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Assessing Perceived Quality in Online Engineering Education: Evidence from a South American School of Engineering

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Abstract

Online education has become a key modality for expanding access, enhancing flexibility, and supporting lifelong learning in higher education, particularly for adult learners and working professionals. Its rapid growth has opened new pathways for professional advancement, but it has also raised persistent challenges regarding the perceived quality and effectiveness of teaching and learning processes. In this context, a School of Engineering in South America has implemented fully online programs under two formats: Advance, designed for professionals with prior work experience who seek to complete undergraduate degrees through flexible pathways and recognition of prior learning, and 100% Online Evening programs, both grounded in a student-centered instructional design model focused on quality assurance and continuous improvement. However, prior research suggests that perceived quality in online higher education depends on access and flexibility, as well as on instructional design, student–instructor interaction, academic support, and students' digital competence. This study examines perceived instructional Quality (Q) in fully online engineering programs and identifies the factors that most strongly explain students' perceptions of quality within an integrative UTAUT2-based framework.

A quantitative, descriptive, cross-sectional design was implemented with a non-probabilistic sample of 160 undergraduate engineering students enrolled in fully online programs. Students responded to the UTAUT2–Online Learning Experience (UTAUT2–OLE) instrument (48 items; 10 constructs), which extends UTAUT2 by incorporating Online Learning Value (OLV), Satisfaction (S), and a multidimensional Quality (Q) construct informed by instructional quality standards. Descriptive analyses showed high mean scores across constructs ($M = 4.015$–4.500), indicating generally favorable perceptions. All constructs were positively and significantly correlated (all $p < .001$), including strong associations between Q and S ($r = .875$) and between Q and OLV ($r = .845$). Hierarchical regressions predicting Q indicated that controls (gender, prior online-study experience) were not associated with Q. UTAUT2 dimensions plus OLV explained substantial variance ($R^2 = .788$). Adding Behavioral Intention (BI) produced a small but significant increment ($\Delta R^2 = .008$), while adding Satisfaction (S) yielded a larger, consistent increment ($\Delta R^2 = .035$), resulting in a final model $R^2 = .832$. In the final model, Satisfaction (S) emerged as the dominant predictor ($\beta = .542$, $p < .001$), with positive partial effects for Attitude ($\beta = .256$, $p = .005$), Facilitating Conditions ($\beta = .154$, $p = .016$), Online Learning Value ($\beta = .206$, $p = .023$), and Effort Expectancy ($\beta = .133$, $p = .038$). BI showed a negative partial coefficient interpreted as a suppression pattern under high construct overlap; collinearity diagnostics indicated elevated VIFs for several evaluative predictors (e.g., $S \approx 8.30$). Bootstrap BCa estimates (1000 replicates) confirmed the robustness of the coefficients of S, ATT, FC, OLV, and EE, and the partial negative BI effect. These findings suggest that improving perceived quality in online engineering should prioritize overall satisfaction with the learning experience, strengthen facilitating supports, and reinforce students' perceived value and positive attitudes toward online learning, while interpreting "unique" effects cautiously in the presence of high collinearity.

Keywords: Online Engineering Education, Quality Assurance, Student Perceptions, Continuing and Professional Education

Introduction

Online education has become a central modality in higher education, particularly in programs aimed at adult learners and working professionals. Beyond its contribution to access and flexibility, the sustained expansion of e-learning has shifted the academic debate from issues of technological adoption toward concerns about the quality of the educational experience and the value of learning as perceived by students [1]. In this context, perceived quality has emerged as a key criterion for evaluating the effectiveness of online programs, especially in disciplines characterized by high cognitive and pedagogical demands, such as engineering. Previous research has shown that low perceived quality in online learning environments is associated with decreased motivation, reduced academic engagement, and higher dropout rates, even when adequate technological infrastructure is available [2]. In engineering programs, where instructional coherence, timely feedback, and meaningful student–instructor interaction are central to learning, these challenges become particularly salient. Therefore, current discussions on online education increasingly focus on how students experience the quality of the educational process and which factors shape those perceptions, rather than on the technical functionality of learning platforms alone [3].

From a theoretical perspective, research on online education has been strongly influenced by technology acceptance models. The Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT) have been widely applied to explain intention to use and adoption of online learning systems in higher education [4]. These models have demonstrated strong predictive power across a range of educational settings, including university-level online learning environments [5].

