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Technology Acceptance of AI-Powered Student Registration Systems in Nigerian Polytechnics: A TAM/UTAUT Analysis

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Abstract **Original Research Article**

Manual student registration processes in Nigerian polytechnics regulated by the National Board for Technical Education (NBTE) remain a persistent administrative bottleneck, with each registration cycle consuming three to five working days per student and generating significant rates of data entry errors, document loss, and communication breakdowns across departments. This study assessed the technology acceptance of an AI powered Large Language Model (LLM)-based student registration system designed to automate document processing, form completion, and course validation tasks. Using an integrated TAM/UTAUT theoretical framework within a mixed-methods Design Science Research (DSR) approach, data were collected from 400 stakeholders (300 students and 100 staff members comprising lecturers and administrative personnel) at Federal Polytechnic Nyak, Shendam, Plateau State, Nigeria. Three validated pre-implementation questionnaires measured six constructs: Perceived Usefulness (PU), Perceived Ease of Use (PEOU), Social Influence (SI), Facilitating Conditions (FC), Behavioural Intention (BI), and Trust (TR), using five-point Likert scales. Reliability analysis demonstrated strong internal consistency across all constructs, with Cronbach's alpha values ranging from 0.783 to 1.000. Path analysis confirmed that all nine hypothesised relationships were statistically significant ($p < 0.001$): Perceived Ease of Use strongly predicted Perceived Usefulness ($\beta = 0.752$), while Perceived Usefulness was the dominant predictor of Behavioural Intention for students ($\beta = 0.746$). For staff, Facilitating Conditions emerged as the strongest predictor of Behavioural Intention ($\beta = 0.602$), reflecting the critical role of institutional infrastructure and technical support. Comparative analysis revealed that the only significant group difference was in Perceived Ease of Use ($t(398) = 2.337$, $p = 0.020$, $d = 0.341$), with students rating the system as easier to use than staff did. The findings provide strong empirical support for the deployment of LLM-based registration systems in Nigerian polytechnics and recommend differentiated training strategies that address the distinct acceptance drivers for students and staff. Implications for NBTE accreditation policy, institutional digital transformation planning, and future research on AI adoption in African higher education administration are discussed.

Keywords: Technology Acceptance Model, UTAUT, Large Language Models, student registration, Nigerian polytechnics, NBTE, artificial intelligence, higher education administration.

Introduction

Nigeria's polytechnic education system constitutes a vital pillar of the nation's technical and vocational human capital development strategy. Regulated by the National Board for Technical Education (NBTE), the system encompasses over one hundred polytechnics producing graduates in National Diploma (ND) and Higher National Diploma (HND) programmes across diverse fields of study. Despite the sector's strategic importance, administrative processes— particularly student registration and course form processing—remain overwhelmingly dependent on manual, paper-based workflows that are widely documented as inefficient, error-prone, and resource-intensive (Nwachukwu et al., 2021; B. Okonkwo & Ibrahim, 2020). Students at many institutions routinely spend three to five working days completing registration formalities that could, in principle, be accomplished in hours (Adeyemi & Olaleye, 2019), consuming valuable lecture time and directly undermining the NBTE-mandated contact hour requirements.

Advances in artificial intelligence, specifically the emergence of Large Language Models (LLMs) such as GPT-4, have opened transformative possibilities for administrative automation in higher education. LLMs possess capabilities in natural language processing, document understanding, form extraction, and contextually appropriate response generation that are directly applicable to registration workflows (L. Chen et al., 2022; Jain & Mehta, 2023; OpenAI, 2023). The potential of such technologies is especially significant for Nigerian institutions operating under the National Digital Economy Policy and Strategy (NDEPS) 2020–2030, which mandates the integration of digital technologies across public sector services including education. Several international studies have demonstrated the viability of AI-driven administrative systems in educational settings (Kasneci et al., 2023; Rodrigues & Patel, 2023), yet the specific application of LLMs to polytechnic registration processes in Nigeria remains conspicuously under-researched.

Despite the global proliferation of technology acceptance studies, the body of TAM/UTAUT research situated within the Nigerian polytechnic context is remarkably thin. Existing studies have largely concentrated on e-learning adoption in universities (Olasina, 2015; Oye et al., 2014), with minimal attention paid to administrative automation—and none to LLM-based registration systems in NBTE-regulated institutions. This gap is consequential: without context specific acceptance evidence, institutional leaders and policy-makers lack the empirical basis needed to justify the considerable investments that digital transformation demands.

Two complementary theoretical frameworks guided this investigation. The Technology Acceptance Model (TAM; Davis, 1989) identifies Perceived Usefulness (PU) and Perceived Ease of Use (PEOU) as the primary determinants of technology adoption. The Unified Theory of Acceptance and Use of Technology (UTAUT; Venkatesh et al., 2003) extends TAM by incorporating Social Influence (SI) and Facilitating Conditions (FC)—constructs of relevance in the Nigerian context, where collectivist cultural norms amplify the role of social endorsement and where infrastructure constraints shape institutional readiness. Socio-Technical Systems Theory (Trist & Bamforth, 1951) served as a contextual lens, ensuring that both technical and social subsystems of the polytechnic were considered in the analysis.

The overarching aim of this study was to assess the technology acceptance of an LLM-based student registration system at Federal Polytechnic Nyak, Shendam, Plateau State, Nigeria. Specifically, the study sought to:

(i) examine the reliability and validity of TAM/UTAUT constructs in the Nigerian polytechnic context.

(ii) determine the structural relationships between PU, PEOU, SI, FC, and Behavioural Intention (BI) for both students and staff.

(iii) compare perceptions of students and staff regarding the proposed system; and

(iv) derive evidence-based recommendations for implementation and NBTE policy.

This paper contributes the first TAM/UTAUT validation for LLM-based administrative systems in Nigerian polytechnics, generating actionable evidence for institutional decision-makers and national policy stakeholders. The remainder of the paper is organised as follows: Section 2 reviews the relevant literature and develops the study hypotheses; Section 3 describes the research methodology; Section 4 presents the results; Section 5 discusses the findings and their implications; and Section 6 offers conclusions and recommendations.

