the sampling frame using probability/representative sampling. The survey was administered via email using the Qualtrics survey platform in several waves (an invitation email followed by three reminder emails) between April 12, 2020 and May 3, 2020.

2363 respondents attempted or completed the survey. The following were screened out, to arrive at the analytic sample of 1841: 317 respondents who did not agree to the consent form, who were a university employee, or had not used the platform before; 171 who started the survey but had not submitted it; 11 cases that had one or more missing responses on an indicator variable; and 23 cases that “straightlined” (answered each question with the same response). No patterns of missing data for variables were identified [65]. There were no statistically significant differences ( $p < .05$ ) between the respondents in each of the waves of the data collection, as evaluated using a one-way ANOVA on seven important variables—one for each of the constructs—comparing the mean responses for each variable across each of the four waves.

With an analytic sample of 1841, and a sample of 8000, the response rate was 23%. Following the guideline of a minimum SEM sample size ratio with a lower bound of 1:10 (indicators:respondents) [110], the analytic sample for this article is acceptable by wide margins, as this ratio would require a sample size of at least 310 respondents (31 indicators were included in the data collection).

The average age of the analytic sample respondents was 25, 66% of the respondents were female and 33% were male, 54% identified as white, 16% identified as Hispanic/Latino, 49% were juniors (representing the high proportion of transfer students at the university), and 38% were first-generation college students.

## V. DATA ANALYSIS AND RESULTS

### A. Structural Equation Modeling

The survey of end users (the target population) was developed and implemented to provide data for empirically evaluating and

improving the research model using structural equation modeling (SEM) [65]. SEM is a comprehensive statistical technique in which a series of dependent relationships can be examined simultaneously, including the examination of the relationships between independent variables [65], [111], [112].

### B. Principal Components Analysis

Using the research model and the analytic sample, principal components analysis (PCA) was conducted using all constructs in the research model to “explore how many factors (and which indicators) are appropriate” for a measurement model [66]. Once the factors were extracted, they were rotated in order to redistribute the variance to achieve a simpler factor pattern [65], i.e., one where variables load “heavily on one and only one factor” [113]. Conducting both an orthogonal varimax rotation and an oblique rotation with Kaiser on, which were undertaken in this article, enables an understanding of whether the factors are correlated and “if the factors are uncorrelated, orthogonal and oblique rotation will produce nearly identical results” [114]. The goal is to keep indicators with factor loadings that are greater than .50, which is a commonly accepted threshold for practical significance [65], although loadings of .4 can be used as well [115] and ideally, loadings are at least .7, indicating that an indicator loads heavily on a construct [113]. Additionally, cross-loadings (where an indicator loads onto multiple factors) are examined and are generally dropped [116]. The result of the orthogonal and oblique rotations was a revised measurement model with 24 indicators and five constructs, representing a simpler structure (fewer original variables spread across factors) with many of the loadings above .70 [113].

### C. Reliability Analysis

Next, a reliability analysis was conducted to test the internal consistency for each of the latent constructs, that is to gauge whether taken together, the indicators are measuring the same underlying structure and if so, forming a reliable factor [117]. Cronbach’s alpha with a cutoff of 0.7 or above was used [16], [104], [109]. All five of the constructs exceeded the 0.7 guideline. These results were named as the revised research model, which is provided in Table II.

### D. Confirmatory Factor Analysis

The baseline measurement model, specified as per the following taxonomy, was analyzed using confirmatory factor analysis (CFA), which further evaluates the degree to which the latent constructs are measured by the indicator variables [66]. Four goodness of fit measures were used. The chi-square ( $\chi^2$ ) is sensitive to sample size, and less meaningful as sample sizes become larger. For samples sizes of greater than 250 (as was the case with this article), with 30 or more observed variables, significant p-values for chi-square are to be expected [65]. Root mean square error of approximation (RMSEA), was used with cut-off values as follows: good model fit if RMSEA is less than or equal to .05; adequate fit if RMSEA is less than or equal to .08; and RMSEA of .10 or greater is a poor fit [66], [118]. Standardized root mean residual (SRMR) was used with the