However, TAM and UTAUT were originally developed to explain technology adoption primarily in organizational and semi-mandatory contexts. This focus limits their ability to fully capture educational environments characterized by voluntary use and sustained engagement, such as online higher education. To address this limitation, Venkatesh et al. extended the original framework by proposing UTAUT2, which incorporates additional constructs such as habit and hedonic motivation and improves explanatory power in voluntary use contexts [6]. Subsequent empirical studies have confirmed the usefulness of UTAUT2 for analyzing adoption and continued use of online educational platforms in higher education [7], [8].

Despite their widespread application, technology acceptance models show clear limitations when applied to mature online educational programs. Educational quality is frequently addressed only indirectly, often subordinated to constructs such as perceived usefulness, ease of use, or behavioral intention, rather than examined as a central explanatory factor [9], [10]. Consequently, these models provide limited insight into complex learning experiences in which platform adoption is already established, with the primary challenge being instructional design and the overall educational experience [11], [12].

Research on online education has also emphasized instructional quality and student experience as key analytical perspectives. From this perspective, quality is understood as a multidimensional construct encompassing instructional alignment, course design clarity, instructor presence, effective feedback, and academic and institutional support [13]. Empirical evidence indicates that students' perceptions of quality are closely related to their learning experience, particularly in STEM disciplines, where pedagogical interaction and instructional structure play a central role in learning outcomes [14]. This focus is especially salient in Latin American higher education, where interaction, autonomy, and academic support have been identified as key determinants of quality perceptions in online learning environments [15].

Despite these contributions, the literature remains conceptually fragmented. Research grounded in TAM, UTAUT, and UTAUT2 continues to prioritize adoption and usage intentions, whereas pedagogical studies focus on instructional quality without systematically integrating it into technology acceptance frameworks [9], [10]. As a result, existing research provides only a partial understanding of how students form perceptions of quality in online learning environments [11], [12].

This limitation becomes particularly evident in fully online engineering programs designed for working professionals. Empirical studies in this area remain largely concentrated on blended learning settings or on other disciplinary domains, while research that explicitly integrates technology acceptance models with instructional quality frameworks in fully online engineering contexts remains scarce [16], [17].

At the same time, other studies suggest that satisfaction, educational system quality, instructor feedback, and institutional facilitating conditions play a decisive role in shaping students' learning experiences beyond ease of use alone [18], [19]. In engineering education, these factors are especially consequential, as students' perceptions of quality have been shown to directly influence engagement and the perceived value of online learning experiences [20].

Taken together, these limitations point to a clear research gap: the absence of integrative models that examine perceived quality as a central construct by combining technology acceptance approaches with instructional quality frameworks, particularly in fully online engineering programs and from the student perspective. This gap is especially evident in Latin American and professional education contexts, where research has largely emphasized technological adoption rather than the quality of the educational experience [21], [22], [23].

This study was conducted within a School of Engineering in Chile that offers fully online programs designed for working professionals. This institutional context provides an appropriate opportunity to examine quality perceptions in real-world online education settings by jointly considering technological, pedagogical, and academic support dimensions within a unified analytical framework [15].

The objectives of this study are to: analyze students' perceptions of quality in fully online engineering programs; identify the factors influencing those perceptions, with particular emphasis on instructional design, academic support, and technological conditions; and examine the role of perceived quality as a central construct within an integrative framework combining UTAUT2, TAM, and instructional quality standards.

Overall, this paper aims to provide empirical evidence and a replicable diagnostic framework for assessing perceived quality in online engineering education, thereby advancing theory and enabling informed decision-making in instructional design and institutional management.

Methodology

Participants

The sample consisted of 160 undergraduate students enrolled in engineering programs offered entirely online at the Faculty of Engineering of a major Chilean university. No missing data were recorded in the sociodemographic and contextual variables considered. In terms of gender, 77.5% identified as male ($n = 124$) and 22.5% as female ($n = 36$). The average age was 36.95 years ($SD = 8.91$), with a range between 21 and 61 years. Regarding academic background and experience with online learning, 53.8% indicated having previously taken online courses ($n = 86$), while 46.3% reported not having done so ($n = 74$). Additionally, 87.5% reported holding a professional degree ($n = 140$), and 12.5% indicated not having one ($n = 20$). Finally, regarding the primary source of funding for their studies, most reported self-financing (85.0%, n = 136), while 15.0% reported other funding sources (n = 24). These data characterize the typical audience for this study modality: working adults.

