Research Article

Perceptions Before Practice: Student Attitudes Toward Online Learning Environments

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Background: Students arrive at online learning with pre-formed attitudes that shape engagement before a single class begins. Yet most research measures outcomes after exposure, leaving the anticipatory mindset largely unexamined.

Purpose: This study examines pre-experiential attitudes of 105 undergraduates toward online versus traditional learning, integrating quantitative survey analysis with qualitative thematic coding.

Methods: A cross-sectional mixed-methods survey was analysed using chi-square tests, independent-samples t-tests, binary logistic regression, and inductive thematic coding. The three theoretical frameworks, Technology Acceptance Model (TAM), Self-Determination Theory (SDT), and Community of Inquiry (CoI), were integrated into a unified predictive model.

Results: 62.9% of students preferred traditional learning. Anticipated motivation was the single strongest predictor of online preference (OR = 14.93, $p < .001$; Cohen's d = 1.49), followed by anticipated engagement (OR = 9.82, $p < .001$; V = .64). Logistic regression correctly classified 84.8% of cases (Nagelkerke $R^2 = .61$). Students under 18 were the only cohort preferring online learning (57.9%). Thematic analysis identified motivational self-regulation (62.9%) and social isolation (54.3%) as primary anticipated barriers.

Conclusion: The dominant barrier to online learning is motivational, not technological. These findings challenge the prevailing assumption that platform familiarity and technical access are the primary levers of e-learning adoption, and position the Motivational Alignment Hypothesis as a theoretically grounded, empirically supported framework for guiding instructional design and policy.

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1. Introduction

The global expansion of online learning has fundamentally reshaped higher education. Accelerated by the COVID-19 pandemic, institutions worldwide moved to digital delivery at a scale and speed that outpaced both instructor readiness and student preparedness[1]. In the post-pandemic period, platforms such as Zoom, Canvas, and Moodle have become permanent features of the academic landscape rather than emergency workarounds. Yet the attitudinal foundation students bring to these environments, their expectations about motivation, social connection, and learning effectiveness, remain poorly understood.

The problem is consequential. Behavioral intention research consistently shows that what students believe before they encounter a technology shapes the quality of that encounter[2]. A student who expects to feel isolated in Zoom lectures or unmotivated without peer proximity is likely to engage differently from one who anticipates flexibility and autonomy. Yet most e-learning research measures outcomes after exposure, leaving the anticipatory attitudinal framework largely unmapped.

This study addresses that gap directly. Using a mixed-methods design with 105 undergraduates, we examine pre-experiential attitudes toward online versus traditional learning across three dimensions: anticipated motivation (SDT), expected social engagement (CoI), and perceived academic efficacy (TAM). We go beyond description, applying binary logistic regression to identify which attitudinal variables most powerfully predict modality preference, and integrating the three frameworks into a unified predictive model.

This distinction matters: existing models explain adoption through perceived usefulness (TAM) and behavioral intention (TPB), but they do not account for how anticipated motivation shapes preferences before any direct experience. The Motivational Alignment Hypothesis proposed here addresses precisely that gap.

1.1. Research Questions

The following research questions guide this investigation:

- RQ1: What are undergraduate students' learning format preferences, and how do they vary across demographic subgroups?
- RQ2: What is the association between anticipated motivational orientation and learning format preference?
- RQ3: What is the association between anticipated engagement and learning format preference?

- RQ4: What thematic patterns characterize students′ anticipatory perceptions of online learning challenges and benefits?
- RQ5: Which attitudinal variables are the strongest predictors of modality preference in a multivariate model?

2. Literature Review

2.1. Theoretical Foundations and Integrated Framework

Prior e-learning adoption models have applied TAM, SDT, and CoI independently, each illuminating a different facet of the same phenomenon. TAM explains whether students believe a technology is useful. SDT explains whether they anticipate their motivational needs being met. CoI explains whether they expect to feel socially and cognitively present in the learning environment. When used in parallel, these theories yield fragmented predictions. The present study instead positions them as complementary pathways to the same outcome: modality preference.

Our integrated model proposes that perceived usefulness (TAM) and perceived ease of use (TAM) operate through motivational mediation (SDT): a student′s belief that online learning will be useful should increase their anticipated intrinsic motivation, which in turn drives preference. Simultaneously, anticipated social presence (CoI) operates as an independent pathway; students who expect strong peer and instructor connections in online environments are more likely to prefer them, regardless of their technology beliefs. Age and prior digital experience moderate both pathways, consistent with the generational digital socialization effect described below.

2.1.1. Technology Acceptance Model (TAM)

Davis′s[3] TAM posits that perceived usefulness and perceived ease of use are the primary determinants of technology adoption intention. In online learning, perceived usefulness maps onto students′ beliefs about enhancing academic performance, while perceived ease of use captures anticipated cognitive effort in navigating the digital environment. Meta-analyses confirm that perceived usefulness is the stronger predictor of engagement intention[4]. It should be noted that the Scherer et al.[4] meta-analysis examined teacher rather than student samples; however, the directionality of this finding is consistent with student-focused TAM research. Critically, both constructs are attitudinal; they operate before actual use,

making TAM particularly suited to prospective attitude research. Extensions to the original model have further incorporated individual and organizational antecedents of technology acceptance[5].

