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The behavioral intentions to integrate AI in teaching science among distance and contact education student teachers: a comparative study

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ABSTRACT

Integrating Artificial Intelligence could reduce educational challenges and improve learning outcomes in teaching science. However, the intention of teachers to use these technologies is poorly understood. Informed by the Theory of Planned Behavior, this comparative survey study examined the behavioral intentions of science student teachers from two South African universities to integrate AI into teaching science. An online questionnaire was used to collect data from purposively sampled final-year students from Central University ($n = 97$) and East Coast University ($n = 85$). Data analysis involved Exploratory Factor Analysis to identify the structure of constructs, ordinal logistic regression to identify predictors of behavioral intention, and the Mann-Whitney U test to compare behavioral intentions between the two samples. The results suggested that the constructs conformed to the Theory of Planned Behavior with high reliability (Cronbach's Alpha: .846–.935). Seven factors explained 72.67% of the variance, with strong loadings. Both samples demonstrated a positive intention to integrate AI, with the Central University reporting higher control beliefs ($p = .005$). However, Ordinal Logistic Regression indicated the constructs did not significantly predict behavioral intentions ($p > .05$). The findings highlight the importance of providing context-specific training programs to support the integration of AI in science education.

IMPACT STATEMENT

This study examined South African science student teachers' intentions to integrate Artificial Intelligence (AI) into teaching, comparing distance and contact education contexts. The findings show strong readiness to embrace AI, highlighting opportunities for innovation in science education. However, differences in control beliefs reveal structural inequities in training, access, and support that shape confidence in AI adoption. By exposing these disparities, the study demonstrates the need for responsive, hands-on professional development and equitable resource provision. It advances educational practice and policy by offering evidence to strengthen AI integration, bridge systemic gaps, and promote sustainable, equitable improvements in science education.

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1. Introduction

Teacher training in most countries, including South Africa, is delivered through distance and contact education modes, each with distinct advantages and challenges. Distance education, often referred to as distance learning, facilitates learning through digital technologies, allowing students to engage with educational content remotely (Lembani et al., 2020). Distance education has become prominent due to its flexibility and accessibility, particularly highlighted during the COVID-19 pandemic, as it breaks geographical barriers by allowing student teachers to access training resources remotely (Tashkenbayeva et al., 2022). While

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distance learning supports self-paced learning, it often lacks direct interaction, potentially limiting the development of practical skills, which can hinder the development of practical teaching competencies (Ferreira, 2015; Zacharias & Giossos, 2017). Furthermore, the success of distance education for teacher training depends on the availability of resources and students' digital literacy skills; the absence of these skills may impact engagement and communication between students, their peers, and educators.

In contrast, contact learning, often referred to as traditional or face-to-face learning, is an educational approach where students and instructors engage in direct, in-person interaction within a physical classroom environment (Duffy et al., 2002; Xia et al., 2013). It provides a structured setting where students and instructors engage, facilitating collaboration among peers and mentors and fostering a sense of community and shared learning (Ferreira, 2015). Additionally, interpersonal engagement in these settings promotes the development of communication and teamwork skills essential for effective teaching. The supportive environment allows students to ask questions, clarify doubts, and refine their techniques, ensuring they are better prepared for the complexities of classroom teaching.

However, the extent to which these training approaches influence teachers' behavioral intentions to integrate Artificial Intelligence (AI) tools in teaching science is poorly understood. These tools have been demonstrated to support teachers in fostering critical thinking and science process skills among students, thereby improving learning outcomes (Mnguni, 2025). Despite this, there is limited research on how teacher training modes affect the behavioral intentions of student teachers to integrate AI into teaching science. The current study compares science student teachers from a distance and a contact teacher training institution in South Africa to elucidate their intentions for integrating AI into science teaching. These insights can inform teacher-training curricula that support the integration of AI in science education, particularly in addressing educational challenges in South Africa and other developing countries.

1.1. Current trends in AI integration in education

AI originated in the 1950s when McCarthy and his colleagues proposed the creation of computers that could perform tasks traditionally handled by humans (McCarthy et al., 2006). This idea was based on Turing's groundbreaking research, which explored the possibility of machines exhibiting cognitive capabilities (Turing, 1950). Over time, AI has evolved to emulate human cognitive processes, enabling machines to engage in activities such as teaching, learning, reasoning, problem-solving, and understanding natural language.

The integration of AI tools in education has experienced significant growth in the 21st century, thereby fundamentally transforming teaching and learning practices (Li, 2025; Mnguni, 2025; Ramnarain et al., 2024). This expansion encompasses a diverse range of AI-based tools, from instructional resources to advanced applications embedded in educational environments, designed to enhance pedagogical effectiveness (Celik, 2023). Since the COVID-19 pandemic, there has been a significant increase in AI-driven educational systems that utilize advanced technologies to create immersive and interactive learning experiences (Kashive et al., 2020). AI-enhanced assessment systems, for instance, streamline evaluation and feedback processes, offering efficient and timely support for teachers (Hwang et al., 2020). These tools enhance instructional quality and address individual learning needs through adaptive systems that personalize content delivery, thereby improving student comprehension and engagement (Capuano & Caballé, 2020; Gligorea et al., 2023). Interactive AI applications, including augmented and virtual reality simulations, further demonstrate their utility by making complex scientific concepts accessible through experiential learning (Halabi, 2020). Similarly, Intelligent Tutoring Systems using Natural Language Processing provide tailored educational support (Billings et al., 2024; Shin, 2022), while AI-driven analytics identify struggling students for early intervention (Huang & Rust, 2018). By automating repetitive tasks like assessment grading and lesson preparation, AI enables teachers to devote more time to personalized and interactive teaching approaches (Adelana et al., 2024). This transformative potential of AI highlights its pivotal role in optimizing educational outcomes and addressing diverse challenges in contemporary education.

