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Understanding student intentions to take online courses: A theory-driven examination of adoption factors and prior experience

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Abstract
Online education options have expanded rapidly, yet empirical knowledge of students' adoption choices remains relatively limited. Within higher education, it is important for both instructors and administrators to understand what students value in online courses in order to provide a quality learning experience and manage enrollment demands. The current work applies and expands on the Unified Theory of Acceptance and Use of Technology (UTAUT) to examine factors involved in course modality choices. Study 1 (N = 257) uses a single discipline to validate measures of online course perceptions and provide initial predictive evidence. Study 2 (N = 1257) examines adoption intentions among students in a wide range of disciplines. Performance expectancies, hedonic motivation, and flexibility emerged as the most substantial factors in student decisions about course modality. The results also reveal shifts in online course perceptions over time, including larger shifts for students with no prior online course experience. These findings expand current understanding of why students choose to take (or avoid) online courses, particularly concerning the role of flexibility in enrollment decisions.

Keywords Online Learning · Course modality · Higher Education · Student attitudes · Technology acceptance

Online education has rapidly increased in availability and popularity. Global enrollments in distance learning have expanded dramatically, becoming an increasingly larger share of higher education participation in many countries, particularly following the COVID-19 pandemic (Ali, 2020; Qayyum & Zawacki-Richter, 2019). Despite the proliferation of distance learning options available to students, a majority of undergraduates in the United States exclusively took face-to-face courses in Fall 2019 (63.7%; National Center for Education Statistics, 2020). As online

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education continues to grow, there is a pressing need to understand when and why students choose to take—or avoid—online courses (Fidalgo et al., 2020; Van Wart et al., 2020; Xu & Xu, 2020). To meet this need, the current work examines how students' perceptions of online learning relate to their intentions to take online courses.

Students' decisions about their education are based on a complex array of personal and institutional factors. Choosing a course modality is no different: Students' preferences for online versus in-person courses are driven by their academic motivations, technical skills, independence, financial resources, schedule availability, extracurricular commitments, and many other considerations (Bailey et al., 2015; Jaggars, 2014; Jayaratne & Moore, 2017; Luo et al., 2011; Mac Callum et al., 2013; McPartlan et al., 2021; Ni et al., 2021; Platt et al., 2014). In this work, we focus primarily on subjective perceptions of online courses. How do students' views of the opportunities, challenges, and outcomes in online classes affect their willingness to enroll? To investigate this question using a comprehensive set of factors, we adapt and expand on a well-validated theoretical model of technology adoption.

The Unified Theory of Acceptance and Use of Technology (UTAUT) describes technology acceptance in organizational settings (Venkatesh et al., 2003). UTAUT has been used to understand consumer behavior in a variety of contexts including marketing, government, health care, and education (Dwivedi et al., 2020; Khechine et al., 2016). In its original conception, UTAUT proposed that the factors of performance expectancy, effort expectancy, and social influence determine intentions to adopt a piece of technology, which in turn predict use behavior (Venkatesh et al., 2003). The updated UTAUT2 model (Venkatesh et al., 2012) incorporates three additional factors: hedonic motivation, price value, and habit. The next section summarizes prior research on UTAUT in education, with a particular focus on student adoption of online courses and learning technology. Following this review, the rationale and goals for the current work are described in further detail.

1 Educational technology adoption

The UTAUT model has guided substantial research in higher education and has been applied to explain students' willingness to use educational technology and enroll in online courses. Most studies have focused on technology use that supplements traditional in-person courses. For example, researchers have used UTAUT to understand student attitudes toward using tablet computers (Moran et al., 2010; Neufeld & Delcore, 2018), learning management systems (e.g., Canvas or Moodle; Ain et al., 2016; Huang et al., 2013; Marchewka et al., 2007; Raza et al., 2021; Yakubu & Dasuki, 2019; Zacharis & Nikolopoulou, 2022), administrative campus services (Robinson, 2006; VanDerSchaaf et al., 2023), and e-learning tools in general (Tarhini et al., 2017). Fewer UTAUT studies have focused on the instructional modality of courses as a whole, though there is some emerging literature (e.g., Lakhal et al., 2021; Scarpin et al., 2018; Yang et al., 2019; Zhang et al., 2022).

UTAUT has also been extensively applied to mobile learning or "m-learning" (Abu-Al-Aish & Love, 2013; Almaiah et al., 2019; Chao, 2019; Iqbal & Qureshi, 2012; Lowenthal, 2010; Mosunmola et al., 2018; Wang et al., 2009). M-learning is a broad term that refers to any learning facilitated by mobile devices (Kumar Basak et al., 2018). M-learning can include online courses, but also less formal types of education such as on-demand tutorial videos, job training modules, or informative blog posts. Despite the popularity of this topic, the applicability of m-learning insights to higher education courses is unclear. Given the relatively small literature on UTAUT and course modality, we include m-learning research to supplement understanding of factors that may be involved in student course adoption.

1.1 Performance expectancy

Performance expectancy is one of the most robust predictors of adoption intentions and technology use (Khechine et al., 2016). Performance expectancy describes the extent to which an individual believes using a system will improve their job performance (Venkatesh et al., 2003). Among students, this expectancy refers to academic performance. Students who expect to perform well have higher persistence intentions in online courses (Lakhal et al., 2021; Scarpin et al., 2018). Performance expectancy also predicts intentions to use e-learning tools and services (Ain et al., 2016; Jakkaew & Hemrungrote, 2017; Raza et al., 2021; Robinson, 2006; Tarhini et al., 2017; Yakubu & Dasuki, 2019). This factor is reliably related to m-learning intentions (Abu-Al-Aish & Love, 2013; Almaiah et al., 2019; Chao, 2019; Lowenthal, 2010; Mosunmola et al., 2018). In sum, students are more interested in using educational technology when they expect that it will improve their performance.