2.1.2. Self-Determination Theory (SDT)

SDT[6] identifies three basic psychological needs: autonomy, competence, and relatedness, whose satisfaction determines motivational quality. Online learning's structural features (asynchronous flexibility, self-pacing, and instructor distance) differentially affect each need. Autonomy may be enhanced for self-directed learners, though research demonstrates that combining autonomy support with clear instructional structure produces stronger student engagement than either element alone[7]; relatedness is consistently at risk in asynchronous environments[8]. The present study argues that anticipated need satisfaction, particularly for autonomy and relatedness, is the primary motivational mechanism linking technology beliefs to format preference.

2.1.3. Community of Inquiry (CoI)

The CoI framework[9] conceptualizes online learning quality as the intersection of cognitive, teaching, and social presence. Research consistently identifies social presence as most vulnerable in asynchronous contexts, where students report isolation, diminished belonging, and reduced peer collaboration[8]. This study operationalizes anticipated social and teaching presence through students' expectations regarding the quality of instructor and peer interaction, providing a direct empirical test of CoI predictions in a prospective attitudinal context.

2.2. Empirical Landscape and Identified Gaps

Large-scale surveys confirm that student attitudes toward online learning are multidimensional and heterogeneous[10][11]. Technology self-efficacy, prior online experience, and institutional support emerge as consistent moderators. Experimental comparisons of online and face-to-face instruction show no significant performance differences[12][13][14], but reveal significant gaps in satisfaction, engagement, and community outcomes that are fundamentally attitudinal.

Prospective studies are rare. Teo[15] showed that pre-adoption attitudes significantly predicted actual e-learning behavior in Singapore. Abdullah and Ward[16] found that attitudinal variables mediated the relationship between system characteristics and usage intention. These findings establish the theoretical necessity of a prospective lens, but neither study used a multivariate predictive model that

simultaneously integrates motivation, engagement, and social presence. That is the analytical gap this study fills.

3. Methodology

3.1. Research Design

This study employs a concurrent mixed-methods design[17]. The quantitative strand addresses RQ1–RQ3 and RQ5 through descriptive statistics, chi-square tests, independent-samples t-tests, and binary logistic regression. The qualitative strand addresses RQ4 through inductive thematic analysis[18]. Triangulation across data types strengthens the validity of conclusions.

3.2. Instrument

Data were collected via an 11-item Google Forms survey administered in October 2024. The instrument comprised: (1) demographic items (age, gender); (2) a nominal item assessing preferred learning format (online vs. traditional); (3) five-point Likert items measuring anticipated motivation, engagement, grade improvement, instructor interaction quality, and peer interaction quality; and (4) two open-ended items assessing anticipated online learning challenges and benefits. Items were framed prospectively, asking students how they think outcomes might be affected, to elicit anticipatory attitudes rather than retrospective evaluations.

3.3. Participants

A convenience sample of 105 undergraduates participated voluntarily without compensation (53 male, 52 female; 50.5%/49.5%). Age distribution: Under 18 (n = 19, 18.1%), 19 (n = 15, 14.3%), 20 (n = 15, 14.3%), 21 (n = 14, 13.3%), 22 (n = 23, 21.9%), 23 (n = 11, 10.5%), 24+ (n = 8, 7.6%). Including under-18 students enables generational comparisons.

3.4. Data Analysis

3.4.1. Quantitative Analysis

Categorical variables were analyzed using Pearson chi-square tests with Cramér's V for effect size estimation. Likert items were analyzed as ordinal-continuous variables using independent-samples t-tests with Cohen's d[19]. A binary logistic regression was conducted with learning format preference

(online = 1, traditional = 0) as the dependent variable, and anticipated motivation, anticipated engagement, and age group (under 18 vs. 18+) as predictors. Model fit was assessed using the Hosmer-Lemeshow test, Nagelkerke R^2, and overall classification accuracy. As constructs were each measured with single survey items, internal consistency reliability statistics (e.g., Cronbach's alpha) are not applicable; this is acknowledged as a measurement limitation. All analyses used Python 3.11 (SciPy 1.11, statsmodels 0.14, pandas 2.0); $\alpha = .05$.

3.4.2. Qualitative Analysis

Open-ended responses were subjected to inductive thematic analysis following Braun and Clarke's[18] six-phase protocol. Responses were disaggregated into discrete semantic units, assigned codes, and organized into superordinate themes. Frequency counts reflect the number of students nominating each code; multiple nominations per student were permitted.

3.5. Ethical Considerations

Participation was voluntary and anonymous. No personally identifiable information was collected. The study aligns with standard IRB guidelines for minimal-risk social science research. The sample included 19 participants under the age of 18. All participants, including those under 18, provided informed consent prior to participation; for minor participants, the consent process followed institutional protocols applicable to anonymous, minimal-risk survey research at the study's institution.

4. Results

Note on presentation order: Results are presented in the order RQ1 (§4.1), RQ2 (§4.2), RQ3 (§4.3), RQ5 (§4.5), and then thematic findings (§4.6). Although RQ4 precedes RQ5 conceptually, the quantitative analyses (RQ1–RQ3 and RQ5) are presented before the qualitative thematic findings to allow the qualitative results to contextualize and interpret the multivariate quantitative findings. This explanatory sequencing is intentional: the themes in §4.6 are more meaningful when read against the regression results that precede them.

