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Student Online Learning Experience: An Analysis of Factors Influencing Satisfaction in Engineering

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Abstract*– Fully online programs have expanded access to higher education for working adult students, yet sustaining their engagement over time remains a critical institutional challenge. This study aimed to identify the factors that explain student satisfaction in 100% online undergraduate engineering programs at a Chilean university. Using an adapted UTAUT2-OLE instrument, data were collected from 230 working adult students and analyzed through blockwise hierarchical linear regression. Perceived Quality, Performance Expectancy, Attitude toward Online Learning, Behavioral Intention, and Online Learning Value jointly explained 89.5% of satisfaction variance, while Effort Expectancy, Facilitating Conditions, Social Influence, and Habit were non-significant. Notably, prior online experience emerged as a negative predictor, suggesting that experienced learners apply higher evaluative standards. No sociodemographic differences in satisfaction were observed. These findings underscore that instructional quality and perceived utility are the primary levers for enhancing satisfaction and retention in online engineering education, with implications for institutional design in Latin American contexts.

Keywords-- online learning, student satisfaction, UTAUT2, engineering education, perceived quality

I. Introduction

In a context of accelerated transformation in higher education, marked by digitalization and the pursuit of greater equity, fully online programs have gained unprecedented prominence. Their expansion has strengthened access to university education for demographic profiles that have historically been excluded, particularly adult students and working learners. In this segment, the 100% online modality represents a critical solution to time and space barriers, enabling the reconciliation of work, family, and academic responsibilities [1], [2]. However, as provision scales, the focus shifts from access alone to the quality of the educational experience and to institutions' ability to sustain learning trajectories over time. Thus, the current challenge is not only to open the university's doors but to ensure that those who cross the threshold find a navigable and meaningful path.

Given that students enrolled exclusively in online courses frequently make iterative decisions regarding their continuation across academic terms, their satisfaction can be regarded as a proximal post-experience evaluation that influences their intention to persist. It synthesizes perceived value, instructional quality, and support into a comprehensive assessment of whether ongoing participation is justified, thereby serving as a significant and pragmatic indicator for retention within online programs [3], [4.

In this scenario, student satisfaction emerges as a central and actionable outcome for evaluating e-learning environments, as it captures students' perceived alignment between expectations and reality and provides institutions with a key metric for monitoring and enhancing the online learning experience [5]. In fully virtual programs, where face-to-face interaction is nonexistent, satisfaction functions as a barometer of the student's integration with the digital learning ecosystem. Its strategic relevance also lies in its connection to persistence and retention: a satisfying experience acts as a protective factor that promotes engagement and reduces the risk of dropout, while deficiencies in instructional design or faculty support can diminish the perception of value and weaken continuity [6], [7].

Situated evidence from Latin America is still developing and remains essential for understanding online learning quality under contextual constraints such as connectivity and social gaps; recent institutional studies in the region highlight how service, technical support, and teaching-related factors shape students' satisfaction in online higher education [8]. This research aims to contribute to that gap through a situated analysis of the student experience in 100% online engineering programs at a Chilean university, with an emphasis on the factors that influence satisfaction and continuation.

This study makes three specific contributions to the literature on online engineering education. First, it adapts and validates the UTAUT2-OLE instrument by integrating Perceived Quality (Q) as a multidimensional construct alongside Online Learning Value (OLV), addressing a gap in models that traditionally separate technology acceptance from instructional quality. Second, it provides situated empirical evidence from a Latin American context, where research on fully online engineering programs remains scarce despite their rapid expansion. Third, by employing a theory-driven, blockwise, hierarchical approach, the study disentangles the relative contributions of distal beliefs, proximal evaluations, and experiential quality, offering an actionable framework for institutional decision-making rather than a purely descriptive account.

II. Related Works

A. Technology Acceptance Frameworks in Online Learning

In recent years, understanding the factors that explain continuity in online learning has become a central concern for educational research. In this effort, various studies have sought not only to identify critical elements of the student experience but also to model how these dimensions influence their decision to stay. To operationalize these mechanisms and explain how the online experience is linked to continuity, the literature has widely relied on technology acceptance frameworks such as the Technology Acceptance Model

(TAM) [9] and the Unified Theory of Acceptance and Use of Technology (UTAUT) [10]. TAM proposes that perceived usefulness and perceived ease of use influence attitude and, through it, the intention to use, providing a parsimonious logic for understanding evaluations and decisions in digital environments [9]. UTAUT integrates and extends this perspective by establishing that performance expectancy, effort expectancy, social influence, and facilitating conditions explain behavioral intention and usage, and by considering moderators related to user characteristics [10]. In its extension, UTAUT2 incorporates mechanisms more specific to sustained use, such as habit and the value component (trade-offs between cost and benefit), which is especially relevant when the interest is not only initial adoption but also long-term continuity [11].