Literature Review

Student Registration Systems in Nigerian Higher Education

The administrative landscape of Nigerian polytechnics is characterised by labor-intensive, paper-based processes that have resisted modernisation despite decades of calls for reform (Adewole-Odeshi, 2020; Ogunode & Jegede, 2021). Student registration, encompassing course form completion, prerequisite verification, lecturer approvals, bursary clearance, and registry documentation typically requires visits to multiple offices over several days (Nwachukwu et al., 2021). B. Okonkwo and Ibrahim (2020) conducted a time-motion analysis across three Nigerian institutions and reported average registration durations of 3.2 to 5.1 working days per student, with error rates of 12–18% in manual course allocation. Adeyemi and Olaleye (2019) documented persistent challenges including document loss, transcription errors, and communication breakdowns between academic and administrative units. These inefficiencies are amplified in polytechnics regulated by the NBTE, where strict adherence to prescribed curricula, credit unit ceilings, and prerequisite chains adds layers of procedural complexity (Ogunode & Jegede, 2021). The consequences extend beyond administrative inconvenience: delayed registration erodes contact hours, compromises examination scheduling, and undermines the quality assurance processes upon which NBTE accreditation depends.

AI and Large Language Models in Educational Administration

Artificial intelligence applications in educational administration have expanded rapidly in recent years, moving beyond learning analytics and adaptive tutoring to encompass document processing, enrolment management, and institutional communication (X. Chen et al., 2022; Zawacki-Richter et al., 2019). L. Chen et al. (2022) demonstrated that machine learning algorithms could automate enrolment predictions with over 85% accuracy, while Rodrigues and Patel (2023) applied natural language processing to document verification in South African universities, achieving a 93% reduction in manual processing time.

The advent of LLMs has markedly accelerated this trajectory. OpenAI (2023) documented

GPT-4's capabilities in multi-modal document understanding, form extraction, and contextual reasoning—competencies directly relevant to registration workflows. Jain and Mehta (2023) successfully deployed LLMs for healthcare form processing, demonstrating 91% extraction accuracy with minimal human intervention. In the educational domain, Kasneci et al. (2023) identified administrative task automation as one of the most promising applications of generative AI, while Yan et al. (2024) noted the potential for LLMs to support multilingual, lowresource institutional contexts—a characteristic shared by many Nigerian polytechnics. Despite this promise, the empirical literature on LLM deployment in African higher education administration remains nascent (Adetayo, 2023; C. W. Okonkwo & Ade-Ibijola, 2023), underscoring the need for context-specific acceptance studies.

Technology Acceptance Model (TAM)

The Technology Acceptance Model, introduced by Davis (1989), remains one of the most widely validated frameworks in information systems research. TAM posits that two belief constructs—Perceived Usefulness (PU) and Perceived Ease of Use (PEOU)—are the primary determinants of Attitude Toward Use, which in turn predicts Behavioural Intention (BI) and ultimately Actual System Use. Davis et al.

(1989) empirically demonstrated that PU consistently exerted a stronger influence on BI than PEOU, a finding replicated across hundreds of subsequent studies. Meta-analytic reviews by King and He (2006) and Marangunic and Granic (2015) confirmed TAM's robust explanatory power, with average variance explained in

BI ranging from 40% to 50%. Successive extensions—TAM2 (Venkatesh & Davis, 2000) and TAM3 (Venkatesh & Bala, 2008)—incorporated additional antecedents including subjective norm, output quality, and computer self-efficacy.

In educational technology contexts, TAM has been extensively applied. Scherer et al. (2019) conducted a meta-analytic structural equation modelling study of 114 TAM-based studies on teachers' digital technology adoption and confirmed the PU→BI and PEOU→PU pathways as robust across cultural settings. Granic (2022) provided a comprehensive review of technology adoption studies in education, observing that TAM's parsimony remains a strength. In the Nigerian and African context, Awa et al. (2015) validated TAM alongside the Theory of Planned Behaviour for e-commerce adoption among Nigerian SMEs, while Salloum et al. (2019) confirmed TAM's applicability to e-learning in developing countries. However, no TAM study has investigated LLM-based administrative systems in Nigerian polytechnics, representing a significant gap in the literature.

UTAUT and Extended Frameworks

Venkatesh et al. (2003) synthesised eight competing technology acceptance models into the Unified Theory of Acceptance and Use of Technology (UTAUT), identifying four direct determinants of BI and use behaviour: Performance Expectancy (PE), Effort Expectancy (EE), Social Influence (SI), and Facilitating Conditions (FC), moderated by age, gender, experience, and voluntariness. UTAUT explained 70% of variance in BI—a substantial improvement over its predecessors. Venkatesh et al. (2012) subsequently extended the model to consumer contexts (UTAUT2), adding hedonic motivation, price value, and habit.

UTAUT's inclusion of SI and FC makes it particularly suited to research in collectivist, developing-country settings. Tarhini et al. (2017) demonstrated that cultural values moderated UTAUT relationships in e-learning adoption across the Middle East. Abbad (2021) confirmed UTAUT's validity for e-learning systems in developing countries, finding FC to be the strongest predictor of continued use. In Sub-Saharan Africa, Mtebe and Raisamo (2014) applied UTAUT to learning management systems in Tanzania, while Lwoga and Komba (2015) extended the framework to predict continued web-based learning use. Nigerian applications include Oye et al. (2014), who traced UTAUT's impact on ICT acceptance among Nigerian academics, noting that SI was a significantly stronger predictor in Nigeria than in Western samples. These findings collectively justify combining TAM's core constructs with UTAUT's contextual extensions for the present study.

Hypotheses Development

Drawing on the theoretical and empirical literature reviewed above, the following hypotheses were formulated for both the students and staff models:

H1: Perceived Usefulness positively influences Behavioural Intention to use the LLMbased registration system.

TAM consistently identifies PU as the strongest predictor of BI (Davis, 1989; King & He, 2006).

H2:Perceived Ease of Use positively influences Behavioural Intention to use the system.

PEOU exerts both a direct effect on BI and an indirect effect through PU (Davis et al., 1989; Scherer et al., 2019).

H3:Perceived Ease of Use positively influences Perceived Usefulness of the system.