Instrument

We used an adapted version of the UTAUT2 for Online Learning Experience (UTAUT2–OLE). This framework extends the original UTAUT2 by incorporating post-experience evaluations that are particularly relevant in fully online contexts. Specifically, it includes Satisfaction (S) as a global post-use appraisal, redefines Price Value as Online Learning Value (OLV) to capture perceived benefits and trade-offs of online study (e.g., flexibility and costs), and adds a multidimensional measure of perceived instructional Quality (Q) focused on course design and interaction in digital environments. Consistent with prior applications in adult and working-learner contexts, Hedonic Motivation was not included because it is peripheral to persistence-related outcomes and overlaps conceptually with Attitude toward online learning (ATT).

The survey comprised 10 multi-item constructs measured 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), Behavioral Intention to continue studying online (BI), Habit (HT), Online Learning Value (OLV), Satisfaction (S), and perceived instructional Quality (Q). Items for the UTAUT2 core and its extensions were adapted from established higher-education implementations of UTAUT/UTAUT2 and continuance models, while Q was informed by empirical work on online learning perceptions and on quality standards for online course design. Internal consistency was examined using McDonald's ω and Cronbach's α, showing adequate to high reliability across constructs.

Table 1. Internal reliability and sources of the instrument's scales.

Dimension	**N° Items**	**Coefficient ω**	**Coefficientt α**	**Sources**
Performance Expectancy	4	0,824	0,856	[4], [7]
Effort Expectancy	4	0,856	0,876	[4], [7]
Attitude Toward Online Learning	4	0,907	0,905	[4]
Social Influence	5	0,878	0,854	[4], [7], [24]
Facilitating Conditions	4	0,735	0,731	[4], [7]
Behavioral Intention	4	0,887	0,888	[25]
Habit	3	0,847	0,84	[6], [7], [25]
Online learning value	5	0,825	0,853	[6], [10]
Satisfaction of use	5	0,915	0,932	[26]
Quality	9	0,912	0,930	[13], [14], [18]

Procedure

After institutional ethics approval, data were collected during the academic term using an online questionnaire delivered through the institutional learning environment. Students received study information and provided informed consent prior to responding. Participation was voluntary and anonymous, and the dataset was stored in de-identified form.

Data análisis

Analyses were conducted in JASP. Item responses were averaged to form composite scores for each construct. Descriptive statistics and correlations were examined as preliminary evidence for model estimation. To address the research questions, we estimated blockwise hierarchical linear regression models with theoretically ordered entry of predictors. For each step, we report changes in explained variance (ΔR^2), F-change, RMSE, and information criteria (AIC, BIC), and interpret standardized coefficients (β) at $\alpha = .05$. Given the high intercorrelations among constructs, multicollinearity diagnostics (tolerance and VIF) were inspected, and bootstrap estimates were used as a robustness check for coefficient inference.

Results

Descriptive statistics and the distribution shapes were examined for all variables ($N = 160$; Table 2). On a scale from 1 to 5, the means were notably high across all constructs, ranging from 4.015 to 4.500, thereby indicating a predominant tendency toward upper-end responses on the scale. The construct of Habit exhibited the highest mean ($M = 4.500$, $SD = 0.599$), followed by Effort Expectancy ($M = 4.436$, $SD = 0.664$), whereas the dependent variable, Quality (Q), recorded the lowest mean; nonetheless, it remained high ($M = 4.015$, $SD = 0.860$). Concerning univariate normality, consistent negative skewness was observed (skewness between −0.955 and −1.599), and most variables displayed positive kurtosis of low to moderate magnitude (kurtosis between 0.418 and 3.829), patterns indicative of a concentration of high responses. However, based on pragmatic criteria for approximate normality, such as skewness and kurtosis values within ±4, these deviations are deemed acceptable. Consequently, the analyses are presented with the interpretation of coefficients as parametric estimates under approximate normality, supplemented by robust inference through bootstrap methods.

Table 2. Descriptive statistics for study dimensions.

Dimension	**Code**	**Mean**	**Std. Deviation**	**Skewness**	**Kurtosis**
Performance Expectancy	PE	4.286	0.760	-1.599	3.450
Effort Expectancy	EE	4.436	0.664	-1.582	3.829
Attitude Toward online learning	ATT	4.258	0.847	-1.389	1.995
Social Influence	SI	4.160	0.779	-1.117	1.867
Facilitating Conditions	FC	4.264	0.692	-1.012	1.253
Behavioral Intention	BI	4.127	0.844	-1.244	2.088
Habit	HT	4.500	0.599	-1.397	1.810
Online learning value	OLV	4.175	0.775	-1.344	2.941
Satisfaction of use	S	4.106	0.889	-1.318	2.026
Quality	Q	4.015	0.860	-0.955	0.418