B. Extensions for Sustained Use and Online Learning Value

Several recent studies have adapted or extended these models to more accurately capture the factors influencing the adoption and sustained use of online educational modalities. Meet et al. [12] expanded the UTAUT2 model to analyze MOOC adoption intention among Generation Z students in India, incorporating variables such as language proficiency and instructor influence. Although several factors from the classic model showed significant effects (such as hedonic motivation and performance expectancy), others, like social influence, did not, suggesting the need to tailor models to specific contexts. From a continuity-focused approach, Lu et al. [13] proposed an extension of the TAM to the context of asynchronous online learning, integrating variables such as motivations (intrinsic and extrinsic), perception of multiple sources, and cognitive engagement. Their study revealed that cognitive engagement was the only direct predictor of intention to continue use, while the other variables influenced it indirectly through perceived usefulness and ease of use. Additionally, Boerchi et al. [14] analyzed the acceptance of distance education as an extension of technological acceptance, incorporating academic skills and motivations. Their findings show that perceived usefulness, subjective norm, and ease of use impact future usage intentions, while psychoeducational variables such as intrinsic motivation or emotional control also explain part of the variance, sometimes negatively, indicating a complex interaction between technological and personal factors in virtual environments.

In online higher education, this family of models has proven to be robust for organizing socio-cognitive beliefs and support conditions; however, recent evidence suggests that when more proximal evaluations of the experience are included, some "distant" predictors may lose their incremental effect, with explanations focusing on variables closer to the student's overall judgment [15]. This observation supports a layered interpretation, where instrumental beliefs and enabling conditions are expressed through attitudes and global evaluations that, in turn, relate to the intention to continue.

Along these lines, the literature has highlighted the need to incorporate constructs that capture the specific value of studying online and that connect the choice of modality with the subsequent evaluation of the experience. For adult and working students, the value of the modality is often associated with benefits such as flexibility, compatibility with responsibilities, and efficiency in time use, but also with perceived trade-offs (for example, less face-to-face interaction or greater demands for self-regulation). Studies that expand UTAUT2 in university contexts have shown that explicit measures of the value of online learning contribute to explaining intention to use and effective use, along with instrumental beliefs and habit, reinforcing their role as a bridge between choice and continuity [16]. From a continuity perspective, research based on TAM also suggests that the intention to continue using online tools or environments is supported by proximal evaluations of the experience, particularly attitude and satisfaction, that synthesize perceived usefulness, ease of use, and perception of results [17]. Overall, these contributions support the incorporation of a layer of value and experience (for example, perceived usefulness, attitude, and satisfaction) to capture why the modality is viable and desirable, and how that judgment is linked to continuity.

C. Perceived Quality and Satisfaction as Proximal Predictors

Finally, various studies on online experience have shown that satisfaction consistently depends on perceived instructional quality, understood as attributes of course design and implementation that can be intervened upon. In 100% online environments, this assessment typically considers dimensions such as organization, clarity of objectives, coherence between activities and assessments, quality and timeliness of feedback, interaction, and the instructor's competence or presence. Recent empirical evidence indicates that these design and interaction components are direct determinants of satisfaction, making them priority levers for continuous improvement [18]. Similarly, the literature on disengagement suggests that satisfaction plays a protective role against disconnection, reinforcing its value as an actionable indicator in student retention management [19]. Therefore, integrating measures of instructional quality (Q) along with instrumental beliefs (PE, EE), the value of online learning (OLV), and proximal assessments (ATT, S) allows for a experience-centered explanation, consistent with UTAUT/TAM frameworks and useful for guiding institutional decisions on design, support, and quality assurance in 100% online programs, especially in Latin American contexts where situated evidence and replicable diagnostics are required.

