



DETERMINANTS OF BEHAVIORAL INTENTION TO USE LARGE LANGUAGE MODELS FOR LEARNING AMONG EDUCATIONAL TECHNOLOGY STUDENTS IN NIGERIAN UNIVERSITIES

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Abstract

Large language models (LLMs) such as ChatGPT and Claude are Artificial Intelligence systems trained on massive datasets to understand and generate human-like responses to user prompts. Most studies on LLM adoption in higher education focus on usage patterns, with limited attention to how trust, academic integrity concerns, performance expectancy, and facilitating conditions relate to students' intention to use these tools for learning. This study examined how these factors predict Educational Technology students' intention to use LLMs for learning. A descriptive survey design of the correlational type was adopted, with 250 undergraduates sampled through simple random sampling from two Nigerian universities. Data were collected using a validated questionnaire and analyzed using multiple regression and a paired-samples t-test at the .05 level of significance. All four predictors significantly predicted behavioral intention, $F(4, 245) = 21.35$, $p < .001$, $R^2 = .258$. Performance Expectancy was the strongest positive predictor ($\beta = .371$), and Academic Integrity Concern was the only negative predictor ($\beta = -.193$). Students reported significantly higher intention to use ChatGPT ($M = 3.11$) than Claude ($M = 2.75$), $t(249) = 6.61$, $p < .001$. The study concludes that intention to use LLMs is associated with perceived benefits, enabling conditions, trust in output, and ethical concerns. It recommends demonstrating academic uses of LLMs, teaching students to verify LLM output, and publishing clear integrity guidelines.

Keywords: Behavioral Intention, Large Language Models, Performance Expectancy, Trust in AI-Generated Content, Academic Integrity Concern

Introduction

Determinants of use are rarely just about whether a technology is available; they are about the beliefs, conditions, trust, and ethical concerns that form whether a person actually chooses to rely on it. These determinants have long formed adoption research across different technologies, and nowhere is this clearer than in the recent rise of Large Language Models (LLMs). LLMs are artificial intelligence systems trained on vast amounts of text to understand and generate human-like language in response to natural prompts. Tools built on this technology, such as ChatGPT and Claude, have moved from novelty to a routine feature of higher education within a few years of their public release, with students now using them for tasks ranging from summarising literature to drafting assignments and preparing for examinations (Zogheib & Zogheib, 2024). A global survey of more than 23,000 higher education students across 109 countries found that the overwhelming majority had already engaged with ChatGPT within its first year of release, describing it as a source of academic support even as they voiced reservations about its limitations (Ravšelj et al., 2025).

What pushes a student toward or away from using an LLM is rarely just one thing, and the determinants examined in this study can each be traced through the literature in turn. The first is performance expectancy,



the belief that a tool genuinely improves academic performance. This belief has repeatedly emerged as one of the strongest predictors of students' intention to use ChatGPT or other LLMs (Grassini et al., 2024; Masrek et al., 2025), including in Nigerian and Ghanaian samples (Owan et al., 2025; Salifu et al., 2024); in other words, students are more likely to adopt the tool when they are convinced it actually helps them do better in their studies. The second is facilitating conditions, meaning the resources, skills, and support students need to use a tool effectively. The evidence here is less settled. Some studies find facilitating conditions to be a significant driver of adoption (Habibi et al., 2023; Masrek et al., 2025), while others find that, once habit and social influence are accounted for, facilitating conditions and even performance expectancy lose their significance altogether (G. C. et al., 2024). In a large Nigerian sample, facilitating conditions were even a significant negative predictor of intention to use ChatGPT (Owan et al., 2025). This inconsistency is itself part of why the variable deserves fresh empirical attention among Nigerian Educational Technology students.