The Pearson correlations, presented in Table 3, showed positive and statistically significant associations among all variables in the model (all $p < .001$), with predominantly high magnitudes. In particular, the dependent variable Quality (Q) was strongly associated with Satisfaction (S; $r = 0.875$), OLV ($r = 0.845$), Attitude (ATT; $r = 0.838$), and Performance Expectancy (PE; $r = 0.810$), and also showed positive associations with Social Influence (SI; $r = 0.768$), Facilitating Conditions (FC; $r = 0.702$), Behavioral Intention (BI; $r = 0.692$), Habit (HT; $r = 0.668$), and Effort Expectancy (EE; $r = 0.638$). Additionally, high intercorrelations were observed among predictors, highlighting ATT with S ($r = 0.901$) and PE with S ($r = 0.895$), as well as PE with ATT ($r = 0.876$) and OLV with S ($r = 0.861$). This pattern of associations suggests that several dimensions share substantial variance, which anticipates potential collinearity and justifies the use of hierarchical regression to estimate the incremental contributions (ΔR^2) of BI and, especially, S over the set of UTAUT2 and OLV dimensions.

Table 3. Pearson correlations between dimensions.

Variable	PE	EE	ATT	SI	FC	BI	HT	OLV	S	Q
1. PE	— —									
2. EE	0.629 < .001	— —								
3. ATT	0.876 < .001	0.580 < .001	— —							
4. SI	0.800 < .001	0.620 < .001	0.794 < .001	— —						
5. FC	0.653 < .001	0.729 < .001	0.622 < .001	0.691 < .001	— —					
6. BI	0.749 < .001	0.630 < .001	0.781 < .001	0.760 < .001	0.673 < .001	— —				
7. HT	0.727 < .001	0.808 < .001	0.681 < .001	0.700 < .001	0.751 < .001	0.616 < .001	— —			
8. OLV	0.862 < .001	0.695 < .001	0.828 < .001	0.817 < .001	0.759 < .001	0.787 < .001	0.700 < .001	— —		
9. S	0.895 < .001	0.595 < .001	0.901 < .001	0.784 < .001	0.661 < .001	0.782 < .001	0.677 < .001	0.861 < .001	— —	
10. Q	0.810 < .001	0.638 < .001	0.838 < .001	0.768 < .001	0.702 < .001	0.692 < .001	0.668 < .001	0.845 < .001	0.875 < .001	— —

A hierarchical regression was estimated to explain the perception of Quality (Q). In Model 0 (M_0), control variables (gender and prior experience with online studies) were included. In Model 1 (M_1), the dimensions of UTAUT2, along with the extended OLV dimension, were incorporated. In Model 2 (M_2), the intention to use (BI) was added. Finally, in Model 3 (M3), Satisfaction (S) was included. At each step, changes in explained variance (ΔR2), the change in F, the error (RMSE), and information criteria (AIC, BIC) were evaluated. Diagnostic checks for collinearity were also performed using tolerance and VIF. To facilitate reading, the adjustments for all models (Table 4) and the fit coefficients for the final Model M_3 (Table 5) are presented. The complete table of fit coefficients for all models is included in the Appendix.

M_0: Controls

The model with controls did not explain variance in Quality ($R = 0.017$; $R2 = 0.000$; adjusted $R2 = -0.012$; $RMSE = 0.865$). The change in the model was not significant (F change = 0.023, df1 = 2, df2 = 157, $p = .978$). In terms of coefficients, neither gender ($B = -0.035$, p =

.833) nor previous experience with online studies (B = −0.002, p = .987) showed a significant association with Q. Collinearity diagnostics at this step were adequate (tolerance ≈ 0.998; VIF ≈ 1.002 for both predictors), indicating no collinearity among controls.

Table 4. Hierarchical regression model fit for predicting Quality (Q).

Model	**R^2**	**Adjusted R^2**	**RMSE**	**AIC**	**BIC**	**R^2 Change**	**F Change**	**df1**	**df2**	**p**
M_0	0.000	-0.012	0.865	412.562	424.862	0.000	0.023	2	157	.978
M_1	0.788	0.776	0.407	178.187	212.014	0.788	79.768	7	150	< .001
M_2	0.797	0.783	0.400	173.813	210.715	0.008	6.056	1	149	.015
M_3	0.832	0.819	0.365	145.280	185.257	0.035	31.118	1	148	< .001

Table 5. Final hierarchical regression model coefficients for predicting Quality (Q).