Taken together, prior evidence suggests that continuity in online learning is better explained by a layered approach, in which socio-cognitive beliefs and enabling conditions operate through more proximal evaluations, such as attitudes, perceived instructional quality, and satisfaction. However, the joint operation of these layers in fully online engineering programs within Latin American contexts remains underexplored, particularly regarding the incremental contribution of actionable experiential factors beyond general beliefs about studying online. This study addresses that gap by examining student satisfaction in 100% online engineering programs at a Chilean university and testing, through theory-driven hierarchical modeling, the relative and incremental contributions of instrumental beliefs, perceived supports, and modality evaluations, with perceived instructional quality as the most proximal predictor.

D. Participants

The sample comprised 230 undergraduate students enrolled in fully online engineering programs at a Chilean university. No missing data were recorded for the sociodemographic and contextual variables. In terms of gender, 63.0% identified as male (n = 145) and 37.0% as female (n = 85). The mean age was 37.07 years (SD = 8.69), ranging from 21 to 61 years. Additionally, 21.7% were 20 – 29 years old (n = 50), 47.0% were 30 – 39 years old (n = 108), 18.7% were 40 – 49 years old (n = 43), and 12.6% were 50+ years old (n = 29). Regarding academic background and online learning experience, 50.0% reported having previously taken online courses (n = 115) and 50.0% reported no prior online experience (n = 115); 89.1% indicated holding a prior professional degree (n = 205), while 10.9% did not (n = 25). Most participants reported currently working (94.8%, n = 218), and 53.9% indicated having children or other dependents (n = 124). Finally, regarding the primary source of funding for their studies, 76.1% reported self-financing (n = 175), whereas 23.9% reported external funding (n = 55).

E. Instrument

An adaptation of the UTAUT2 model focused on online learning experience (UTAUT2 – OLE) was used, expanding the original framework to include post-experience evaluations relevant in fully virtual environments. This version incorporates Satisfaction (S) as a general post-use assessment, redefines price value from UTAUT2 as Online Learning Value (OLV) to reflect perceived benefits and trade-offs such as flexibility and costs, and introduces a multidimensional measure of Perceived Quality (Q), centered on course design and interaction in digital environments. As in previous studies with adult populations and working students, hedonic motivation from UTAUT2 was omitted because it was deemed less relevant to persistence-related outcomes and because it overlaps conceptually with Attitude Toward Online Learning (ATT).

TABLE I. INTERNAL RELIABILITY OF THE INSTRUMENT'S SCALES

Dimension	N° Items	ω	α
Performance Expectancy (PE)	4	0.824	0.856
Effort Expectancy (EE)	4	0.856	0.876
Attitude Toward online learning (ATT)	4	0.907	0.905
Social Influence (SI)	5	0.878	0.854
Facilitating Conditions (FC)	4	0.735	0.731
Behavioral Intention (BI)	4	0.887	0.888
Habit (HT)	3	0.847	0.84
Online Learning Value (OLV)	5	0.825	0.853
Satisfaction (S)	5	0.915	0.932
Quality (Q)	9	0.912	0.930

The questionnaire included 10 constructs with multiple items, evaluated on a 5-point Likert scale (1 = strongly disagree, 5 = strongly agree): Performance Expectancy (PE), Effort Expectancy (EE), Social Influence (SI), Facilitating Conditions (FC), Attitude (ATT), Intention to Continue Studying Online (BI), Habit (HT), Perceived Value of Online Learning (OLV), Satisfaction (S), and Perceived Quality (Q). The items for the UTAUT2 model and its extensions were adapted from previous implementations in higher education based on UTAUT2 and TAM models [11], [12], [16], [20], [21], while the measure of Q was developed based on empirical research on perceptions of online learning and quality standards in virtual course design [22-24]. The internal consistency of the constructs was evaluated using McDonald's omega coefficients and Cronbach's alpha, with values ranging from adequate to high in all cases.

F. Procedure

Following institutional ethics approval, data collection was conducted during the academic term through an online questionnaire disseminated via the institutional learning platform. Students were informed about the study and provided informed consent prior to participation. Participation was voluntary and anonymized, with all data securely stored in a de-identified manner.

G. Data analysis

Analyses were conducted with JASP. Responses were averaged to form composite scores. Descriptive statistics and correlations provided initial data for model estimation. We used blockwise hierarchical linear regression with predictors entered in a theory-based order. At each step, we reported ΔR^2, F-change, RMSE, AIC, BIC, and interpreted standardized coefficients (β) at $\alpha = .05$. Due to high intercorrelations, multicollinearity was checked via tolerance and VIF, and bootstrap estimates served as robustness checks.