While AI holds promise for transforming education, concerns have been raised regarding its potential to erode academic standards and diminish students' critical thinking and engagement (Hamamra et al., 2024). Generative AI tools like ChatGPT, although capable of enhancing productivity and supporting learning, can facilitate unethical academic conduct, such as plagiarism. In this regard, scholars have raised concerns about students' increasing reliance on AI to generate academic work, often bypassing essential cognitive tasks such as analysis, synthesis, and argument construction (Dong et al., 2025; Hamamra et al., 2024). This trend risks fostering a culture of academic complacency, where surface-level outputs replace deep learning. Moreover, educators face heightened challenges in detecting AI-generated content, complicating efforts to uphold academic integrity and evaluate genuine student competencies effectively.

1.2. Teachers' behavioural intentions towards integration of AI in teaching science

Teachers' behavioral intentions are pivotal in the successful and ethical integration of AI into science education. Behavioral intentions refer to an individual's conscious decision or motivation to perform a specific behavior, shaped by attitudes, subjective norms, and perceived behavioral control (Ajzen, 2014). They serve as strong predictors of whether the behavior will be executed. According to Almogren et al. (2024) and Mnguni et al. (2024a), favorable behavioral intentions and attitudes toward technology integration are vital for successful adoption. However, significant variability exists in teachers' intentions to embrace AI due to self-efficacy, perceived usefulness, and technological competence (Ayanwale et al., 2022). Teachers with high self-efficacy are likelier to adopt AI, while those lacking confidence in their skills often hesitate. Perceived usefulness further influences willingness; teachers who recognize AI's potential to enhance learning outcomes are more inclined to use it in their classrooms (Willy, 2022). These findings suggest that addressing these motivational factors through targeted professional development could significantly enhance teachers' intentions toward AI adoption.

Despite the promising benefits of AI, several barriers impede its integration into science education. For example, inadequate training and professional development opportunities leave many teachers unprepared to use AI tools effectively for teaching (James et al., 2019). This challenge is particularly pronounced in under-resourced schools, where disparities in access to technological infrastructure hinder the adoption of technology (Chemwei, 2019). Ethical concerns, including data privacy and algorithmic bias, also shape teachers' attitudes and influence their intentions to use AI (Gagné, 2023). Institutional support is equally crucial for positive intentions to integrate AI in teaching. Schools that provide robust technological infrastructure, administrative backing, and peer collaboration foster positive intentions and greater adoption of AI tools (Dai et al., 2023). In contrast, schools without such support struggle with sporadic and unsustainable implementation efforts.

To promote AI integration in science education, it is essential to understand and address teachers' behavioral intentions and the factors affecting them (Mnguni et al., 2024a). Enhancing self-efficacy, demonstrating AI's usefulness, and providing clear ethical guidelines can strengthen these intentions. When coupled with professional development and adequate institutional resources, these initiatives empower teachers to leverage AI's capabilities, enhancing instructional strategies and student learning outcomes.

1.3. Problem statement

Despite the growing recognition of AI as a transformative tool in education, the behavioral intentions of science teachers to integrate AI in teaching science remain under-explored (Li, 2025), particularly in developing countries like South Africa (Mnguni et al., 2024a, 2024b). This gap may be particularly evident among science student teachers from distance and contact education programs, where variations in training approaches may impact their preparedness for integrating AI. Examining these behavioral intentions is crucial, as they play a significant role in the effective adoption of digital technologies. Furthermore, research focused on student teachers is crucial as they represent the future workforce, and their preparedness will thus shape the integration of AI in education.

Comparing behavioral intentions of student teachers trained in different learning modes could provide insights into how teacher training modes impact the adoption of educational technologies (Mnguni et al., 2024a). These insights are significant for shaping teacher education and professional development programs that cater to diverse educational contexts. Findings from such research will also inform

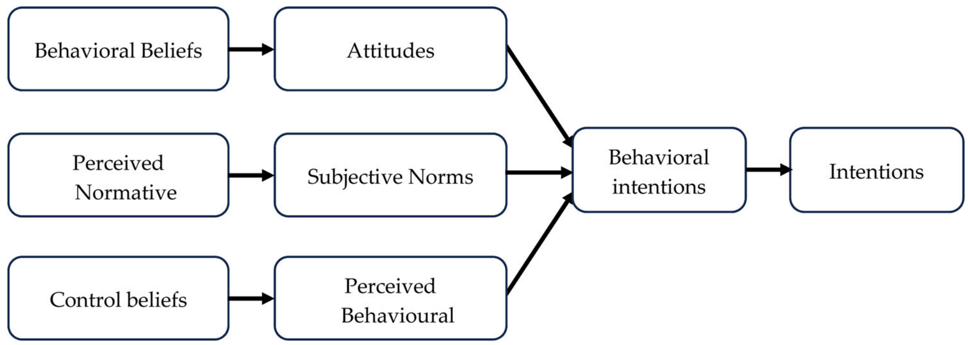

Figure 1. Constructs influencing behavioral intentions based on the theory of planned behavior.

resource allocation, training design, and teacher support strategies to foster effective AI integration in science education. Therefore, by addressing this research gap, we offer timely contributions to understanding the factors influencing AI adoption in South African classrooms and other similar developing contexts, ensuring the equitable and effective use of educational technologies.