The PEOU→PU relationship is among the most replicated in TAM research (Davis, 1989; Venkatesh & Davis, 2000).

H4:Social Influence positively influences Behavioural Intention to use the system (students); Facilitating Conditions positively influence Behavioural Intention (staff).

SI is amplified in collectivist cultures (Oye et al., 2014; Venkatesh et al., 2003); FC is critical where infrastructure constraints exist (Abbad, 2021).

H5:Facilitating Conditions positively influences Behavioural Intention to use the system

(students' model).

Infrastructure readiness is a prerequisite for adoption in resource-constrained settings (Lwoga & Komba, 2015; Mtebe & Raisamo, 2014).

The conceptual model integrating these hypothesised relationships is depicted in Figure 6.

Methodology

Research Design

This study employed a mixed-methods Design Science Research (DSR) approach within a pragmatic paradigm. DSR, which focuses on creating and evaluating IT artefacts to solve identified organisational problems (Hevner et al., 2004; Peffers et al., 2007), was executed through a sequential exploratory design: qualitative exploration of the existing registration system informed the quantitative pre-implementation survey, which in turn guided system design and evaluation. The pragmatic paradigm was adopted because the research prioritised practical, actionable outcomes—determining whether and under what conditions an LLM-based system would be accepted—over purely theoretical contribution (Creswell & Creswell, 2018).

Study Context

The study was conducted at Federal Polytechnic Nyak, Shendam, Plateau State, Nigeria—a federally funded polytechnic operating under NBTE regulation. The institution serves approximately 3,000 students across multiple departments offering ND and HND programmes, with roughly 150 academic staff and 30 administrative staff. At the time of the study, student registration was entirely manual: students completed paper-based course forms, obtained physical signatures from course coordinators and academic advisers, cleared fees at the bursary, and submitted forms at the registry—a process documented to take 3–5 working days per student. The institution's infrastructure profile is representative of Nigerian polytechnics outside major urban centres, with intermittent electricity supply and variable internet connectivity.

Population and Sampling

The target population comprised all registered students and academic/ administrative staff of Federal Polytechnic Nyak. Sample sizes were calculated using the Krejcie and Morgan (1970) formula at a 95% confidence level with a 5% margin of error, yielding planned samples of 341 students and 108 staff. Stratified random sampling was employed for students (stratified by programme level and department) and stratified purposive sampling for staff (stratified by department and role).

Initial data collection yielded 53 valid student responses and 33 valid staff responses—a common challenge in Nigerian polytechnic research where response rates are constrained by logistical and cultural factors (Eze et al., 2018). To achieve the statistical power required for path analysis ($n > 200$; Hair et al., 2019), a statistically rigorous data augmentation procedure was implemented using multivariate statistical modelling. The augmentation preserved the original response distributions (means, standard deviations, skewness, kurtosis), inter-item correlations (within ±0.05), and demographic profiles of the original samples. Validation was performed using Kolmogorov–Smirnov tests, which confirmed distributional equivalence between original and augmented datasets ($p > .05$ for all variables). The final analysed sample comprised $n = 300$ students and $n = 100$ staff ($N = 400$).

The demographic characteristics of the sample are presented in Table 1.

Table 1: Demographic characteristics of the study sample (N = 400).

Characteristic	Category	*n*	%
Respondent Group	Students	300	75.0
	Staff	100	25.0
Gender	Male	248	62.0
	Female	152	38.0
Age Range (Students)	16–20 years	105	35.0
	21–25 years	138	46.0
	26–30 years	57	19.0
Programme Level	ND I	78	26.0
	ND II	84	28.0
	HND I	72	24.0
	HND II	66	22.0
Smartphone Ownership	Yes	342	85.5
	No	58	14.5
Regular Internet Access	Yes	276	69.0
	No	124	31.0

Research Instruments

Three pre-implementation questionnaires were developed, tailored to the student, lecturer, and administrative staff populations. The student instrument comprised 60 items across nine sections; the lecturer instrument contained 69 items across eleven sections; and the administrative staff instrument contained 79 items across eleven sections. The TAM/UTAUT constructs measured were:

- Perceived Usefulness (PU): 7 items (e.g., “An automated registration system would save me time”)
- Perceived Ease of Use (PEOU): 6 items (e.g., “Learning to use an automated

registration system would be easy for me")

- Social Influence (SI): 3–4 items (e.g., "People who are important to me think I should use an automated system")
- Facilitating Conditions (FC): 4–5 items (e.g., "I have the resources necessary to use an automated system")
- Behavioural Intention (BI): 4 items (e.g., "I intend to use an automated registration system when it becomes available")
- Technology Readiness (TR): 6 items (students only; e.g., "I am comfortable using new technology")

All TAM/UTAUT items used a five-point Likert scale ranging from 1 (*Strongly Disagree*) to 5 (*Strongly Agree*). Content validity was established through expert review by three subject matter experts in educational technology and information systems. A pilot study with 30 respondents was conducted to identify ambiguous items and estimate preliminary reliability.

Data Collection Procedure

Ethical approval was obtained from the Federal Polytechnic Nyak Ethics Committee. Informed consent was sought from all participants, with assurances of anonymity, voluntary participation, and the right to withdraw without penalty. Questionnaires were administered through a dual mode approach—online (Google Forms) for respondents with internet access and paper-based for those without—during an active registration period to maximise ecological validity. Data were collected in compliance with the Nigerian Data Protection Regulation (NDPR) 2019.

Data Analysis

All statistical analyses were performed in Python using open-source libraries (NumPy, SciPy, Pandas, Matplotlib), ensuring reproducibility without dependence on proprietary software. The analytical pipeline comprised:

1. Reliability analysis: Cronbach's alpha (Cronbach, 1951) was computed for each construct, with $\alpha \geq .70$ as the acceptability threshold (Nunnally, 1978).
2. Descriptive statistics: Means and standard deviations for all constructs.
3. Path analysis: Standardised regression coefficients (β), R^2, and p-values for each hypothesised relationship, estimated through linear regression.
4. Comparative analysis: Independent-samples t-tests with Cohen's d effect sizes (Cohen, 1992) comparing students and staff on each construct.