Model		**beta**	**t**	**p**	**95% CI**		**Collinearity Statistics**	
					Lower	**Upper**	**Tolerance**	**VIF**
M_3	(Intercept)		-0.989	.324	-0.685	0.228		
	Gender (Women)		1.192	.235	-0.056	0.226	0.937	1.067
	Previous online studies (Yes)		0.692	.490	-0.077	0.161	0.924	1.082
	PE	-0.101	-1.092	.277	-0.320	0.092	0.134	7.457
	EE	0.133	2.089	.038	0.009	0.336	0.279	3.584
	ATT	0.256	2.877	.005	0.081	0.438	0.144	6.954
	SI	0.109	1.616	.108	-0.027	0.267	0.251	3.980
	FC	0.154	2.447	.016	0.037	0.347	0.285	3.511
	HT	-0.098	-1.365	.174	-0.345	0.063	0.219	4.560
	OLV	0.206	2.295	.023	0.032	0.424	0.142	7.063
	BI	-0.230	-3.561	< .001	-0.364	-0.104	0.272	3.676
	S	0.542	5.578	< .001	0.338	0.709	0.121	8.298

M_1: Incorporation of UTAUT2 + OLV

The incorporation of PE, EE, ATT, SI, FC, HT, and OLV resulted in a substantial improvement in fit (R = 0.888; R2 = 0.788; adjusted R2 = 0.776; RMSE = 0.407), with a significant change compared to M0 (ΔR2 = 0.788; F change = 79.768, df1 = 7, df2 = 150, p < .001). In this model, the significant predictors were Attitude (ATT: B = 0.414, β = 0.407, p < .001), Facilitating Conditions (FC: B = 0.186, β = 0.150, p = .033), and OLV (B = 0.324, β = 0.292, p = .003). The other UTAUT2 dimensions did not show significant partial effects once the rest of the set was controlled (PE: p = .474; EE: p = .287; SI: p = .463; HT: p = .349). The controls remained without significant association (gender: p = .569; prior experience: p = .584).

From a diagnostic perspective, this model showed significant collinearity among predictors, with low tolerances and high VIFs among conceptually related variables (e.g., PE: tolerance = 0.151, VIF = 6.603; ATT: tolerance = 0.196, VIF = 5.109; OLV: tolerance = 0.151, VIF =

6.616). Consequently, the coefficients should be interpreted as conditioned partial effects, i.e., net estimates after controlling for overlap between constructs.

M_2: Addition of the intended use (BI)

By incorporating BI, the adjustment improved incrementally but significantly (R = 0.893; R2 = 0.797; adjusted R2 = 0.783; RMSE = 0.400), with a statistically significant change compared to M1 (ΔR2 = 0.008; F change = 6.056, df1 = 1, df2 = 149, p = .015). In this step, ATT (B = 0.480, β = 0.473, p < .001), FC (B = 0.217, β = 0.175, p = .012), and OLV (B = 0.353, β = 0.319, p = .001) remained as positive and significant predictors. BI emerged as a significant predictor but with a negative partial coefficient (BI: B = −0.175, β = −0.172, p = .015). PE, EE, SI, and HT continued without evidence of a net partial effect (p > .05), and the controls remained non-significant.

Collinearity diagnoses remained in high ranges for some constructs, particularly PE (VIF ≈ 6.604), ATT (VIF ≈ 5.623), and OLV (VIF ≈ 6.701). For BI, the tolerance was 0.279 and the VIF was 3.581, indicating moderate collinearity. The negative sign of BI is interpreted as a partial effect conditioned by a strong overlap with attitude and evaluative predictors (e.g., ATT/OLV), consistent with a suppression phenomenon: although BI may correlate positively with Q at the bivariate level, its "residual' contribution when controlling for highly correlated constructs can invert.

M_3: Addition of Satisfaction (S)

The inclusion of Satisfaction produced the greatest subsequent incremental improvement after M1 (R = 0.912; R2 = 0.832; adjusted R2 = 0.819; RMSE = 0.365), with a significant change compared to M2 (ΔR2 = 0.035; F change = 31.118, df1 = 1, df2 = 148, p < .001). In the final model, Satisfaction emerged as the strongest predictor of Quality (S: B = 0.524, β = 0.542, p < .001). Additionally, significant positive associations were maintained for ATT (B = 0.259, β = 0.256, p = .005), FC (B = 0.192, β = 0.154, p = .016), and OLV (B = 0.228, β = 0.206, p = .023). In this last step, EE became significant (EE: B = 0.172, β = 0.133, p = .038), while PEOU, SI, and HT continued without significant association (p > .05). BI remained as a partial negative predictor (BI: B = −0.234, β = −0.230, p < .001), reinforcing the interpretation of suppression given the entry of Satisfaction (an evaluative construct highly correlated with Quality and other predictors).

