

Understanding Pre-service Science Teachers' Intentions to Integrate Generative AI: Cognitive, Affective, and Contextual Predictors

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Abstract

This study examined pre-service secondary science teachers' attitudes towards the use of generative artificial intelligence in their future classrooms. The research employed an extended Technology Acceptance Model that included cognitive, affective, ethical, and contextual predictors of intention to use GenAI. A survey was completed by 203 pre-service science teachers from a public teacher education institute in South India. Hierarchical regression and mediation analyses were conducted to test the hypotheses. The final model explained 70.3 per cent of the variance in the intention to use GenAI. Perceived usefulness emerged as the strongest predictor of intention. Attitude toward GenAI partially mediated the relationship between perceived usefulness and intention. Ethical concerns positively predicted intention, which challenged the assumption that ethical awareness acts as a barrier to adoption. Teacher training also independently predicted intention to use GenAI. Perceived ease of use, self-efficacy, and trust did not contribute uniquely to the model. These findings suggest that teacher education programs should focus on demonstrating pedagogical benefits, fostering positive attitudes, engaging constructively with ethical issues, and providing structured institutional preparation. The results inform targeted training to prepare future educators for AI-infused classrooms.

1. Introduction

The integration of Generative Artificial Intelligence (GenAI) in education is transforming how we teach and learn, offering new possibilities for personalising instruction and supporting teaching practice (Grassini, 2023). As GenAI technologies become more advanced and accessible, educators are increasingly exploring ways to integrate these tools into their classrooms, including online and blended learning environments where AI-supported feedback, content generation, and adaptive practice are becoming routine features of course design. One of the most significant impacts of GenAI in education is its ability to provide personalised learning experiences tailored to each student's needs, thereby improving engagement and academic outcomes (Baidoo-Anu & Ansah, 2023).

Successfully integrating GenAI into education, however, depends less on the technology itself than on teachers' attitudes and beliefs, since they will ultimately decide how or whether to use these tools in their classrooms. The teacher education years are the most apt point to understand these inclinations, before habits of practice are set (Escotet, 2023). Understanding pre-service teachers' attitudes towards GenAI is therefore crucial for identifying knowledge gaps and training needs, and for ensuring that teacher education programs prepare candidates for the realities of AI-infused classrooms, whether in-person, online, or blended.

This paper examines pre-service secondary school science teachers' attitudes towards leveraging GenAI to support their teaching, with a specific focus on their pedagogical approaches and assessment methods. We aim to understand how these future educators perceive the role of GenAI, including their beliefs about its effectiveness, its benefits, and the challenges of integrating it into classroom practice. The study draws its sample from pre-service teachers enrolled at a public teacher education institute in

South India; findings are interpreted with this specific institutional and regional context in mind rather than as a claim about pre-service teachers generally.

To ground this investigation, the study employs an extended Technology Acceptance Model (TAM), building on Davis's (1989) framework, as its conceptual lens. The core of TAM posits that a teacher's willingness to adopt GenAI is primarily driven by their perception of its usefulness in improving learning outcomes and by their sense of its ease of use. We extend this foundation with additional cognitive and affective constructs relevant to teacher education: Self-Efficacy in using GenAI, Attitude Toward GenAI, Trust in GenAI, and Ethical Concerns regarding its use. The model also incorporates two contextual dimensions, perceptions of GenAI's role in teacher training and perceived benefits and challenges of GenAI, that capture how institutional support and preparation shape adoption, alongside a measure of future readiness for GenAI in education. Together, these constructs allow the study to examine not only whether pre-service teachers find GenAI useful and easy to use, but also how their attitudes, trust, and ethical concerns interact with institutional preparation to shape their overall readiness to integrate GenAI into practice.

The study's potential to provide teacher education programs and policymakers with a more granular understanding of the factors that influence future educators' acceptance of GenAI is significant. The findings can inform the development of targeted training and support systems, including within online and blended teacher-preparation coursework, so that teachers are better equipped to use GenAI's capabilities thoughtfully, and so that teacher education programs can more precisely address the specific dimensions (attitudinal, ethical, or institutional) that most influence readiness, rather than treating GenAI adoption as a single, undifferentiated outcome.

2. Literature Review

2.1 GenAI in Education

GenAI is described as a disruptive yet potentially transformative technology for 21st-century learning, provided that policy frameworks, pedagogical practices, and teacher preparedness align with its strengths and limitations (Shahzad et al., 2025; Bahroun et al., 2023). Both empirical and theoretical studies highlight the dual nature of GenAI. While it offers opportunities for individualised support and adaptive learning, it raises concerns about accuracy, academic integrity, and excessive dependence on AI systems (Xiao et al., 2025). These challenges necessitate critical literacy and robust governance mechanisms to inform their educational use (Sun & Zhou, 2024; Chan & Hu, 2023).

Research consistently identifies GenAI's capacity to enable personalised learning pathways, scaffold learners' progress, and support rapid idea generation. Such affordances can enhance accessibility and address diverse learner needs (Kasneci et al., 2023). The potential is evident as GenAI fosters tailored feedback, differentiated learning tasks, and creative ideation through intelligent assistance (Winkler et al., 2023). GenAI can also assist educators in designing lesson plans, drafting syllabi, generating a

variety of assessment items, and developing illustrative examples or case studies (Bozkurt, 2023). It can support brainstorming, essay outlining, perspective-based debates, and collaborative creation of stories or code in learners (Cooper, 2023).

2.2 Teacher Readiness and Acceptance

Teachers generally perceive AI as a promising tool that can personalise learning and improve academic outcomes (Reina-Parrado et al., 2025; Ghimire & Neupane, 2024), viewing these educational tools as useful, easy to use, and having the potential to enhance AI literacy among young students (Yim & Wegerif, 2024). Educators specifically recognise AI's ability to aid in tasks such as test creation, creative task development, and student progress tracking (Jose & Jose, 2024).

The development of positive attitudes towards such innovations is critically influenced by teachers' intrinsic motivation and passion for teaching, as personal satisfaction and a love for the profession enhance enthusiasm and commitment (Savaş & Dolapci, 2024). Teachers' beliefs in the effectiveness of student-centred approaches influence their implementation and commitment to active learning, where positive attitudes can help overcome barriers such as limited time and resources (Qafa et al., 2024). Importantly for the present study, these attitudes are not uniform: Khan and Khan (2024) found that prospective teachers' attitudes vary significantly by subject stream and socio-economic status. This has a direct bearing on the current sample, which is drawn entirely from science-stream pre-service teachers at a single institution is a design choice that controls for subject-stream variation (a strength, in that it isolates GenAI-specific attitudes from cross-subject differences) but also means the findings should not be assumed to generalise to pre-service teachers in other subject streams or socio-economic contexts, a point we return to in the Discussion and Limitations.

2.3 Ethical and Pedagogical Concerns in AI Adoption

Significant challenges to the adoption of AI in education include insufficient technological content knowledge (CK), technical difficulties, and a lack of stakeholder acceptance (Yim & Wegerif, 2024). These barriers are reflected in teachers' own reports of low AI competence and infrequent use, indicating a clear need for comprehensive professional development and training (Sadykova & Kayumova, 2024). Perhaps the most immediate and widely discussed challenge is the potential for students to misuse it when completing assignments, thereby threatening conventional assessment methods (Dakakni & Safa, 2023). Further complicating its use, GenAI has inherent issues, such as hallucinations and factual misrepresentations, that can actively deter learning (Farrokhnia et al., 2023). Equity concerns compound these pedagogical ones: AI-based detection and evaluation tools have themselves been shown to carry systematic bias, for instance, disproportionately flagging non-native English writers' work as AI-generated (Liang et al., 2023), which raises fairness questions that pre-service teachers will need to navigate alongside the more commonly discussed concerns about student misuse.

2.4 Gaps and Need for the Study

There is a need for ongoing research and evaluation to better understand the impact of AI on education (Moore & Tsay, 2024). According to Sun et al. (2024), there is a lack of research on pre-service STEM instructors' readiness to incorporate AI into their teaching. A study highlights that pre-service teachers frequently anticipate guiding their future students in the responsible use of AI, yet often lack foundational knowledge themselves (Zaugg, 2024). Much of the existing research on pre-service teachers specifically has emphasised the integration of technology into pedagogical methods without addressing the affective dimensions of their attitudes toward GenAI. More broadly, qualitative studies of educators' attitudes toward AI such as Aghaziarati et al. (2023), who interviewed 28 practicing educators across educational levels and identified four themes (Pedagogical Impacts, Ethical and Social Considerations, Technological Challenges and Opportunities, and Perceptions of AI in Education), have been valuable in surfacing the range of concerns educators hold, but have not, by design, addressed the underlying psychological and behavioural constructs that predict technology integration, nor have they focused specifically on pre-service teachers prior to entering the classroom.