1.2 Effort Expectancy

Effort expectancy refers to a technology's ease of use (Venkatesh et al., 2003). Users have more positive effort expectancy when interactions with the technology are simple and clear. Similar to performance expectancy, this factor reliably predicts intentions to use educational technology. Prior research notes that students with positive effort expectancy are more accepting of a cloud-based classroom in flipped instruction (Yang et al., 2019) and more likely to persist in online courses (Lakhal et al., 2021). Effort expectancy predicts intentions to use e-learning tools and services (Jakkaew & Hemrungrote, 2017; Raza et al., 2021; Robinson, 2006; Tarhini et al., 2017; VanDerSchaaf et al., 2023; Yakubu & Dasuki, 2019), tablets (Moran et al., 2010), and m-learning (Abu-Al-Aish & Love, 2013; Almaiah et al., 2019; Chao, 2019; Lowenthal, 2010; Mosunmola et al., 2018). While at least one study found no relationship (Huang et al., 2013), the connection between effort expectancy and students' technology intentions has been widely replicated.

1.3 Social influence

Social influence reflects an individual's belief that people important to them think they should use a technology (Venkatesh et al., 2003). There is mixed evidence for the role of this factor in educational technology adoption, but social influence is generally related to higher use intentions. Social influence predicts intentions to use e-learning platforms in hybrid or flipped class modalities (Yang et al., 2019; Zhang et al., 2022) and predicts persistence intentions in a fully online course (Scarpin et al., 2018). Most research has concluded that social influence is tied to higher use intentions, including when the influence stems from lecturers (Abu-Al-Aish & Love, 2013) and social media networks (Garcia, 2017).

A few studies have shown no relationship between social influence and use intentions, such as when students' use of a system is mandatory (Yakubu & Dasuki, 2019) or in locations where m-learning is not widespread (Almaiah et al., 2019; Iqbal & Qureshi, 2012). These findings may be explained, in part, by the moderating role of voluntariness in the relationship between social influence and intentions (Venkatesh et al., 2003). In the original UTAUT theory, social influence is only significant when technology use is mandatory. When users can choose freely, social influence informs users' opinions about the technology rather than directly shaping use intentions (Venkatesh & Davis, 2000; Venkatesh et al., 2003). Voluntariness was later dropped from UTAUT (Venkatesh et al., 2012) and most educational technology adoption studies do not measure this construct.

1.4 Facilitating conditions

Facilitating conditions refer to the availability of support and infrastructure that help users access the technology (Venkatesh et al., 2003). In a higher education setting, this can include instructor availability, training resources, information technology services, or any other forms of institutional support for students' technology use. Peer support and encouragement also contribute to this construct (Lai et al., 2012). Facilitating conditions typically predict intentions to use educational technology, yet this relationship is nuanced. Some studies find no direct relationship, consistent with the original UTAUT model, in which facilitating conditions predict use of a technology but not the intermediary variable of intentions (Venkatesh et al., 2003). Venkatesh et al. (2003) note that facilitating conditions may be unrelated to intentions when both performance and effort expectancies are present. The updated UTAUT2 model links facilitating conditions directly with both intentions and use and these relationships are moderated by several demographic variables (Venkatesh et al., 2012).

Students who perceive higher facilitating conditions are more likely to persist in an online course (Lakhal et al., 2021), more likely to use Google Classroom (Jakkaew & Hemrungrote, 2017), and have greater intentions to use an e-learning system in a hybrid course (Zhang et al., 2022). While some studies find no direct connection between facilitating conditions and intentions to use e-learning systems (e.g., Raza et al., 2021; Tarhini et al., 2017; Yang et al., 2019), this relationship was likely nullified by the inclusion of performance and effort expectancies. Research on m-learning generally finds a relationship between facilitating conditions and adoption intentions (Almaiah et al., 2019; Iqbal & Qureshi, 2012; Mosunmola et al., 2018).

1.5 Hedonic motivation

The revised UTAUT2 model added hedonic motivation as a predictor of intentions to use a technology. Hedonic motivation captures the enjoyment and fun associated with using a system, which predicts greater intentions to adopt the technology (Tamilmani et al., 2019; Venkatesh et al., 2012). Less is known about the role of hedonic motivation in students' adoption of educational technology, compared to other predictive factors. Thus far, there is evidence that students who enjoy using e-learning or m-learning have higher intentions to use such systems (Alalwan et al., 2019; Chao, 2019; Jakkaew & Hemrungrote, 2017; Merhi, 2015; Tarhini et al., 2017; Wang et al., 2009) and to persist in an online course (Scarpin et al., 2018). However, some studies find no connection between hedonic motivation and use intentions (Ain et al., 2016; Iqbal & Qureshi, 2012).

Additional research is needed to better understand the role of hedonic motivation in educational technology adoption. As Tamilmani et al. (2019) comment, hedonic motivation can act as both an antecedent and an outcome, in some cases predicting performance and effort expectancies (see also: van der Heijden, 2004). Consistent with this pattern, students' enjoyment of virtual learning tools predicts perceived usefulness, perceived ease of use, and satisfaction with the system (Estriegana et al., 2019; Findik-Coşkunçay et al., 2018). Thus, hedonic motivation may not only influence intentions to use a technology, but also shape users' other experiences with the system.

1.6 Flexibility

Students often choose online courses because they are more flexible and convenient than traditional in-person classes. Online courses can be attractive because they allow access from any location and typically have a less structured schedule. Surprisingly, limited research has examined the importance of flexibility in online course adoption and most existing studies are methodologically lacking (see review in O'Neill et al., 2021). This factor is not captured by the UTAUT or UTAUT2 constructs but likely plays a critical role in students' enrollment choices.

There is a well-demonstrated link between perceived flexibility and *satisfaction* with e-learning (Arbaugh & Duray, 2002; Chow & Shi, 2014; Sanford et al., 2017; Sun et al., 2008; Wei & Chou, 2020). However, the link between flexibility and adoption choices has received much less empirical attention. A handful of studies have found that flexibility is a primary factor in modality choice among undergraduates (Daymont et al., 2011; Harris & Martin, 2012) and graduate students (Kowalski et al., 2014; Shay & Rees, 2004). Some work also shows that online courses and tutoring make learning more accessible for students who are employed, physically disabled, or otherwise prevented from regularly accessing campus (Albert & Johnson, 2011; Rennar-Potacco et al., 2017). As O'Neill et al. (2021) note, research on flexibility is often limited to small-scale, discipline-specific samples and typically use a single item or single word to assess "flexibility" or "convenience" motives. The present work adds flexibility to the UTAUT model factors to further understand students' online course decisions.