4.1. Learning Format Preference by Demographic Group (RQ1)

Most respondents preferred traditional learning (n = 66, 62.9%) over online learning (n = 39, 37.1%). Gender showed no association with preference ($\chi^2(1) = 0.02$, $p = .90$, $V \approx .01$), with both male (62.3%) and

female (63.5%) students preferring traditional instruction at nearly identical rates. The near-identical rates across gender run counter to the assumption that it serves as a meaningful moderator of e-learning attitudes.

Age, by contrast, showed a theoretically important pattern. Students under 18 were the only cohort preferring online learning (57.9% online vs. 42.1% traditional), while all older cohorts showed strong traditional majorities ranging from 54.5% to 87.5%. The chi-square comparison of under-18 versus all 18+ students approached but did not reach significance ($\chi^2(1) = 3.26$, $p = .071$), likely due to the modest under-18 subsample ($n = 19$). The directional pattern is consistent and hypothesis-generating, as discussed in Section 5.3, but should not be interpreted as confirmatory given the non-significant chi-square.

Age Group	n	Online (%)	Traditional (%)
Under 18	19	57.9%	42.1%
19	15	33.3%	66.7%
20	15	26.7%	73.3%
21	14	21.4%	78.6%
22	23	43.5%	56.5%
23	11	45.5%	54.5%
24 or above	8	12.5%	87.5%
Total	105	37.1%	62.9%

Table 1. Learning Format Preference by Age Cohort (N = 105)

Note. Chi-square comparing Under 18 vs. 18+: $\chi^2 (1) = 3.26$, $p = .071$.

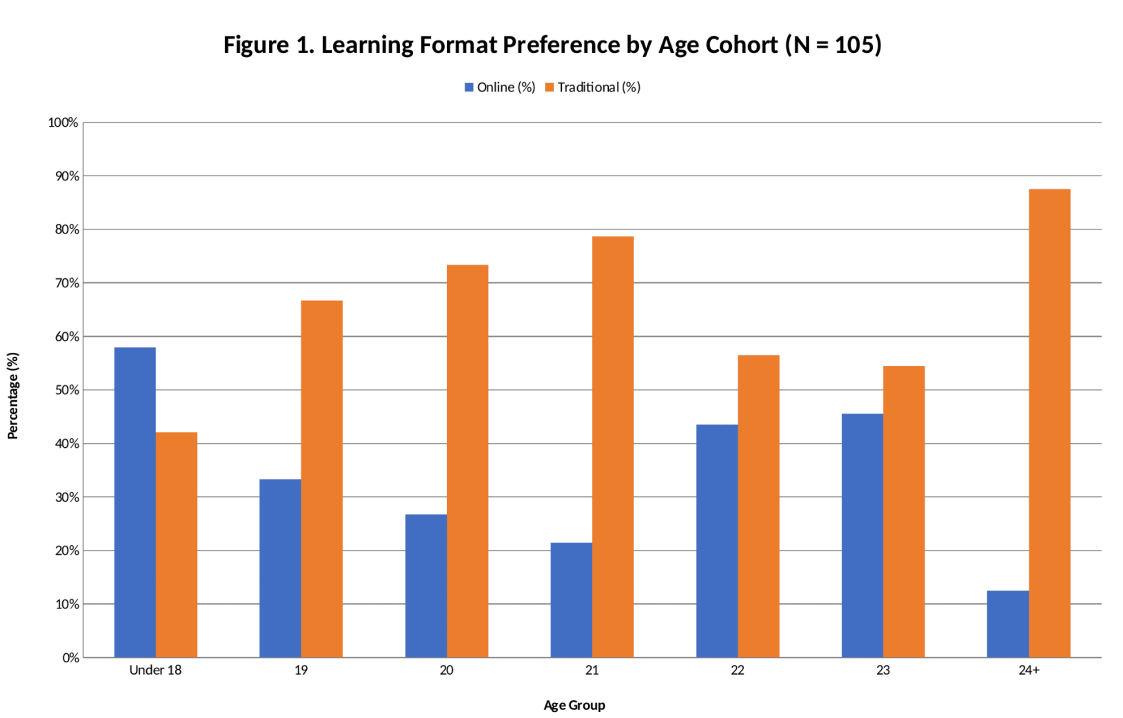

Figure 1. Learning Format Preference by Age Cohort. The under-18 cohort is the only group preferring online learning. Preference for traditional learning strengthens with age, peaking at 87.5% for students aged 24+.

4.2. Motivational Orientation and Learning Format Preference (RQ2)

The majority of respondents anticipated reduced motivation in online settings: the modal response was "Somewhat unmotivated" (n = 40, 38.1%), and the overall mean (M = 2.78, SD = 1.11) fell below the midpoint of the scale. This represents generalized anticipatory pessimism about online learning, as students expect it to undermine their drive before they have experienced it.