This study deconstructs "perception" into specific, measurable dimensions derived from established models, such as the Technology Acceptance Model. It differentiates between an individual's internal states, such as self-efficacy and attitude, and their external evaluations, and further separates broader concerns, such as ethical implications, from more practical, day-to-day beliefs, such as perceived ease of use. It introduces dimensions of preparedness and support systems, such as the role of teacher training and future readiness, which are essential for translating attitudes into actual implementation yet are often absent from broader thematic analyses. We note, in turn, that this quantitative, psychometric approach carries its own trade-off: unlike the qualitative work it builds on, it cannot capture the open-ended nuance, contradictions, or lived context behind a given rating, nor does it include any behavioural or observed-use data. We treat this as a limitation rather than an oversight, and return to it in the Discussion. To investigate these gaps, the study tests the following primary and secondary hypotheses, derived from the extended TAM framework described above.

Primary Hypotheses

H1. Perceived Usefulness, Perceived Ease of Use, and Self-Efficacy will significantly predict Intention to Use, with Perceived Usefulness expected to be the strongest predictor, consistent with prior TAM-based findings in teacher populations.

H2. Trust in GenAI will positively, and Ethical Concerns will negatively, predict Intention to Use, beyond the core cognitive predictors.

H3. Attitude Toward GenAI will mediate the relationship between Perceived Usefulness and Intention to Use.

H4. A composite model including cognitive (Usefulness, Ease, Self-Efficacy) and affective (Trust, Ethics, Attitude) predictors will explain significantly more variance in Intention to Use than either set of predictors alone.

Secondary Hypotheses

H5. Perceptions of GenAI's Role in Teacher Training will significantly predict Intention to Use beyond the core predictors.

H6. Perceived GenAI Benefits and Challenges will significantly predict Intention to Use beyond the core predictors.

H7. Future Readiness for GenAI in Education will moderate the effect of Perceived Usefulness on Intention to Use, such that the relationship is stronger among those with higher future readiness.

3. Methodology

3.1 Research Design

The study used a quantitative, cross-sectional survey-based design to investigate pre-service science teachers' (PSTs) readiness to integrate Generative Artificial Intelligence (GenAI) into educational practice. The design was suited to capturing participants' perceptions, attitudes, and self-reported competencies at a single point in time and to examining the structural relationships among constructs derived from an extended Technology Acceptance Model (TAM). As a single-time-point, self-report design, the study establishes associations rather than causation between constructs; this limitation is discussed further in the Discussion.

3.2 Instrument Development and Structure

The instrument consisted of 50 items rated on a five-point Likert scale (Strongly Disagree = 1 to Strongly Agree = 5), designed to capture participants' perceptions across 10 dimensions reflecting attitudinal and readiness aspects of GenAI integration: Perceived Usefulness (Items 1, 12, 33, 35, 43), Perceived Ease of Use (Items 9, 19, 38, 44, 45), Self-Efficacy (Items 3, 27, 31, 46, 47), Attitude Toward GenAI (Items 15, 22, 26, 42, 48), Trust in GenAI (Items 8, 11, 20, 28, 30), Ethical Concerns Regarding GenAI (Items 7, 21, 23, 29, 50), GenAI Benefits and Challenges (Items 2, 5, 6, 25, 49), GenAI's Role in Teacher Training (Items 17, 18, 24, 36, 39), Future Readiness for GenAI in Education (Items 10, 13, 16, 32, 37), and GenAI Integration in Teaching Practices (Items 4, 14, 34, 40, 41).

The questionnaire's face and content validity were established by three subject-matter experts who served as Assistant Professors at a central teacher education institute in India. Its internal factor structure, reliability, and discriminant validity were further examined empirically on the final analytic sample (N = 203). Subscale-level internal consistency, assessed via Cronbach's alpha, ranged from .506 (GenAI Benefits and Challenges) to .788 (Attitude Toward GenAI) across the ten dimensions (omnibus α = .941 across all 50 items). Five of the ten subscales fell below the conventional .70 threshold (Perceived Ease of Use, Trust in GenAI, Ethical Concerns, GenAI Benefits and Challenges, and GenAI's Role in Teacher Training), indicating that several dimensions should be interpreted with some caution.

An exploratory factor analysis with parallel analysis (principal axis factoring, oblique rotation) was conducted on the 50 items to examine whether they empirically separate into the proposed 10 dimensions. Parallel analysis suggested a five-factor solution rather than a ten-factor solution (see Fig. 1). A single dominant factor accounted for approximately 37% of common variance. It spanned items drawn from several of the hypothesised dimensions (Perceived Usefulness, Attitude, Future Readiness, GenAI's Role in Teacher Training, and GenAI Integration in Teaching Practices). At the same time, Ethical Concerns emerged as a clearly distinct factor with minimal cross-loading. This indicates that while the ten dimensions are theoretically motivated by the extended TAM framework, several are not fully empirically separable in this sample, particularly the dimensions reflecting general positive orientation toward GenAI, which share substantial common variance.

Consistent with this, Heterotrait-Monotrait ratio (HTMT) analysis showed that several dimension pairs exceeded the conventional .85 threshold for discriminant validity (see Fig. 2). Most notably, the dependent variable (GenAI Integration in Teaching Practices) was not clearly distinguishable from Perceived Usefulness (HTMT = 1.11), Attitude (1.02), GenAI's Role in Teacher Training (1.00), and Future Readiness (1.05). This finding tempers the interpretive strength of the regression results reported below and is addressed directly in the Discussion. Common method bias was assessed using Harman's single-factor test; an unrotated single factor accounted for 27.0% of total variance, below the 50% threshold conventionally used as a rough indicator against a dominant method factor, though this is interpreted alongside the more diagnostic HTMT findings above rather than as a standalone reassurance.

3.3 Population and Sample

The population for the study comprised 234 pre-service science teachers who had completed their course-mandated teaching internship and were enrolled in a public teacher education institute that admitted students from five southern Indian states and two union territories, across both integrated and stand-alone teacher education programs. The survey was distributed to the entire eligible population rather than a randomly selected subsample; 203 of 234 eligible PSTs submitted complete responses, a response rate of 86.7%, corresponding to a margin of error of approximately $\pm 2.46\%$ at 95% confidence for population-level estimates. Given this response rate relative to a finite, fully enumerable population, the achieved sample is treated as a near-census rather than a probability sample, and inferential statistics are interpreted accordingly as describing relationships within this cohort rather than generalising via sampling-based inference to a broader unsampled population. The final analytic sample, therefore, comprised 203 respondents (146 female, 57 male), drawn from both undergraduate and postgraduate teacher education programs.

3.4 Data Analysis and Statistics

Descriptive statistics were computed for all 10 dimensions. To test the study hypotheses, hierarchical multiple regression was performed with GenAI Integration in Teaching Practices as the dependent variable. Core cognitive predictors (Perceived Usefulness, Perceived Ease of Use, Self-Efficacy) were entered in Block 1; affective predictors (Trust, Ethical Concerns, Attitude) were added in Block 2;

secondary predictors (GenAI's Role in Teacher Training, GenAI Benefits and Challenges) were added in Block 3. A separate interaction term (Perceived Usefulness $\times$ Future Readiness) was tested to assess moderation.

Block 1 explained 63.2% of the variance in GenAI Integration ($R^2 = .632$), with Perceived Usefulness as the only significant predictor ($\beta = .72, p < .001$). Block 2 significantly improved model fit ($\Delta R^2 = .056, F(3,196) = 11.70, p < .001$), with Attitude Toward GenAI ($\beta = .26, p < .001$) and Ethical Concerns ($\beta = .15, p < .001$) emerging as significant predictors alongside Perceived Usefulness ($\beta = .46, p < .001$); Perceived Ease of Use, Self-Efficacy, and Trust were non-significant. Block 3 also significantly improved model fit ($\Delta R^2 = .015, F(2,194) = 4.77, p = .010$), with GenAI's Role in Teacher Training emerging as a significant predictor ($\beta = .19, p = .002$); GenAI Benefits and Challenges was non-significant. In the full model, Perceived Usefulness ($B = .338, SE = .064, p < .001$), Attitude ($B = .198, SE = .062, p = .002$), Ethical Concerns ($B = .125, SE = .045, p = .006$), and GenAI's Role in Teacher Training ($B = .169, SE = .055, p = .002$) were significant positive predictors; Perceived Ease of Use, Self-Efficacy, Trust, and GenAI Benefits and Challenges were not (all $p > .54$). The full model explained 70.3% of variance in the outcome ($R^2 = .703$, adjusted $R^2 = .690$).