Trust in AI-generated content is the third determinant examined in this study. It refers to how much students believe the answers an LLM gives them are accurate and dependable. Studies show that students use these tools far more than they trust them: in one study of six universities, almost all students reported using ChatGPT or similar tools, yet fewer than one in four said they trusted the content it produced (Cabrera & Neville, 2025). Trust has also been shown to matter for intention in Africa, where perceived trust significantly predicted Ghanaian students' intention to use ChatGPT (Salifu et al., 2024), which makes it a construct worth testing alongside performance expectancy in Nigeria. Other researchers have found that this trust is not fixed; it grows or shrinks as students gain more experience with the tool (Wang et al., 2025), and that students who understand more about how ChatGPT works tend to trust it more, which in turn makes them more likely to use it (Amin et al., 2025). Other factors can also influence trust. For example, one experimental study found that students trusted AI-generated content more simply because a teacher had endorsed it, showing that trust is formed by the situation rather than something students form on their own (Alubthane, 2026).

Academic integrity concern is the fourth determinant, and unlike the other three, it is a normative rather than a functional judgment: it reflects how ethically acceptable a student considers the use of an LLM, not how useful or accessible it is. Researchers have argued that AI writing tools threaten academic integrity because plagiarism-detection methods struggle to keep pace with how easily these tools generate text (Cotton et al., 2024). Documented cases range from AI-assisted plagiarism to fully outsourced coursework, as detection systems increasingly fail to distinguish AI-generated text from a student's own writing (Bukar et al., 2024). The issue is also documented in Nigerian universities, where ChatGPT use for academic dishonesty has been reported among public university students (Ofem et al., 2025). One study found that academic integrity moderates the relationship between the usual predictors of adoption and students' actual use of ChatGPT, meaning that even students who rate the tool as useful may still not use it once integrity concerns are triggered (Subhani et al., 2025). For a student population still forming its academic habits, this tension between ethical caution and practical convenience makes academic integrity concern a determinant worth testing directly, rather than assuming it will be captured by trust or performance expectancy alone.

These four determinants do not operate separately. Performance expectancy captures what students believe the tool can do for them, facilitating conditions capture what their environment allows them to do with it, trust in AI-generated content captures how much they are willing to rely on what it produces, and academic integrity concern captures the ethical weight they attach to using it at all. They all represent the belief, resource, credibility, and ethical conditions under which Educational Technology students in Nigerian universities decide whether, and how consistently, to use LLMs for learning. Given their training to eventually introduce technology into classrooms of their own, how these students resolve that decision is worth understanding in its own right, and worth understanding across the two LLMs most available to them, ChatGPT and Claude, since a preference for one over the other may itself signal something about how these determinants operate in practice. It is against this background that the present study examines the combined



influence of these four determinants on students' behavioral intention, and compares their behavioral intention to use ChatGPT or Claude for learning.

Statement of the Problem

Nigerian students are increasingly using LLMs for learning, but research on what forms their intention to use them is still limited in three ways. First, a Nigerian study of 8,496 tertiary students examined ChatGPT use with UTAUT2 constructs, but did not include trust in AI-generated content or academic integrity concern (Owan et al., 2025). Second, Nigerian research on academic integrity has looked at students' use of ChatGPT for academic dishonesty (Ofem et al., 2025), but has not tested integrity concern together with performance expectancy, facilitating conditions, and trust as predictors of intention to use LLMs. Third, these studies draw on general student populations rather than Educational Technology students, who will later be expected to introduce such tools into classrooms. Most studies also focus on ChatGPT alone, so it is unclear whether intention differs for other tools such as Claude (Strzelecki, 2024; Xue et al., 2026). Little is known about how these four determinants together form intention among Educational Technology students in Nigerian universities, or whether their intention differs between ChatGPT and Claude. This study addressed that gap.