1.4. Research aim and question

Considering the above, this research compared the behavioral intentions of science student teachers from distance and contact universities in South Africa to inform training programs for effective adoption of AI in science teaching. Our question was, 'How do the behavioral intentions to integrate AI in teaching science compare among science student teachers from distance and contact universities in South Africa?'

2. Theoretical framework: the theory of planned behaviour

We employ the Theory of Planned Behaviour (Figure 1) to examine student teachers' intentions for integrating AI into science teaching. The Theory of Planned Behaviour predicts behaviour through three key constructs: attitudes, subjective norms, and perceived behavioural control (PBC), all of which are influenced by behavioural, normative, and control beliefs (Ajzen, 2014). Subjective norms and normative beliefs encompass external social influences that may shape student teachers' willingness to adopt AI in their teaching practices. Behavioral beliefs focus on the perceived benefits of AI use, thereby enhancing the likelihood of adoption. PBC evaluates teachers' confidence in overcoming challenges, emphasizing the availability of resources and their knowledge. This is particularly relevant in South Africa, where systemic and technological constraints may hinder the adoption of AI (Ajzen & Madden, 1986).

While critics argue the Theory of Planned Behaviour oversimplifies behavior by neglecting emotional and moral dimensions (Sniehotta et al., 2014), its consideration of psychosocial factors makes it a robust framework for predicting technology adoption (Teo, 2011). The inclusion of PBC enhances its applicability, particularly in addressing institutional barriers. We identified enablers and barriers to AI adoption by analyzing these constructs, offering targeted insights for teacher training and policy development. Empirical validation of the Theory of Planned Behavior highlights its significance in examining how beliefs, social norms, and perceived control influence student teachers' readiness to integrate AI into education. This framework aligns well with our research objectives in the South African context, providing a systematic basis for understanding and supporting the effective adoption of AI in science education.

3. Research methods

We used a quantitative research approach to examine the behavioral intentions of science student teachers from two South African universities. We employed a non-experimental comparative descriptive survey design to assess and compare participants' intentions regarding the integration of AI into science teaching. This design offers a comprehensive perspective on the differences and similarities in behavioral intentions, providing valuable insights into the adoption of AI in teaching practices.

3.1. Study participants

We used purposeful sampling to select final-year Bachelor of Education students from Central University (n = 97) and East Coast University (n = 85), which offer teacher training through distance and contact modes, respectively. The universities were pseudonymized for confidentiality. All participants were trained to teach high school science subjects, specifically Life Sciences, Natural Sciences, and Physical Sciences.

The comparable sample sizes enabled meaningful comparisons between Central University, a distance education institution, and East Coast University, a traditional, face-to-face institution. Central University's students are geographically dispersed, while East Coast University's students are campus-based. Sampling in these universities, therefore, captures the diversity of teacher training experiences and educational modalities, which could influence readiness to integrate AI in South Africa. By selecting final-year students, we sought to ensure that the study reflected the behavioral intentions of student teachers at the nexus of pre-service training and in-service practice. In this regard, all participants were trained to teach in the Further Education and Training (FET) phase (grades 10–12). This purposive selection provided valuable insights into their readiness and capabilities for integrating AI into teaching science.

East Coast University had a higher proportion of female participants (75.3%) compared to Central University (57.7%), while Central University had more male participants (41.2% vs. 24.7%). East Coast University's participants were predominantly younger, with 80.9% in the 18–24 age group, whereas Central University showed greater age diversity, including 36.1% aged 25–34 and 12.4% aged 35–44. Teaching experience also varied, with 48.5% of Central University participants having less than one year of experience, compared to 36% at East Coast University. In contrast, East Coast University had a slightly larger group with 6–10 years of experience (23.6%). These demographic differences reflect the diverse profiles of student teachers, which may influence their perspectives on integrating AI into science education.

3.2. Data collection

Using a structured, close-ended questionnaire, we collected data through a self-administered online survey in the first semester of 2024. The instrument, guided by the Theory of Planned Behavior, measured the seven constructs of the theory (Figure 1) and biographical data. Specialists in science teacher education and a pilot study were used to determine the instrument's criterion-related validity, content validity, and face validity. Feedback from these was used to refine the instrument, including rewording some items to eliminate ambiguity and simplify technical jargon for clarity. Some items were shortened to reduce survey fatigue. Additionally, the Likert scale was modified to ensure a fair distribution of options, thereby enhancing its ability to accurately capture participants' perspectives. Furthermore, unnecessary or repetitive items were eliminated, refining the survey to emphasize the key elements of the Theory of Planned Behavior components through 35 close-ended items, which made up the final instrument (see Appendix A). The Instrument was previously validated and used to explore teacher preparedness for integrating AI into teaching (Mnguni et al., 2024b). However, it was further validated for the current study as described in the data analysis section below.

3.3. Data analysis

We employed multiple data analysis techniques to ensure the validity and reliability of the findings regarding the behavioral intentions of science student teachers to integrate AI into science teaching. We conducted the Exploratory Factor Analysis (EFA) to examine the structure of the survey instrument, aligning measured variables with the constructs of the Theory of Planned Behavior. Cronbach's Alpha reliability analysis was performed to assess the instrument's internal consistency. This statistical test assessed the consistency with which the survey items measured each construct, ensuring that the

Table 1. Total variance explained by extracted factors.