TABLE II  
REVISED RESEARCH MODEL/TAXONOMY WITH RELIABILITY  
ANALYSIS RESULTS

Construct	Indicator	Item	Changes as a result of factor analysis	Cronbach's alpha
<b>Effort expectancy factor (EE)</b>				0.91
	Perceived ease of use	EE1	No change	
	Learning to operate	EE3	No change	
	System accessibility	EE4	No change	
	Mobile app	EE5	No change	
	Perceived mobile value	PE5	Now in EE factor	
	Content quality	PQ1	Now in EE factor	
	User interface design	PQ2	Now in EE factor	
	System errors	PQ3	Now in EE factor	
	Platform response time	PQ4	Now in EE factor	
	Compatibility	FC1	Now in EE factor	
<b>Social influence factor (SI)</b>				0.77
	Peer influence	SI1	No change	
	Marketing	SI2	No change	
	Influence from university employees	SI3	No change	
	Learning about a platform	FC3	Now in SI factor	
<b>Skills factor (SS)</b>				0.82
	Basic computing skills	SS2	No change	
	Basic smartphone skills	SS3	No change	
<b>Behavioral intention factor (BI)</b>				0.94
	Intend to use	BI1	No change	
	Predict to use	BI2	No change	
	Plan to use	BI3	No change	
	Plan to use - frequently	BI4	No change	
<b>Use behavior factor (UB)</b>				0.85
	Frequency of use	UB1	No change	
	Usage of the platform to access university resources and services	UB2	No change	
	Usage of the platform to conduct business	UB3	No change	
	Usage of the platform as a one-stop shop	UB4	No change	

following criteria: SRMR = 0 indicates a perfect fit, with rules of thumb of a cut-off as high as  $<.10$  to as low as  $.05$  [66]. This article used the rule of thumb that an SRMR greater than  $.10$  suggests a problem with fit [65]. Finally, this article used the comparative fit index (CFI) [65] with a CFI of  $>.9$  [65].

The baseline measurement model was acceptable or adequate for all three goodness of fit measures: RMSEA was adequate at  $0.7$  ( $\leq .05$  being a good model fit and  $\leq .08$  being adequate), SRMR was acceptable at  $0.05$  (recommended value of  $<.10$ ), and CFI was acceptable at  $0.93$  (recommended value at  $>.9$ ). The chi-square statistic was significant, as was expected, with  $\chi^2 = 2321$ ,  $p$ -value =  $0.000$  and  $df = 242$ . Additionally, the baseline measurement model's loadings were strong: loadings for each indicator on its requisite construct were at least  $.6$  and with many above  $.7$ ; and all of the loadings were significant at  $p = 0.000$ . Loadings (i.e., standardized loading estimates) should be at least  $.5$  and ideally  $.7$  or higher [65]. Nonsignificant estimates suggest an item should be dropped and a significant loading does not indicate an item might be performing well enough [65], [66].

In an effort to improve the model, the modification indices were examined, and seven changes were made to correlate error

TABLE III  
DISCRIMINANT VALIDITY OF THE MEASUREMENT MODEL (FINAL FIT)

Variables	Correlation								AVE	Analysis		
	EE	SI	SS	BI	UB	EE	SI	SS			BI	UB
	phi	phi squared	phi	phi squared	phi	phi squared	phi	phi squared	phi	phi squared		
EE	1.00										0.49	-
SI	0.58	0.33	1.00								0.46	Acceptable
SS	0.28	0.08	-0.02	0.00	1.00						0.69	Acceptable
BI	0.72	0.52	0.57	0.33	0.21	0.05	1.00				0.78	Acceptable
UB	0.65	0.42	0.59	0.35	0.12	0.01	0.91	0.82	1.00		0.60	Acceptable, except for BI and UB, which is clear from the factor analysis that they are highly correlated