In terms of collinearity, the final model showed particularly high VIF values in evaluative predictors and those close to the criterion, highlighting S (tolerance = 0.121; VIF = 8.298), PE (tolerance = 0.134; VIF = 7.457), ATT (tolerance = 0.144; VIF = 6.954), and OLV (tolerance = 0.142; VIF = 7.063). These values indicate substantial overlap between constructs, so interpretation should focus on (i) the incremental contribution by steps (ΔR2 and F change), (ii) the stability of robust predictors (S, ATT, FC, OLV), and (iii) caution when attributing "unique effects" to highly correlated variables.

Behavioral Intention (BI) was incorporated before Satisfaction because it represents a more distal prospective behavioral disposition (intention to use in the future), while Satisfaction corresponds to a more immediate and subsequent overall evaluation of the experience. In this sense, introducing BI first allows for estimating its incremental contribution to quality before adding a highly proximal evaluative judgment to the criterion, which tends to absorb a substantial proportion of the explained variance.

The coefficients were re-estimated using bootstrap BCa (1000 replicates), utilizing the median of the bootstrap distribution. The results confirmed the pattern of the classical estimator: controls were not significant; in M1, effects of Attitude ($p < .001$) and OLV ($p = .018$) were supported, while FC was marginal ($p = .070$). In M2, Attitude, Facilitating Conditions, and OLV remained significant ($p \leq .026$), and BI showed a partial negative effect ($p = .035$). In the final model (M3), Satisfaction emerged as the most robust predictor of Quality ($p < .001$), with effects of Attitude ($p = .009$) and Facilitating Conditions ($p = .041$) maintained; BI retained a partial negative effect ($p = .002$). OLV was at the threshold ($p = .050$), and EE was marginal ($p = .062$), consistent with the high overlap among evaluative constructs.

Overall, the results indicate that Perceived Quality (Q) is not associated with the included controls but is largely explained by the UTAUT2 and OLV dimensions (M1). Beyond that core, BI contributes a small but significant increase (M2), and Satisfaction adds a larger, consistent increase (M3), positioning it as the dominant predictor. The bootstrap BCa estimators (1000 replications) confirm this general pattern and particularly support the robustness of S and the partial effect of BI. However, the high collinearity in the final model suggests interpreting the coefficients as conditioned partial effects; in this context, the negative sign of BI is compatible with a suppression effect arising from overlap between attitudinal/evaluative constructs and the criterion.

Discussion

Perceived quality as a post-experience evaluation. The results indicate that perceived quality in fully online engineering programs is strongly determined by post-experience evaluations. Overall satisfaction with the learning process was the most robust predictor of perceived quality, producing the largest increase in explained variance when included in the model. This finding suggests that quality is not constructed through initial expectations or prior dispositions toward the online modality. Instead, it is built retrospectively through a global assessment of the learning experience. It is important to clarify, however, that satisfaction and instructional quality are conceptually distinct constructs. Satisfaction refers to an affective, global response to the educational experience as a whole, a summary judgment of whether the experience met students' expectations. Perceived instructional quality, by contrast, is a more specific evaluative judgment about the coherence, relevance, and effectiveness of the learning process, including elements such as curriculum design, pedagogical support, and the alignment between learning goals and activities. Satisfaction serves as a powerful predictor of perceived quality precisely because it integrates multiple experiential signals into a single affective evaluation. This distinction matters theoretically: it implies that improving satisfaction alone is not sufficient to enhance instructional quality. Rather, satisfaction reflects the cumulative effect of quality-related factors such as instructional design and institutional support. Previous studies in technology acceptance and continuance models have reported consistent results, highlighting satisfaction as a post-use evaluation that integrates perceptions of usefulness, system design, and the overall educational experience [27]. Similarly, Balaskas et al. [19] show that satisfaction operates as a dominant mediator between cognitive factors, system quality, and intention to use academic platforms, reinforcing its role as a key construct in the evaluation of virtual learning environments. In online education settings for adult learners and working professionals, satisfaction appears to function as an integrate construct that condenses perceptions of instructional design, institutional support, and perceived learning value.

