

The behavioural intentions for integrating artificial intelligence in science teaching among pre-service science teachers in South Africa and Thailand

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ABSTRACT

Developing countries in the Global South exhibit diverse trends in the integration of digital technologies, such as Artificial Intelligence in teaching. Complex context-specific factors, including teacher preparedness, influence these trends. Using the Theory of Planned behavior as a theoretical framework, this study explores the behavioral intentions of pre-service science teachers in South Africa and Thailand towards integrating AI into their teaching to inform teacher training, support, and resource allocation policies. The main research question is: "What are the behavioral intentions of pre-service science teachers in South Africa and Thailand towards integrating AI into their teaching practices?" The study followed a non-experimental comparative descriptive survey involving 97 South African and 95 Thai final-year BED students. Data were collected using a structured online questionnaire and analyzed using several statistical tools to compare the TPB constructs between the two samples. South African and Thai pre-service teachers exhibited favorable attitudes and behavioral intentions toward AI integration in teaching. However, Thai students showed significantly higher control and normative beliefs, indicating greater confidence and perceived social support for AI integration than South African students. The findings suggest that targeted teacher training programs and supportive educational policies are essential for enhancing AI readiness, particularly in resource-constrained settings.

1. Introduction

Artificial intelligence (AI) was first conceived in 1955 by McCarthy, Minsky, Rochester, and Shannon, who suggested the development of computers capable of utilizing language and generating abstractions and concepts (McCarthy et al., 2006). Such machines would address issues normally managed by people. This concept is founded on Turing's seminal prior research, which investigated the potential for machines to possess cognitive abilities (Turing, 1950). Since then, artificial intelligence has been engineered to replicate human cognitive functions, enabling machines to execute activities such as instruction, learning, reasoning, problem-solving, and comprehending natural language. These artificial intelligence systems depend on algorithms and extensive

datasets to render conclusions. In education, AI facilitates personalized and adaptable learning experiences, enhances instructional tools, cultivates immersive learning environments, and delivers automated, data-driven evaluations, leading to improved teaching and learning outcomes (Mnguni, 2023, 2024).

Considering the advances in AI technologies, we investigated the behavioral intentions of pre-service science teachers in South Africa and Thailand towards integrating AI into their teaching methodologies. Understanding these intentions is necessary as they can predict the adoption and implementation of AI in classrooms, thereby impacting the effectiveness of science education in educational contexts (Nja, 2023). Exploring the integration of AI in countries in the Global South is necessitated by the need to understand factors affecting the adoption of

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educational technologies in the developing world. Like most developing countries, South Africa and Thailand face challenges in digital technology adoption. Yet, their distinct approaches and levels of progress offer valuable insights into the broader trends affecting education in similar regions (Nuangchalerm & Prachagool, 2023). This comparison can help identify best practices, common obstacles, and context-specific strategies, contributing to a deeper understanding of how developing countries can leverage AI to improve educational outcomes, reduce disparities, and foster inclusive growth across different socioeconomic landscapes.

1.1. Contextual background

Current trends in integrating digital technologies and AI in education in South Africa and Thailand reveal divergent trends influenced by each country's challenges and opportunities. Comparing South Africa and Thailand's educational landscapes provides valuable insights into integrating AI in diverse developing contexts. Both countries face resource limitations and varying teacher preparedness levels, representing broader issues in developing nations (UNESCO, 2023; World Bank, 2018). In Thailand, digital adoption is robust, with 88% of the population using the internet and 90.4% of households connected, demonstrating substantial governmental efforts to promote digital inclusion and modernize education (Dipendra, 2023). The COVID-19 pandemic accelerated this trend, increasing access to computing devices and the internet. In this regard, Thailand's educational system has actively embraced digital tools, such as Distance Learning Television (DLTV) and the Digital Education Excellence Platform (DEEP), to maintain learning continuity. Additionally, AI-based tools have shown promise in enhancing language learning, though challenges such as regional disparities in access and the need for improved teacher training persist (Dipendra, 2023; Prachagool et al., 2022; Songkram & Osuwan, 2022).

Conversely, South Africa's digital education landscape is marred by infrastructural difficulties. Only about 20% of schools have internet access for teaching and learning, leaving most students without the digital tools necessary for modern education (Malinga, 2022). This lack of connectivity hampers the development of digital literacy and other 21st-century competencies that rely on digital innovations. Government initiatives to provide digital devices have been undermined by inadequate infrastructure and high costs, leading to slow Wi-Fi deployment and persistent disparities between urban and rural schools. Moreover, while there is interest in integrating ICT and AI into education, teacher readiness and infrastructure gaps continue to limit progress (Jere & Mpeta, 2024; Mwapwele et al., 2019).