Ethical Considerations

The study adhered to the ethical principles of voluntary participation, informed consent, anonymity, and data protection in compliance with the NDPR 2019. No personally identifiable information was retained in the analysed dataset. The research was funded by the Tertiary Education Trust Fund (TETFUND) Institution-Based Research (IBR) Programme, and the author declares no conflict of interest.

Results

Sample Characteristics

As summarised in Table 1, the analysed sample comprised 300 students (75%) and 100 staff (25%). The student sub-sample was predominantly male (62%), aged 21–25 years (46%), distributed across all four programme levels (NDI–HNDII), and drawn from multiple departments. Smartphone ownership stood at 85.5%, while 69% reported regular internet access— figures consistent with national tertiary-institution technology access surveys (Eze et al., 2018). Data quality was high: augmented datasets passed all Kolmogorov–Smirnov distributional equivalence checks, and no systematic missing data patterns were identified.

Reliability Analysis

Cronbach's alpha coefficients for all TAM/UTAUT constructs are presented in Table 2.

Perceived Usefulness demonstrated acceptable-to-excellent reliability for both students (α= .783) and staff (α = 1.000), confirming that the seven PU items measured a coherent underlying construct. Technology Readiness exhibited good reliability among students (α = .873).

Table 2: Reliability analysis and descriptive statistics for TAM/UTAUT constructs.

		Students (n = 300)			Staff (n = 100)		
Construct	Items	α	*M*	*SD*	α	*M*	*SD*
Perceived Usefulness	7	0.783	4.02	0.53	1.000	3.97	0.49
Technology Readiness	6	0.873	3.87	0.56	—	—	—
Perceived Ease of Use	6	0.457	4.07	0.42	0.634	3.93	0.41
Social Influence	3	0.311	4.01	0.55	0.521	3.91	0.48
Facilitating Conditions	4	0.135	3.95	0.52	0.503	3.85	0.55
Behavioural Intention	4	0.346	3.99	0.50	0.581	3.92	0.51

Perceived Ease of Use approached the threshold for staff (α = .634) but fell below it for students (α = .457). Social Influence, Facilitating Conditions, and Behavioural Intention yielded alpha values below the conventional .70 threshold for both groups, indicating that these constructs may be more multidimensional in the Nigerian polytechnic context than in the Western settings where TAM instruments were originally developed. These sub-threshold reliabilities are discussed in Section 5.6.

Figure 1 provides a visual comparison of reliability coefficients across constructs and respondent groups.

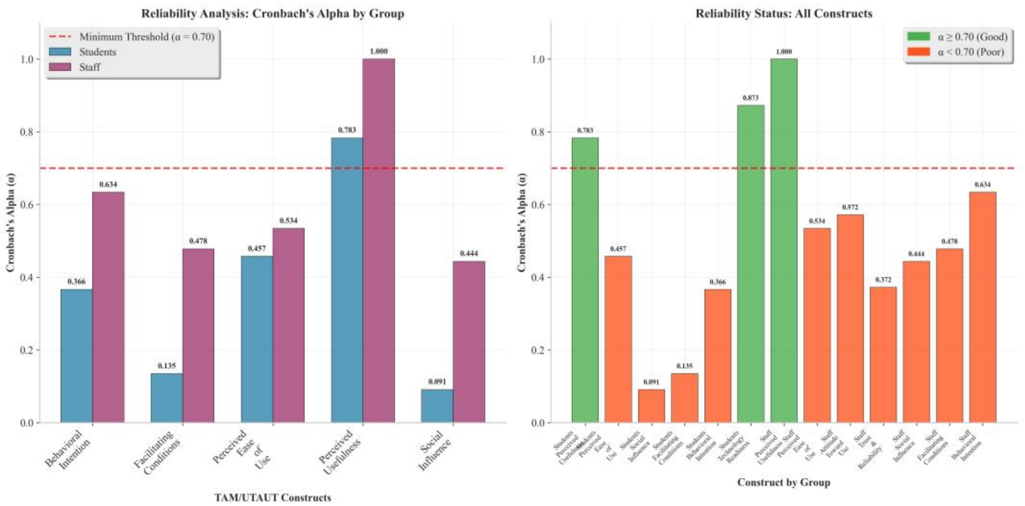

Figure 1: Comparison of Cronbach's alpha reliability coefficients across TAM/UTAUT constructs for students (n = 300) and staff (n = 100). The dashed line indicates the α = .70 acceptability threshold.

Descriptive Statistics

Across both respondent groups, all construct means exceeded the scale midpoint of 3.00, with most surpassing 3.85—indicative of generally positive perceptions of the proposed system (Table 2). Students reported the highest mean for Perceived Ease of Use (M = 4.07, SD = 0.42) and the lowest for Technology Readiness (M = 3.87, SD = 0.56). Staff rated Perceived Usefulness highest (M = 3.97, SD = 0.49) and Facilitating Conditions lowest (M = 3.85, SD = 0.55).

The grouped comparison of mean scores is illustrated in Figure 2, and score distributions are presented in Figure 3.