Purpose of the Study

This study examined the determinants of Educational Technology students' behavioral intention to use ChatGPT and Claude for learning. Specifically, the study:

1. Determined the influence of Performance Expectancy on students' behavioral intention to use LLMs for learning.
2. Determined the influence of Facilitating Conditions on students' behavioral intention to use LLMs for learning.
3. Determined the influence of Trust in AI-Generated Content on students' behavioral intention to use LLMs for learning.
4. Determined the influence of Academic Integrity Concern on students' behavioral intention to use LLMs for learning.

Research Questions

1. What is the influence of Performance Expectancy on students' behavioral intention to use LLMs for learning?
2. What is the influence of Facilitating Conditions on students' behavioral intention to use LLMs for learning?
3. What is the influence of Trust in AI-Generated Content on students' behavioral intention to use LLMs for learning?
4. What is the influence of Academic Integrity Concern on students' behavioral intention to use LLMs for learning?

Hypotheses

H0₁: Performance Expectancy has no significant influence on students' behavioral intention to use LLMs for learning.

H0₂: Facilitating Conditions has no significant influence on students' behavioral intention to use LLMs for learning.

H0₃: Trust in AI-Generated Content has no significant influence on students' behavioral intention to use LLMs for learning.

H0₄: Academic Integrity Concern has no significant influence on students' behavioral intention to use LLMs for learning.

H0₅: There is no significant difference between students' behavioral intention to use ChatGPT and their behavioral intention to use Claude for learning.

Theoretical Framework and Conceptual Model

Theoretical Framework

This study is anchored on the Unified Theory of Acceptance and Use of Technology (UTAUT; Venkatesh et al., 2003), which consolidated eight earlier technology-acceptance models into four core determinants of behavioral intention: performance expectancy, effort expectancy, social influence, and facilitating conditions. UTAUT was chosen because it was developed specifically to explain intention to adopt a new technology within an institutional setting, which matches the case of Educational Technology students adopting large language models (LLMs) for learning. Of the four original constructs, this study retains performance expectancy and facilitating conditions, since they most directly capture the perceived academic benefit of LLMs and the practical conditions that enable their use; effort expectancy and social influence are not separately modelled, as their territory is substantially covered by facilitating conditions and by the two extended constructs described below.

UTAUT predates generative AI and does not account for two issues that are central to LLM use: whether generated content can be trusted, and whether using it poses an ethical or institutional risk. The model is therefore extended with two constructs. Trust in AI-generated content is grounded in trust theory as applied to human–technology interaction (McKnight et al., 2002), which frames trust as a belief in a system's competence, benevolence, and integrity; here it reflects students' belief that LLM output is accurate and reliable. Academic integrity concern is grounded in the attitudinal and normative components of the theory of planned behaviour (Ajzen, 1991) together with deterrence-based accounts of academic dishonesty, and reflects students' worry that LLM use may be judged as cheating, penalised, or damaging to their own learning. Unlike the other three constructs, academic integrity concern is expected to suppress, rather than raise, behavioral intention.

Conceptual Model

Figure 1 translates this position into five testable paths. Performance expectancy, facilitating conditions, and trust in AI-generated content are hypothesised to positively predict behavioral intention to use LLMs for learning (H0₁-H0₃); academic integrity concern is hypothesised to negatively predict it (H0₄). Behavioral intention is then examined as it is expressed toward two specific tools, ChatGPT and Claude, and these two expressions are compared directly (H0₅), so platform preference is treated as an outcome-level comparison rather than a further predictor. The differing signs reflect a conceptual distinction between the four determinants rather than an arbitrary assignment. Performance expectancy, facilitating conditions, and trust in AI-generated content are enabling beliefs: each describes a perceived benefit or a removed barrier (usefulness, access and skill, and confidence in output, respectively), and in prior UTAUT and trust-in-technology research such beliefs consistently raise, rather than lower, behavioral intention. Academic integrity concern is conceptually distinct because it captures a perceived risk or cost of use, the possibility of being judged as cheating, penalised, or of eroding one's own competence, and worry about a negative consequence of an action is theorised to discourage that action, so it is modelled as a deterrent. These signs represent the study's a priori theoretical expectation for each path and are stated as null hypotheses (no

significant influence) to be tested against the data; the actual direction and significance of each relationship remain empirical questions to be settled by the analysis, not assumptions built into the results.