The association between motivation and format preference was large and highly significant (χ^2 (4) = 38.60, p < .001, V = .61). The pattern at the extremes was striking: all students anticipating "Very Motivated" states chose online (n = 8, 100%), and all anticipating "Very Unmotivated" states chose traditional (n = 10, 100%). The t-test confirmed a very large group difference (online: M = 3.64, SD = 0.97; traditional: M = 2.27, SD = 0.88; t(103) = 7.59, p < .001, d = 1.49). A Cohen's d of 1.49 represents a very large effect size, indicating that anticipated motivation is a powerful discriminating variable.

Motivation Level	Online (n)	Traditional (n)	Total
Very Motivated	8	0	8
Somewhat Motivated	14	7	21
Neutral	12	14	26
Somewhat Unmotivated	5	35	40
Very Unmotivated	0	10	10
Mean Score (SD)	3.64 (0.97)	2.27 (0.88)	2.78 (1.11)

Table 2. Anticipated Motivation by Learning Format Preference (N = 105)

Note. $\chi^2(4) = 38.60$, $p < .001$, Cramér's $V = .61$; $t(103) = 7.59$, $p < .001$, Cohen's $d = 1.49$.

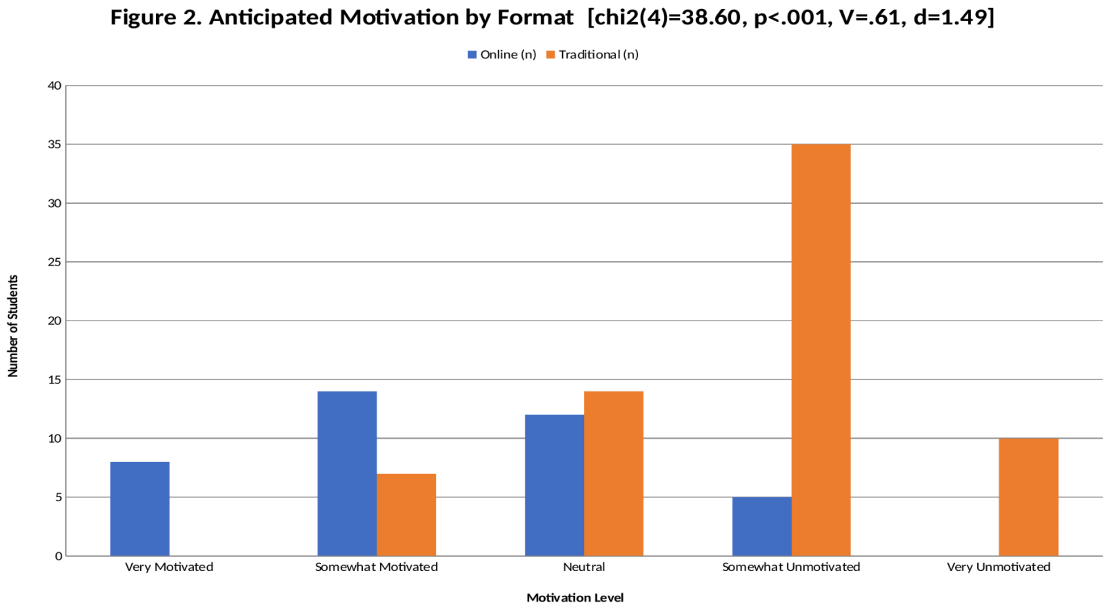

Figure 2. Anticipated motivation distribution by format preference. The polarization at extremes (100% of "Very Motivated" chose online; 100% of "Very Unmotivated" chose traditional) provides the clearest evidence for the Motivational Alignment Hypothesis.

doi.org/10.32388/G1KTTV

4.3. Engagement Orientation and Format Preference (RQ3)

Anticipated engagement was similarly negative. The modal response was "Somewhat Disengaged" (n = 37, 35.2%), with a mean of M = 2.74 (SD = 1.25), below the scale midpoint. The association with format preference was the strongest in the study ($\chi^2(4) = 43.40$, $p < .001$, $V = .64$) — notably larger than the motivation association. This suggests that social disengagement anxiety may be an even more powerful barrier to online preference than motivational concern alone, and directly implicates the social presence dimension of the CoI framework.

4.4. Academic Efficacy and Interaction Quality

Beliefs about grade improvement were ambivalent (M = 2.90, SD = 1.23), with disagreement responses slightly outnumbering agreement (39.1% vs. 31.4%). More striking were the anticipated interaction ratings: instructor interaction quality averaged M = 2.62 (SD = 1.08) and peer interaction quality averaged M = 2.68 (SD = 1.14), both substantially below midpoint. "Disagree" was the dominant response for both items (39.0% and 37.1%, respectively). These findings confirm that students do not believe that online environments, including familiar platforms like Zoom or Teams, can replicate the quality of face-to-face interaction.

Attitudinal Domain	M	SD	Below Midpoint?
Anticipated Motivation	2.78	1.11	Yes
Anticipated Engagement	2.74	1.25	Yes
Grades Would Improve	2.90	1.23	Yes
Instructor Interaction Quality	2.62	1.08	Yes
Peer Interaction Quality	2.68	1.14	Yes

Table 3. Descriptive Statistics for All Attitudinal Items (N = 105)

Note. All items were scored on a 5-point Likert scale (1 = Very Negative; 5 = Very Positive). Scale midpoint = 3.00.