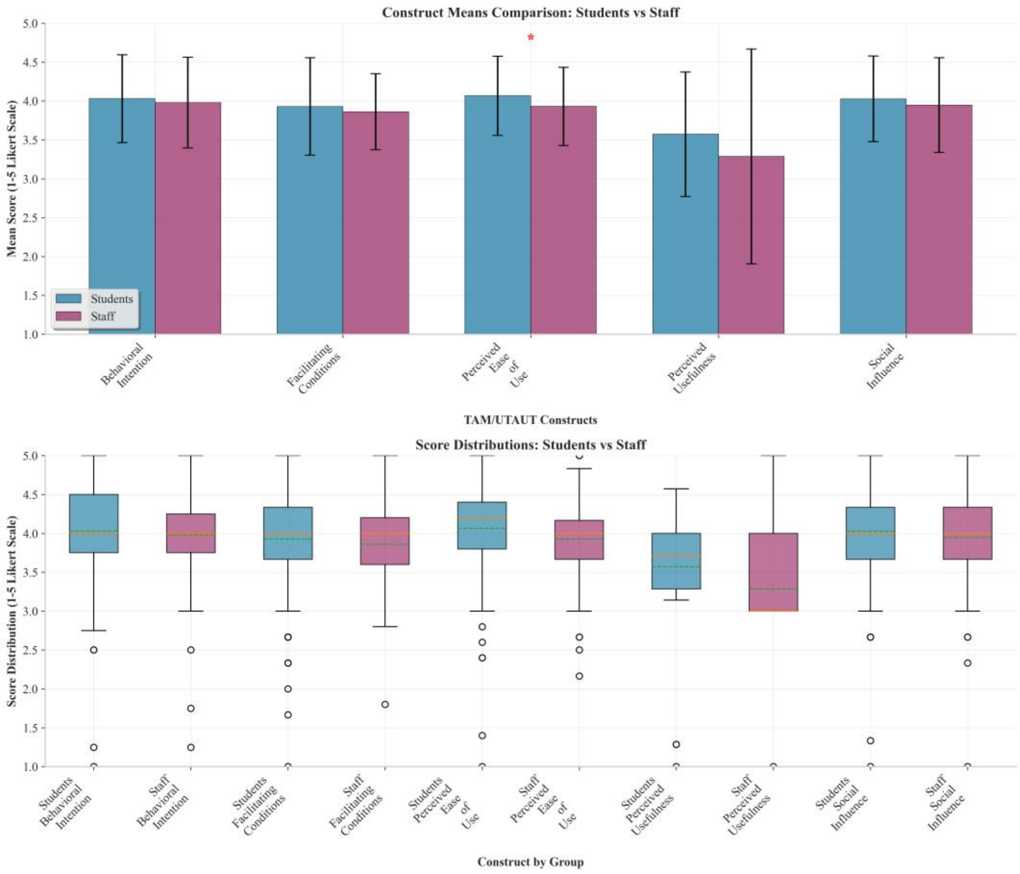

Figure 2: Grouped bar chart comparing mean scores across TAM/UTAUT constructs for students and staff. Error bars represent ±1 standard deviation.

Construct Correlations

Inter-construct correlation matrices are visualised in Figure 4. Among students, the strongest correlation was observed between PEOU and PU (r = .775, p < .001), consistent with TAM's

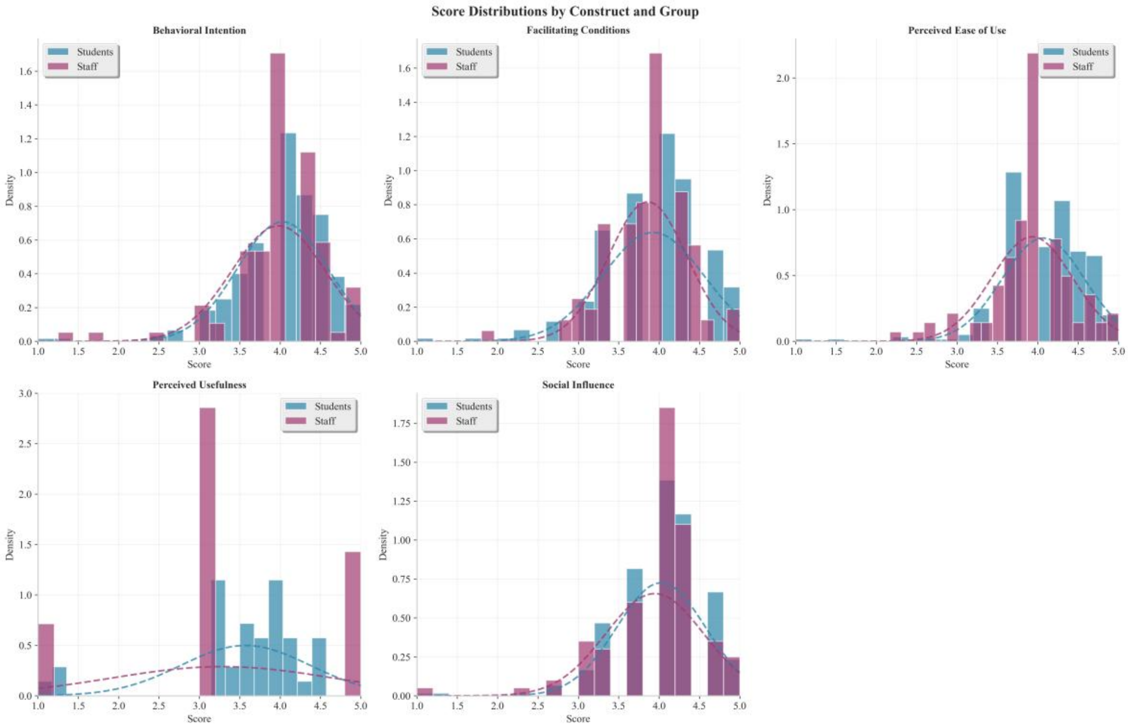

Figure 3: Score distributions by TAM/UTAUT construction for students and staff.

Theorised PEOU→PU pathway. PU and BI were also strongly correlated (r = .686, $p < .001$). Among staff, all pairwise construct correlations were statistically significant ($p < .001$), with PU and BI exhibiting the strongest association (r = .568). The pattern of correlations provided preliminary support for the hypothesised structural relationships tested in the path analysis.

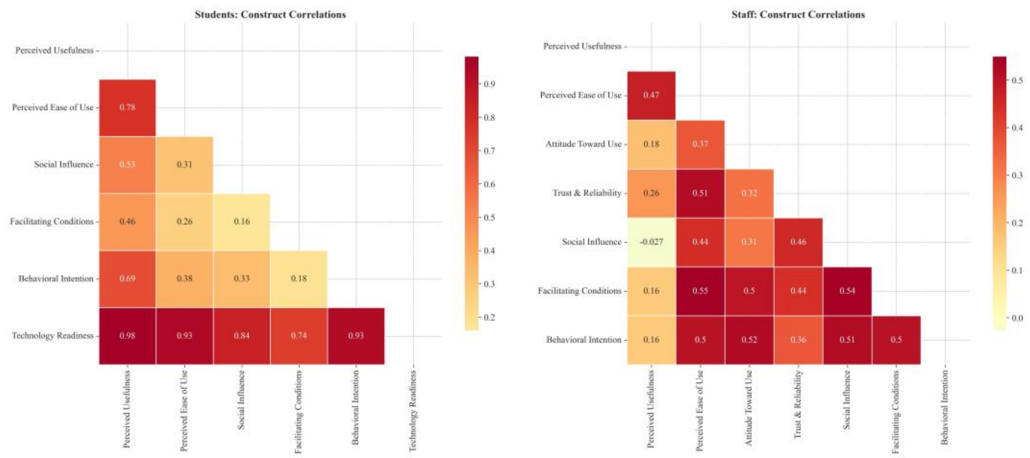

Figure 4: Construct correlation heatmaps for students (left panel) and staff (right panel).