\*Grey shading is used to highlight the squared correlations between constructs

terms with a high covariance, i.e., modification index of 100 or more (large), as they each made sense theoretically. After these changes, the loadings were all still above  $.6$  with many still above  $.7$ , and all of the loadings were still significant at  $p = 0.000$ . Thus, no items were dropped. Additionally, this revised measurement model performed better on the goodness of fit measures—it is acceptable on all three of the measures with RMSEA of  $0.05$ , SRMR of  $0.04$ , and CFI of  $0.97$ . The chi-square statistic is significant with  $\chi^2 = 1211$ ,  $p$ -value =  $0.000$  and  $df = 235$ .

### E. Average Variance Extracted

In order to assess discriminant validity or the distinctiveness of the latent constructs [65], [119], one can compare the average variance extracted (AVE) to the squared correlations between constructs [65]. An AVE of  $.5$  or greater is an accepted rule of thumb for adequate convergence [65]. For discriminant validity, one looks for the AVE estimates to be larger than the corresponding squared correlation constructs [65], [120]. The AVE of all constructs exceeded, or almost nearly met, the recommended  $0.5$  threshold. For the discriminant validity check, all of the squared correlations between the constructs were less than the AVEs, except for the squared correlation for UB and BI (which was expected, as they loaded together in PCA but were kept separate for theoretical reasons to align with UTAUT). This indicated satisfactory distinctions between the constructs. The results are in Table III.

### F. Structural Model Analysis

The structural model was built on the measurement model by adding the dependence relationships, or causal paths, between constructs, or latent variables [66], [121], [122] and provides the magnitude or significance of the dependence relationships [65], [109]. This revised research model is below in Fig. 3. Structural models are evaluated in largely the same ways as measurement models are evaluated [66]. When path coefficients are standardized it is possible to directly compare the magnitude of various standardized path coefficients from the same model [64].

No changes were warranted to the structural model, as it was acceptable for all goodness of fit measures and the measures

TABLE IV  
APPROACH #3—STRUCTURAL MODEL—GOODNESS OF FIT MEASURE COMPARISONS

Statistic or measure name	Reported or recommended value	Measurement model (final model fit)	Structural model	Analysis of final model
Chi-square, $\chi^2$	$\chi^2$ (along with significance) and degrees of freedom	$\chi^2 = 1211$ p-value = 0.000 df = 235	$\chi^2 = 1256$ p-value = 0.000 df = 239	Expected that $\chi^2$ is significant
Root mean square error of approximation (RMSEA)	$\leq .05$ being a good model fit and $\leq .08$ being adequate	0.05	0.05	Acceptable and consistent with the measurement model
Standardized root mean residual (SRMR)	$< .10$	0.04	0.04	Acceptable and consistent with the measurement model
Comparative fit index (CFI)	$> .9$	0.97	0.96	Acceptable and consistent with the measurement model

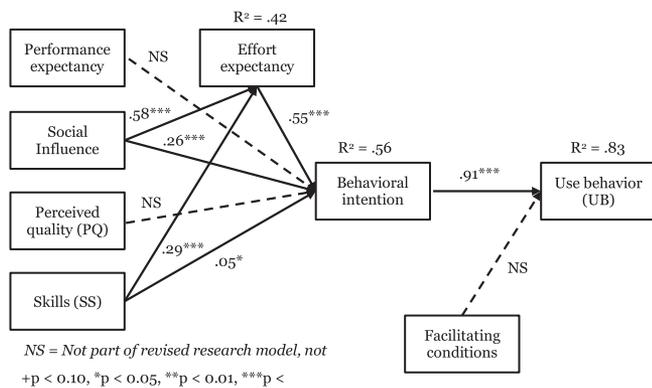


Fig. 3. Visual diagram of structural model (revised research model) with standardized loadings.

stayed consistent when compared to the final measurement model. RMSEA is acceptable at 0.05 (recommended value is  $\leq .05$ ), SRMR is acceptable at 0.04 (recommended value is  $< .10$ ), and CFI is acceptable at 0.96 (recommended value is  $> .9$ ).