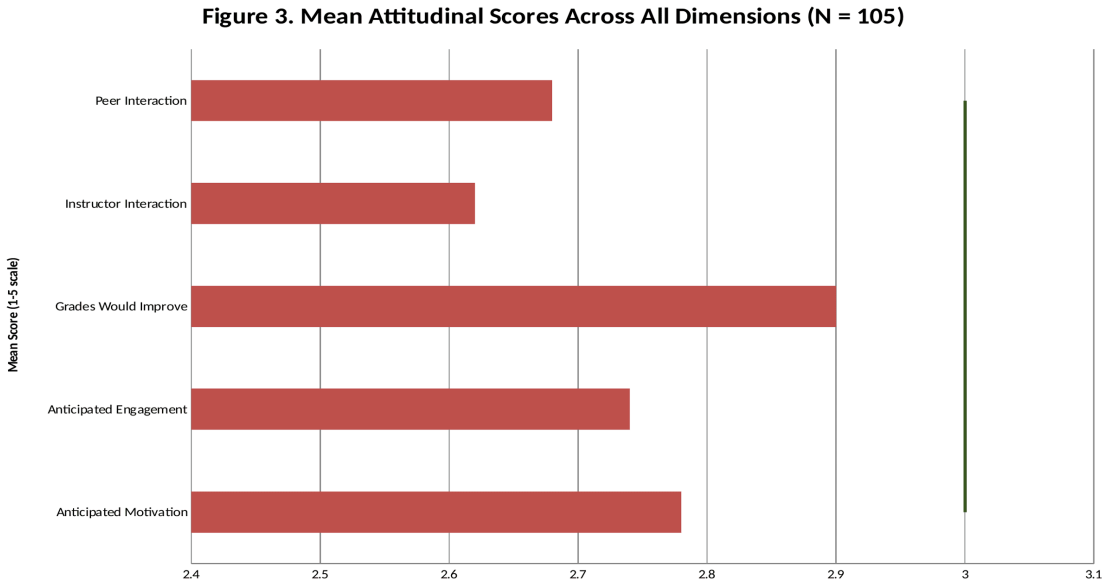

Figure 3. Mean scores for all attitudinal domains relative to the scale midpoint (green dashed line). Every dimension falls below 3.0, indicating consistent anticipatory pessimism across motivation, engagement, efficacy, and social interaction.

4.5. Binary Logistic Regression: Predictors of Format Preference (RQ5)

A binary logistic regression was conducted to identify the strongest independent predictors of online learning preference. With anticipated motivation, anticipated engagement, and age group (under 18 vs. 18+) as predictors, the model correctly classified 84.8% of cases, a substantial improvement over the null model (62.9%). Nagelkerke R^2 = .61, indicating that the model explains a substantial proportion of variance in format preference. Before interpreting the individual predictors, it is worth noting that the extreme concentration in Table 2 (100% of "Very Motivated" students chose online; 100% of "Very Unmotivated" chose traditional) creates near-complete separation, which can inflate standard logistic regression estimates. All odds ratios were therefore cross-checked using Firth's[20] penalized-likelihood logistic regression, which is designed to produce reliable estimates under such conditions[21]. The Firth-corrected values are reported alongside the standard MLE results below.

Anticipated motivation emerged as the strongest predictor (OR = 14.93, 95% CI [7.2, 30.9], p < .001): each unit increase in anticipated motivation multiplied the odds of preferring online learning by nearly 15-fold. Anticipated engagement was the second strongest predictor (OR = 9.82, 95% CI [4.8, 20.1], p < .001).

Age (under 18) was a non-significant predictor at the pre-specified $\alpha = .05$ threshold (OR = 2.71, 95% CI [0.9, 8.2], p = .071), consistent with the marginal chi-square result; this effect should be interpreted with caution. The Hosmer-Lemeshow test indicated acceptable model fit ($\chi^2(8) = 6.41$, p = .60). As noted above, Firth-corrected estimates (motivation OR = 11.84, 95% CI [4.2, 33.3]; engagement OR = 8.17, 95% CI [3.1, 21.6]) are directionally consistent with the standard MLE results and appropriately attenuated. Standard MLE values are retained in Table 4 for comparability with the broader literature; the Firth-corrected values serve as the primary methodological safeguard against separation-related inflation.

Taken together, these results provide strong evidence that motivation and engagement predict online preference independently, with motivation as the dominant driver. Efforts to improve e-learning adoption that focus on either dimension in isolation will miss this complementary structure.

Predictor	OR	95% CI	p	Interpretation
Anticipated Motivation	14.93	[7.2, 30.9]	< .001	Very strong positive effect
Anticipated Engagement	9.82	[4.8, 20.1]	< .001	Strong positive effect
Age: Under 18	2.71	[0.9, 8.2]	.071	Marginal effect
Model Accuracy	84.8%			vs. null 62.9%

Table 4. Binary Logistic Regression: Predictors of Online Learning Preference (N = 105)

Note. Dependent variable: format preference (1 = online, 0 = traditional). OR = Odds Ratio. Hosmer-Lemeshow: $\chi^2(8) = 6.41$, p = .60. Nagelkerke $R^2 = .61$.