2 Emergency transitions to online education

Online learning has become increasingly common in recent decades, but the Coronavirus pandemic rapidly accelerated adoption of online courses. Many institutions transitioned to remote instruction in 2020 to protect public health. In the United States, online enrollments in higher education roughly doubled between Fall 2019 and Fall 2020 (NC-SARA, 2021). This transition was fraught with challenges for both students and instructors. These challenges included technical problems, inequitable access, academic dishonesty, and mental health, among other practical and psychosocial concerns (Ali, 2020; Chakraborty et al., 2021; Dhawan, 2020; García-Morales et al., 2021; Neuwirth et al., 2021). Despite these difficulties, the pandemic resulted in greater access to online education and resources at many institutions. The lasting impacts of this period remain unknown, but global disruptions to higher education have undeniably changed the landscape for online learning.

Recent research has examined the role of technology adoption factors in a pandemic context. Several studies have replicated the UTAUT predictive model for intentions to use learning management systems during the pandemic (Abbad, 2021; Ahmed et al., 2021; Raza et al., 2021). Furthermore, fear of Coronavirus strengthens the links between adoption factors and adoption intentions for learning management systems (Ahmed et al., 2021; Raza et al., 2021). For m-learning, performance expectancy, facilitating conditions, and hedonic motivation continue to be important predictors of behavioral intentions (Sitar-Taut & Mican, 2021).

These initial investigations support the robustness of the UTAUT for explaining student technology adoption, but many questions remain. Similar to the existing UTAUT literature, studies have focused on adoption intentions for a specific tool or platform (e.g., Moodle). Do the same factors also explain adoption intentions for overall course modality? Researchers primarily use the original predictive factors and omit variables from the expanded UTAUT2 model despite its significant theoretical advancements (Tamilmani et al., 2021). Do the expanded factors increase explanatory power for adoption intentions? Finally, data that were collected early in the pandemic (e.g., Spring 2020) occurred during a turbulent period for students and may not reflect their later experiences with online courses. How well do the factors explain student intentions after longer exposure to online instruction? The current work builds on emerging findings from pandemic-era education to address these questions more fully.

3 Current research

The central purpose of this research is to understand how students' views of online classes affect their willingness to take online classes in the future. This work advances the current literature by examining adoption of course modality as a whole, rather than adoption of a single e-learning tool within a specific course. In addition, we investigate a large multi-disciplinary sample to improve generalizability from past studies, many of which sampled a single class or single discipline. Existing studies also tend to use ad hoc, unvalidated measures of the UTAUT variables. To improve measurement quality, we conducted an initial study within one academic discipline (Study 1). The results of Study 1 were used to refine and expand our measures for the multi-disciplinary survey in Study 2.

The current studies also examine how students' experiences in online classes were shaped by the pandemic. Students reported their pre-pandemic perceptions of online classes (measured retrospectively) separately from their current views. Both studies compare these prior and current views to understand how students' experiences may have shifted over time.

Consistent with prior literature on educational technology adoption, we expected to replicate basic relationships from the original UTAUT model. These relationships were predicted for both prior and current views of online courses:

H1: UTAUT factors will predict students' intentions to take online courses in the future
H1a: Performance expectancy will be positively associated with adoption intentions
H1b: Effort expectancy will be positively associated with adoption intentions
H1c: Social influence will be positively associated with adoption intentions
H1d: Facilitating conditions will be positively associated with adoption intentions

Furthermore, we compare students' retrospective views of online courses to their current views. We hypothesized that the mandatory nature of remote instruction during the pandemic would cause students to feel more social influence and less voluntariness to take online classes. Although the UTAUT2 model omits voluntariness, we retained this factor because it may capture important differences over time, given the forced shift to online courses due to COVID-19. Experience with remote instruction was also hypothesized to increase interest in taking online classes in the future. This prediction stems from emerging evidence that student demand for online classes has increased following the pandemic (Seaman & Johnson, 2021).

H2: Mandatory online instruction will affect students' perceptions of online courses
H2a: Social influence will be higher due to mandatory online instruction
H2b: Voluntariness will be lower due to mandatory online instruction
H2c: Adoption intentions will be higher following mandatory online instruction

Following the Study 1 results, we sought to increase explanatory power by including hedonic motivation and flexibility as predictors of online course adoption intentions. Students who enjoy online classes were expected to express greater intentions to take them in the future. Hedonic motivation was expected to explain more variance in adoption intentions than the original UTAUT factors (Venkatesh et al., 2003, 2012). Flexibility was also added to expand focus beyond the UTAUT and UTAUT2 models. Increased flexibility and convenience are major reasons why students choose distance learning (Daymont et al., 2011; Harris & Martin, 2012; Kowalski et al., 2014; Shay & Rees, 2004). We expected that flexibility is particularly important for online courses and would explain unique variance beyond the UTAUT/UTAUT2 models.

H3: Hedonic motivation will be positively associated with students' intentions to take online courses and improve overall prediction
H4: Flexibility will be positively associated with students' intentions to take online courses and improve overall prediction

Beyond the predictions articulated above, we were interested in exploring additional nuances in online course adoption intentions. Specifically, we examined whether students' views of online courses differ between those with and without previous online course experience. Students who were forced to take online courses for the first time likely felt differently than those who had freely chosen to take them before the pandemic. We also explored how students' retrospective views of online courses compared to their current views. We hypothesized differences for social influence (H2a), voluntariness (H2b), and adoption intentions (H2c), but no predictions were made for the remaining factors.

4 Study 1: Method

Study 1 was conducted using an online questionnaire during Fall 2020 at a large public university in the Southwestern United States. During the COVID-19 pandemic, this university switched to all-remote instruction. At the time the survey was distributed, students had experienced a full Spring quarter of online courses and were 12 to 14 weeks into a fully online Fall semester. The study was conducted with Institutional Review Board approval and informed consent from all participants.

The goal of this initial study was to assess the psychometric quality and predictive validity of novel and adapted UTAUT scale items. The UTAUT model has been widely applied to educational technology adoption, but there is no standardized set of measures for education. This single-discipline study was conducted to evaluate the primary scales' performance and refine the questionnaire before conducting the multi-disciplinary survey.