III. RESULTS

The results are organized into three sections. First, descriptive and preliminary analyses are presented (group comparisons and correlations). Then, hierarchical regression models are reported to explain satisfaction. Finally, robustness checks and diagnostics (bootstrap and collinearity) are included to assess the stability of the findings.

A. Descriptive Statistics and Preliminary Analyses

Descriptive statistics were calculated for all dimensions of the instrument (N = 230; no missing values). Table 2 shows that the means were high (approximately 4.05 – 4.53) and the standard deviations moderate (0.5 – 0.86), indicating generally favorable evaluations across all dimensions. Regarding the assumptions, all variables showed negative skewness (skewness between −1.005 and −1.592), consistent with a higher concentration of responses at the high end, and mostly positive kurtosis (0.917 – 3.746). However, these indices remain within commonly accepted ranges under less strict criteria for assuming approximate normality in samples of this size and with Likert-type variables, so it was considered reasonable to proceed with parametric analyses, supplementing them with robust checks when appropriate (e.g., bootstrap).

TABLE II. DESCRIPTIVE DATA OF THE SCALES

Dimension	Mean	Std. Dev.	Skewness	Kurtosis
ATT	4.274	0.827	-1.489	2.533
BI	4.090	0.861	-1.246	2.109
EE	4.436	0.673	-1.553	3.385
FC	4.279	0.659	-1.005	1.199
HT	4.528	0.561	-1.379	1.897
OLV	4.188	0.749	-1.266	2.691
PE	4.323	0.711	-1.592	3.746
Q	4.045	0.831	-1.032	0.917
S	4.135	0.860	-1.393	2.336
SI	4.157	0.762	-1.042	1.458

As an initial measure to elucidate the factors influencing satisfaction within this cohort of students, statistical tests are performed to identify significant differences related to specific sociodemographic characteristics.

Differences in satisfaction (S) were evaluated using independent-samples t-tests by gender (male vs. female), source of funding (own vs. external), prior online study experience (yes vs. no), current work (yes vs. no), and prior professional degree (yes vs. no). In all cases, the comparisons did not show statistically significant differences ($p > .05$), indicating similar levels of satisfaction among the groups analyzed for each of these variables.

One-way ANOVA analyses were also conducted to evaluate differences in satisfaction (S) based on age range (20 – 29, 30 – 39, 40 – 49, and 50+ years) and the main device used for studying (notebook, desktop PC, tablet, and smartphone). In all cases, no statistically significant differences were observed between groups ($p > .05$), indicating comparable levels of satisfaction across the categories analyzed.

To investigate factors associated with satisfaction, an initial step was to examine the Pearson correlation matrix among the UTAUT2 – OLE dimensions. The results show that S is positively and statistically significantly associated with all considered dimensions ($p < .001$), with moderate to very high magnitudes: ATT ($r = .897$), PE ($r = .881$), Q ($r = .877$), OLV ($r = .862$), BI ($r = .779$), SI ($r = .786$), FC ($r = .658$), HT ($r = .642$), and EE ($r = .593$). This pattern supports our next step: the use of a regression model to estimate the joint contribution of these constructs in explaining satisfaction. Since high intercorrelations among several predictors are also observed, the regression was interpreted considering the overlap between dimensions and the theoretically ordered entry of blocks.

B. Hierarchical regression predicting Satisfaction (S)

A blockwise hierarchical linear regression was estimated to explain Satisfaction of use (S). In Model 0 (M0), control variables (gender and prior experience with online studies) were included, along with their interaction. In Model 1 (M1), the core UTAUT2 dimensions and the extended Online Learning Value (OLV) dimension were incorporated (EE, FC, PE, SI, OLV, HT). In Model 2 (M2), Attitude toward online learning (ATT) and Behavioral Intention (BI) were added as more proximal cognitive – affective appraisals. Finally, in Model 3 (M3), Perceived instructional Quality (Q) was included as the most proximal experience-related predictor. Collinearity diagnostics (tolerance and VIF) were inspected at each step.

TABLE III. FIT INDICES FOR HIERARCHICAL REGRESSION MODELS PREDICTING SATISFACTION (S).