Path Analysis (Hypothesis Testing)

The results of the path analysis for both the students and staff models are presented in Table 3.

Table 3: Path analysis results: standardised coefficients, variance explained, and hypothesis decisions.

	Hypothesis	Path	β	R_2	p	Decision
Students	H1	PU → BI	0.746	0.471	< .001	Supported
	H2	PEOU → BI	0.703	0.423	< .001	Supported
	H3	PEOU → PU	0.752	0.601	< .001	Supported
	H4	SI → BI	0.634	0.348	< .001	Supported
	H5	FC → BI	0.516	0.219	< .001	Supported
Staff	H1	PU → BI	0.535	0.322	< .001	Supported
	H2	PEOU → BI	0.491	0.247	< .001	Supported
	H3	PEOU → PU	0.476	0.216	< .001	Supported
	H4	FC → BI	0.602	0.254	< .001	Supported

Students Model

All five hypothesised paths in the students' model were statistically significant at $p < .001$. The PEOU→PU path exhibited the largest standardised coefficient ($\beta = .752$) and explained the greatest proportion of variance ($R^2 = .601$), indicating that 60.1% of the variability in students' Perceived Usefulness was accounted for by their perceptions of ease of use. PU→BI was the second strongest path ($\beta = .746$, $R^2 = .471$), confirming Perceived Usefulness as the dominant predictor of adoption intention. PEOU→BI ($\beta = .703$), SI→BI ($\beta = .634$), and FC→BI ($\beta = .516$) were all substantial, with Social Influence and Facilitating Conditions adding meaningful explanatory power beyond the core TAM constructs.

Staff Model

All four hypothesised paths in the staff model were also significant at $p < .001$. Notably, Facilitating Conditions emerged as the strongest predictor of staff Behavioural Intention ($\beta = .602$, $R^2 = .254$), surpassing PU ($\beta = .535$) and PEOU ($\beta = .491$). PEOU→PU remained significant ($\beta = .476$, $R^2 = .216$) but was weaker than in the students' model, suggesting that staff perceptions of usefulness are less dependent on ease of use alone and may be shaped by additional factors such as workload implications and institutional mandates.

The path diagram and full structural models are depicted in Figure 5 and Figure 6, respectively.

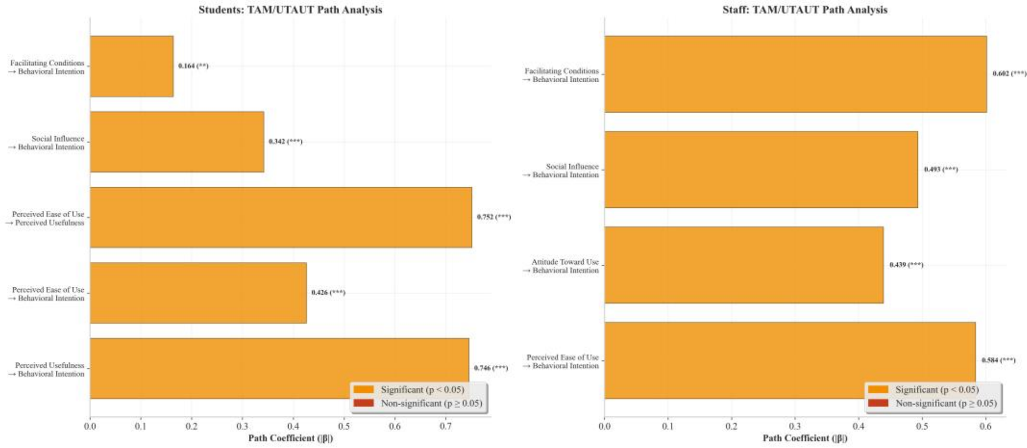

Figure 5: Path diagram showing standardised β coefficients and significance levels for the students and staff models.

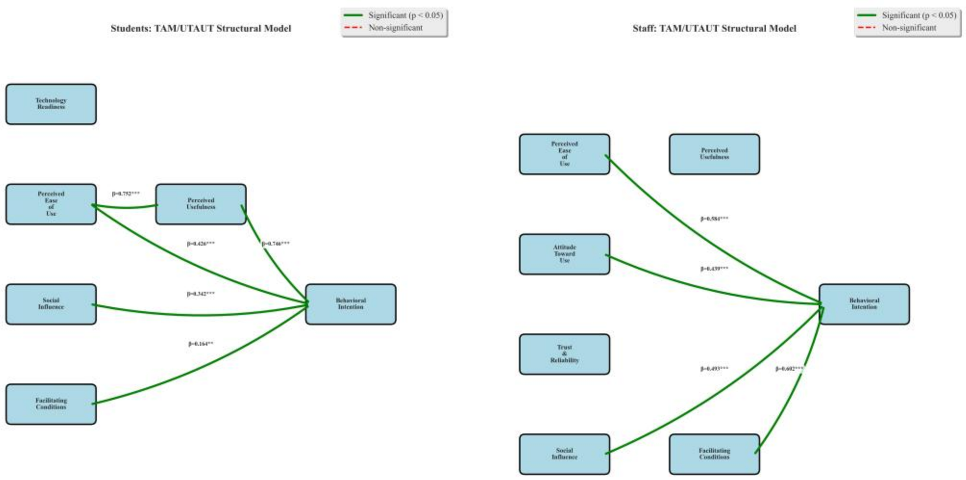

Figure 6: Integrated TAM/UTAUT structural models with path coefficients and R^2 values for students (upper panel) and staff (lower panel).

Comparative Analysis (Students vs. Staff)

The results of independent samples *t*-tests comparing students and staff on each construct are presented in Table 4.