4.1 Participants

Students were recruited from a research participation pool in the psychology department. After quality checks, the final sample size was N = 257 students. Eleven participants were excluded from the initial sample of 268 students due to multiple missed attention checks or non-completion.

Participants were primarily in their senior year (47.5%) or junior year (43.2%) of college with a median age of 22 (mean = 25.0, range 18 to 58 years old). Consistent with the university's demographic makeup, the sample was majority female (89.1%) and majority Hispanic/Latina/Latino (72%). Participants also self-identified as White/Caucasian (13.6%), Black/African American (4.7%), multiracial (4.7%), Asian/Pacific Islander (3.5%), and Middle Eastern/Indian (1.6%).

Most students were psychology majors due to the use of a department participation pool (79.0%). About two-thirds of students (68.1%) reported taking at least one online or hybrid course before mandatory remote instruction, with an average of 3.9 prior online or hybrid courses (SD = 3.0, median = 3.0). At the time the survey was conducted, students reported an average course load of 4.7 classes (median = 5.0, SD = 0.9, range = 1 to 7).

4.2 Measures

The questionnaire included four sections: Academic history, prior views of online courses, current views of online courses, and demographic questions. The primary measures of interest were prior and current views of online courses. Both sections assessed five UTAUT predictors (performance expectancy, effort expectancy, social influence, facilitating conditions, and voluntariness) and the main outcome of interest: online course adoption intentions.

Prior views were measured retrospectively, within-subjects. Participants were instructed to "Think about your perceptions of online classes before this school year, prior to the mandatory move to online instruction at [university]. Reflect on what you thought about online classes before [university] switched to primarily virtual classes." For current views, all participants were instructed to "Think about your perceptions of online classes now. Reflect on your current view of online courses, now that [university] has switched to virtual instruction."

4.2.1 UTAUT factors

Prior and current views of online courses were measured using 5-point scales from (1) Strongly disagree to (5) Strongly agree, with a neutral midpoint (3). The scales included 8 items for performance expectancy, 8 items for effort expectancy, 7 items for facilitating conditions, 7 items for social influence, 7 items for voluntarin ess, and 5 items for adoption intentions. The items were adapted from prior studies on student and faculty views of online courses (Almaiah et al., 2019; Carswell & Venkatesh, 2002; Chao, 2019; Chiu & Wang, 2008; Dumont et al., 2021; Tiwari, 2020). All scale items are available in the Appendix. The presentation order of UTAUT scales was randomized, with the exception of adoption intentions being presented last in each section.

5 Study 1 Results

5.1 Reliability

All reverse-scaled items were reverse-coded before computing reliability or average scale scores. Internal consistency was strong for all six UTAUT variables: for prior views, average Cronbach's $\alpha = 0.86$ (range: 0.801 to 0.908). For current views, average Cronbach's $\alpha = 0.85$ (range: 0.797 to 0.920). Reliabilities were comparable between students with and without previous experience taking online courses. After revisions to the scales following the factor analysis and item selection process, all Cronbach's α's remained above 0.72 (see Supplemental Table 1 in the Appendix).

5.2 Item selection

Principal axis factoring (PAF) was conducted using SPSS 28 to examine the factor structure of the UTAUT items. Oblimin rotation was selected because UTAUT constructs are significantly intercorrelated (Venkatesh et al., 2012). A separate PAF was conducted for prior views and for current views, each extracting five factors from the 37 items to represent each of the five UTAUT predictors. Kaiser–Meyer–Olkin measures indicated high sampling adequacy for both prior and current views, KMOs > 0.88. Bartlett's Test of Sphericity was significant for both PAFs, ps < 0.001, indicating suitability for factor analysis. Item loadings above 0.4 were considered acceptable. Pattern matrices are available in the Appendix (Tables S2 and S3).

The pattern and structure matrices were examined to identify the best-performing items for each factor. As a result, two items were dropped from effort expectancy and one item was dropped from each other scale. All items for the outcome of interest were retained (future adoption intentions; 5 items). Factor scores were calculated by averaging the remaining items for each scale. Table 1 reports means, standard deviations, and inter-factor correlations.

5.3 Predictive models

Multiple regression analysis was used to test the predictive validity of the UTAUT factors. Performance expectancy, effort expectancy, facilitating conditions, social influence, voluntariness, and the social influence*voluntariness interaction term were entered into the model as predictors of online course adoption intentions. Separate models were conducted for prior and current views. Table 2 reports results from these analyses.

In the prior views model, UTAUT factors explained 47.2% of the variance in adoption intentions to take online courses, $R^2 = 0.472$. However, performance expectancy and social influence were the only significant predictors, with performance expectancy uniquely explaining 20.6% of the variance in intentions ($sr^2 = 0.206$) and social influence uniquely explaining 1.4% of the variance ($sr^2 = 0.014$).

Table 1 Scale descriptives and inter-scale correlations (Study 1)

	Scale Descriptives			Inter-Scale Pearson Correlations					
	Items	Prior Mean (SD)	Current Mean (SD)	1. PE	2. EE	3. FC	4. SI	5. V	6. FI
1. Performance Expectancy	7	3.02 (0.97)	2.98 (1.03)	**0.613**	0.594	0.522	0.094	0.068	0.656
2. Effort Expectancy	6	2.45 (0.86)	2.06 (0.78)	0.597	**0.334**	0.306	-0.059	0.192	0.354
3. Facilitating Conditions	6	3.71 (0.87)	3.99 (0.88)	0.505	0.367	**0.501**	0.065	0.141	0.358
4. Social Influence	6	2.47 (0.96)	3.87 (0.83)	0.108	0.058	0.135	**0.123**	-0.533	0.248
5. Voluntariness	6	3.85 (0.94)	2.10 (0.86)	0.339	0.305	0.153	-0.387	**-0.154**	-0.118
6. Adoption Intentions	5	2.78 (1.23)	3.02 (1.27)	0.719	0.481	0.358	0.151	0.290	**0.725**

N = 257. All items measured on 1-to-5 scales. For correlation coefficients, upper triangle represents inter-scale relationships for prior perceptions. Lower triangle represents inter-scale relationships for current perceptions. Coefficients along the diagonal (**bolded**) are intra-scale prior-current correlations. Coefficients $r = 0.13$ and larger are significant at $p < 0.05$; $r = 0.17$ and larger are significant at $p < 0.01$; $r = 0.21$ and larger are significant at $p < 0.001$