Component	Initial eigenvalues	% of variance	Cumulative %
1	8.888	26.142	26.142
2	3.798	11.170	37.312
3	3.488	10.260	47.572
4	2.551	7.503	55.075
5	2.264	6.658	61.733
6	1.163	6.459	68.192
7	1.522	4.477	72.669

instrument produced stable and reliable responses. Ordinal Logistic Regression was employed to identify the extent to which the Theory of Planned Behaviour constructs influenced behavioral intentions. This technique was chosen because the dependent variable (behavioral intention) was ordinal, making it suitable for regression modeling that examines the relationship between multiple independent variables and an ordered categorical outcome. The model's goodness of fit was evaluated using Pearson and Deviance tests, and pseudo-R-squared values were calculated to determine the proportion of variance explained by the predictors.

Additionally, a Mann-Whitney U test was conducted to compare differences in behavioral intentions and related constructs between student teachers from two different universities. This non-parametric test was selected due to the ordinal nature of the survey data and the potential for non-normal distribution. Each of these statistical techniques was selected to ensure a comprehensive analysis of the data.

4. Results

4.1. Factor analysis: Exploring the underlying constructs of student teachers' intentions toward AI integration

An Exploratory Factor Analysis was conducted to assess the underlying structure of the questionnaire items. This confirmed that the measured variables aligned with the theoretical constructs of the Theory of Planned Behavior. The instrument's reliability was evaluated using Cronbach's Alpha to demonstrate internal consistency across all components.

The Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy was .839, indicating that the sample size was sufficient for factor analysis and that the item correlations were strong enough to reveal an underlying structure. Bartlett's Test of Sphericity yielded a significant result ($\chi^2 = 4370.353$, $p < .001$), confirming that inter-item correlations were adequate for factor analysis. The significance of Bartlett's test further indicated that the correlation matrix was not an identity matrix, reinforcing the appropriateness of applying factor analysis to the dataset.

Factor analysis extracted seven factors with eigenvalues exceeding 1, collectively explaining 72.67% of the total variance (Table 1). The first factor accounted for 26.14% of the variance, while the second and third contributed 11.17% and 10.26%, respectively. The first five factors collectively accounted for 61.73% of the total variance, highlighting their significance in explaining the underlying structure of the dataset. These findings highlight the robustness and alignment of the identified factor structure with the theoretical framework.

The communalities, representing the portion of variance in each variable explained by the extracted factors, ranged between 0.374 and 0.885, indicating that the factors account for a significant amount of variance in the measured items (Table 2). One item was removed due to low communalities, falling below the threshold of 0.3. The analysis of the rotated component matrix supports the validity of the Theory of Planned Behavior constructs in the context of AI integration in science education. Notably, items measuring Behavioral Intentions loaded strongly on the third component, with examples like BI1 showing a loading of 0.897, highlighting teachers' commitment to future adoption. Similarly, Normative Beliefs had strong loadings, such as NB1 with a loading of 0.810, underscoring the influence of social expectations on intention formation. Teachers' Attitudes toward AI integration were also favorable, as seen in A2, with a loading of 0.818 on the first component. Furthermore, Control Beliefs showed high loadings, exemplified by CB3 at 0.878, reflecting teachers' confidence in overcoming implementation challenges. Overall, these seven components collectively explain 72.67% of the variance, affirming the

Table 2. Rotated factor loadings and communalities for student teachers' behavioural intention for integrating AI in teaching science.

	Component							
Item code	1	2	3	4	5	6	7	Communalities (extraction)
A 1							.857	.781
A 2							.818	.735
A 3							.848	.789
A 4							.807	.787
A 5							.732	.605
BB 1	.816							.721
BB 2	.785							.727
BB 3	.808							.721
BB 4	.880							.807
BB 5	.782							.693
SN 1						.380		.465
SN 2						.698		.585
SN 3						.806		.855
SN 4						.753		.841
SN 5						.748		.762
NB 1				.810				.743
NB 2				.743				.685
NB 3				.858				.848
NB 4				.823				.747
PBC 1				.333	.597			.647
PBC 2					.795			.751
PBC 3					.823			.741
PBC 4					.753			.698
PBC 5					.630			.541
CB 1		.820						.745
CB 2		.776						.713
CB 3		.878						.823
CB 4		.735						.664
CB 5		.832						.760
I 1			.897					.838
I 2			.934					.885
I 3			.863					.756
I 4			.930					.874
I 5			.543					.374

Extraction Method: Principal Component Analysis.
Rotation Method: Varimax with Kaiser Normalization.

Table 3. Reliability analysis of the theory of planned behaviour scale components.

Constructs	Reliability	Number of items
Attitudes	.846	5
Behavioral Beliefs	.935	5
Subjective Norms	.903	5
Normative Beliefs	.932	4
Perceived Behavioral Control	.899	5
Control Beliefs	.934	5
Behavioural Intentions	.884	5

applicability of the Theory of Planned Behaviour in predicting teachers' intentions to adopt AI in science education.

4.2. Reliability of the theory of planned behaviour scale components

The Cronbach's Alpha values for the Theory of Planned Behaviour scale components indicate high reliability (Table 3). Attitudes (.846), Behavioral Beliefs (.935), Subjective Norms (.903), Normative Beliefs (.932), Perceived Behavioral Control (.899), Control Beliefs (.934), and Behavioral Intentions (.884) all show strong internal consistency, with values well above the acceptable threshold of .70. This suggests the questionnaire items reliably measure the intended constructs, ensuring dependable results for the study.