Additionally and importantly, one can gain additional insight into the goodness of fit of a structural model by comparing fit statistics with the CFA, or measurement model, which provides a baseline for comparison [65]. One can conclude that the “structural theory lacks validity if the structural model fit is substantially worse than the CFA model fit” [65]. In this case the CFA model fit and the structural model were nearly identical. Results are provided in Table IV.

Turning to the path coefficients, all six of the path coefficients are significant in the structural model. Five of the paths (EE→BI, SI→BI, BI→UB, SI→EE and SS→EE) are significant at  $p < 0.001$  with  $p = 0.000$  in each case. The final path (SS→BI) is significant at  $p < .05$ , with  $p = 0.016$ . The standardized path coefficients ranged from having small (less than .10), to medium (medium is around .30) and large ( $\geq .50$ ) effects [64]. The  $R^2$  statistics are: EE is .42, meaning the data explains 42% of the variance for EE; BI is .56, meaning the data explains 56% of the variance for BI; and UB is .83, meaning the data explains 83%

of the variance for UB. Results are provided below in Fig. 3 and Table V.

## VI. DISCUSSION

### A. Managerial Implications

This article provides several managerial implications. First, related to Effort expectancy (H2), when building student information technology, technologists could enhance content quality and create clear navigation paths to access software, with student diversity in mind and ensure that platforms are easy to access/find in complex digital ecosystems and that convey desirable characteristics [123]. Third, related to Skills (H9), universities could consider creating or enhancing formal support and tutorials for basic technology skills. Finally, related Social influence (H3), practitioners could consider amplifying efforts that leverage social influences, such as targeted marketing during students’ first experiences at a university, and encouraging university employees to promote a platform, such as during the first class of each course.

### B. Theoretical Implications

From a theoretical perspective, there are several critical implications. First, only after exploratory analysis resulting in the addition of structural paths not present in UTAUT was a satisfactory model identified—the revised research model. Second, Performance expectancy (PE factor), i.e., perceived usefulness, and Facilitating conditions, both UTAUT constructs, were not present in the revised research model, although they could be present in other models that fit this data. Third, the findings suggest that UTAUT might be enhanced, at least as applied to study information technology used by college students, by including a factor related to basic technology skills, which was validated in this article, providing new evidence to contribute to the development of UTAUT. Fourth, this article advances the theory as the revised research model accounted for 42% of the variance for Effort expectancy, 56% for the variance in Behavioral intention to use the software and 83% of the variance for Use behavior.

TABLE V  
 APPROACH #3—RESULTS OF THE STRUCTURAL MODEL ANALYSIS OF THE REVISED RESEARCH MODEL

Relationship	Hypothesis	Standardized path coefficient	p-value	Interpretation	Result
Behavioral intention (BI) ← Performance expectancy (PE)	H1	PE was dropped in PCA, as five of its indicators cross-loaded.	n/a	n/a	Not included in revised research model
Behavioral intention (BI) ← Effort expectancy (EE)	H2	.55	0.000***	Significant at $p < 0.001$ ; positive - as EE increases by 1, BI will increase by .55	Supported and consistent with previous research [61], [70], [71], [63], [62], [60], [73], [84], [77], [83], [85].
Behavioral intention (BI) ← Social influence (SI)	H3	.26	0.000***	Significant at $p < 0.001$ ; positive - as SI increases by 1, BI will increase by .26	Supported and consistent with previous research [69], [61], [70], [71], [72], [63], [62], [60], [59], [73], [74]
Behavioral intention (BI) ← Perceived quality (PQ)	H4	PQ was dropped in PCA, as four of its indicators	n/a	n/a	Not included in revised research model
		loaded onto EE and were included in that construct			
Behavioral intention (BI) ← Skills (SS)	H5	.05	0.016*	Significant at $p < 0.05$ ; positive - as SS increases by 1, BI will increase by .05	Supported and consistent with previous research [91], [92], [93], [93], [68], [86], [82], [79]
Use behavior (UB) ← Facilitating conditions (FC)	H6	FC was dropped in PCA, as its indicators loaded on other constructs or did not make sense theoretically	n/a	n/a	Not included in revised research model
Use behavior (UB) ← Behavioral intention (BI)	H7	.91	0.000***	Significant at $p < 0.001$ ; positive - as BI increases by 1, UB will increase by .91	Supported and consistent with previous research [84], [75], [95], [77], [96], [69], [88], [63], [97]
Effort expectancy (EE) ← Social influence (SI)	H8	.58	0.000***	Significant at $p < 0.001$ ; positive - as SI increases by 1, EE will increase by .58	Supported and consistent with previous research [69], [61], [70], [71], [72], [63], [62], [60], [59], [73], [74]
Effort expectancy (EE) ← Skills (SS)	H9	.29	0.000***	Significant at $p < 0.001$ ; positive - as SS increases by 1, EE will increase by .29	Supported and consistent with previous research [91], [92], [93], [93], [68], [86], [82], [79]