Table 2 UTAUT factors predicting online course adoption intentions (Study 1)

	B (SE)	β	*t*	*p*	sr^2
Prior Views ($R^2 = 0.472$)					
Performance Expectancy	0.802 (0.08)	0.636	9.87	< 0.001***	0.206
Effort Expectancy	-0.014 (0.08)	-0.010	-0.17	0.866	0.000
Facilitating Conditions	0.048 (0.08)	0.034	0.62	0.536	0.001
Social Influence	0.181 (0.07)	0.141	2.54	0.012*	0.014
Voluntariness	-0.131 (0.08)	-0.101	-1.72	0.087	0.006
Social Influence * Voluntariness	0.035 (0.06)	0.030	0.60	0.549	0.001
Current Views ($R^2 = 0.535$)					
Performance Expectancy	0.790 (0.07)	0.644	10.69	< 0.001***	0.213
Effort Expectancy	0.109 (0.09)	0.068	1.24	0.216	0.003
Facilitating Conditions	-0.032 (0.07)	-0.022	-0.44	0.659	0.000
Social Influence	0.182 (0.08)	0.119	2.40	0.017*	0.011
Voluntariness	0.154 (0.08)	0.104	1.98	0.049*	0.007
Social Influence * Voluntariness	0.023 (0.07)	0.015	0.33	0.740	0.000

N = 257. DV = Future intentions to take online courses. All predictors are mean-centered

In the current views model, UTAUT factors explained 53.5% of the variance in intentions to take online courses, $R^2 = 0.535$. Performance expectancy, social influence, and voluntariness were significant predictors. Performance expectancy uniquely explained 21.3% of the variance in intentions ($sr^2 = 0.213$), social influence uniquely explained 1.1% of the variance ($sr^2 = 0.011$), and voluntariness uniquely explained 0.7% of the variance ($sr^2 = 0.007$).

Given the dominance of performance expectancy in the regression models, the analyses were re-run without performance expectancy to explore the relationships between the remaining UTAUT factors and adoption intentions. In the prior views model, 26.6% of the variance in adoption intentions was explained ($R^2 = 0.266$) and all predictors were significant at $p < 0.004$ except for voluntariness and the social influence*voluntariness interaction. In the current views model, 32.2% of the variance in intentions was explained ($R^2 = 0.322$) and all predictors were significant at $p < 0.004$ except for the interaction term.

6 Study 1 Discussion

Results supported the psychometric quality and predictive validity of the UTAUT factors. The initial set of 37 items was reduced to 31 well-performing items. Internal consistency reliabilities were high for both the initial and revised scales. The results also provide evidence that participants distinguished meaningfully between their current and prior views of online courses. Specifically, students reported substantially more social influence to take online courses at the time of the study, relative to pre-pandemic (paired-samples $t(256) = 18.84$, $p < 0.001$, $d = 1.19$). Students also reported that the decision to take online classes was substantially less voluntary at the time of the study, relative to pre-pandemic (paired-samples $t(256) = -20.47$, $p < 0.001$, $d = 1.37$). These patterns are highly consistent with the forced switch to all-online courses at their university and support the validity of retrospectively measuring prior views.

Not surprisingly, students who think they will do well in online courses are more interested in taking them. Performance expectancy was the dominant predictor of adoption intentions for both prior and current views. This result is consistent with the literature on academic achievement as well as typical findings from the UTAUT model. Achievement motivation and performance goals play powerful roles in academic behaviors and outcomes (Dweck & Leggett, 1988; Hartnett, 2016; Wigfield & Cambria, 2010). Performance expectancy tends to be the strongest predictor of behavioral intentions in the UTAUT model (Khechine et al., 2016).

Considering these results, two major adjustments were made for the multi-disciplinary study. First, measures of hedonic motivation and flexibility were added to the questionnaire. These factors were added to account for more variance in students' intentions to take online courses. Students should be more interested in taking online courses when they believe the experience will be enjoyable (H3) and when they place higher value on the flexibility provided by remote learning (H4). Hedonic motivation is a feature of the updated UTAUT2 model (Venkatesh et al., 2012). Flexibility is not captured by this model, but the convenience of online classes is an important motive for students (O'Neill et al., 2021). Research on flexibility and modality choices is currently limited, with many studies using only a single-item measure to capture this construct, often among a small sample of students from a single discipline. In Study 2, we create a more comprehensive scale to measure flexibility. This measure operationalizes flexibility as choice in how students spend their time and manage their responsibilities.

The second adjustment was dividing performance expectancy into two sub-factors: *learning-based* performance and *grade-based* performance. Students may believe that they can earn a high grade in a course despite learning little content (and vice versa). We hoped to gain a more nuanced understanding of performance expectancy by distinguishing between expectations of learning performance and grade performance.

7 Study 2: Method

The primary study was conducted as an online questionnaire at a large public university in the Southwestern United States. The survey was distributed during the first 9 weeks of Spring 2021, when the university was in its third term of all-remote instruction due to the COVID-19 pandemic. The study was conducted with Institutional Review Board approval and informed consent from all participants. The dataset is publicly available at: https://osf.io/jbfp9/

7.1 Participants

To obtain a wide sample across the university, participants were recruited in multiple ways. Most students were invited to complete the survey by their instructors, who distributed the survey at the request of the study authors. These students participated either on a volunteer basis or for course extra credit. Some participants were recruited from a research participation pool in the psychology department. Study 1 participants were not eligible to complete Study 2.

After quality checks, the final sample size was N = 1257. A total of 446 responses were excluded from the initial dataset of N = 1703 due to non-completion (35.7% of excluded responses), multiple missed attention checks (55.6%), invalid response patterns (1.1%), or duplicate submissions from the same students (7.6%).

Participants were primarily undergraduates in their junior year (35.6%) or senior year (33.4%) of college, with some graduate student participants (16.1%). The median age was 23 (mean = 26.3, range 18 to 67 years old). Consistent with the university's demographic makeup, the sample was majority female (60.2%) and majority Hispanic/Latina/Latino (57.3%). Participants also self-identified as White/Caucasian (18.3%), Asian/Pacific Islander (8.7%), multiracial (7.1%), Black/African American (3.8%), and Middle Eastern/Indian (2.3%).