The results of the instrument validation process provided strong evidence for the reliability and validity of the questionnaire used to assess science student teachers' intentions regarding the integration of AI in science teaching. After the instrument was validated, the behavioral intentions of student teachers

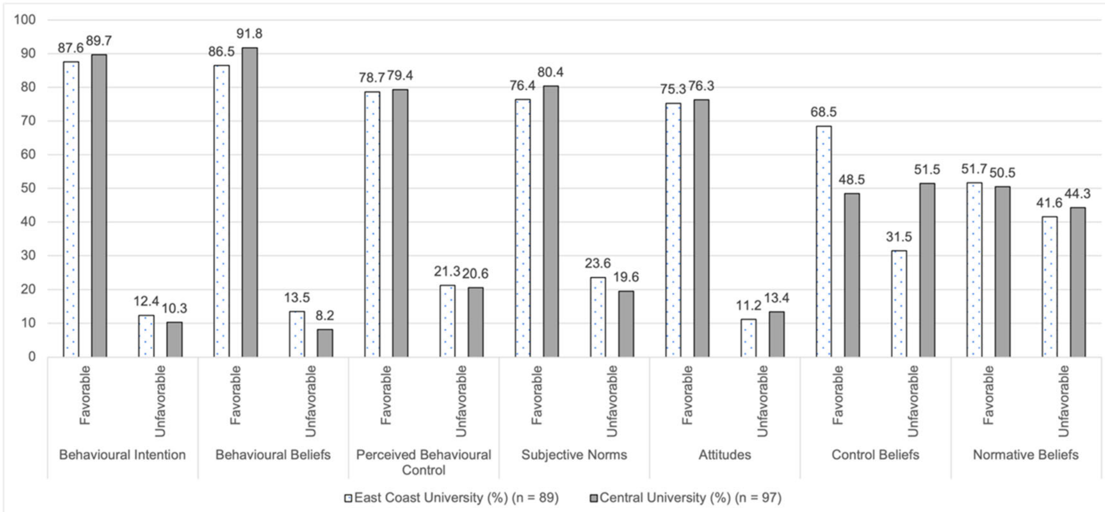

Figure 2. Comparison of science student teachers' behavioral intentions towards AI integration at East Coast University and Central University.

at the two universities were explored, with a focus on comparing their attitudes toward integrating AI into their future teaching practices.

4.3. Science student teachers' behavioral intentions toward AI integration

Data were analyzed to determine the central tendency among participants regarding their behavioral intentions toward integrating AI in science teaching (Figure 2). A higher proportion of participants from both institutions reported a favorable behavioral intention, with 87.6% of East Coast University and 89.7% of Central University participants expressing a willingness to integrate AI into their teaching. Attitudinal positivity was also strong, with 75.3% of East Coast University and 76.3% of Central University respondents reporting favorable attitudes towards AI integration. Behavioral beliefs are notably higher among Central University participants (91.8%) than East Coast University (86.5%). Subjective norms followed a similar trend, with a higher proportion of respondents reporting favorable responses from Central University (80.4%) compared to East Coast University (76.4%). Normative beliefs were relatively balanced but slightly more unfavorable among Central University respondents. The two groups ' perceived behavioral control was almost identical, around 79%. However, a significant divergence is observed in control beliefs, where 68.5% of East Coast University participants reported favorable control beliefs compared to 48.5% of Central University participants, indicating a higher perceived ability to integrate AI among East Coast University respondents. The data suggest a generally strong support for AI integration, with some differences in control and normative beliefs.

4.4. Regression analysis of factors influencing behavioral intentions to integrate AI in teaching science among student teachers

The factors influencing behavioral intentions to integrate AI in science teaching among student teachers at East Coast University and Central University were explored using Ordinal Regression Analysis. The model-fitting results reveal varying levels of predictive power between the universities. At the East Coast University, the ordinal logistic regression model was nearly statistically significant ($\chi^2(6) = 10.984$, $p = .089$), indicating the predictors may have a moderate influence on behavioral intentions. However, they did not meet the conventional significance threshold. In contrast, the model for Central University showed no significant predictive power ($\chi^2(6) = 2.937$, $p = .817$), suggesting that the predictors had little to no impact on student teachers' behavioral intentions in this context.

The goodness-of-fit statistics regarding the evaluation of model adequacy showed that at the East Coast University, both the Pearson ($\chi^2(156) = 158.659$, $p = .426$) and deviance ($\chi^2(156) = 102.500$, $p = 1.000$) tests

Table 4. Parameter estimates for ordinal logistic regression (df = 1).