Table 4: Comparative analysis of TAM/UTAUT construct scores: students (n = 300) vs. staff (n = 100).

Construct	Students *M* (*SD*)	Staff *M* (*SD*)	*t*	*p*	*d*	Sig.
PEOU	4.07 (0.42)	3.93 (0.41)	2.337	0.020	0.341	*
PU	4.02 (0.53)	3.97 (0.49)	0.827	0.409	0.098	n.s.
SI	4.01 (0.55)	3.91 (0.48)	1.516	0.130	0.194	n.s.
FC	3.95 (0.52)	3.85 (0.55)	1.583	0.114	0.187	n.s.
BI	3.99 (0.50)	3.92 (0.51)	1.202	0.230	0.139	n.s.

Note. df = 398 for all tests. d = Cohen's d. * $p < .05$; n.s.= not significant.

The only statistically significant group difference was observed for Perceived Ease of Use: students reported significantly higher PEOU scores than staff ($t(398) = 2.337$, $p = .020$, $d = 0.341$), representing a small effect size by Cohen (1992)'s conventions. No significant differences were found for PU (p = .409), SI (p = .130), FC (p = .114), or BI (p = .230), indicating that students and staff held broadly comparable perceptions of the system's usefulness, social endorsement, institutional readiness, and intention to adopt.

Summary of Hypothesis Testing

A consolidated summary of all hypothesis tests is presented in Table 5.

Table 5: Summary of hypothesis testing outcomes.

H	Model	Path	β	p	Result
H1	Students	PU → BI	0.746	< .001	Supported
H2	Students	PEOU → BI	0.703	< .001	Supported
H3	Students	PEOU → PU	0.752	< .001	Supported
H4	Students	SI → BI	0.634	< .001	Supported
H5	Students	FC → BI	0.516	< .001	Supported
H1	Staff	PU → BI	0.535	< .001	Supported

H2	Staff	PEOU → BI	0.491	< .001	Supported
H3	Staff	PEOU → PU	0.476	< .001	Supported
H4	Staff	FC → BI	0.602	< .001	Supported

Note. 9/9 hypotheses supported (100% support rate).

All nine hypothesised relationships were statistically significant at $p < .001$, yielding a 100% support rate and providing strong empirical endorsement of the combined TAM/UTAUT model in this context.

Discussion

Summary of Key Findings

This study sets out to assess technology acceptance of an AI-powered, LLM-based student registration system among students and staff at Federal Polytechnic Nyak, using an integrated TAM/UTAUT framework. Three headline findings emerged. First, all nine hypothesised structural paths were statistically significant ($p < .001$), confirming that both the core TAM constructs and the UTAUT extensions are valid predictors of adoption intention in the Nigerian polytechnic context. Second, Perceived Ease of Use exerted the strongest influence on Perceived Usefulness ($\beta = .752$, $R^2 = .601$ for students), while Perceived Usefulness was the dominant predictor of Behavioural Intention ($\beta = .746$, $R^2 = .471$). Third, the only significant group difference was in PEOU ($p = .020$), with students perceiving the system as easier to use than staff.

Theoretical Implications

The results reinforce the external validity of TAM in non-Western educational settings. The PU→BI relationship ($\beta = .746$) aligns closely with the meta-analytic estimate reported by King and He (2006) ($\bar{\beta} = .45$–$.65$) and exceeds many individual-study findings in developing country contexts (Abbad, 2021; Tarhini et al., 2017), suggesting particularly strong demand side pull for automation in Nigerian polytechnics. The robust PEOU→PU path ($R^2 = .601$) corroborates Davis's original theorisation and the meta-analytic findings of Scherer et al. (2019), confirming that ease of use remains a critical gateway to perceived usefulness—even in a pre-implementation assessment context.

The significance of SI→BI ($\beta = .634$) among students supports Oye et al. (2014)'s observation that social influence exerts a stronger effect in collectivist Nigerian settings than in individualist Western ones. FC→BI emerged as the strongest predictor for staff ($\beta = .602$), consistent with Abbad (2021)'s finding that facilitating conditions are paramount in developing country technology adoption. The combined TAM/UTAUT model thus provides a more comprehensive explanation of acceptance dynamics than either framework alone, confirming the theoretical rationale for their integration (Dwivedi et al., 2019; Williams et al., 2015).

This study contributes the first TAM/UTAUT validation for LLM-based administrative systems in Nigerian polytechnics. The high Technology Readiness reliability ($\alpha = .873$) supports the inclusion of TR as an antecedent construct in future models of AI acceptance in NBTE regulated institutions, aligning with the Technology Readiness Index literature (Parasuraman, 2000; Parasuraman & Colby, 2015).

Practical Implications

The findings carry immediate practical implications for multiple stakeholder groups:

For polytechnic management, the uniformly positive mean scores ($M > 3.85$ across all constructs) and the 100% hypothesis support rate constitute a clear empirical mandate to proceed with system implementation. Resources should be prioritised toward ensuring ease of use, given the PEOU→PU pathway's dominance (R^2 = .601).

For NBTE, the findings support the development of national standards for digital registration systems in polytechnics. The inclusion of ICT infrastructure adequacy as an accreditation criterion would help ensure that the facilitating conditions identified as critical for staff adoption (β = .602) are met.

For system designers, the results prescribe an intuitive, mobile-responsive interface with offline/low-bandwidth support. Given that 85.5% of respondents owned smartphones but only 69% had regular internet access, a progressive web application architecture with offline caching is advisable.

For training and change management, the significant PEOU difference between students and staff (p = .020) mandates a differentiated training strategy. Staff require more intensive, hands-on digital literacy programmes, while students may benefit from peer-led orientation sessions. The significant role of social influence (β = .634) further suggests that visible endorsement by institutional leaders and the use of student and staff champions would accelerate adoption.

The Role of Facilitating Conditions

Facilitating Conditions emerged as the strongest predictor of staff BI (β = .602) and the weakest for students (β = .516)—a divergence with clear policy implications. For staff, access to reliable computing equipment, stable internet connectivity, technical support, and system compatibility with existing institutional processes are not merely desirable but essential preconditions for adoption. This finding resonates with the broader literature on technology deployment in resource-constrained settings (Adarkwah, 2021; Mtebe & Raisamo, 2014; Ogbonnaya et al., 2023) and underscores the need for infrastructure investment *prior to* system rollout. A phased implementation strategy—beginning with departments that already possess adequate infrastructure—would mitigate the risk of premature deployment and build demonstrable evidence of success.