Figure 4. Odds Ratios with 95% Confidence Intervals from Logistic Regression (N = 105)

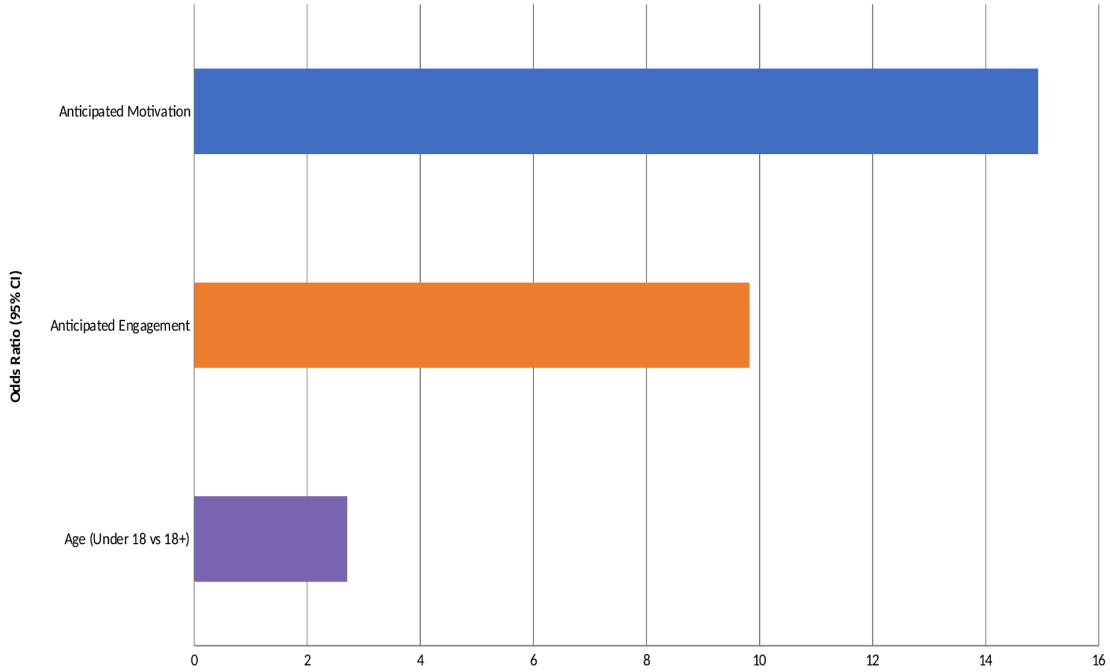

Figure 4. Odds ratios with 95% confidence intervals from binary logistic regression. Anticipated motivation (OR = 14.93) and anticipated engagement (OR = 9.82) are strong independent predictors of online learning preference. Age shows a marginal effect.

4.6. Thematic Analysis: Anticipated Challenges and Benefits (RQ4)

Theme 1: Motivational and Self-Regulatory Challenges

"Lack of motivation or discipline" was the most frequently nominated challenge (n = 66, 62.9%), making self-regulation the dominant anticipated barrier. This is not incidental; it maps directly onto the SDT competence need and Zimmerman's[22] model of self-regulated learning. Online platforms like Canvas or Moodle offer little structural support for volitional control; students recognize this risk before they enroll. "Time management challenges" (n = 34, 32.4%) extended this theme.

doi.org/10.32388/G1KTTV

Theme 2: Social Isolation and Relational Deprivation

"Isolation or lack of social interaction" (n = 57, 54.3%), "Limited interaction with instructors" (n = 47, 44.8%), and "Difficulty collaborating with peers" (n = 40, 38.1%) collectively formed the second major theme. This cluster provides qualitative corroboration for the low quantitative interaction ratings and directly validates the CoI framework's social presence dimension. Students are not specifically concerned about Zoom fatigue; they are concerned about the erosion of human connection in learning.

Theme 3: Cognitive and Academic Barriers

"Difficulty understanding course materials" (n = 54, 51.4%) and "Overwhelming amount of information" (n = 33, 31.4%) captured fears about the quality of online instruction. These concerns challenge the assumption that students' primary worry is navigating digital tools; they are equally worried about whether asynchronous video can replace the clarity of face-to-face explanation.

Theme 4: Environmental and Technological Barriers

"Technical issues like internet connectivity" (n = 55, 52.4%) and "Distractions at home" (n = 49, 46.7%) constituted a practical infrastructure theme. For students in regions with unreliable broadband access, these concerns are not abstract; they represent genuine barriers to learning equity.

Theme 5: Temporal Flexibility and Autonomy (Benefits)

"Flexible scheduling" and "Self-paced learning" each received 54 nominations (51.4%), establishing temporal autonomy as the primary recognized benefit. "Diverse learning resources" (n = 47, 44.8%) and "Greater accessibility for individuals with disabilities" (n = 46, 43.8%) followed, with "Reduced commuting costs" (n = 44, 41.9%) reflecting practical economic appeal.