University of current study			Estimate	Std. Error	Wald	Sig.	95% confidence interval Lower bound	Upper bound
East Coast University	Threshold	[Behavioural Intention = 1.00]	−2.639	.950	7.717	.005	−4.501	−.777
		[Behavioural Intention = 2.00]	.193	.899	.046	.830	−1.570	1.956
		[Behavioural Intention = 3.00]	2.747	1.303	4.442	.035	.192	5.301
	Location	Attitude	−.181	.150	1.453	.228	−.475	.113
		Behavioural Beliefs	−.128	.380	.114	.736	−.874	.617
		Subjective Norms	.103	.437	.056	.813	−.753	.959
		Normative Beliefs	−.211	.289	.537	.464	−.777	.354
		Perceived Behavioral Control	−.642	.324	3.940	.047	−1.276	−.008
		Control Beliefs	−.022	.253	.008	.929	−.518	.473
Central University	Threshold	[Behavioural Intention = 1.00]	−.164	.844	.038	.846	−1.818	1.490
		[Behavioural Intention = 2.00]	2.876	.911	9.964	.002	1.090	4.662
	Location	Attitude	.063	.148	.178	.673	−.228	.353
		Behavioural Beliefs	.195	.397	.241	.623	−.584	.974
		Subjective Norms	−.159	.382	.172	.678	−.908	.591
		Normative Beliefs	−.225	.258	.759	.384	−.731	.281
		Perceived Behavioral Control	.408	.326	1.564	.211	−.231	1.047
		Control Beliefs	.109	.206	.280	.597	−.295	.513

were non-significant, indicating a robust fit between the model and the observed data. Similarly, the model for the Central University showed an acceptable fit based on the deviance statistic ($\chi^2(98) = 108.469$, $p = .221$). However, the Pearson chi-square for Central University was marginally significant ($\chi^2(98) = 118.152$, $p = .081$), suggesting potential concerns regarding the fit, though not conclusively problematic.

The pseudo-R-square results reflected the models' ability to explain variance in behavioral intentions. For East Coast University, Nagelkerke's R^2 value of .134, Cox and Snell's R^2 of .116, and McFadden's R^2 of .062 indicate a modest level of explanatory power. While these figures are relatively small, they suggest that the predictors contribute to explaining behavioral intentions in this context. In contrast, the model for Central University demonstrated minimal explanatory power, with Nagelkerke's R^2 at .036, Cox and Snell's R^2 at .030, and McFadden's R^2 at .017, confirming that the predictors had little impact on behavioral intentions among Central University's student teachers.

The parameter estimates in Table 4 reveal distinct differences in how the predictors affected behavioral intentions across the two universities. At East Coast University, none of the predictors demonstrated statistical significance in explaining behavioral intentions. Specifically, attitudes (Estimate = −0.181, SE = 0.150, Wald $\chi^2(1) = 1.453$, $p = .228$) and behavioral beliefs (Estimate = −0.128, SE = 0.380, Wald $\chi^2(1) = 0.114$, $p = .736$) showed no meaningful influence on student teachers' behavioral intentions. However, perceived behavioral control was a significant negative predictor (Estimate = −0.642, SE = 0.324, Wald $\chi^2(1) = 3.940$, $p = .047$), indicating that reduced perceived control corresponded with stronger intentions to integrate AI in teaching science. In contrast, none of the predictors, including attitudes (Estimate = 0.063, SE = 0.148, Wald $\chi^2(1) = 0.178$, $p = .673$) and behavioral beliefs (Estimate = 0.195, SE = 0.397, Wald $\chi^2(1) = 0.241$, $p = .623$) were statistically significant at the Central University. The predictors (i.e. attitudes, behavioral beliefs, control beliefs, normative beliefs, perceived behavioral control, and subjective norms) had no substantial impact on the behavioral intentions of Central University's student teachers. These results suggest that while perceived behavioral control plays a role at East Coast University, none of the examined factors significantly shape behavioral intentions at Central University, indicating potential contextual differences in the determinants of behavioral intentions between the two universities.

4.5. Comparative analysis of behavioral intentions for integrating AI in teaching science

The Mann-Whitney U test compared the attitudes, behavioral beliefs, behavioral intentions, control beliefs, normative beliefs, perceived behavioral control, and subjective norms of science student teachers from East Coast University and Central University regarding their integration of AI in teaching science. The results (Table 5) indicate that there are no significant differences between science student teachers from East Coast University and Central University in their attitudes ($p = .806$), behavioral beliefs ($p = .179$), subjective norms ($p = .157$), normative beliefs ($p = .455$), PBC ($p = .242$), and behavioral intention ($p = .794$). However, a significant difference was found in control beliefs ($p = .005$), where Central

Table 5. Mann-Whitney U test results comparing science student teachers from east Coast university ($n = 89$) and Central university ($n = 97$) regarding their attitudes, behavioral beliefs, behavioral intention, control beliefs, normative beliefs, perceived behavioral control, and subjective norms.

	Attitudes	Behavioural beliefs	Subjective norms	Normative beliefs	Perceived behavioural control	Control beliefs	Behavioral intention
Mann-Whitney U	4249.000	3896.500	3874.000	4059.500	3917.500	3415.500	4231.500
Wilcoxon W	9002.000	8649.500	8627.000	8812.500	7922.500	7420.500	8236.500
Z	−.245	−1.343	−1.415	−.748	−1.169	−2.835	−.261
Asymp. Sig. (2-tailed)	.806	.179	.157	.455	.242	.005	.794

Note: Grouping Variable: University of current study.

University participants reported higher favorable control beliefs than their East Coast University counterparts. This indicates that Central University student teachers may feel more confident in their ability to control and implement AI in their teaching practices.

5. Discussion

This research provides insights into the behavioral intentions of science student teachers from distance and contact education universities regarding the integration of AI into their teaching practices. A nuanced interpretation of the findings, in relation to existing literature, highlights key themes and their implications for teacher training programs.