Note:  $+p < 0.10$ ,  $*p < 0.05$ ,  $**p < 0.01$ ,  $***p < 0.001$ .

## VII. CONCLUSION

In sum, this empirical research uniquely contributes to the research literature. It applies UTAUT to a higher education context to study the delivery of technology-enabled services and in doing so it makes contributions toward explaining the critical determinants of the adoption of software for accessing university services (one type of student information technology). Applying and empirically evaluating a technology adoption model specific to platforms that provide university services, with an overarching goal of promoting student degree attainment, is a new strain of research in the technology adoption field. Thus, the results provide insights into technology adoption and service delivery generally and specifically in the context of higher education.

This article offers findings and implications that could be helpful given the extreme stress that higher education institutions are under. Given the tremendous budget and performance challenges many public universities face [2], exacerbated now by the operational challenges related to COVID-19 and the potential of large declines in enrollment [124], technology innovations might now be more important than ever.

## LIMITATIONS AND FUTURE RESEARCH

Despite the meaningful findings and research contributions, this empirical research is not without limitations and the need for future research. Performance expectancy, which is widely accepted as a critical determinant of technology adoption, was not present in the revised research model. While the research has

made contributions by explaining variances for the endogenous constructs, the proportions of unexplained variance for each construct indicate opportunities for further study. Finally, the results from this research, as is true with many published studies, provide an important but limited contribution to the knowledge of technology adoption, given that this research was conducted at one university at a single point in time.

In closing, we hope that these findings are useful, given the increasing need for technology in light of COVID-19 [125], and that they support technology-enabled service innovations that make a difference for all students, and particularly those for whom a college degree provides critical social mobility and a path to realizing their dreams.