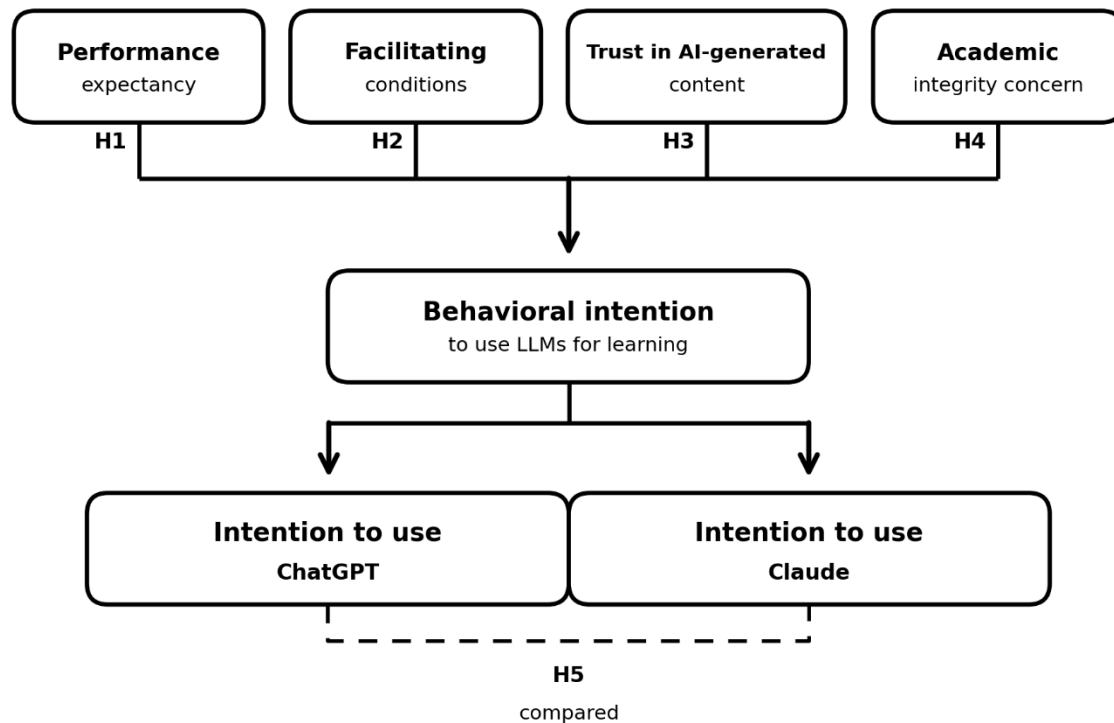


Figure 1. Conceptual model of the determinants of behavioral intention to use LLMs for learning. Performance expectancy, facilitating conditions, and trust in AI-generated content are expected to relate positively to behavioral intention, and academic integrity concern negatively; these directions are theoretical expectations, and each hypothesis is tested in null form.

Methodology

Research Design and Population

This study adopted a descriptive survey research design of the correlational type, suited to examining the relationships between the four predictor variables (performance expectancy, facilitating conditions, trust in AI-generated content, and academic integrity concern) and behavioral intention, and to compare behavioral intention across ChatGPT and Claude. The population comprised Educational Technology undergraduate students from two Nigerian universities that offer the programme. Both are federal universities: University A in Kwara State and University B in Oyo State. They were selected because both are federal institutions that offer Educational Technology as a degree programme, and both provide students with campus ICT facilities and internet access. A sample of 250 undergraduates was drawn using simple random sampling to give every eligible student an equal chance of selection, with 121 respondents from University A and 129 from University B.