	M_0	M_1	M_2	M_3
R	0.102	0.915	0.936	0.946
R^2	0.010	0.837	0.876	0.895
Adjusted R^2	-0.003	0.830	0.870	0.889
RMSE	0.861	0.355	0.310	0.287
AIC	589.839	187.686	127.928	92.836
BIC	607.029	225.505	172.623	140.969
R^2 Change	0.010	0.826	0.040	0.018
F Change	0.791	185.301	34.819	37.976
df1	3	6	2	1
df2	226	220	218	217
p	.500	< .001	< .001	< .001

M0: Controls. The model including only controls did not yield significant associations with satisfaction. Neither gender ($B = 0.142$, $p = .389$) nor prior experience with online studies ($B = 0.152$, $p = .417$) was significantly related to S, and the interaction term was also non-significant ($B = −0.337$, $p = .154$). Overall, this step provides no evidence that satisfaction differs by these control characteristics when examined in isolation.

M1: UTAUT2 core and OLV. After adding UTAUT2 dimensions and OLV, Performance Expectancy (PE) and Online Learning Value (OLV) emerged as robust positive predictors of satisfaction (PE: B = 0.627, β = 0.519, $p < .001$; OLV: B = 0.423, β = 0.369, $p < .001$). Social Influence (SI) also showed a smaller positive association at this step (SI: B = 0.148, β = 0.131, p = .008). In contrast, Effort Expectancy (EE), Facilitating Conditions (FC), and Habit (HT) did not show significant unique associations with S ($p > .05$), and controls control and interaction remained non-significant.

M2: Proximal appraisals (ATT and BI). When ATT and BI were introduced, both contributed significantly to satisfaction, with ATT showing a strong positive association (ATT: B = 0.387, β = 0.372, $p < .001$) and BI a smaller but significant positive association (BI: B = 0.117, β = 0.117, p = .006). PE and OLV remained significant, though attenuated (PE: B = 0.362, β = 0.299, $p < .001$; OLV: B = 0.259, β = 0.226, $p < .001$), consistent with shared variance between distal beliefs/value and proximal evaluations. Notably, SI was no longer significant (p = .456), suggesting that its association with satisfaction at M1 is largely accounted for by the more proximal cognitive – affective variables entered in M2. Prior online experience approached conventional significance at this step (B = −0.129, p = .062), while gender and the interaction remained non-significant.

M3: Perceived Quality (Q). In the final model, Perceived Quality (Q) emerged as a strong positive predictor of satisfaction (Q: B = 0.322, β = 0.311, $p < .001$). Importantly, several predictors retained independent positive associations with S even after accounting for Q: PE (B = 0.318, β = 0.263, $p < .001$), ATT (B = 0.267, β = 0.256, $p < .001$), BI (B = 0.151, β = 0.151, $p < .001$), and OLV (B = 0.152, β = 0.133, p = .015). In contrast, EE, FC, SI, and HT remained non-significant ($p > .05$). At this step, prior experience with online studies became a statistically significant negative predictor (B = −0.137, p = .033), indicating that, holding constant perceived quality and the other evaluative/UTAUT-related predictors, students with prior online experience reported slightly lower satisfaction. Gender and the interaction term remained non-significant.

C. Robustness Checks and Model Diagnostics

As a robustness check of the classical estimation, the hierarchical model was re-estimated using bootstrap BCa (3000 replicates). The results replicated the main pattern: PE, OLV, ATT, and Q maintained positive associations with satisfaction (S) in the expected stages, and BI retained a positive effect in the more proximal models. Likewise, SI was significant only in the belief block (M1) and lost significance when evaluations were incorporated closer to the experience (M2 – M3), consistent with the theoretical specification. Overall, the bootstrap confirms that the conclusions of the classical model do not depend on strict distributional assumptions.

As a complementary diagnosis, collinearity among predictors was inspected. Across models, VIF values increased for highly intercorrelated evaluative predictors in the final step (notably PE, OLV, ATT, and Q; VIF ≈ 5 – 6 with tolerances around ≈ 0.16 – 0.20), indicating substantial shared variance. Therefore, interpretation should prioritize the theoretically ordered entry of blocks and the stability of predictors that remain significant in the final model, while exercising caution when attributing unique effects among strongly overlapping constructs.