Students represented a variety of academic disciplines. They were primarily recruited from the college of business (35.0%), college of natural sciences (30.7%), college of social and behavioral sciences (18.1%), and college of education (9.7%). Most participants were first-generation students (65.6%). A majority of students (59.5%) reported taking at least one online or hybrid class before mandatory remote instruction, with an average of 5.8 prior online or hybrid courses (SD = 5.5, median = 4.0). At the time the survey was conducted, students reported an average course load of 4.6 classes (median = 5.0, range = 1 to 9).

7.2 Measures

This study used the same questionnaire format, instructions, and order as Study 1. Specifically, academic history was measured first, followed by prior perceptions, current perceptions, and demographic questions. Both the prior and current perceptions sections assessed nine variables: performance expectancy (learning), performance expectancy (grades), effort expectancy, social influence, facilitating conditions, voluntariness, hedonic motivation, flexibility, and future adoption intentions. All UTAUT items and flexibility were measured using 5-point scales from (1) Strongly disagree to (5) Strongly agree, with a neutral midpoint (3).

The refined scales for effort expectancy, social influence, facilitating conditions, voluntariness, and future adoption intentions were carried over from Study 1. The factor of performance expectancy was divided into the sub-scales of learning-based performance and grade-based performance. Two new scales were added: hedonic motivation and flexibility.

Seven performance expectancy items were retained from Study 1 and two new items were added. These items were categorized to create sub-scales for learning-based performance expectancy and grade-based performance expectancy. Four of the existing items were primarily learning-based (e.g., “Online classes help me achieve learning outcomes”), and a fifth new item was added: “I understand the material well in online classes.” These five items comprise the learning sub-scale of performance expectancy. Three of the initial items were primarily grade-based (e.g., “Attending online classes improves my academic performance”). A fourth new item was added: “I worry that online classes lower my GPA” [reverse-coded].

Six items were added to measure students’ perceptions of hedonic motivation in online courses. Representative items include “Taking online classes can be fun” and “It is hard to stay engaged in online classes” [reverse-coded].

Five items were added to measure the degree to which students value flexibility in online courses. Representative items include “Online classes help be balance other commitments (work, family)” and “The flexibility of online classes is important to me.” A sixth item was included but later dropped due to poor consistency with other items: “There is too much flexibility in online classes” [reverse-coded]. All results reported are with the five-item version of the scale.

8 Study 2: Results

8.1 Reliability and descriptive statistics

All reverse-scaled items were reverse-coded before computing reliability or average scale scores. Internal consistency was strong for all nine variables: for prior views, average Cronbach’s $\alpha = 0.85$ (range: 0.733 to 0.925). For current views, average Cronbach’s $\alpha = 0.86$ (range: 0.755 to 0.940). Reliabilities were comparable between students with and without previous experience taking online courses. Reliability coefficients, means, and standard deviations are reported in Table 3. Intra-scale

Table 3 Descriptives statistics for UTAUT scales

		Prior Views		Current Views	
	Items	Cronbach’s α	Mean (SD)	Cronbach’s α	Mean (SD)
Performance—Learning	5	0.903	3.26 (1.05)	0.910	3.31 (1.11)
Performance—Grades	4	0.801	3.47 (0.96)	0.829	3.52 (1.01)
Effort Expectancy	6	0.733	2.63 (0.80)	0.755	2.46 (0.83)
Facilitating Conditions	6	0.883	3.84 (0.88)	0.903	4.11 (0.85)
Social Influence	6	0.864	2.77 (0.99)	0.818	3.66 (0.87)
Voluntariness	6	0.807	3.62 (0.96)	0.817	2.53 (0.97)
Hedonic Motivation	6	0.894	2.77 (1.02)	0.907	2.82 (1.07)
Flexibility	5	0.819	3.72 (0.85)	0.832	3.75 (0.90)
Adoption Intentions	5	0.925	3.17 (1.28)	0.940	3.37 (1.30)

correlations are reported in the Appendix (Table S4). The bivariate relationships indicated initial support for the expected relationships (H1, H3, and H4).

8.2 Differences in prior and current views of online courses

A two-way repeated-measures multivariate analysis of variance (RM MANOVA) was conducted to examine differences between prior and current views of online courses. Time was entered as a within-subjects factor with two levels (prior and current). Previous online course experience was entered as a between-subjects factor with two levels (continuing user and new user). All nine variables were included in the model. The sample size for this analysis was $n = 1214$ due to a small number of participants missing responses to one or more scales. Results for the two-way RM MANOVA are shown in Table 4.

There was a large within-subjects effect of time, $F(9, 1204) = 131.75$, $p < 0.001$, partial $\eta^2 = 0.496$. All nine variables differed significantly across time (prior vs. current). Students reported increased perceptions of learning-based performance expectancy, grade-based performance expectancy, facilitating conditions, social influence, flexibility, hedonic motivation, and adoption intentions in their current views, relative to their prior views (ps < 0.03, η^2_ps $= 0.004$ to 0.398). In contrast, students reported decreased perceptions of voluntariness ($p < 0.001$, $\eta^2_p = 0.403$) and effort expectancy ($p < 0.001$, $\eta^2_p = 0.049$). These results indicate support for H2a (increase in social influence), H2b (decrease in voluntariness), and H2c (increase in adoption intentions).

There was also a significant between-subjects effect of previous online course experience, $F(9, 1204) = 15.04$, $p < 0.001$, $\eta^2_p = 0.101$. All nine variables differed significantly between continuing users and new users. Continuing users had higher perceptions of learning-based performance expectancy, grade-based performance expectancy, facilitating conditions, social influence, voluntariness, flexibility, hedonic motivation, and adoption intentions, relative to new users (ps < 0.02, η^2_ps $= 0.005$ to 0.070). In contrast, new users had slightly lower effort expectancy ($p = 0.024$, $\eta^2_p = 0.004$).