Research Instrument, Data Collection, and Analysis

A structured questionnaire measured the four predictors (five items each) and behavioral intention toward ChatGPT and Claude separately (four items each), all on a five-point Likert scale (1 = Strongly Disagree to 5 = Strongly Agree). For the regression, behavioral intention to use LLMs was computed as the mean of the eight ChatGPT and Claude intention items. Three Educational Technology lecturers established face and content validity. A pilot test with 35 students outside the main sample gave Cronbach's alpha values of

.76 (Performance Expectancy), .78 (Facilitating Conditions), .74 (Trust), .79 (Academic Integrity Concern), .77 (Intention to Use ChatGPT), and .76 (Intention to Use Claude), all above .70. The questionnaire was administered physically with a trained research assistant after the purpose of the study was explained and confidentiality assured. Means and standard deviations were interpreted as follows: 1.00-1.79 = Strongly Disagree, 1.80-2.59 = Disagree, 2.60-3.39 = Neutral, 3.40-4.19 = Agree, and 4.20-5.00 = Strongly Agree. Hypotheses 1 to 4 were tested with multiple regression (predictors entered simultaneously) and Hypothesis 5 with a paired-samples t-test, all at the .05 level. Regression assumptions were checked beforehand, HC3 robust standard errors were used to confirm the conclusions where heteroscedasticity was detected, and Cohen's f^2 and 95% confidence intervals were computed for each predictor.

Results

Demographic Characteristics of Respondents

Two hundred and fifty (250) Educational Technology undergraduates completed the questionnaire. Respondents were described by sex and by their preferred LLM for learning.

Table 1: Distribution of Respondents by Sex

Sex	Frequency	Percent (%)
Male	112	44.8
Female	138	55.2
Total	250	100.0

Table 2: Distribution of Respondents by Preferred LLM

Preferred LLM	Frequency	Percent (%)
ChatGPT	146	58.4
Claude	104	41.6
Total	250	100.0

More female (55.2%) than male (44.8%) students participated, and a majority of respondents (58.4%) preferred ChatGPT over Claude (41.6%) for learning.

Answering the Research Questions

The decision rule applied throughout this section is that mean scores were interpreted as follows: 1.00 to 1.79 = Strongly Disagree, 1.80 to 2.59 = Disagree, 2.60 to 3.39 = Neutral, 3.40 to 4.19 = Agree, and 4.20 to 5.00 = Strongly Agree.

Research Question 1: What is the influence of Performance Expectancy on students' behavioral intention to use LLMs for learning?

Table 3: Descriptive Statistics for Performance Expectancy (PE) Items

S/N	Item	Mean	SD
1	Using LLMs such as ChatGPT and Claude helps me complete academic tasks more quickly.	3.46	1.13
2	Using LLMs improves the quality of my academic work.	3.32	1.21
3	Using LLMs increases my chances of achieving better grades.	3.46	1.20



S/N	Item	Mean	SD
4	I find LLMs useful for understanding difficult course concepts.	3.44	1.22
5	Using LLMs for learning is advantageous to me.	3.52	1.25
-	Total	3.44	0.98

Students agreed with the Performance Expectancy items (grand mean = 3.44, SD = 0.98), indicating a moderately favourable view of the academic benefits of LLMs. Item means ranged from 3.32 to 3.52, and only the item on improved quality of academic work (M = 3.32) fell in the neutral band. The influence of Performance Expectancy on behavioral intention is reported with the hypothesis tests (Table 9).

Research Question 2: What is the influence of Facilitating Conditions on students' behavioral intention to use LLMs for learning?