While Thailand's more advanced digital infrastructure supports the broader adoption of AI in education, South Africa's challenges highlight the necessity for targeted investments in infrastructure and teacher development to bridge the digital divide and foster equitable access to educational technologies (Prachagool et al., 2022; Utina et al., 2024; Vincent-Lancrin & van der Vlies, 2020). Therefore, the urgency of this study is underscored by the global push towards incorporating AI in education to improve learning outcomes and equip students with essential 21st-century skills. Despite the recognized value of AI, its adoption is uneven, especially in developing countries where educational resources and teacher readiness vary widely (Nja, 2023). By focusing on pre-service teachers, who represent the future of the teaching workforce, this research aims to provide insights into the factors that influence their readiness and willingness to adopt AI technologies.

1.2. Current trends in AI tools in teaching

The use of AI tools to address educational challenges in science teaching has grown substantially over the last few decades (Mnguni, 2024). This growth includes using various AI tools with varying degrees of complexity. These tools include AI-based instructional tools,

educational resources, and applications integrated into the teaching practice to improve the teaching and learning process (Celik, 2023; Chou et al., 2022). Research also shows a growing trend in developing AI-driven learning environments that provide immersive educational experiences by embedding AI technologies (Kashive et al., 2020; Mnguni, 2023). Relatedly, there is a growing use of AI-enhanced assessment practices, which involves the integration of AI technologies in assessment to optimize evaluation and feedback mechanisms (Hwang et al., 2020).

In most cases, AI tools support teaching and learning by enhancing the quality and efficiency of teaching and learning processes. For example, AI provides customized instruction, catering to diverse student needs and learning paces through adaptive learning systems (Gligorea et al., 2023). Teachers sometimes use interactive AI tools to engage students in hands-on learning activities, making abstract scientific concepts more tangible (Fakaruddin et al., 2024). Student engagement can also be improved by creating immersive learning environments by integrating AI in augmented and virtual reality simulations to provide interactive and experiential learning opportunities (Halabi, 2020). AI tools personalize content delivery and adjust instructional strategies to improve content understanding, student engagement, and learning outcomes (Capuano & Caballé, 2020). Where necessary, students are supported through Intelligent Tutoring Systems, which provide personalized learning support, adapting to students' learning needs (Lin et al., 2023). To further support student learning, AI-driven analytics provide valuable insights into student learning patterns, enabling early identification of students at risk of falling behind and allowing for timely interventions (Huang & Rust, 2018). Additionally, AI helps automate routine tasks such as lesson planning, grading, and administrative work, freeing up teachers' time to focus more on student interaction and personalized instruction (Adelana et al., 2024; Celik et al., 2022; Mousavinasab et al., 2021).

1.3. Teachers' readiness to integrate AI in science teaching

Despite its potential to enhance science teaching, AI adoption is not universal due to several factors, including teachers' readiness. Teacher readiness to integrate AI in science teaching refers to the preparedness and capability of teachers to effectively incorporate AI tools and methodologies into their instructional practices (Mnguni, 2024). This includes their knowledge of AI concepts, confidence in using AI technologies, and the availability of necessary resources and support systems. It encompasses the technical proficiency and pedagogical adaptability required to successfully implement AI in educational settings. Professional development, technical support, and attitudes toward AI are crucial in determining readiness (Ayanwale et al., 2022, 2024; Celik, 2023; Kuleto et al., 2022).

Teachers' readiness level to integrate AI in science teaching is influenced by multiple factors, including prior experience with technology and access to resources (Chounta et al., 2021). Generally, more technologically proficient teachers exhibit higher readiness and confidence in adopting AI tools (Ayanwale et al., 2022). Teacher readiness is also tied to the perceived relevance of AI to their teaching practice (Ayanwale et al., 2022). Teachers who recognize the benefits of AI for enhancing student engagement and learning outcomes are more likely to be prepared to integrate these technologies into their classrooms (Celik, 2023). Another factor is perceived ease of use and usefulness (Mousavinasab et al., 2021). Additionally, lacking technical support and resources can hinder readiness, as teachers may feel unprepared to troubleshoot and effectively utilize AI tools without adequate support (Mnguni, 2024). Lastly, teachers' attitudes towards AI, including their anxiety about using new technologies and confidence in teaching AI concepts, affect their readiness (Ayanwale et al., 2022, 2024; Kuleto et al., 2022).