Variance inflation factors were below 4 for all predictors in all three models, indicating no severe multicollinearity. Residual diagnostics indicated approximate normality (Shapiro-Wilk $W = .989, p = .118$) and borderline evidence of heteroscedasticity (Breusch-Pagan = 15.05, $p = .058$); the regression was additionally estimated using heteroscedasticity-consistent (HC3) standard errors as a robustness check, under which Perceived Usefulness, Attitude, Ethical Concerns, and GenAI's Role in Teacher Training all remained significant (all $p < .02$).

Mediation of Perceived Usefulness $\rightarrow$ Attitude Toward GenAI $\rightarrow$ GenAI Integration in Teaching Practices was tested using structural equation modelling in the lavaan package (Rosseel, 2012) in R (R Core Team, 2025), using bootstrapping (2,000 resamples) to obtain bias-corrected 95% confidence intervals for indirect effects. The indirect effect was significant ($\beta = .241, 95\% \text{ CI } [.139, .350]$), as was the direct effect of Perceived Usefulness on GenAI Integration ($\beta = .454, \text{ CI } [.314, .591]$), indicating partial mediation. A separate moderation test (Perceived Usefulness $\times$ Future Readiness) was non-significant ($b = .036, p = .301$), indicating no support for moderation. Descriptive statistics and hierarchical regression models were computed in Jamovi (version 2.7) and R; the mediation model was computed in R via lavaan. All analyses were evaluated at $\alpha = .05$, with standardised β reported alongside raw B throughout.

4. Results

4.1 Sample Characteristics

The final analytic sample comprised 203 pre-service science teachers. The survey was completed by 203 of 234 eligible individuals (response rate = 86.7%), representing a near-census of the target cohort. The sample included 146 females (71.9%) and 57 males (28.1%) participants, with a mean age of 21.4

years (SD = 1.8, range = 19–28). All continuous dimension scores exhibited acceptable univariate skewness and kurtosis ($|\text{skew}| < 2$, $|\text{kurtosis}| < 7$), supporting the use of maximum-likelihood estimation in subsequent regression and structural equation models.

4.2 Descriptive Statistics and Scale Reliabilities

Table 1 presents the means, standard deviations, medians, and internal consistency estimates (Cronbach’s α) for the ten study dimensions. Across the 5-point Likert scale, mean scores ranged from 3.37 (TAI: Trust in AI) to 3.85 (ECR: Ethical Concerns and ITP: Intention to Use), indicating that, on average, pre-service teachers held moderately positive perceptions. The highest mean was observed for Ethical Concerns ($M = 3.85$, $SD = 0.53$), suggesting heightened awareness of ethical issues surrounding GenAI. In contrast, Trust in AI was comparatively lower ($M = 3.37$, $SD = 0.61$), reflecting a more cautious disposition.

As reported in the Instrument Development section, internal consistency varied considerably across subscales. Cronbach’s α ranged from .506 (BC: Benefits & Challenges) to .788 (ATT: Attitude Toward AI), with five of the ten subscales falling below the conventional .70 threshold. The omnibus reliability across all 50 items was strong ($\alpha = .941$), indicating that the instrument as a whole measures a coherent general factor, but several theorised subdimensions do not achieve sufficient internal consistency for individual-level inference. This marginal reliability for scales such as BC, ECR, and TAI should be kept in mind when interpreting their non-significant or counter-intuitive regression coefficients.

Table 1
Descriptive statistics and alpha reliabilities

Dimension	M	SD	Median	α	ω	N Items
PU	3.726	0.598	3.800	.734	.745	5
PEOU	3.576	0.565	3.600	.670	.686	5
SE	3.584	0.631	3.600	.746	.753	5
ATT	3.820	0.594	4.000	.788	.791	5
TAI	3.374	0.608	3.400	.650	.654	5
ECR	3.850	0.526	3.800	.602	.628	5
BC	3.630	0.551	3.600	.506	.550	5
ARTT	3.653	0.592	3.600	.666	.704	5
FRAE	3.707	0.573	3.800	.741	.744	5
ITP	3.851	0.528	3.800	.695	.700	5
<i>Note.</i> PU = Perceived Usefulness; PEOU = Perceived Ease of Use; SE = Self-Efficacy; ATT = Attitude Toward AI; TAI = Trust in AI; ECR = Ethical Concerns; BC = Benefits & Challenges; ARTT = AI-Related Teacher Training; FRAE = Future Readiness for AI in Education; ITP = Intention to Use. α = Cronbach's alpha; ω = McDonald's omega.						

4.3 Bivariate Correlations

Table 2 displays the Pearson product-moment correlations among all dimension means. Consistent with the HTMT results reported in the Methods, several correlations were notably strong. Intention to Use (ITP) correlated most highly with Perceived Usefulness ($r = .786, p < .001$), Future Readiness ($r = .756, p < .001$), Attitude ($r = .751, p < .001$), and Teacher Training ($r = .704, p < .001$). These large correlations (all exceeding .70) reinforce the earlier observation that participants do not sharply differentiate between cognitive appraisals of usefulness, affective orientations, and behavioural intention.

Moderate positive correlations emerged between ITP and Benefits & Challenges ($r = .529, p < .001$), Self-Efficacy ($r = .473, p < .001$), and Ethical Concerns ($r = .483, p < .001$). The association between ITP and Perceived Ease of Use was weaker but still significant ($r = .419, p < .001$), and the weakest relationship among the predictors was between ITP and Trust ($r = .574, p < .001$). Among the independent variables, Perceived Usefulness was strongly correlated with Attitude ($r = .788, p < .001$) and Future Readiness ($r = .798, p < .001$). In contrast, Ethical Concerns showed only modest correlations with PU ($r = .403, p < .001$) and PEOU ($r = .231, p = .001$), indicating that ethical considerations are relatively orthogonal to technology acceptance beliefs (see Table 2). Figure 3 provides a visual summary of the correlation matrix, with colour intensity reflecting the magnitude and direction of associations.

Table 2
Correlation Matrix

PU	PU	PEOU	SE	ATT	TAI	ECR	BC	ARTT	FRAE	ITP
	1.000									
PEOU	.413	1.000								
SE	.487	.654	1.000							
ATT	.788	.456	.520	1.000						
TAI	.616	.489	.483	.605	1.000					
ECR	.403	.231	.265	.443	.315	1.000				
BC	.588	.416	.440	.546	.561	.345	1.000			
ARTT	.712	.414	.440	.677	.615	.432	.445	1.000		
FRAE	.798	.434	.460	.817	.621	.373	.552	.720	1.000	
ITP	.786	.419	.473	.751	.574	.483	.529	.704	.756	1.000

4.4 Hypothesis Testing: Hierarchical Regression

A three-block hierarchical multiple regression was conducted to predict Intention to Use (ITP). Variables were entered in theoretically motivated blocks: Block 1 (core TAM variables: Perceived Usefulness, Perceived Ease of Use, Self-Efficacy); Block 2 (affective and relational variables: Trust, Ethical Concerns, Attitude); Block 3 (contextual variables: Benefits & Challenges, Teacher Training). This ordering allowed assessment of the incremental predictive validity of each conceptual layer. Variance inflation factors (VIFs) in the final model ranged from 1.316 to 3.437, well below the conventional threshold of 5, indicating that multicollinearity does not unduly inflate standard errors.

Model 1 was significant, $F(3, 199) = 114.07, p < .001$, and accounted for 63.20% of the variance in ITP ($R^2 = .632$, Adjusted $R^2 = .626$). Among the three core predictors, only Perceived Usefulness emerged as a significant unique contributor, with a standardised coefficient of $\beta = .720$ ($t = 14.48, p < .001$). In unstandardised terms, a one-unit increase in PU was associated with a 0.636-unit increase in ITP, holding the other predictors constant. Perceived Ease of Use ($\beta = .072, t = 1.26, p = .211$) and Self-Efficacy ($\beta = .075, t = 1.25, p = .213$) did not contribute uniquely. This suggests that, once usefulness is accounted for, perceptions of ease and confidence add little explanatory power.

Model 2, which added Trust, Ethical Concerns, and Attitude, significantly improved model fit, $\Delta R^2 = .056$, $F(3, 196) = 11.70, p < .001$. The full model explained 68.79% of the variance ($R^2 = .688$, Adjusted $R^2 = .678$). In this expanded model, PU remained a strong predictor but was partially attenuated ($\beta = .461, t = 6.77, p < .001$). Attitude emerged as a significant positive predictor ($\beta = .258, t = 3.70, p < .001$), indicating that favourable affective orientations toward GenAI translate into higher intention, over and above

perceptions of utilitarian usefulness. Ethical Concerns also became a significant positive predictor ($\beta = .151, t = 3.37, p = .001$), which is a result that runs counter to the hypothesised negative direction (H2). Trust, however, was not significant ($\beta = .060, t = 1.09, p = .278$).