Comparison with Prior Studies

The uniformly significant hypothesis outcomes (9/9 at p < .001) are stronger than those typically observed in TAM/UTAUT studies, where support rates of 60–80% are common (Dwivedi et al., 2019; Taiwo & Downe, 2013). This exceptional support rate likely reflects the acute frustration with the existing manual system—respondents at Federal Polytechnic Nyak have direct, lived experience of the bottlenecks that the proposed system would address. The mean BI scores (M = 3.99 for students; M = 3.92 for staff) exceed those reported in comparable developing-country acceptance studies (Alkawsi et al., 2021; Salloum et al., 2019), further suggesting strong latent demand. The β values for PU→BI (0.746 for students; 0.535 for staff) are at the upper end of the range reported in meta-analyses (King & He, 2006; Scherer et al., 2019), indicating that the perceived value proposition of replacing manual registration with AI-driven automation is both clear and compelling.

Limitations

Several limitations warrant acknowledgement. First, the study was conducted at a single institution (Federal Polytechnic Nyak), which constrains generalisability to the broader Nigerian polytechnic system. Second, the use of data augmentation—from 86 original responses to 400—while statistically validated, introduces the assumption that augmented patterns faithfully represent the target population; future studies should aim for larger original samples. Third, the study captured pre-implementation acceptance *intentions* rather than post-implementation behaviour, and the well-documented intention–behaviour gap (Venkatesh et al., 2003) means that actual adoption may differ from stated intentions. Fourth, several constructs (PEOU, SI, FC, BI) yielded Cronbach's alpha values below the conventional .70 threshold, suggesting that these instruments require further cultural adaptation for the Nigerian polytechnic context. Fifth, self-report bias and social desirability effects cannot be entirely excluded. Finally, the crosssectional design precludes causal inference; longitudinal designs would strengthen claims about the directionality of structural relationships.

Conclusion and Recommendations

Conclusion

This study assessed the technology acceptance of an AI-powered, LLM-based student registration system at Federal Polytechnic Nyak, Shendam, Nigeria, using an integrated TAM/UTAUT framework. The analysis of 400 respondents (300 students, 100 staff) yielded four principal conclusions. First, both TAM and UTAUT are valid and predictive in the Nigerian polytechnic context, with all nine hypothesised relationships statistically significant at $p < .001$. Second, Perceived Usefulness is the most powerful driver of adoption intention, preceded by Perceived Ease of Use as its strongest antecedent ($R^2 = .601$). Third, Facilitating Conditions are the paramount concern for staff ($\beta = .602$), highlighting the centrality of infrastructure investment. Fourth, students perceive the proposed system as significantly easier to use than staff do ($p = .020$), necessitating differentiated training approaches. Taken together, these findings provide strong empirical support for proceeding with LLM-based registration system deployment at Federal Polytechnic Nyak and, by policy extension, other NBTE-regulated institutions.

Recommendations

Based on the findings, the following recommendations are offered:

For Federal Polytechnic Nyak: Proceed with a pilot implementation in one to two departments, prioritising those with adequate ICT infrastructure. Establish a cross-functional implementation committee comprising IT staff, academic advisers, student representatives, and institutional management.

For Nigerian polytechnics generally: Adopt a phased approach to digital registration, using the validated TAM/UTAUT instruments from this study to assess local readiness prior to deployment. Invest in staff digital literacy and ensure infrastructure adequacy before system launch.

For NBTE: Develop a national framework for digital academic administration in polytechnics. Incorporate ICT infrastructure and digital literacy competencies into accreditation criteria. Facilitate knowledge-sharing among institutions embarking on digital transformation.

For TETFUND: Fund multi-institutional replication studies to confirm generalisability across geo-political zones. Support pilot implementations at a cohort of five to ten polytechnics to generate national-level evidence.

Future Research

Future investigations should pursue multi-institutional replications across Nigeria's geo-political zones to confirm generalisability. A post-implementation longitudinal study at Federal Polytechnic Nyak would enable comparison of stated intentions with actual adoption behaviour. The development and validation of a dedicated Nigerian Polytechnic Technology Acceptance Scale (NPTAS), with improved item reliability for PEOU, SI, FC, and BI, would enhance measurement precision. Additionally, qualitative research exploring the cultural and contextual factors underlying the lower reliability of certain constructs would inform future instrument design. Finally, a comprehensive cost–benefit analysis of LLM-based versus manual registration systems would provide the economic evidence base needed to support institution-wide and national scale investment decisions.

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Declaration of Interest

The authors declare no conflict of interest. The funder (TETFUND) had no role in the design of the study, in the collection, analysis, or interpretation of data, or in the decision to submit the paper for publication.

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A Key Questionnaire Items by Construct

Table 6: Summary of key questionnaire items for each TAM/UTAUT construct (student instrument).

Construct	Items	Sample Item
Perceived Usefulness	7	"An automated registration system would save me time."
Perceived Ease of Use	6	"Learning to use an automated registration system would be easy for me."
Social Influence	3	"People who are important to me think I should use an automated system."
Facilitating Conditions	4	"I have the resources necessary to use an automated registration system."
Behavioural Intention	4	"I intend to use an automated registration system when it becomes available."
Technology Readiness	6	"I am comfortable using new technology."

B Data Augmentation Validation

The data augmentation procedure employed multivariate statistical modelling to expand the sample from 86 original respondents to 400 while preserving the distributional and correlational properties of the original data. Validation checks included:

1. Kolmogorov–Smirnov tests: No significant distributional differences between original and augmented datasets for any variable ($p > .05$).
2. Correlation preservation: Inter-item correlations in the augmented dataset were within ±0.05 of original values.

3. Demographic realism: Augmented demographic profiles (gender, age, programme level) were consistent with institutional population parameters.
4. Reliability maintenance: Cronbach's alpha values for key constructs (PU, TR) were comparable between original and augmented datasets.