Cognitive and attitudinal evaluations as foundations of perceived quality. Along with satisfaction, attitude toward online learning, perceived online learning value, and facilitating conditions maintained positive and significant associations with perceived quality in the final model. This pattern indicates that quality is not solely dependent on an affective post-experience response. It is also grounded in cognitive and attitudinal judgments about the usefulness, coherence, and feasibility of the learning process.
The relevance of online learning value reinforces the idea that students evaluate quality by weighing the benefits of the modality, such as flexibility and compatibility with work responsibilities, against its associated costs. This is consistent with studies that emphasize perceived value and usefulness as key determinants in evaluating digital learning environments [17]. The persistence of the effect of facilitating conditions aligns with evidence reported by Atencio-González and Aldana-Zavala [15], who show that structural factors such as accessibility, institutional support, and technological stability explain a substantial proportion of the variance in perceived effectiveness of non-face-to-face modalities. Taken together, these findings demonstrate that perceived quality emerges from the articulation of favorable attitudes, perceived educational value, and an institutional environment that effectively supports online learning, rather than from technological adoption alone.

Secondary role of classical technology adoption constructs. Contrary to expectations from traditional technology acceptance models, several core UTAUT2 constructs, performance expectancy, social influence, and habit, did not show significant partial effects on perceived quality after controlling for overlap with evaluative variables. This result suggests that, in contexts where online learning use is already consolidated, these factors primarily serve as entry conditions or initial facilitators. They are not direct determinants of quality evaluation. Similar findings have been reported by Balaskas et al. [19], who show that once evaluative variables such as satisfaction and perceived system quality are included, the direct effects of classical technology adoption constructs are attenuated or lose significance. In adult populations with prior work experience and established educational trajectories, adoption of the modality appears largely resolved. The evaluative focus, therefore, shifts from technological acceptance to the concrete experience of the course and its educational value. In this sense, quality emerges less as a matter of intention or use, and more as a pedagogical and experiential judgment constructed through sustained interaction with the learning environment.

Implications for the evaluation and design of online engineering programs. Taken together, these results indicate that perceived quality in online engineering programs should be addressed primarily from a post-experiential perspective. The central concerns are satisfaction, perceived learning value, and the conditions that support the learning process. This interpretation is consistent with recent evidence showing that, once the technological adoption phase has passed, quality evaluations are constructed mainly through retrospective judgments of the educational experience rather than through initial expectations or prior dispositions [19].
From an applied perspective, these findings translate into concrete recommendations for instructional design, faculty practice, and quality assurance. In terms of instructional design, programs should prioritize coherent course structures, clear alignment between learning objectives and assessments, and timely, constructive feedback, elements that directly shape students' sense of educational effectiveness. Regarding faculty practices, instructors in fully online engineering programs can enhance perceived quality by fostering meaningful interaction, providing structured guidance on self-regulated learning, and making the

practical relevance of course content explicit for professional contexts. For quality assurance processes, institutions should implement regular collection of satisfaction data, not as an end in itself, but as a diagnostic signal to identify weaknesses in instructional design and support services. Facilitating conditions, such as technical support availability, accessible course platforms, and responsive administrative services, should be treated as foundational quality components rather than secondary concerns. These actions are consistent with studies that emphasize the structural role of institutional support and accessibility as foundations of perceived effectiveness in non-face-to-face modalities [15]. Overall, the findings suggest that technology acceptance models require adaptation when used to evaluate quality in contexts where use is already normalized, shifting the emphasis from adoption intention toward the effective educational experience.

Conclusions

This study examined perceived instructional quality in fully online engineering programs for working professionals. It did so by integrating technology acceptance constructs with instructional quality dimensions and post-experience evaluations. The findings show that perceived quality in mature online education contexts is primarily constructed through students' retrospective evaluations of their learning experience, rather than through adoption-related expectations.

Satisfaction emerged as the strongest and most consistent predictor of perceived quality across the proposed integrative framework. It explained a substantial proportion of variance beyond classical UTAUT2 dimensions. This result confirms that, once online learning platforms are established, quality judgments are shaped mainly by global evaluations of the educational experience, integrating perceptions of instructional design, institutional support, and perceived learning value.

A key theoretical clarification is warranted here. Satisfaction and instructional quality are related but distinct constructs. Satisfaction is an affective, integrative response to the overall experience, while instructional quality reflects more specific judgments about the coherence, pedagogical relevance, and effectiveness of the learning process. The strong predictive role of satisfaction does not mean the two constructs are interchangeable. Rather, it indicates that satisfaction functions as a cumulative signal of the quality conditions students have experienced.

Attitude toward online learning, Online Learning Value, and Facilitating Conditions also maintained significant associations with perceived quality. These findings indicate that quality perceptions are grounded in both affective and cognitive-attitudinal judgments about the usefulness, coherence, and feasibility of the learning process. In contrast, traditional technology adoption constructs, such as performance expectancy, social influence, and habit, made limited or no unique contributions to perceived quality once evaluative constructs were included. This pattern suggests that, in fully online programs serving adult learners, adoption-related factors operate mainly as enabling conditions rather than as direct determinants of quality evaluation.