5.1. Interpretation of the findings

The first key finding of this study is that the constructs of the Theory of Planned Behavior exhibited strong internal consistency and factorial validity. High factor loadings for attitude, subjective norms, and perceived behavioral control, along with acceptable Cronbach's alpha values, confirmed the reliability and structural integrity of the measurement model. These results suggest that the Theory of Planned Behavior framework is theoretically sound for capturing student teachers' beliefs and dispositions toward AI integration. However, its predictive power for behavioral intention was limited in this context. At East Coast University, perceived behavioral control exhibited a statistically significant inverse relationship with behavioral intention, whereas other constructs, including attitudes, subjective norms, and behavioral beliefs, did not significantly predict intention at either institution. This challenges the Theory of Planned Behavior's core proposition that these constructs shape intention (Ajzen, 2014). Similar anomalies have been reported elsewhere. Kiriakidis (2017) argues that external factors such as resource availability and institutional support can overshadow internal cognitive variables in resource-constrained settings. We propose that external factors not captured by the Theory of Planned Behavior may be influencing behavioral intentions in our sample. This interpretation aligns with research highlighting how systemic, infrastructural, and socio-cultural barriers support impede technology adoption in South Africa (Gcabashe, 2024; Mavuru & Ramaila, 2022; Mhlongo et al., 2023; Mnguni, 2025). These barriers can diminish the influence of constructs such as perceived control and subjective norms by constraining teachers' autonomy and agency. Additionally, rural-urban disparities in infrastructure and the emotional burden of persistent educational inequities may further discourage innovation (Barakabitze et al., 2019; Howie, 2010; Munoriyarwa, 2024; Mwapwele et al., 2019; Stols et al., 2015). Internal factors such as self-efficacy may also moderate these relationships. This interplay underscores the need for more comprehensive theoretical models and targeted interventions, such as professional development and resource provision, to facilitate the integration of AI in science education.

Nevertheless, we also found favorable behavioral intentions among the participants to integrate AI into their teaching practices, irrespective of their institution. The uniformly favorable behavioral intentions align with findings by AlKanaan (2022) and Mnguni (2025), who reported similar favorable attitudes among student teachers for adopting AI in education, reflecting an increasing recognition of AI's potential to enhance teaching methodologies and learning outcomes (Haleem et al., 2022). As highlighted by

Ramnarain et al. (2024), student teachers recognize AI's potential to enhance teaching science by supporting learner autonomy, accommodating diverse needs, and overcoming systemic challenges such as resource shortages.

Our findings also revealed a significant difference in control beliefs between participants from the two universities, with participants from East Coast University (contact education) reporting significantly more favorable control beliefs. In contrast, most Central University (distance education) participants expressed unfavorable control beliefs, indicating a lack of confidence in their ability to control and implement AI effectively in teaching. This disparity likely arises from the contrasting educational modalities. East Coast University's contact-based approach facilitates structured, direct interactions with instructors, peers, and resources, fostering a collaborative environment where students gain hands-on experience with AI technologies (Lembani et al., 2020). This interactive and supportive setting enhances self-efficacy and confidence in overcoming implementation challenges. Conversely, Central University's distance education model, while flexible and accessible, often limits immediate support, practical exposure, and access to necessary technological infrastructure. These challenges may leave student teachers feeling less equipped to effectively integrate AI tools. These findings add nuance to existing research, which suggests that distance education generally enhances teachers' self-efficacy and skills with information and communication technology (Paetsch et al., 2023). Our results extend this understanding by showing that distance education participants may face unique barriers when integrating more advanced technologies, such as AI, into teaching science, requiring tailored interventions to bolster control beliefs.

5.2. Implications for teacher training

The findings highlight critical implications for enhancing teacher training programs to support the integration of AI in diverse educational contexts. At East Coast University, the significant influence of perceived behavioral control on behavioral intention suggests that training should include hands-on workshops utilizing readily accessible AI tools, such as ChatGPT, to build digital confidence and pedagogical competence. These workshops should simulate classroom scenarios to foster practical application. In contrast, student teachers at distance institutions, who often operate in resource-constrained environments, require tailored interventions that address both infrastructural limitations and pedagogical needs. For example, training could focus on lightweight, mobile-accessible AI platforms and open educational resources that function in low-bandwidth settings. Equipping students with skills in curating and critically evaluating AI-generated content can also enhance their instructional capacity without over-relying on high-tech infrastructure. Moreover, programs should integrate modules on digital ethics, data privacy, and policy navigation to prepare student teachers for the systemic and institutional challenges that influence the adoption of AI. Embedding these elements into teacher education could ensure more equitable and context-responsive preparation, especially for those in under-resourced or distance education settings.

5.3. Limitations and future research

While our findings offer valuable insights, several limitations warrant consideration. The relatively small sample sizes may constrain the generalizability of results beyond the study context. Additionally, reliance on self-reported online survey data introduces potential biases, such as social desirability and recall bias, which may affect the accuracy of reported intentions. The cross-sectional design further limits causal inferences, offering only a temporal snapshot of participants' behavioral intentions. Importantly, although the instrument showed strong psychometric properties, the Theory of Planned Behavior constructs failed to significantly predict behavioral intention at either institution. This finding raises questions about the explanatory power of the Theory of Planned Behavior in this context. Possible explanations may include contextual factors not captured by the model, such as variations in technology readiness or self-efficacy, suggesting the need for expanded theoretical frameworks. Future studies could benefit from qualitative follow-ups to explore the nuanced socio-educational dynamics influencing AI adoption. We also acknowledge that the exclusive focus on student teachers from two universities limits the applicability of findings, particularly given the diverse educational landscape of South Africa and the exclusion of in-service teachers whose perspectives may differ substantially. Relatedly, the study encountered demographic imbalances between the two institutions, particularly in terms of gender and age distributions. While these disparities were acknowledged, we chose not to statistically control for these variables in the regression models, as doing so could risk inferring causal relationships that may inadvertently reinforce social stereotypes. Our focus was on understanding behavioral intention through psychological constructs grounded in the Theory of Planned Behaviour framework. Nonetheless, future research should investigate how demographic variables interact with attitudes toward AI integration, ideally employing designs that are both ethically sensitive and methodologically robust. Longitudinal studies could also establish causal relationships and track changes in AI integration intentions over time. Expanding the sample to include more institutions and incorporating in-service teachers would provide a more comprehensive perspective on AI integration across different career stages. Qualitative methods, such as interviews or focus groups, could offer deeper insights into the complex factors influencing AI adoption. Investigating diverse educational settings, including urban and rural schools with varying resources, would further enhance the relevance of the findings and provide more actionable recommendations for policy and practice.