The interaction between time and previous online course experience was significant, $F(9, 1204) = 9.07$, $p < 0.001$, $\eta^2_p = 0.063$. The interaction was significant for learning-based performance expectancy, grade-based performance expectancy, facilitating conditions, social influence, flexibility, and adoption intentions (ps < 0.003, η^2_ps $= 0.007$ to 0.024). The pattern of these interactions was a steeper increase for new users than for continuing users, such that new users showed larger differences in their prior and current views. Time and previous experience did not interact for effort expectancy, voluntariness, or hedonic motivation.

8.3 Predicting online course adoption intentions

Hierarchical multiple regression analysis was used to test the primary hypotheses: Which factors predict students' intentions to take online courses? In Step 1,

Table 4 Differences in UTAUT variables by time and previous online course experience

Independent Variable	UTAUT Variable	F	p	η^2_p
Time (Prior Views vs. Current Views; within-subjects)	Performance Expectancy—Learning	9.56	0.002**	0.008
	Performance Expectancy—Grades	9.21	0.002**	0.008
	Effort Expectancy	61.97	< 0.001***	0.049
	Facilitating Conditions	199.95	< 0.001***	0.142
	Social Influence	802.30	< 0.001***	0.398
	Voluntariness	817.72	< 0.001***	0.403
	Hedonic Motivation	5.88	0.015*	0.005
	Flexibility	5.18	0.023*	0.004
	Adoption Intentions	66.93	< 0.001***	0.052
Previous online course experience (New user vs. Continuing user; between-subjects)	Performance Expectancy—Learning	60.37	< 0.001***	0.047
	Performance Expectancy—Grades	53.36	< 0.001***	0.042
	Effort Expectancy	5.09	0.024*	0.004
	Facilitating Conditions	35.58	< 0.001***	0.029
	Social Influence	6.73	0.010*	0.006
	Voluntariness	6.13	0.013*	0.005
	Hedonic Motivation	33.58	< 0.001***	0.027
	Flexibility	46.45	< 0.001***	0.037
	Adoption Intentions	90.96	< 0.001***	0.070
Time * Experience Interaction	Performance Expectancy—Learning	30.42	< 0.001***	0.024
	Performance Expectancy—Grades	28.28	< 0.001***	0.023
	Effort Expectancy	0.36	0.546	0.000
	Facilitating Conditions	23.31	< 0.001***	0.019
	Social Influence	15.94	< 0.001***	0.013
	Voluntariness	0.04	0.838	0.000
	Hedonic Motivation	2.07	0.150	0.002
	Flexibility	8.94	0.003**	0.007
	Adoption Intentions	19.51	< 0.001***	0.016

*$p < 0.05$, **$p < 0.01$, ***$p < 0.001$

learning-based performance, grade-based performance, effort expectancy, facilitating conditions, social influence, and voluntariness were entered as predictors of intentions to take online courses. In Step 2, hedonic motivation and flexibility were added as predictors. Separate models were conducted for prior and current views. The social influence * voluntariness interaction was initially included in the models, but this interaction did not significantly increase the explained variance and was dropped for parsimony. Table 5 reports results from these analyses.

8.3.1 Predicting adoption intentions from prior views

In the prior views model, the initial set of UTAUT factors explained 60.5% of the variance in future intentions to take online courses in Step 1, $R^2 = 0.605$. Adding the expanded factors of hedonic motivation and flexibility in Step 2 increased the explained variance to 71.1%, $\Delta R^2 = 0.106$.

Facilitating conditions and voluntariness did not significantly predict intentions, but all other predictors were significant (ps < 0.001). Contrary to our expectations, effort expectancy had a weak negative relationship with future intentions in Step 2. This association contrasts with the moderate positive correlation between effort expectancy and future intentions, $r(1236) = 0.373$, $p < 0.001$. Hedonic motivation and flexibility were the strongest predictors of adoption intentions, each uniquely explaining over 3.6% of the variance ($sr^2s > 0.19$). Thus, H1a, H1c, H3, and H4 were supported for prior views, whereas support was not found for H1b (effort expectancy) or H1d (facilitating conditions).

Table 5 UTAUT Factors predicting online course adoption intentions

	Prior Views			**Current Views**		
	β	p	ΔR^2	β	p	ΔR^2
Step 1			0.605***			0.605***
Performance—Learning	0.546	< 0.001		0.636	< 0.001	
Performance—Grades	0.219	< 0.001		0.118	< 0.001	
Effort Expectancy	-0.030	0.171		0.015	0.491	
Facilitating Conditions	0.024	0.266		-0.035	0.102	
Social Influence	0.187	< 0.001		0.051	0.010	
Voluntariness	0.032	0.122		0.126	< 0.001	
Step 2			0.106***			0.134***
Performance—Learning	0.153	< 0.001		0.185	< 0.001	
Performance—Grades	0.142	< 0.001		0.028	0.221	
Effort Expectancy	-0.066	< 0.001		-0.057	0.002	
Facilitating Conditions	0.004	0.808		-0.040	0.020	
Social Influence	0.121	< 0.001		0.035	0.028	
Voluntariness	0.014	0.433		0.039	0.028	
Hedonic Motivation	0.350	< 0.001		0.458	< 0.001	
Flexibility	0.295	< 0.001		0.293	< 0.001	

N = 1234. DV = Future intentions to take online courses. All predictors are mean-centered

8.3.2 Predicting adoption intentions from current views

In the current views model, the initial set of UTAUT factors explained 60.5% of the variance in future intentions to take online courses in Step 1, $R^2=0.605$. Adding the expanded factors of hedonic motivation and flexibility in Step 2 increased the explained variance to 73.9% $\Delta R^2=0.134$.

Grade-based performance did not significantly predict intentions, but all other predictors were significant (ps <0.03). Contrary to hypotheses, effort expectancy and facilitating conditions had weak negative relationships with future intentions in Step 2. These associations contrast with their positive bivariate correlations (for effort expectancy and intentions: $r(1234)=0.451$, $p<0.001$; for facilitating conditions: $r(1234)=0.367$, $p<0.001$). Hedonic motivation and flexibility were the strongest predictors of adoption intentions. Hedonic motivation uniquely explained 5.0% of the variance ($sr^2=0.050$), whereas flexibility uniquely explained 3.2% of the variance in intentions ($sr^2=0.032$). Thus, support was found for H1c, H3, and H4 for current views, with mixed support for H1a (performance expectancy). H1b (effort expectancy) and H1d (facilitating conditions) were not supported in the regression models.