Model 3, the final model, entered Benefits & Challenges and Teacher Training, yielding a small but statistically significant increase in explained variance ($\Delta R^2 = .015$), $F(2, 194) = 4.77, p = .010$. The final model was highly significant, $F(8, 194) = 57.23, p < .001$, accounting for 70.26% of the variance ($R^2 = .703$, Adjusted $R^2 = .690$). As shown in Table 3, four predictors remained statistically significant. Perceived Usefulness remained the strongest unique predictor ($\beta = .382, t = 5.27, p < .001$), affirming its central role in shaping adoption intentions. Attitude continued to exert a significant positive influence ($\beta = .222, t = 3.20, p = .002$), while Ethical Concerns, though slightly attenuated from Model 2, maintained significance ($\beta = .124, t = 2.76, p = .006$) and remained in the positive direction. Teacher Training emerged as a significant contextual predictor ($\beta = .189, t = 3.08, p = .002$), highlighting the importance of formal institutional preparation in fostering adoption intentions. Conversely, Perceived Ease of Use ($\beta = .018, t = 0.34, p = .735$), Self-Efficacy ($\beta = .024, t = 0.43, p = .667$), Trust ($\beta = .010, t = 0.18, p = .858$), and Benefits & Challenges ($\beta = .032, t = 0.61, p = .544$) did not contribute uniquely to the full model (see Table 3).

Summary of Hypotheses

Of the seven primary hypotheses derived from the extended Technology Acceptance Model, three were supported in the hypothesised direction. Hypothesis 1 (Perceived Usefulness $\rightarrow$ Intention to Use) received the strongest support, with Perceived Usefulness emerging as the largest unique predictor in the final model. Hypotheses 3 (Attitude $\rightarrow$ Intention) and 4 (Teacher Training $\rightarrow$ Intention) were also supported, confirming that both affective dispositions and institutional preparation contribute independently to adoption intentions. Hypothesis 2 (Ethical Concerns $\rightarrow$ Intention) was statistically significant but in the opposite direction to that hypothesised: greater ethical concerns were associated with higher, not lower, intention to use GenAI. This is addressed in detail in the Discussion. Hypotheses 5 (Perceived Ease of Use $\rightarrow$ Intention), 6 (Self-Efficacy $\rightarrow$ Intention), and 7 (Trust $\rightarrow$ Intention) were not supported. A complete summary of all hypotheses, including standardised coefficients and significance levels, is provided in Table 4.

Table 4
Summary of Hypotheses Testing

Hypothesis	Path	β	<i>p</i>	Supported?
H1	Perceived Usefulness → Intention to Use	.382	< .001	✓
H2	Ethical Concerns → Intention to Use	.124	.006	✓ (reversed)
H3	Attitude → Intention to Use	.222	.002	✓
H4	Teacher Training → Intention to Use	.189	.002	✓
H5	Perceived Ease of Use → Intention to Use	.018	.735	X
H6	Self-Efficacy → Intention to Use	.024	.667	X
H7	Trust → Intention to Use	.010	.858	X
<i>Note.</i> β = standardised regression coefficient from the final hierarchical regression model (Model 3). ✓ = supported; X = not supported. H2 was significant but in the opposite direction to that hypothesised.				

Table 3
Hierarchical Regression

Predictor	Model 1		Model 2		Model 3		VIF
	B (SE)	β	B (SE)	β	B (SE)	β	
(Intercept)	1.015 (0.172)	—	0.524 (0.191)	—	0.468 (0.192)	—	—
PU	0.636 (0.044)	.720***	0.407 (0.060)	.461***	0.338 (0.064)	.382***	3.437
PEOU	0.067 (0.054)	.072	0.028 (0.051)	.030	0.017 (0.050)	.018	1.904
SE	0.063 (0.050)	.075	0.022 (0.047)	.026	0.020 (0.046)	.024	2.007
TAI	—	—	0.052 (0.048)	.060	0.009 (0.050)	.010	2.132
ECR	—	—	0.151 (0.045)	.151**	0.125 (0.045)	.124*	1.316
ATT	—	—	0.229 (0.062)	.258***	0.198 (0.062)	.222**	3.152
BC	—	—	—	—	0.031 (0.050)	.032	1.790
ARTT	—	—	—	—	0.169 (0.055)	.189**	2.467
R ²	.632		.688		.703		
Adjusted R ²	.626		.678		.690		
ΔR^2	—		.056***		.015**		
F	114.07***		71.69***		57.23***		
Note. ΔR^2 values represent the change in R^2 from the preceding model.							

4.5 Mediation Analysis

To examine the mechanism through which Perceived Usefulness (PU) influences Intention to Use (ITP), we tested a mediation model with Attitude (ATT) as the hypothesised intermediary. The model was estimated using maximum likelihood with bootstrapped standard errors and bias-corrected 95% confidence intervals (2,000 resamples). Because the model was just identified, global fit indices are perfect (CFI = 1.000, RMSEA = 0.000); inference relies on the bootstrapped intervals. The path from PU to ATT (*a* path) was strong and significant (*a* = .783, SE = .049, *z* = 16.03, *p* < .001), indicating that participants who perceive AI as more useful also hold more positive attitudes, with PU accounting for

62.1% of the variance in ATT. The path from ATT to ITP (*b* path) was also significant ($b = .308$, $SE = .070$, $z = 4.43$, $p < .001$). The direct effect of PU on ITP, controlling for ATT (*c'* path), remained significant ($c' = .454$, $SE = .070$, $z = 6.48$, $p < .001$), confirming that PU exerts influence on intention even when attitude is statistically controlled.

The indirect effect ($a \times b$) was estimated at .241 ($SE = .055$), with a bootstrapped 95% confidence interval of [.139, .350] that excludes zero, confirming a statistically significant indirect effect. The total effect of PU on ITP was .695 ($SE = .040$, 95% CI [.611, .768]). The proportion of the total effect mediated was 34.7% (indirect/total), indicating partial mediation: Perceived Usefulness influences Intention to Use through both a direct, utilitarian route and an indirect, affective route via Attitude (see Table 5). Figure 4 presents the path diagram of the mediation model with standardised coefficients, visualising the direct and indirect pathways.

Table 5
Mediation Coefficients

Effect	Label	Estimate	SE	*z*	*p*	95% CI
PU → ATT	a	.783	.049	16.032	< .001	[.681, .874]
ATT → ITP	b	.308	.070	4.428	< .001	[.175, .441]
PU → ITP	c'	.454	.070	6.483	< .001	[.314, .591]
Indirect	a × b	.241	.055	4.388	< .001	[.139, .350]
Direct	c'	.454	.070	6.483	< .001	[.314, .591]
Total	c' + indirect	.695	.040	17.322	< .001	[.611, .768]
<i>Note.</i> Bootstrapped standard errors and bias-corrected 95% confidence intervals based on 2,000 resamples. Estimates are standardised. CI = confidence interval.						

4.6 Moderation Analysis

A separate moderation analysis tested whether Future Readiness (FRAE) moderates the relationship between PU-ITP. Both PU and FRAE were mean-centred prior to forming the interaction term. The overall model was significant, $F(3, 199) = 132.1$, $p < .001$, accounting for 66.56% of the variance ($R^2 = .666$, Adjusted $R^2 = .661$). The main effect of PU remained robust ($B = .450$, $SE = .060$, $t = 7.48$, $p < .001$), and the main effect of FRAE was also significant ($B = .332$, $SE = .063$, $t = 5.27$, $p < .001$). However, the interaction term between PU and FRAE was not significant ($B = .036$, $SE = .035$, $t = 1.04$, $p = .301$). This indicates that the strength of the positive PU-ITP relationship does not differ across levels of Future Readiness; the slope is uniform regardless of how prepared teachers feel for AI's future role. Therefore, the moderation hypothesis is not supported. A simple-slopes plot for visual inspection is shown in Fig. 5, confirming the parallel slopes.

4.7 Residual Diagnostics and Model Robustness

To verify the reliability of the regression inferences, diagnostic checks were performed on the final Model 3. The Shapiro-Wilk test for normality of residuals was non-significant ($W = .989, p = .118$), supporting the assumption of normally distributed errors. The Breusch-Pagan test for homoscedasticity approached but did not reach conventional significance ($BP = 15.05, df = 8, p = .058$), suggesting that heteroscedasticity is not a pronounced concern; nonetheless, we adopted a conservative approach by re-estimating the model with HC3 robust standard errors. Under the robust estimator, all four significant predictors retained their statistical significance: PU ($p < .001$), ECR ($p = .015$), ATT ($p = .009$), and ARTT ($p = .008$), confirming that the pattern of significance is stable.