Table 4: Descriptive Statistics for Facilitating Conditions (FC) Items

S/N	Item	Mean	SD
1	I have the internet access/data required to use LLMs for learning.	3.52	1.14
2	I have a device (phone, laptop, or tablet) that lets me use LLMs conveniently.	3.36	1.16
3	I have the skills and knowledge required to use LLMs effectively.	3.45	1.22
4	Support is available to help me use LLMs when I need it.	3.46	1.24
5	Using LLMs fits well with the way I study.	3.59	1.25
-	Total	3.48	0.96

Students agreed with the Facilitating Conditions items (grand mean = 3.48, SD = 0.96). Item means ranged from 3.36 to 3.59, and only the item on having a suitable device (M = 3.36) fell in the neutral band. The influence of Facilitating Conditions on behavioral intention is reported with the hypothesis tests (Table 9).

Research Question 3: What is the influence of Trust in AI-Generated Content on students' behavioral intention to use LLMs for learning?

Table 5: Descriptive Statistics for Trust in AI-Generated Content (TR) Items

S/N	Item	Mean	SD
1	I trust the accuracy of the information provided by LLMs.	3.58	1.12
2	I believe LLMs give reliable answers to academic questions.	3.50	1.13
3	I am confident that LLMs do not mislead me with false information.	3.60	1.20
4	I trust LLMs to give me balanced, unbiased responses.	3.68	1.18
5	I trust the content generated by LLMs.	3.72	1.24
-	Total	3.62	0.93

Students agreed with all the Trust in AI-Generated Content items (grand mean = 3.62, SD = 0.93), with item means ranging from 3.50 to 3.72. The influence of Trust in AI-Generated Content on behavioral intention is reported with the hypothesis tests (Table 9).

Research Question 4: What is the influence of Academic Integrity Concern on students' behavioral intention to use LLMs for learning?

Table 6: Descriptive Statistics for Academic Integrity Concern (AIC) Items

S/N	Item	Mean	SD
1	I worry that using LLMs for assignments may be considered a form of cheating.	3.39	1.24
2	I am concerned about being penalized for using LLMs inappropriately.	3.39	1.20
3	I worry that relying on LLMs may weaken my own learning and skills.	3.62	1.20
4	I am concerned that using LLMs conflicts with my institution's academic integrity policy.	3.57	1.20
5	I feel uneasy about the ethical implications of using LLMs for academic work.	3.60	1.25
-	Total	3.51	0.97

Students agreed with the Academic Integrity Concern items (grand mean = 3.51, SD = 0.97). They agreed most with worries that relying on LLMs may weaken their own learning ($M = 3.62$), that LLM use may conflict with institutional policy ($M = 3.57$), and that it raises ethical unease ($M = 3.60$). Worry about being seen as cheating and about being penalised (both $M = 3.39$) fell just below the agreement threshold, in the neutral band. The influence of Academic Integrity Concern on behavioral intention is reported with the hypothesis tests (Table 9).

Testing the Hypotheses

Hypotheses 1 to 4 were tested using multiple regression analysis, with Performance Expectancy, Facilitating Conditions, Trust in AI-Generated Content, and Academic Integrity Concern entered simultaneously as predictors of students' behavioral intention to use LLMs for learning. The model summary and ANOVA are presented below, followed by a single table of coefficients for all four predictors.

Table 7: Multiple Regression Model for Behavioral Intention to Use LLMs for Learning

R	R Square	Adjusted R Square	Std. Error	F (df1, df2), p
0.508	0.258	0.246	0.827	$F(4, 245) = 21.35, p < .001$

Predictors: Performance Expectancy, Facilitating Conditions, Trust in AI-Generated Content, Academic Integrity Concern. Dependent Variable: Behavioral Intention to Use LLMs for Learning.

Table 8: ANOVA for the Regression Model

Source	SS	Df	MS	F	Sig.
Regression	58.28	4	14.57	21.35	< .001
Residual	167.19	245	0.68		
Total	225.47	249			

The regression model was statistically significant, $F(4, 245) = 21.35, p < .001$, and accounted for 25.8% of the variance in students' behavioral intention to use LLMs for learning ($R^2 = .258$, Adjusted $R^2 = .246$).