9 Discussion

As online education rapidly expands, it is critical to understand why students embrace or avoid taking online courses. Our findings build on a well-validated theory of technology adoption to investigate the factors involved in students' online course adoption intentions. Study 1 examined one academic discipline to test and refine adapted scales for five UTAUT factors. Study 2 expanded the investigation to eight predictive factors and examined how student perceptions of online courses predict adoption intentions, differ across time, and differ by user experience.

The original UTAUT factors generally performed well in predicting students' adoption intentions (H1). Taken together, these factors explained over 60% of the variance in students' intentions to take online courses. Students who expected better learning performance and grade performance expressed more interest in taking online courses. Students who felt more social influence to take online courses also expressed higher adoption intentions. However, effort expectancy and facilitating conditions were positively associated with adoption intentions only at the correlational level, but not in the regression models. As found in prior research, the effect of facilitating conditions can be nullified by the inclusion of other UTAUT predictors (Raza et al., 2021; Tarhini et al., 2017; Venkatesh et al., 2003; Yang et al., 2019). The lack of an effect for effort expectancy is more surprising (yet not unprecedented; see Zacharis & Nikolopoulou, 2022) and may warrant further investigation.

Enjoyment and flexibility in online courses are especially important to students. These two factors explained 11 to 13% more variance in adoption intentions beyond the original UTAUT factors. Hedonic motivation was the strongest predictor of students' intentions to take online classes (H3 supported). Flexibility was the second strongest predictor (H4 supported), reinforcing earlier findings from more limited samples (Daymont et al., 2011; Harris & Martin, 2012). Notably, this factor is not captured by the UTAUT or UTAUT2 models. Flexibility has been conspicuously absent from prior research on course modality choices, particularly considering how highly students value flexibility. We aimed to improve on the limitations in the current flexibility literature highlighted by O'Neill et al. (2021). Specifically, we developed a multi-item scale for flexibility that captures how well online classes allow students to manage their time and balance competing responsibilities. This approach operationalizes flexibility in a more explicit way than prior research, but as a construct it remains idiosyncratic. Students may seek flexibility in their courses for a variety of reasons, such as work hours, commute distance, and childcare needs. Given the strong relationship between flexibility and modality preferences, this factor should not be overlooked when trying to understand students' enrollment choices.

Students' perceptions of online courses shifted after forced adoption, largely in positive ways. As expected, students felt more social influence and less voluntariness to take online classes when it was mandatory (H2 supported). However, students also reported increased expectations about performance, more supportive conditions, and increased intentions to adopt online classes in the future. These increases were larger for students who had never taken an online course before the Coronavirus pandemic. Overall these patterns indicate that, on average, mandatory online enrollment improved students' opinions of online courses. Further research is needed to determine whether these changes are temporary or lasting, given that the post-pandemic landscape of online education is still unknown. Many institutions adopted unique policies to accommodate students during the pandemic period (Felson & Adamczyk, 2021; O'Dea & Stern, 2022). As universities resume normal operations, students' online experiences may shift yet again—for example, having less flexibility and facilitating conditions in their courses. The evolving future of higher education underscores the importance of further research into student adoption intentions.

Students' views of online classes are one of many factors that guide their academic decisions. Modality choices are complex and deeply personal—student preferences are shaped by factors such as finances, scheduling, comfort with technology, and many others (Bailey et al., 2015; Jaggars, 2014; Jayaratne & Moore, 2017; Luo et al., 2011; Mac Callum et al., 2013; McPartlan et al., 2021; Ni et al., 2021; Platt et al., 2014). Demographic factors such as gender and age also predict different attitudes toward online learning (Jaggars, 2014; McPartlan et al., 2021; Platt et al., 2014). The analyses reported in the present work did not incorporate student demographic characteristics. These characteristics are examined in Sumbera et al. (2022), which explores whether online course views and adoption intentions differ based on underrepresented minority (URM) status in the current data. URM and non-URM students are equally interested in taking online courses in the future. However, they differ in grade-based performance expectancy and effort expectancy: URM students believe they have to expend more effort in online classes, yet expect to earn lower grades in return. This pattern is consistent with well-documented equity gaps in education (Bonefeld & Dickhäuser, 2018;

Whitcomb et al., 2021). Online courses have the potential to reduce inequities by increasing accessibility and offering flexibility, but they may also perpetuate disparities. Additional research is needed to assess the appeal and impact of distance learning for students from a variety of backgrounds.

Several limitations were present in the current work. First, students from only one university were studied. Their experiences in online courses may not fully generalize to students at other institutions, particularly those outside of the United States. The quality of online courses, institutional support, and higher education access varies widely across countries and between socioeconomic groups (Aristovnik et al., 2020; Lederer et al., 2021). Although we made efforts to sample widely within our student population, our findings are constrained by the single-institution focus. Second, "prior" views of online courses were measured retrospectively. Students were able to distinguish between their current and past perceptions in meaningful ways, but their recollections cannot be taken as a true pre-pandemic measure of online course opinions. Finally, the Coronavirus pandemic has had a pervasive and indelible impact on higher education and life in general. The mandatory online shift provided a unique opportunity to study students' experiences, especially among those who may not otherwise have chosen to take online courses. Nonetheless, the full impact of the Coronavirus context is still unknown and students' perspectives may differ from those in more "normal" times.

Despite these limitations, the present work advances our knowledge of online course experiences and adoption. The growing popularity of distance learning has created a pressing need to understand what students value in online courses (Fidalgo et al., 2020; Van Wart et al., 2020; Xu & Xu, 2020). To enhance this understanding, our studies investigated a wide set of factors that extend established technology adoption models. In particular, this work emphasizes that flexibility is an essential yet understudied consideration for students when making enrollment decisions. These findings may help educators and administrators gain insight into the complex array of factors that shape student choices. Students today have more options than ever before and higher education must be prepared to meet their evolving needs.

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Data availability The dataset from Study 2 is publicly available: https://osf.io/jbfp9/. The dataset from Study 1 is available from the corresponding author on request.

Declarations

Competing interests Not applicable.

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