Influence analysis using Cook's distance identified 18 cases exceeding the $4/n$ threshold (0.0197), with a maximum Cook's D of 0.074. This value is modest and well within the range where coefficients remain stable; moreover, the robust standard error estimates provide further assurance that outliers do not unduly drive the regression results. Figure 6 presents the full set of residual diagnostic plots, including residuals versus fitted values, the Q-Q plot, scale-location plot, and residuals versus leverage with Cook's distance contours.

5. Discussion

This study set out to examine pre-service secondary science teachers' attitudes towards leveraging GenAI to support their teaching, employing an extended Technology Acceptance Model (TAM; Davis, 1989) that incorporated cognitive, affective, and contextual predictors of intention to use. The findings offer a clearer picture of the factors shaping future educators' readiness to integrate GenAI into classroom practice, one that both aligns with and challenges existing research in important ways. The final model explained 70.3% of the variance in intention to use, supporting Hypothesis 4 that a composite model including cognitive, affective, and contextual predictors would outperform any single set of predictors alone.

5.1 The Primacy of Perceived Usefulness

The robust finding of this study is the overwhelming dominance of Perceived Usefulness as a predictor of Intention to Use GenAI. In the final model, PU remained the strongest unique predictor ($\beta = .382, p < .001$), accounting for the bulk of explained variance even after controlling for affective and contextual factors. This aligns closely with prior TAM-based research in teacher populations, which has consistently identified perceived usefulness as the primary driver of technology adoption intentions (Davis, 1989; Grassini, 2023). Indeed, across multiple studies of teachers' acceptance of GenAI, perceived usefulness has emerged as one of the strongest predictors of both attitudes toward use and behavioural intention (Jose & Jose, 2024; Reina-Parrado et al., 2025).

What is notable is the magnitude of PU's dominance relative to other predictors in this sample. In Block 1 of the hierarchical regression, PU alone effectively carried the model ($\beta = .720$), with Perceived Ease of Use and Self-Efficacy contributing negligible unique variance. This finding differs somewhat from studies

such as Liu et al. (2025), who found that self-efficacy significantly predicted both perceived usefulness and behavioural intention among pre-service teachers. Similarly, Sun et al. (2025) reported that AI self-efficacy strongly predicted perceived ease of use, a finding that the present study did not observe. The divergence may reflect differences, such as the sampled GenAI experience. Liu et al. (2025) engaged their participants in a structured GenAI-integrated activity using a domain-specific platform, whereas the present study measured general perceptions without a standardised hands-on experience. It may be that self-efficacy becomes a more potent predictor when pre-service teachers have actually used the technology. In the absence of such concrete experience, their generalised confidence beliefs are overshadowed by their assessment of whether GenAI is useful in principle. This interpretation is consistent with the observation that teachers' AI self-efficacy often operates indirectly through perceived ease of use and usefulness, rather than exerting a direct effect on intention (Sun et al., 2025).

The non-significance of Perceived Ease of Use is also worth noting. In the original TAM, ease of use is theorised to influence both usefulness perceptions and behavioural intention directly (Davis, 1989). However, in this study, PEOU contributed nothing uniquely to the prediction of intention in any model block ($\beta = .018$, $*p* = .735$). This suggests that for this cohort of pre-service science teachers, who are digital natives by age and have completed a teaching internship, the question is not whether GenAI is easy to use, but whether it is worth using. GenAI tools such as ChatGPT and Gemini are increasingly familiar and accessible, with a low barrier to entry, and ease-related concerns may have been largely resolved (Bahroun et al., 2023). What remains is a more fundamental pedagogical calculus: Does this technology make me a better teacher? This finding resonates with research on technology adoption more broadly, which has observed that as technologies become more user-friendly and ubiquitous, perceived ease of use declines in relative importance, while perceived usefulness takes on an even more central role (Shahzad et al., 2025).

The mediation analysis confirmed that Attitude Toward GenAI partially mediates the relationship between Perceived Usefulness and Intention to Use (indirect effect = .241, 95% CI [.139, .350]), with 34.7% of the total effect mediated. This finding is consistent with the core logic of TAM, wherein perceived usefulness shapes behavioural intention both directly and indirectly through attitude (Davis, 1989). However, the fact that the direct effect of PU on ITP remained substantial ($\beta = .454$) even after controlling for attitude suggests that a combination of utilitarian calculation and affective orientation drives pre-service teachers' intentions. This dual-pathway logic is important: it implies that interventions aimed at increasing GenAI adoption need to address not only what teachers think about the technology's utility, but also how they feel about it.

5.2 Attitude as a Mediator

The mediation analysis confirmed that Attitude Toward GenAI partially mediates the relationship between Perceived Usefulness and Intention to Use (indirect effect = .241, 95% CI [.139, .350]), with 34.7% of the total effect mediated. This finding is consistent with the core logic of TAM, wherein perceived usefulness shapes behavioural intention both directly and indirectly through attitude (Davis, 1989). However, the fact that the direct effect of PU on ITP remained substantial ($\beta = .454$) even after

controlling for attitude suggests that a combination of utilitarian calculation and affective orientation drives pre-service teachers' intentions. This dual-pathway logic is important as it implies that interventions aimed at increasing GenAI adoption need to address not only what teachers think about the technology's utility, but also how they feel about it.

The strength of the PU→ATT path ($a = .783$) indicates that perceived usefulness is the primary determinant of positive attitudes, accounting for 62.1% of the variance in attitude. This is consistent with research by Wang et al. (2026), who found that perceived usefulness exerts a positive indirect impact on adoption intention via attitude. It also reinforces the practical implication that demonstrating concrete pedagogical benefits through modelled use cases, lesson-planning examples, and evidence of improved student outcomes may be the most effective way to shift both attitudes and intentions simultaneously, a point emphasised in the broader literature on teacher motivation and innovation adoption (Savaş & Dolapci, 2024).

5.3 The Dilemma of Ethical Considerations

Perhaps the most unexpected finding of this study is the positive relationship between Ethical Concerns and Intention to Use ($\beta = .124, p = .006$). Hypothesis 2 hypothesised that greater ethical concerns would be associated with lower intention to use GenAI, which is a prediction grounded in the literature documenting teachers' anxieties about academic integrity, bias, and over-reliance on AI systems (Dakakni & Safa, 2023; Farrokhnia et al., 2023; Liang et al., 2023). Instead, the opposite pattern was obtained: pre-service teachers who reported greater awareness of ethical issues also reported stronger intentions to integrate GenAI into their teaching.

This counterintuitive result requires careful interpretation. Several lines of evidence from recent research suggest that ethical awareness and technology acceptance are not necessarily oppositional. A study of pre-service classroom teachers found that ethical ICT use and acceptance of generative AI were moderately and positively correlated, leading the authors to conclude that ethical orientations toward technology are closely associated with pre-service teachers' openness to emerging AI technologies (Wang et al., 2026). In the same way, research on K-12 teachers' adoption of GenAI found that perceived ethical risks heightened GenAI anxiety, yet did not directly reduce adoption intention; as the authors note, teachers are cautiously willing to experiment despite underlying concerns (Sun et al., 2025).

What may be occurring here is that ethical concern functions not as a deterrent but as a marker of thoughtful engagement. Pre-service teachers who are more attuned to the ethical dimensions of GenAI, such as issues of bias, privacy, academic integrity, and appropriate use, may also be more cognitively engaged with the technology overall. Rather than being paralysed by ethical worries, they may be actively considering how to use GenAI responsibly, which in turn sustains or even amplifies their intention to use it. This interpretation is bolstered by the relatively high mean for Ethical Concerns ($M = 3.85, SD = 0.53$), the highest of all dimensions measured; these future teachers are not indifferent to ethical issues, but they appear to view them as challenges to be managed rather than reasons to abstain (Farrokhnia et al., 2023; Sun & Zhou, 2024).

This finding also aligns with research on teacher-AI collaboration, which suggests that perceived risks can, under certain conditions, promote adaptive responses. In a study applying job demands-resources theory to teacher-AI collaboration, technology acceptance helped teachers cope with AI anxiety induced by perceived risk, and, to some extent, perceived risk promoted improvements in teachers' human-machine compatibility (Xiao et al., 2025). In other words, awareness of risks may motivate teachers to develop the competencies needed to use AI effectively and ethically, rather than leading them to reject the technology outright.