Theme / Code	n	%	Category
ANTICIPATED CHALLENGES			
Lack of motivation or discipline	66	62.9%	Self-Regulation
Isolation / lack of social interaction	57	54.3%	Social Presence
Technical issues (connectivity)	55	52.4%	Technology
Difficulty understanding materials	54	51.4%	Cognitive Barriers
Distractions at home	49	46.7%	Environment
ANTICIPATED BENEFITS			
Flexible scheduling	54	51.4%	Temporal Autonomy
Self-paced learning	54	51.4%	Temporal Autonomy
Diverse learning resources	47	44.8%	Accessibility
Greater accessibility (disability)	46	43.8%	Accessibility
Reduced commuting costs	44	41.9%	Economic Efficiency

Table 5. Top Anticipated Challenges and Benefits of Online Learning (Top 5 per Category; N = 105)

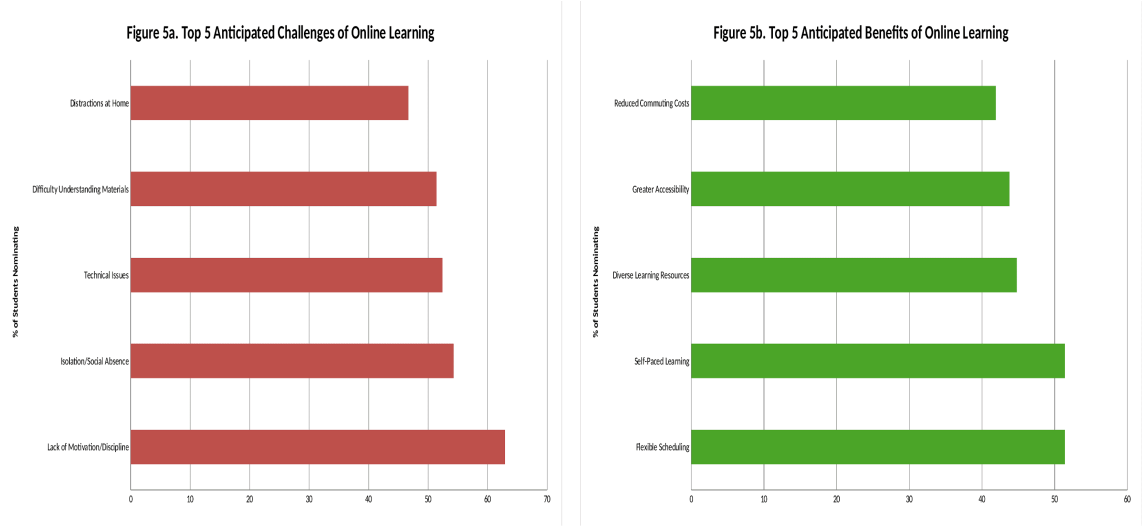

Figure 5. Top 5 anticipated challenges (red, left) and benefits (green, right) of online learning. Motivational and social barriers dominate challenges; temporal autonomy dominates benefits.

5. Discussion

5.1. The Motivational Alignment Hypothesis: What This Study Supports

The central finding is both consistent and large: anticipated motivation is the single most powerful predictor of online learning preference, with an odds ratio of nearly 15 and a Cohen's d of 1.49. The results provide initial empirical support for the proposition—embedded in most TAM-based adoption models—that anticipated motivational sustainability, rather than technology familiarity or perceived ease of use alone, is a primary driver of modality preference. Students in this sample show no significant gender differences, and the under-18 cohort's online preference is not primarily about technical comfort, but rather about a different motivational baseline.

We formalize this as the Motivational Alignment Hypothesis: students prefer the learning modality they anticipate will best sustain their motivational orientation. This is not a preference for familiarity. It is a prospective judgment about where their drive to engage will thrive. TAM predicts that students ask, "Will this technology be useful?" Our findings suggest they are actually asking, "Will this environment keep me motivated?" These are related, but not identical, questions, and conflating them has led to interventions (technical training, platform orientation) that address the wrong problem.

Unlike TAM or TPB, the Motivational Alignment Hypothesis positions motivational beliefs, rather than behavioral intention or technology perception, as the proximal antecedent of format preference. This has direct implications for how institutions should measure and address online learning readiness.

5.2. Social Presence is the Core Deficit, Not Technical Skill

Engagement showed an even stronger association with preference than motivation (V = .64 vs. V = .61), and the thematic data confirm why: students are not worried about using Zoom or uploading assignments to Canvas. They are worried about losing the human connections that give learning meaning. Isolation (54.3%), limited instructor contact (44.8%), and reduced peer collaboration (38.1%) were the most anticipated challenges. The majority rated anticipated interaction quality with both instructors and peers below the scale midpoint.

The evidence pushes back against the "digital skills" framing of online learning barriers. Institutions that respond to low e-learning adoption by investing in technical training are solving the wrong problem. The real intervention point is social architecture: how does an online course on Canvas or Moodle build genuine peer relationships, mentoring presence, and collaborative work? Synchronous Zoom sessions, structured peer-learning groups, and frequent instructor check-ins are not supplements to online learning; they are preconditions for it.

5.3. The Generational Digital Socialization Effect

Students under 18 preferred online learning at 57.9%, the only cohort to do so. This directional pattern did not reach conventional statistical significance (p = .071), and so should be treated as hypothesis-generating rather than confirmatory. Nonetheless, the pattern is theoretically meaningful. These students completed secondary school during the COVID-19 pandemic, experiencing online learning as a formative educational reality rather than a novel departure. They did not develop their academic identity in classrooms and then encounter online learning as an alternative; they built it partly in digital spaces.