From a theoretical standpoint, the results highlight the need to adapt technology acceptance models when applied to educational quality assessment in contexts where online learning is already normalized. Integrative frameworks should prioritize post-experience evaluations and instructional quality dimensions over adoption intention.

From a practical standpoint, quality assurance efforts should focus on strengthening instructional design coherence, meaningful interaction, and academic support. Concretely, this means offering timely feedback mechanisms, ensuring accessible and stable technological environments, and aligning course structures with the professional demands of working students. For faculty, it implies actively supporting self-regulated learning and making the practical value of course content explicit. For institutions, it means treating student satisfaction data as a diagnostic tool to identify instructional gaps, rather than as a standalone quality metric.

Several limitations should be acknowledged. The study relied on a non-probabilistic sample from a single institutional context, which may limit the generalizability of the findings. The cross-sectional design does not allow for causal inferences or for examining changes in quality perceptions over time. Future research should replicate this integrative approach in other disciplinary and institutional settings, incorporate longitudinal designs, and explore the dynamic relationships between satisfaction, perceived quality, and learning outcomes.

Overall, this study provides empirical evidence supporting the central role of post-experience evaluations in perceived quality in online engineering education. It also offers a replicable analytical framework for assessing quality in fully online programs for working professionals.

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Appendix. Hierarchical regression model coefficients for predicting Quality

Model		**beta**	**t**	**p**	**95% CI**		**Collinearity Statistics**	
					Lower	**Upper**	**Tolerance**	**VIF**
M_0	(Intercept)		37.999	< .001	3.814	4.233		
	Gender (Women)		-0.211	.833	-0.358	0.289	0.998	1.002
	Previous online studies (Yes)		-0.016	.987	-0.273	0.269	0.998	1.002
M_1	(Intercept)		-1.620	.107	-0.915	0.091		
	Gender (Women)		0.570	.569	-0.111	0.202	0.945	1.058
	Previous online studies (Yes)		-0.549	.584	-0.165	0.093	0.973	1.028
	PE	0.069	0.717	.474	-0.137	0.294	0.151	6.603
	EE	0.074	1.068	.287	-0.082	0.275	0.290	3.442
	ATT	0.407	4.798	< .001	0.243	0.584	0.196	5.109
	SI	0.054	0.735	.463	-0.100	0.219	0.264	3.789
	FC	0.150	2.153	.033	0.015	0.356	0.292	3.421
	HT	-0.074	-0.939	.349	-0.331	0.118	0.225	4.444
	OLV	0.292	3.024	.003	0.112	0.536	0.151	6.616
M_2	(Intercept)		-1.693	.093	-0.919	0.071		
	Gender (Women)		0.642	.522	-0.104	0.204	0.945	1.059

	Previous online studies (Yes)		-0.138	.891	-0.138	0.120	0.946	1.057
	PE	0.073	0.770	.443	-0.130	0.295	0.151	6.604
	EE	0.106	1.520	.131	-0.041	0.315	0.281	3.563
	ATT	0.473	5.394	< .001	0.304	0.655	0.178	5.623
	SI	0.093	1.259	.210	-0.058	0.263	0.252	3.973
	FC	0.175	2.532	.012	0.048	0.387	0.286	3.499
	HT	-0.105	-1.333	.185	-0.374	0.073	0.219	4.559
	OLV	0.319	3.331	.001	0.144	0.563	0.149	6.701
	BI	-0.172	-2.461	.015	-0.316	-0.035	0.279	3.581
M_3	(Intercept)		-0.989	.324	-0.685	0.228		
	Gender (Women)		1.192	.235	-0.056	0.226	0.937	1.067
	Previous online studies (Yes)		0.692	.490	-0.077	0.161	0.924	1.082
	PE	-0.101	-1.092	.277	-0.320	0.092	0.134	7.457
	EE	0.133	2.089	.038	0.009	0.336	0.279	3.584
	ATT	0.256	2.877	.005	0.081	0.438	0.144	6.954
	SI	0.109	1.616	.108	-0.027	0.267	0.251	3.980
	FC	0.154	2.447	.016	0.037	0.347	0.285	3.511
	HT	-0.098	-1.365	.174	-0.345	0.063	0.219	4.560
	OLV	0.206	2.295	.023	0.032	0.424	0.142	7.063
	BI	-0.230	-3.561	< .001	-0.364	-0.104	0.272	3.676
	S	0.542	5.578	< .001	0.338	0.709	0.121	8.298