It is important, however, to acknowledge an alternative interpretation rooted in measurement. As noted in the Methodology, the Ethical Concerns subscale exhibited marginal internal consistency ($\alpha = .602$), and the broader instrument demonstrated substantial common variance across several theoretically distinct dimensions, as indicated by the HTMT analysis. The positive coefficient for Ethical Concerns may reflect some degree of construct overlap with general positive orientation toward GenAI, rather than a genuinely positive relationship between ethical worry and intention. This possibility is discussed further in the Limitations section.

5.4 The Non-Significant Predictors

The failure of Perceived Ease of Use, Self-Efficacy, and Trust to emerge as significant predictors in the final model is noteworthy. For PEOU and Self-Efficacy, as discussed above, the explanation may lie in the sample and the absence of a standardised hands-on experience. For Trust, however, the non-significance is more puzzling, given that several studies have identified trust as a significant antecedent of AI adoption among teachers (Sun et al., 2025; Wang et al., 2026). In Sun et al.'s (2025) extended TAM study of pre-service teachers, trust significantly influenced attitude toward use; in research on Generation Z pre-service teachers, trust primarily affected perceived usefulness; and in a study of Chinese K-12 teachers, trust and social reinforcement strongly influenced adoption decisions.

One possibility is that trust does not contribute uniquely in this sample because trust in GenAI is already subsumed by perceived usefulness for these participants. The bivariate correlation between Trust and Intention to Use was substantial ($r = .574, p < .001$), and PTrust correlated strongly with perceived Usefulness ($r = .616, p < .001$). When PU is included in the regression, it may absorb variance that trust would otherwise explain, consistent with the theoretical logic that a part of trust operates through its influence on perceived usefulness. This interpretation is supported by research findings that trust primarily affects perceived usefulness (Sun et al., 2025). The null finding for Trust in the final model may therefore reflect statistical suppression rather than substantive irrelevance.

An alternative explanation is that trust in GenAI is still nascent among this cohort. The mean for Trust ($M = 3.37, SD = 0.61$) was the lowest of all dimensions measured, suggesting that pre-service teachers are cautiously uncertain about relying on GenAI systems. In such a context, trust may not yet be sufficiently crystallised to exert an independent effect on intention; it may be a precondition for the formation of usefulness perceptions, but once usefulness is established, trust adds little incremental predictive value.

5.5 The Role of Teacher Training

The significant positive effect of GenAI's Role in Teacher Training ($\beta = .189, p = .002$) in the final model underscores the importance of formal institutional preparation in shaping adoption intentions. This finding is consistent with a growing body of research highlighting the critical role of teacher education programs in preparing future educators for AI-infused classrooms (Zaugg, 2024). The mean for this dimension ($M = 3.65, SD = 0.59$) suggests that participants generally perceived teacher training as relevant to GenAI integration, but the variance in these perceptions meaningfully predicted differences in intention.

This result has clear implications for teacher education curriculum design. Programs that explicitly address GenAI not merely as a technological novelty but as a pedagogical tool with specific affordances, limitations, and ethical considerations are likely to produce graduates who are better prepared and more willing to integrate these tools into their practice (Sadykova & Kayumova, 2024). The finding also aligns with research showing significant improvements in literacy and acceptance among teacher candidates who receive AI training (Yim & Wegerif, 2024). The effect of teacher training on intention was independent of perceived usefulness, attitude, and ethical concerns, suggesting that institutional preparation provides something additional, perhaps a sense of legitimation, a framework for appropriate use, or the confidence that comes from structured guidance (Ghimire & Neupane, 2024; Qafa et al., 2024).

5.6 Theoretical and Practical Contributions

Extending the TAM framework (Davis, 1989), this study demonstrates that cognitive (usefulness), affective (attitude), ethical (concerns), and contextual (training) predictors collectively account for 70.3% of variance in intention thus outperforming core TAM constructs alone (63.2%) and confirming that multiple dimensions shape GenAI acceptance (Sun et al., 2025; Wang et al., 2026). The primacy of perceived usefulness advocates for hands-on professional development that concretely demonstrates pedagogical benefits, such as time savings, differentiated materials, and personalised feedback, rather than abstract discussions (Bozkurt, 2023; Kasneci et al., 2023; Winkler et al., 2023). The unexpected positive effect of ethical concerns calls for reconceptualising ethics as informed engagement rather than a deterrent (Sun & Zhou, 2024; Chan & Hu, 2023), implying that teacher educators should frame ethical challenges as navigable design problems rather than prohibitions (Liang et al., 2023). The significant mediation via attitude (34.7% of total effect) underscores the need to foster positive affective orientations alongside utilitarian appraisals (Savaş & Dolapci, 2024). The independent contribution of teacher training highlights that structured institutional preparation that addresses technical, pedagogical, and ethical dimensions adds unique value beyond individual perceptions (Yim & Wegerif, 2024; Zaugg, 2024). These findings suggest that effective preparation requires a holistic approach addressing utilitarian beliefs, affective states, ethical reflection, and institutional scaffolding together.

6. Conclusion

This study establishes that pre-service science teachers' readiness to adopt GenAI is driven by a constellation of cognitive, affective, and contextual factors, with perceived usefulness, attitude, ethical concern, and teacher training independently predicting intention. The extended TAM framework, accounting for 70.3% of variance, provides a robust foundation for understanding adoption in teacher education contexts. The positive association between ethical concerns and intention suggests that they do not paralyse future educators who are more aware of risks but appear motivated to engage thoughtfully with the technology. This finding challenges deficit-based narratives of teacher resistance.

These findings must be interpreted in light of several limitations. First, the cross-sectional, self-report design precludes causal inference; the directionality implied by the mediation model is theoretically grounded but cannot be empirically confirmed (Moore & Tsay, 2024). Second, the marginally reliable subscales ($\alpha < .70$ for five of ten dimensions) and HTMT evidence of construct overlap suggest the instrument requires refinement, particularly for Trust, Ethical Concerns, and Benefits and Challenges, and serve as a caution that tempers the counter-intuitive ethical concerns finding. Third, the sample is drawn from a single South Indian institution and restricted to science-stream pre-service teachers. This limits generalisability (Khan & Khan, 2024), and findings should not be assumed to transfer to other subject disciplines, geographic regions, or socio-economic contexts. Fourth, the absence of a standardised hands-on GenAI experience means perceptions reflect general awareness rather than concrete use, which may have attenuated the effects of self-efficacy and ease of use. Fifth, the study measured intention rather than actual classroom behaviour, so caution is warranted when translating these findings directly into practice.

Future research should employ longitudinal or experimental designs to establish directionality, validate and refine the instrument across diverse populations, and replicate the model across subject disciplines, institutional types, and cultural contexts. Incorporating structured GenAI activities prior to measurement, as in Liu et al. (2025). This would ground participants' responses in lived experience and clarify whether self-efficacy and ease of use gain predictive power when teachers have actually used the tools. Including observational measures of actual classroom integration would help bridge the intention-behaviour gap. Addressing these limitations will determine whether the observed relationships hold beyond this cohort.

Declarations

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Ethics approval

This study's methodology and extent of human data collected was presented and approved by an 'Institute Review Board' consisting of Head, Department of Education, Head, Department of Extension Education and an external member at the Regional Institute of Education, Mysuru, India, which served as de-facto ethics committee and dissertation approval committee in lines with the WMA Declaration of Helsinki. All methods employed in this study were conducted in accordance with the relevant guidelines and regulations put forth by the committee and the approval granted on 06th of November, 2024.

Consent to participate

Freely given, informed consent was obtained electronically from all the participants and were included voluntarily. The committee had not waived consent and written consent was obtained electronically. They were informed that their data will be used for academic analysis and publishing purposes.

Consent for publication

Not Applicable.

Availability of data and material

All data required for the validation of the study are included within the manuscript. Raw data can be made available on request at the authors' discretion.

Competing interests

There are no competing or conflicting interests associated with this study, its methods or results.

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AI-Use

The contents of this paper are the intellectual property of the Authors, and AI use was restricted to using Grammarly AI for grammatical refinement and cohesion. After using these tools, the authors reviewed and edited the content as needed and took full responsibility for the content of the published article.