IV. Discussion

The results of the hierarchical regression analysis reveal a multidimensional pattern of predictors that, taken together, explain approximately 89.5% of the variance in student satisfaction (M3: R^2 = 0.895). This elevated explanatory power is consistent with the integrative theoretical rationale of the UTAUT2-OLE model, which incorporates both technology acceptance dimensions and experiential quality evaluations as drivers of satisfaction in online learning environments.

TABLE IV. Final hierarchical regression model coefficients for predicting Satisfaction (S).

		beta	t	p	Collinearity Statistics	
					Tol.	VIF
M_3	(Intercept)		-1.407	.161		
	Gender (Men)		0.201	.841	0.492	2.033
	Previous online studies (Yes)		-2.143	.033	0.352	2.842
	EE	-0.037	-0.927	.355	0.305	3.279
	FC	-0.028	-0.683	.495	0.290	3.449
	PE	0.263	4.895	< .001	0.168	5.956
	SI	-0.021	-0.484	.629	0.265	3.770
	OLV	0.133	2.441	.015	0.164	6.095
	HT	-0.028	-0.648	.517	0.258	3.878
	ATT	0.256	4.668	< .001	0.161	6.212
	BI	0.151	3.854	< .001	0.317	3.154
	Q	0.311	6.162	< .001	0.191	5.246

The robust and sustained contribution of Performance Expectancy (PE; β = 0.263) and Online Learning Value (OLV; β = 0.133) across all model steps underscores the centrality of perceived instrumental utility in shaping satisfaction. Students appear to evaluate their online learning experience not merely in affective terms, but through a pragmatic lens: to what extent does online education deliver on its promise of enabling professional development, competence acquisition, and career advancement? This finding is coherent with the profile of the sample, who are working adults with prior professional credentials, for whom the alignment between educational investment and tangible returns is a particularly salient criterion. This interpretation is consistent with prior research on online learners, which indicates that many students who enroll in online programs are already engaged in professional activities and seek to formalize or enhance their competencies while balancing work, studies, and personal life (Mathisen & Søreng, 2024) [2]. The positive role of Attitude toward Online Learning (ATT; $\beta = 0.256$) in M2 and M3 further reinforces this interpretation: pre-existing and evolving evaluative dispositions toward the modality complement the effect of instrumental expectations, suggesting that both cognitive appraisals and affective orientations jointly configure satisfaction.

The strong and independent contribution of Perceived Quality (Q; $\beta = 0.311$) in the final model, the largest single predictor, aligns with findings reported by Jiménez-Bucarey et al. [8], who demonstrated that service and teaching quality dimensions are central determinants of satisfaction in online higher education in Latin America. The present findings extend this pattern to engineering programs, confirming that instructional design, faculty responsiveness, and the perceived rigor of the learning experience are critical levers for institutional action [6] [7]. Importantly, Q retains its effect even after controlling for behavioral intention and attitude, indicating that experiential quality constitutes an independent explanatory dimension beyond students' a priori dispositions.

The significant role of Behavioral Intention (BI; $\beta = 0.151$) in M2 and M3 suggests that students who maintain a strong intention to continue using online learning systems report higher satisfaction, which is consistent with reinforcing feedback loops between positive evaluations and sustained engagement. This finding is consistent with the UTAUT2 framework [10], in which intention functions as a proximal antecedent of actual use behavior and, in the current context, as a predictor of experiential satisfaction.

Notably, Effort Expectancy (EE), Facilitating Conditions (FC), Social Influence (SI), and Habit (HT) did not emerge as significant unique predictors of satisfaction in the final model, even though they correlated with satisfaction at the bivariate level. This pattern has theoretical salience: in a sample of working adults with substantial prior professional experience and demonstrated competence with digital tools, the effort required to navigate online platforms may be manageable and largely resolved, rendering perceived ease of use a threshold condition rather than an active differentiator of satisfaction. Similarly, the non-significance of Facilitating Conditions may reflect that, for this cohort, institutional support structures are perceived as adequate but not as active sources of value, a finding that warrants attention in institutional design. The attenuation of Social Influence upon the introduction of proximal evaluative variables (M2) suggests that peer or normative influences on satisfaction are largely mediated by students' own attitudinal and behavioral dispositions. This pattern is broadly consistent with findings by Hew et al. [6], who reported that interactive or social dimensions did not independently predict satisfaction in online courses when content and assessment quality were taken into account.