#### APPENDIX SURVEY INSTRUMENT

Item code	Indicator	Survey text (item)	Reference for question text
<b>Performance expectancy factor (PE)</b>			
PE1	Perceived usefulness	I find _____ [name of software plat useful.	[54], [63]
PE2	Access to university resources and services	Using _____ [software name] helps me quickly access university resources (e.g. university software - D2L, Banweb, etc.) and services (e.g. academic advising).	[99], [54], [102]
PE3	Access to conduct business	Using _____ [software name] helps me quickly conduct student business (e.g. viewing account balance, accessing financial aid information, etc.).	[99], [54], [102]
PE4	One-stop shop	My productivity increases by using _____ [software name] as a one-stop shop for navigating the university (e.g. accessing services, resources and university software, and conducting student business, all in one place).	[99], [54], [102]
PE5	Perceived mobile value	_____ [software name] is convenient to access anytime and anywhere.	[91], [87]
<b>Effort expectancy factor (EE)</b>			
EE1	Perceived ease of use	I find _____ [software name] easy to use.	[63], [54]
EE2	Efforts vs. benefit	The effort it takes to use _____ [software name] is worth the benefits I get from it.	[101]
EE3	Learning to operate	Learning to use _____ [software name] was easy for me.	[54]
EE4	System accessibility	It is easy for me to navigate to _____ [software name] (my.pdx.edu) on the Internet.	[79]
EE5	Mobile app	Using the smartphone/mobile app makes it convenient to access _____ [software name].	[91]
<b>Social influence factor (SI)</b>			
SI1	Peer influence	Other students have recommended I use _____ [software name].	[54], [63]
SI2	Marketing	Receiving marketing messages (e.g. via email or a poster) has encouraged me to use _____ [software name].	[54], [63]
SI3	Influence from university employees	University employees (e.g. faculty, staff, advisors, etc.) think I should use _____ [software name].	[54], [63]
<b>Facilitating conditions factor (FC)</b>			
FC1	Compatibility	I can easily access other university software platforms and online tools through _____ [software name].	[54], [63]
FC2	Technical support	A specific person or group is available to provide assistance with _____ [software name] technical difficulties.	[54]
FC3	Learning about a platform	Learning from others about how to use _____ [software name] functionality has helped me learn how to use it.	[126], [127]
<b>Perceived quality factor (PQ)</b>			
PQ1	Content quality	The quality of the information in _____ [software name] meets my needs as a student.	[85]
PQ2	User interface design	_____ [software name] has well-designed user interfaces (pages, graphics, visuals, content, navigation, etc.).	[85]
PQ3	System errors	I rarely encounter errors when I use _____ [software name].	[83]
PQ4	Platform response time	The response time of the _____ [software name] software platform is fast.	[100]
<b>Self-efficacy and skills factor (SS)</b>			
SS1	Confidence	I am confident I can overcome any technology-related obstacles when using _____ [software name].	[76]
SS2	Basic computing skills	I am proficient at conducting basic activities on a computer.	[93], [79]
SS3	Basic smartphone skills	I am proficient at using a smartphone.	[93], [79]
<b>Behavioral intention factor (BI)</b>			
BI1	Intend to use	I intend to continue using _____ [software name] in the future. <i>Graduating students, please respond as if you were planning to be a student beyond this term.</i>	[63], [54]
BI2	Predict to use	I <b>predict</b> I will use _____ [software name] during <b>this academic term.</b>	[54]
BI3	Plan to use	I <b>plan</b> to use _____ [software name] during <b>this academic term.</b>	[63], [54]
BI4	Plan to use - frequently	I plan to use _____ [software name] frequently. <i>Graduating students, please respond as if you were planning to be a student beyond this term.</i>	[63], [56]
<b>Use behavior factor (UB)</b>			
UB1	Frequency of use	On average, how often do you use _____ [software name]? [1. Rarely; 2. Several times per term; 3. Several times per month; 4. Weekly; 5. Daily].	[63], [56]
UB2	Usage of the platform to access university resources and services	I use _____ [software name] to access university resources (e.g. university software - D2L, Banweb, etc.) and services (e.g. academic advising).	[63]
UB3	Usage of the platform to conduct business	I use _____ [software name] to conduct student business (e.g. viewing account balance, accessing financial aid information, etc.).	[63]
UB4	Usage of the platform as a one-stop shop	I use _____ [software name] as a one-stop shop for navigating the university (e.g. accessing services, resources and university software, and conducting student business, all in one place).	[63]

The measurement scale for the above target variables is a 5-point Likert scale-1. Strongly disagree; 2. Disagree; 3. Neutral; 4. Agree; 5. Strongly agree - with the exception of the Frequency of use indicator, which uses a 5-point Likert scale, modeled after what was used in Venkatesh 2012 [56], with these text cues: 1. Rarely; 2. Several times per term; 3. Several times per month; 4. Weekly; 5. Daily. Students were asked, if they access \_\_\_\_\_ [software name] on multiple devices, to please respond to the relevant questions with respect to their overall experience across all of their devices.

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