CRedit authorship contribution statement

M Devaraj- Conceptualisation, Literature review; Formal analysis; Writing (original), Investigation;

Dinesh Kumar Patnamsetty- Investigation, Formal Analysis;

Harshith B Nair- Conceptualisation, Writing (original)

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Figures

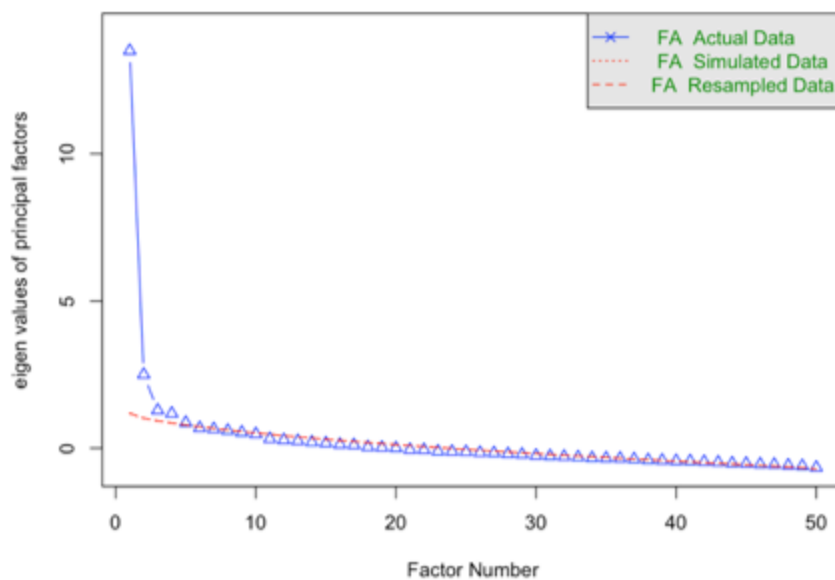


Figure 1

Parallel Analysis Scree Plot

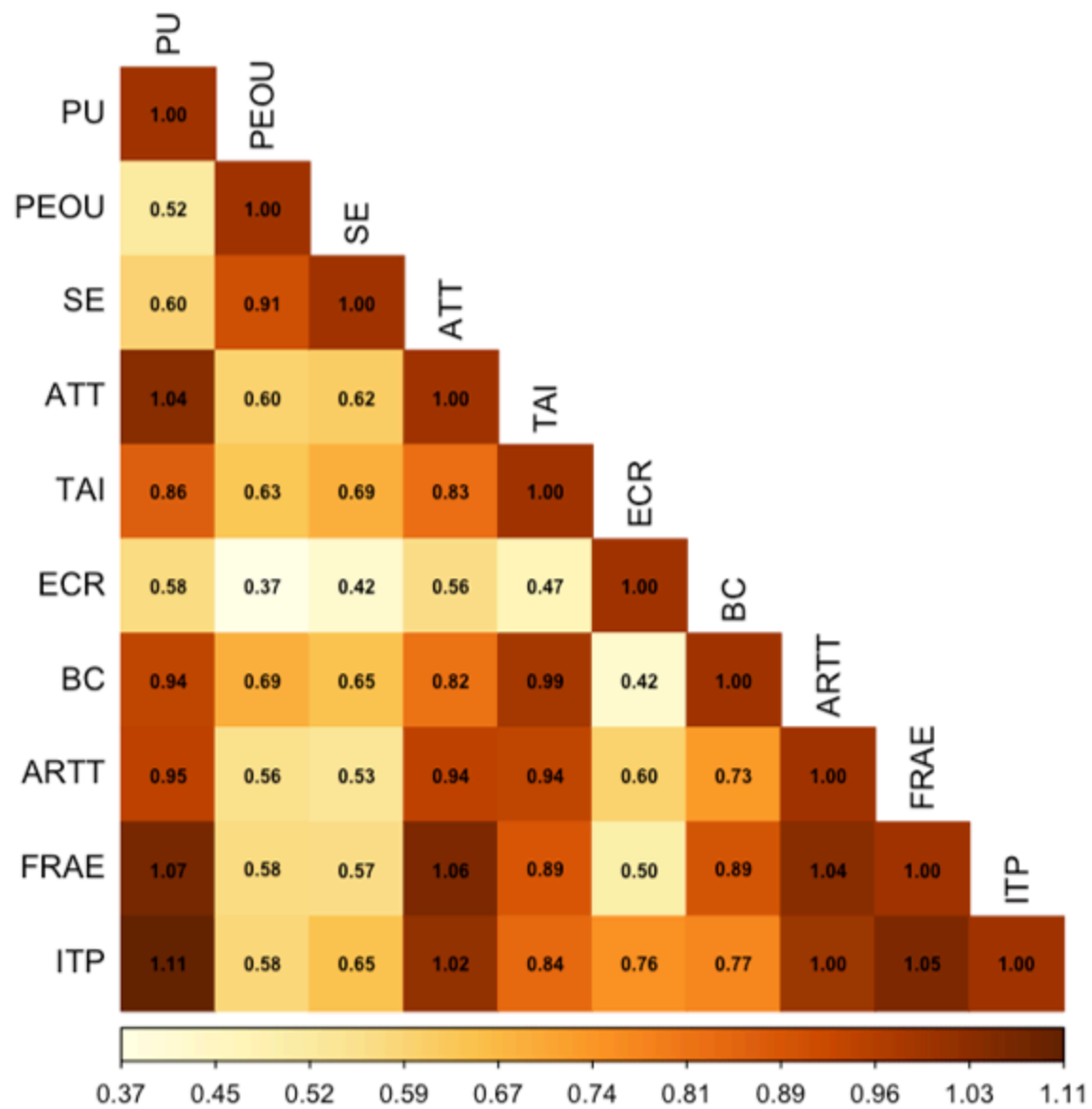


Figure 2

HTMT Matrix Heatmap

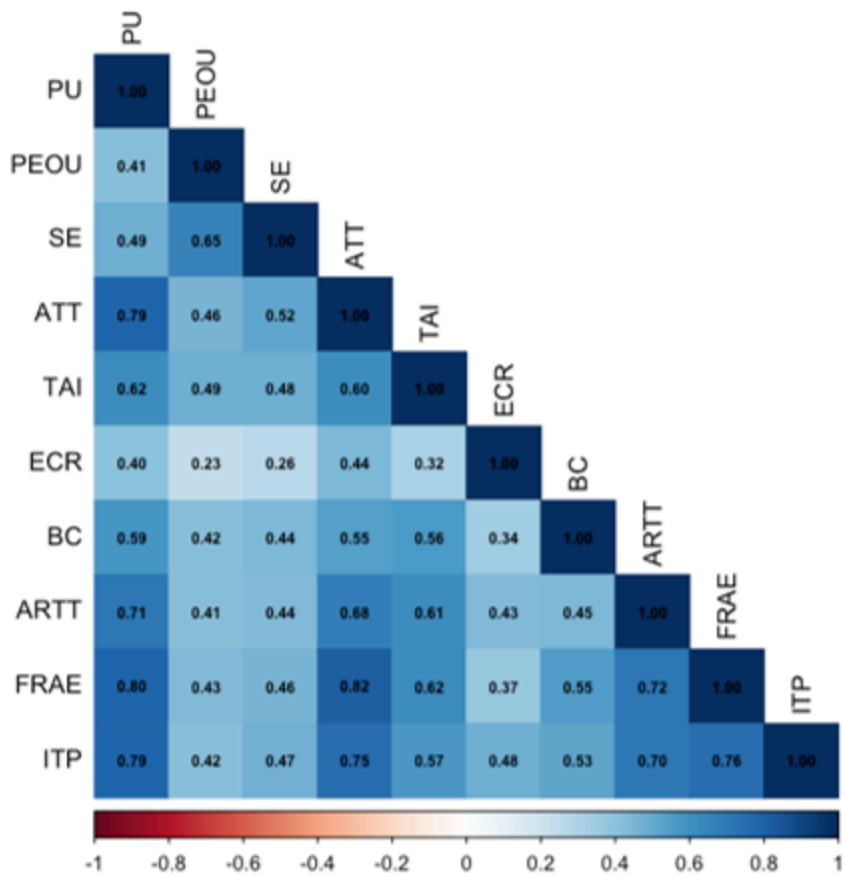


Figure 3

Correlation heatmap

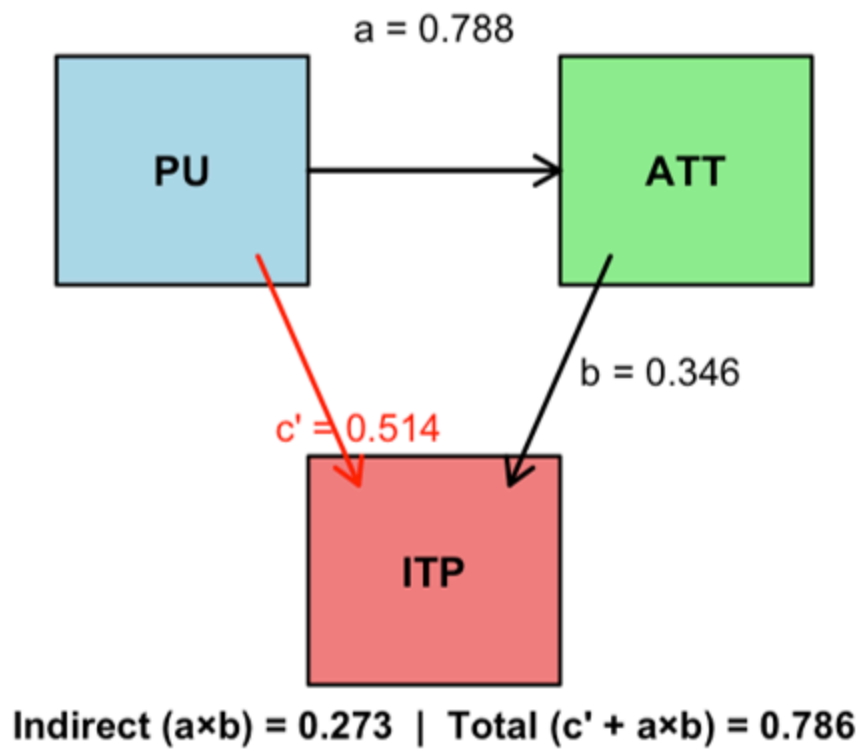


Figure 4

Mediation Path Diagram (Model: $PU \rightarrow ATT \rightarrow ITP$)