Table 9: Regression Coefficients, 95% Confidence Intervals, and Effect Sizes for Predictors of Behavioral Intention to Use LLMs for Learning

Predictor	B	Std. Error	95% CI for B	Beta	t	Sig.	F ²
Performance Expectancy	0.359	0.054	[0.253, 0.466]	0.371	6.654	<.001	0.18
Facilitating Conditions	0.140	0.056	[0.031, 0.250]	0.141	2.520	.012	0.03
Trust in AI-Generated Content	0.200	0.056	[0.089, 0.310]	0.196	3.543	<.001	0.05
Academic Integrity Concern	-0.189	0.054	[-0.296, -0.082]	-0.193	-3.492	.001	0.05



The regression assumptions were checked before interpreting the results. The residuals were normally distributed (Shapiro-Wilk $p = .83$), and the relationship between the predictors and behavioral intention was linear (RESET test $p = .41$). There was no multicollinearity (all VIF values were between 1.01 and 1.03, and tolerance was at least .97). The residuals were independent (Durbin-Watson = 1.84), and no influential cases were found (maximum Cook's $D = .05$). The Breusch-Pagan test indicated mild heteroscedasticity ($p = .009$). The model was therefore re-run with robust (HC3) standard errors, and the conclusions were unchanged: all four predictors remained significant.

Table 9 shows the influence of each determinant on behavioral intention when the other three are held constant. Performance Expectancy had a significant positive influence on behavioral intention and was the strongest predictor ($B = 0.36$, 95% CI [0.25, 0.47], $\beta = .37$, $p < .001$, $f^2 = 0.18$, a medium effect). Trust in AI-Generated Content ($B = 0.20$, 95% CI [0.09, 0.31], $\beta = .20$, $p < .001$, $f^2 = 0.05$) and Facilitating Conditions ($B = 0.14$, 95% CI [0.03, 0.25], $\beta = .14$, $p = .012$, $f^2 = 0.03$) also had significant positive influences, but with small effects. Academic Integrity Concern had a significant negative influence, meaning that greater concern was associated with lower intention ($B = -0.19$, 95% CI [-0.30, -0.08], $\beta = -.19$, $p = .001$, $f^2 = 0.05$, a small effect). None of the confidence intervals includes zero, and H_{01} to H_{04} were therefore rejected. The four predictors explained 25.8% of the variance in behavioral intention ($R^2 = .258$, 95% CI [.16, .33], $f^2 = 0.35$, a large effect).

Hypothesis 5 (H_{05}): There is no significant difference between students' behavioral intention to use ChatGPT and their behavioral intention to use Claude for learning.

Descriptively, respondents reported a higher behavioral intention to use ChatGPT ($M = 3.11$, $SD = 1.00$) than Claude ($M = 2.75$, $SD = 1.09$), and both means fall within the neutral band. A paired-samples t -test was conducted to determine whether this difference is statistically significant.

Table 10: Paired-Samples t -Test Comparing Behavioral Intention to Use ChatGPT and Behavioral Intention to Use Claude

LLM	N	Mean	SD	Mean Diff.	df	t (Sig.)
Behavioral Intention to Use ChatGPT	250	3.11	1.00	0.36	249	6.61 (< .001)
Behavioral Intention to Use Claude	250	2.75	1.09			

Since $p < .001$, which is below .05, the null hypothesis (H_{05}) is rejected. There was a statistically significant difference between students' behavioral intention to use ChatGPT and their behavioral intention to use Claude for learning, $t(249) = 6.61$, $p < .001$, with students reporting higher intention to use ChatGPT ($M = 3.11$, $SD = 1.00$) than Claude ($M = 2.75$, $SD = 1.09$). Although both means fall in the neutral band, the mean difference of 0.36 was statistically significant.

Discussion

The regression model indicates that all four predictors returned statistically significant coefficients. This pattern of results largely supports the extended-UTAUT logic guiding the study, while also adding some important details in ways relevant to Educational Technology students in Nigerian universities.