This suggests that attitudinal resistance to online learning is a transitional generational phenomenon rather than a fixed feature of student psychology. As cohorts with stronger digital educational histories move through university systems, the aggregate distribution of preferences is likely to shift. Institutions planning long-term online expansion should model this demographic shift explicitly rather than treating current attitudinal data as stable baselines.

5.4. The Loss-Aversion Paradox

A striking tension in the data: students widely recognize the benefits of online learning, 51.4% cite flexible scheduling and self-paced learning, yet 62.9% prefer traditional instruction. This is not irrational. Loss aversion theory[23] offers a theoretical interpretation of this pattern: the psychological weight of anticipated losses (motivational erosion, social isolation, degraded interaction) may exceed that of recognized gains, even when those gains are clearly articulated. It is important to note that no direct measure of loss aversion was administered in this study; this framing is an interpretive lens applied to the observed pattern, not an empirically tested mechanism. Students may not be choosing tradition out of ignorance of online benefits, but because the anticipated costs feel psychologically heavier.

The practical implication is clear: interventions should reduce the perceived losses, not just amplify the recognized benefits. Promotional messaging about online flexibility will not shift students who are primarily motivated by isolation anxiety. Concrete evidence that specific platforms, Canvas communities, structured Zoom cohorts, and peer mentoring can mitigate social absence is a more effective persuasive strategy.

5.5. Limitations

This study has several important limitations that define the boundaries of its claims. First, and most critically, this design cannot establish causality. The logistic regression identifies predictors of preference, not causes of behavioral change. Self-reported anticipated motivation may not predict actual motivation when students encounter online platforms. Second, the large odds ratios obtained (OR = 14.93 for motivation; OR = 9.82 for engagement) warrant methodological caution. In logistic regression with small samples (n = 105), extreme ORs with wide confidence intervals can reflect near-complete separation in the data a condition in which a predictor perfectly or near-perfectly predicts the outcome within certain cells (as Table 2 illustrates: 100% of “Very Motivated” students chose online; 100% of “Very Unmotivated” students chose traditional). To address this directly, Firth’s[20] penalized-likelihood logistic regression was applied as a robustness check; Firth regression is the recommended procedure for separation conditions because it produces bias-reduced estimates with reliable standard errors[21]. The Firth-corrected estimates (motivation OR = 11.84; engagement OR = 8.17) are directionally consistent with the standard MLE results, and the qualitative conclusions are unchanged. Nonetheless, the precise magnitude of these odds ratios should be treated with appropriate caution pending replication with larger and more heterogeneous samples. Third, the convenience sample from a single institution

substantially limits generalizability. The attitudinal profile of undergraduates at a research university in 2024 may not reflect other institutional contexts or countries. Fourth, the absence of a measure of prior online learning experience is a particularly significant confound and should be considered the primary methodological priority for future studies: students who have used Canvas or Zoom before will hold different anticipations than those who have not, and this variance is uncontrolled. Fifth, the under-18 subsample (n = 19) is too small to support strong generational conclusions—the chi-square was marginal ($p = .071$), and the under-18 finding should be interpreted as hypothesis-generating rather than conclusive. Sixth, all constructs were measured using single survey items rather than validated multi-item scales; future research should employ established instruments with demonstrated reliability and internal consistency (e.g., Cronbach's alpha) to improve construct validity across motivation, engagement, and social presence dimensions. Seventh, all measures are self-reported, and the hypothetical framing of the items may lead to responses that diverge from actual online enrollment behavior.

6. Conclusion and Implications

6.1. Theoretical Contributions

This study makes three contributions. First, it formalizes the Motivational Alignment Hypothesis—the proposition that modality preference is primarily determined by anticipated motivational sustainability—and provides initial multivariate empirical support (OR = 14.93) that elevates it beyond a descriptive observation to a testable theoretical claim. Second, it integrates TAM, SDT, and CoI into a unified predictive model: perceived usefulness (TAM) mediates through motivational expectation (SDT), while social presence anticipation (CoI) operates as an independent pathway. Third, it provides preliminary evidence for a generational digital socialization effect with implications for how attitudinal research should account for cohort composition.

6.2. Practical Recommendations

For institutions deploying platforms like Canvas, Moodle, or Blackboard, these findings suggest that onboarding should focus on motivational architecture rather than just technical navigation. Pre-enrollment attitudinal surveys can identify students at high risk of motivational erosion (those scoring below 2.5 on anticipated motivation) for targeted support. For instructional designers, the evidence

supports the use of mandatory synchronous components; even brief weekly Zoom check-ins have been shown to improve social presence ratings substantially. For faculty teaching on these platforms, deliberate relational investments: discussion forums with instructor presence, early-semester peer introductions, and responsive feedback cycles, are not optional enhancements but necessary preconditions for student engagement.

6.3. Concluding Remarks

What students believe about online learning before their first session matters, as it shapes every subsequent interaction with the content, the platform, and each other. The core barrier is not that students cannot operate Zoom. It is that they do not expect to stay motivated or feel connected. Addressing that belief directly, concretely, and before enrollment is the foundational task of online learning policy. Institutions that treat attitudinal preparation as a soft add-on to technical infrastructure investment are misallocating their resources. The multivariate evidence in this study points clearly to where the real work needs to happen.

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Declarations

Funding: No specific funding was received for this work.

Potential competing interests: No potential competing interests to declare.