6. Conclusion

This research reveals that distance and contact education science student teachers exhibit highly favorable behavioral intentions to integrate AI into science teaching, demonstrating a willingness to adopt AI. However, significant differences in control beliefs show varying confidence levels, with Central University teachers feeling more capable of implementing AI. Perceived Behavioral Control at East Coast University has a negative impact on intentions to adopt AI in teaching. Conversely, Central University's non-significant predictors suggest exploring additional factors influencing AI adoption. Both groups share favorable attitudes and normative beliefs toward AI, emphasizing the need for tailored teacher training programs. These programs should enhance self-efficacy, improve access to resources, and address specific institutional contexts to support effective AI integration. Fostering these elements can bridge the gap between intention and practice, enriching science education with innovative AI technologies.

Informed consent statement

Informed consent was obtained from all participants involved in the study.

Institutional review board statement

The study was conducted in accordance with the Declaration of Helsinki and approved by the Ethics Committee in the College of Education, University of South Africa (Ref 2023_RPC_040 and Ref 2023/07/05/90291786/25/AM).

Author contributions

LM: Conceptualization; Funding; Investigation; Methodology; Resources; Writing -original draft. MR & DS: Data curation; Formal analysis; Writing - review & editing.

Disclosure statement

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Data availability statement

The data presented in this study are available on reasonable request from the corresponding author. Ethical clearance restrictions apply.

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Appendix A

Table A1. The instrument used for data collection (adopted from Mnguni et al., 2024a).

Construct	Item code	Questionnaire item
Attitude	A 1	Integrating AI in teaching and learning science would be beneficial to the school.
	A 2	Integrating AI in teaching and learning science would be beneficial to my students.
	A 3	Integrating AI in teaching and learning science would benefit me as a teacher.
	A 4	Integrating AI in teaching and learning science would benefit the Department of Basic Education.
	A 5	Integrating AI in teaching and learning science would be beneficial to my colleagues.
Behavioural Beliefs	BB 1	Integrating AI in teaching and learning science would make me a better teacher.
	BB 2	Integrating AI in teaching and learning science would enhance learners' understanding of complex scientific concepts.
	BB 3	Integrating AI in teaching and learning science would improve students' problem-solving and critical-thinking skills.
	BB 4	Integrating AI in teaching and learning science would increase students' interest and motivation to learn science.
	BB 5	Integrating AI in teaching and learning science would facilitate student engagement and active participation.
Subjective Norms	SN 1	My colleagues would approve of me integrating AI in teaching and learning science.
	SN 2	My learners would approve of my integrating AI into teaching and learning science.
	SN 3	My school principal would approve of me integrating AI in teaching and learning science.
	SN 4	My head of department would approve of me integrating AI in teaching and learning science.
	SN 5	The Department of Basic Education would approve of me integrating AI in teaching and learning science.
Normative Beliefs	NB 1	My colleagues believe that I should integrate AI into teaching and learning science.
	NB 2	My learners believe that I should integrate AI into teaching and learning science.
	NB 3	My school principal believes that I should integrate AI into teaching and learning science.
	NB 4	The Department of Basic Education believes that I should integrate AI into teaching and learning science.
Perceived Behavioural Control	PBC 1	I am confident that I can successfully integrate AI into teaching and learning science.
	PBC 2	I have the necessary skills to integrate AI into teaching and learning science.
	PBC 3	I have the necessary training to integrate AI into teaching and learning science.
	PBC 4	I have the necessary support and resources to effectively integrate AI into teaching and learning science.
	PBC 5	I feel confident in integrating AI into teaching and learning science.
Control Beliefs	CB 1	I believe that I have control over the resources and materials required to effectively integrate AI into science education.
	CB 2	I feel confident in adapting and customizing AI-based instructional tools to suit my science classroom's specific needs and goals.
	CB 3	I have control over the technological infrastructure and support necessary for integrating AI in teaching and learning science.
	CB 4	I can overcome any technical challenges that may arise when integrating AI into teaching and learning science.
	CB 5	I believe that I have control over the support and collaboration from colleagues that can facilitate the integration of AI in teaching and learning science.
Behavioral Intentions	I 1	I intend to incorporate AI tools into my teaching science practices.
	I 2	I intend to use AI tools to develop assessment tools for my teaching science.
	I 3	I plan to attend professional development workshops to help me integrate AI into teaching science.
	I 4	I intend to work with my colleagues to integrate AI into teaching science.
	I 5	I intend to use AI tools to plan my science lessons.