Performance Expectancy appeared as the strongest predictor, which is consistent with prior findings that the belief a tool genuinely improves academic performance is the most reliable driver of LLM adoption among students (Grassini et al., 2024; Masrek et al., 2025). This suggests that respondents see LLMs as academically useful, and that this belief was more strongly associated with their intention to use them than any other factor tested. Facilitating Conditions was a significant but comparatively weaker predictor. This is a more modest effect than reported in some UTAUT-based studies (Habibi et al., 2023; Masrek et al., 2025), though it aligns with evidence that facilitating conditions can lose predictive weight once other beliefs are accounted for (G. C. et al., 2024). A plausible reading is that access to devices, data, and skills



is now common enough among this sample that it functions as a baseline enabler rather than a differentiator of intention.

Trust in AI-Generated Content also positively predicted intention. This suggests that respondents are more trusting than the literature's widely cited use-trust gap would suggest (Cabrera & Neville, 2025). One reason may be that trust grows as students become more familiar with how these tools work (Amin et al., 2025). It can also grow when lecturers openly endorse these tools (Alubthane, 2026). Because Educational Technology students are trained to work with digital tools, it is possible that they have built more trust over time, although this study did not compare them with students from other disciplines. Academic Integrity Concern was the only negative predictor. This shows that ethical unease is a real deterrent, not just a minor worry. Its mean score was close to that of Trust, which suggests that students can worry about being judged for using LLMs and still report a moderate intention to use them. This matches Cotton et al.'s (2024) observation that convenience and integrity concerns can exist side by side.

The significant difference between students' intention to use ChatGPT and Claude, favoring ChatGPT, may be partly linked to ChatGPT's earlier arrival and wider visibility. ChatGPT was the first LLM to reach mainstream visibility and has since become the default reference point in most discussions of generative AI in education (Zogheib & Zogheib, 2024; Ravšelj et al., 2025). It is therefore possible that Claude is less familiar to some students, although this study did not measure familiarity or prior exposure. Because the four determinants tested in this study were measured for LLMs in general rather than separately for each platform, this gap cannot be attributed to students observing Claude as less useful, less accessible, less trustworthy, or more ethically risky than ChatGPT. The data also cannot show why students favored ChatGPT. Familiarity is one possible explanation, but other factors not measured here, such as differences in features, cost, or peer and institutional influence, cannot be ruled out. If familiarity does play a role, this would be consistent with evidence that sustained exposure shapes usage patterns and trust in a given AI tool over time (Wang et al., 2025; Amin et al., 2025), but this remains a hypothesis. Future studies should measure familiarity and exposure directly to test it.

Conclusion

Educational Technology students' intention to use LLMs for learning was associated with what they believe the tools can do for them, the conditions that enable use, how much they trust the output, and how much they worry about the ethics of using it. Performance Expectancy was the strongest predictor, Trust in AI-Generated Content and Facilitating Conditions each added a smaller positive contribution, and Academic Integrity Concern was associated with lower intention. The four predictors explained about a quarter of the variance in intention, so other factors also matter. Intention to use ChatGPT was significantly higher than intention to use Claude, although both means fell within the neutral band. The reasons for this difference cannot be established from this study, because familiarity and the four determinants were not measured separately for each platform.

Recommendations

1. Lecturers should demonstrate concrete academic uses of LLMs, such as explaining difficult concepts and improving coursework quality.
2. Universities should keep improving students' access to devices, data, and support for using LLMs.
3. Lecturers should teach students to verify LLM output so that their trust in it remains well founded.
4. Institutions should publish clear guidelines on acceptable and unacceptable use of LLMs in coursework.
5. Lecturers should introduce students to a range of LLMs, including Claude, so that students can make informed choices between them.
6. Future studies should measure familiarity and the four determinants separately for each platform, and include other factors that may explain intention.



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