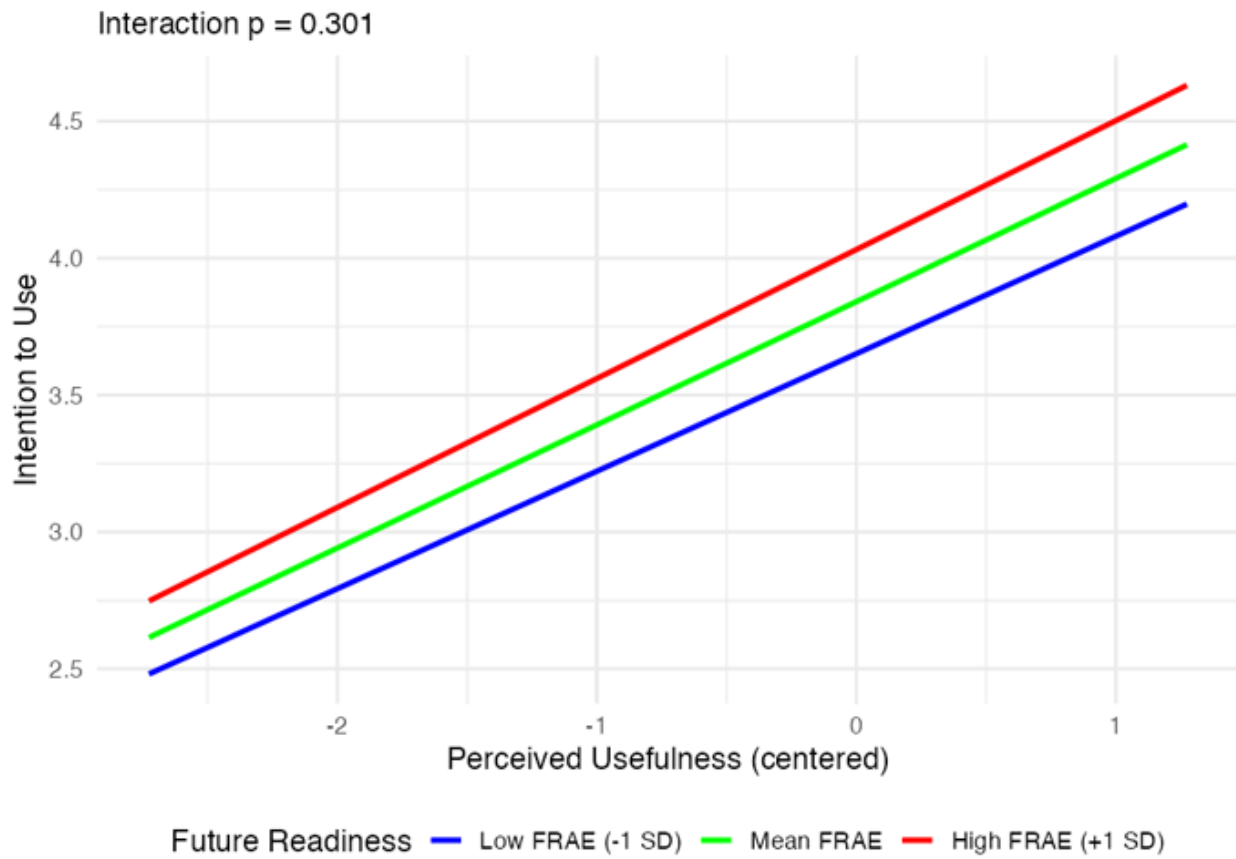


Figure 5

Simple-slopes plot for $PU \times Future\ Readiness$ interaction $\rightarrow ITP$ ($p = 0.301$)

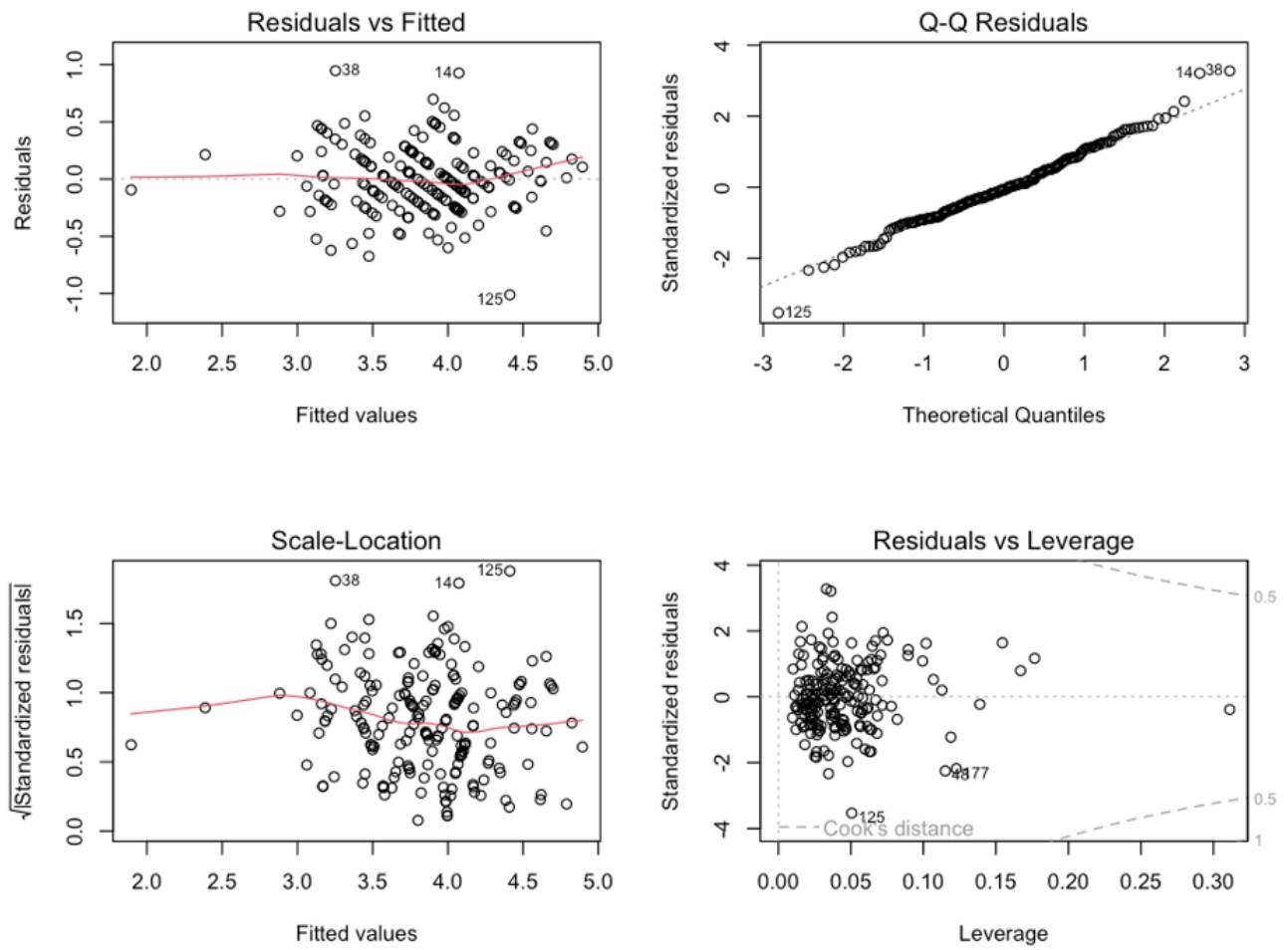


Figure 6

Residual diagnostic plots