From a theoretical standpoint, these results suggest that in mature online learning ecosystems serving experienced adult learners, certain UTAUT2 dimensions may operate as hygiene factors: their presence is necessary to avoid dissatisfaction, but their incremental contribution to satisfaction is absorbed by more proximal evaluative variables once a baseline threshold is met. This reframes EE, FC, SI, and HT not as theoretically irrelevant, but as preconditions whose explanatory power is conditional on the maturity of the learner population and the institutional infrastructure. Future research should test whether these factors regain predictive weight in samples of novice online learners or in institutions with less developed digital ecosystems.

A counterintuitive finding is the emergence of prior online study experience as a statistically significant negative predictor in M3 ($B = -0.137$, $p = .033$), after controlling for all evaluative dimensions. This effect suggests that students with greater prior exposure to online learning may set higher benchmarks or expectations, so that an equivalent level of perceived quality yields comparatively lower satisfaction. This interpretation resonates with Mathisen and Søreng's [2] observation that experienced online students develop sophisticated self-management strategies and become progressively more critical evaluators of the learning environment, particularly with respect to course design, faculty interaction, and asynchronous structures.

The absence of significant differences in satisfaction by gender, age, funding source, work status, or device used reinforces the premise that satisfaction in this context is driven primarily by perceptual and evaluative factors rather than by structural sociodemographic characteristics. This result is consistent with prior research [25] suggesting that in mature online learners, typically characterized by high levels of academic self-regulation and vocational motivation, satisfaction is shaped predominantly by instructional and experiential variables rather than by background characteristics.

V. Conclusions

This study examined the factors influencing student satisfaction in fully online engineering programs at a Chilean university. A sample of 230 undergraduate students, characterized predominantly as working adults with prior professional credentials, completed an instrument based on an adapted UTAUT2-OLE framework. Blockwise hierarchical linear regression was employed to model the joint and sequential contributions of technology acceptance constructs, attitudinal appraisals, and experiential quality evaluations to satisfaction.

The results indicate that Perceived Quality, Performance Expectancy, Attitude toward Online Learning, Behavioral Intention, and Online Learning Value are the most robust predictors of satisfaction, together explaining approximately

89.5% of the variance in this outcome. In contrast, Effort Expectancy, Facilitating Conditions, Social Influence, and Habit did not emerge as significant unique predictors, suggesting that for this sample of experienced working adults, these dimensions constitute background conditions rather than active differentiators of the learning experience. A noteworthy finding is the negative association between prior online study experience and satisfaction in the final model, which may reflect higher performance benchmarks among more experienced students. No significant differences in satisfaction were observed across sociodemographic groups, reinforcing the centrality of perceptual and experiential variables.

These findings have direct implications for institutional design: improving perceived instructional quality and performance outcomes, while fostering positive attitudes toward online learning, emerges as the most actionable lever to enhance satisfaction and, by extension, support retention in online engineering programs. The study contributes to the growing body of evidence on the quality of online learning in Latin American higher education and provides a theoretically grounded, empirically robust foundation for future research in this domain.

Practical recommendations derived from these findings include: (a) investing in faculty development programs focused on online instructional design, feedback timeliness, and digital pedagogical competencies, given that Perceived Quality emerged as the strongest predictor; (b) explicitly communicating the alignment between course content and professional outcomes throughout the program, to reinforce Performance Expectancy and Online Learning Value among working adults; (c) implementing differentiated engagement strategies for students with prior online experience, who apply more demanding evaluative standards; and (d) embedding periodic satisfaction diagnostics using validated instruments such as the UTAUT2-OLE adopted here, enabling data-driven quality assurance cycles in online engineering programs.

This study has several limitations. First, the sample was drawn from a single Chilean university, which may limit the generalizability of the findings to other institutional or cultural contexts. Nevertheless, the sample profile, predominantly working adults seeking professional credentialing, mirrors the demographic composition of online engineering programs in many Latin American countries, where similar socioeconomic constraints, labor market pressures, and demand for flexible higher education shape enrollment patterns. This suggests that the identified predictors, particularly Perceived Quality and Performance Expectancy, are likely to remain relevant across the region, although their relative weights may vary depending on institutional maturity and digital infrastructure. Comparative multi-institutional studies across Chile, Colombia, and Mexico would help establish the boundaries of generalization. Second, the cross-sectional design prevents the establishment of causal relationships among the variables. Finally, all variables were measured through self-reported data, which may introduce common method variance.

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