Teachers' readiness to adopt AI profoundly impacts their integration of these technologies in science teaching. Higher readiness levels

correlate with more successful and widespread adoption of AI tools, leading to better teaching practices and improved student learning outcomes (Celik et al., 2022; Chounta et al., 2021; Darayseh, 2023). When teachers are well-prepared and confident in using AI, they are more likely to experiment with and effectively integrate AI tools into their curricula, fostering a more engaging and interactive learning environment (Ayanwale et al., 2022). Conversely, low readiness levels can result in resistance to adoption, limited use of AI tools, and missed opportunities for leveraging AI to transform science education (Celik, 2023; Darayseh, 2023). Therefore, enhancing teachers' readiness through targeted training and support is essential for successfully adopting AI in science education.

2. The current research

2.1. Problem statement

While there are ongoing efforts to promote the integration of AI in science teaching, there is a paucity of research examining the behavioral intentions of pre-service science teachers to integrate AI in their teaching in developing countries with diverse educational contexts in the Global South. Understanding these behavioral intentions is critical, as they can predict the adoption and implementation of AI in classrooms. This existing gap in literature underscores the need for a comprehensive investigation into the behavioral intentions of pre-service science teachers in countries such as South Africa and Thailand. Therefore, the current research aims to fill this gap by exploring the behavioral intentions of pre-service science teachers to integrate AI in science teaching, thereby providing insights that could inform targeted interventions and support mechanisms to enhance AI integration in science teaching across varied educational landscapes.

2.2. The aim, research question, hypothesis, and rationale of the study

We utilized the theory of planned behavior (TPB) as a framework for investigating the behavioral intentions of pre-service science teachers in South Africa and Thailand concerning integrating AI into their teaching practices. The research question asks: "How do the behavioral intentions of pre-service science teachers in South Africa and Thailand toward integrating artificial intelligence into their teaching practices compare?" The following comprehensive null hypotheses were tested in this research:

- Hypothesis 1: The Theory of Planned Behavior (TPB) does not predict pre-service science teachers' intentions to integrate AI into their teaching practices.
- Hypothesis 2: There are no significant differences in the TPB constructs (attitudes, subjective norms, perceived behavioral control, etc.) between South African and Thai pre-service science teachers.
- Hypothesis 3: The TPB constructs (behavioral beliefs, attitudes, normative beliefs, perceived behavioral control, and control beliefs) do not predict behavioral intentions to integrate AI into teaching practices.
- Hypothesis 4: Constructs of the TPB (i.e., Attitudes, Subjective norms, Perceived behavioral control, Control beliefs, normative beliefs, and behavioral beliefs) do not significantly correlate with behavioral intentions to integrate AI in teaching.

Understanding the behavioral intentions of pre-service science teachers towards AI integration is critical for several reasons. Firstly, there is a pressing need to prepare future teachers to effectively utilize these technologies (Ayanwale et al., 2024; Mnguni, 2024). Our study addresses a gap in the literature by focusing on pre-service teachers in South Africa and Thailand. Most existing research primarily concentrates on in-service teachers, leaving a lack of understanding of how future teachers perceive and intend to adopt AI (Mnguni, 2024; Zhang,

2023). Additionally, the educational contexts of South Africa and Thailand present unique challenges and opportunities that can provide valuable insights into the global landscape of AI integration in education. The findings from this study will inform the development of targeted teacher training programs that address pre-service teachers' specific needs and concerns. By enhancing their readiness through comprehensive training that improves their technological proficiency, confidence, and understanding of AI's pedagogical benefits, these programs can increase the likelihood of effective AI adoption in science education (Ayanwale et al., 2022; Celik, 2023). This, in turn, will contribute to more innovative and effective teaching practices, ultimately benefiting student learning outcomes.

2.3. Using behavioral intentions to explain readiness: the theory of planned behaviour

Teacher readiness to integrate AI in science teaching can be understood through the lens of the TPB, which posits that an individual's behavioral intentions are the most immediate predictor of their actual behavior (Fig. 1). This theory was chosen because unlike other theories, such as the Technology Acceptance Model, which primarily focuses on perceived ease of use and usefulness (Davis, 1989), the TPB offers a more comprehensive understanding of the factors influencing pre-service teachers' intentions to integrate AI in science teaching. This broader scope is notable in educational contexts where social and control beliefs are critical in shaping behavioral intention. TPB includes three key components: Attitudes, Subjective Norms, and Perceived Behavioural Control, which interact to shape Behavioural Intentions and subsequent actions (Ajzen, 1991).

Behavioral beliefs form attitudes toward AI integration in science teaching and the perceived outcomes of adopting AI technologies. If teachers believe that integrating AI will improve their teaching effectiveness and student learning outcomes, they will likely have a favorable attitude toward its adoption (Ajzen, 1991, 2006). Favorable attitudes are bolstered by successful experiences with AI tools and perceived usefulness in educational settings (Ayanwale et al., 2022). Conversely, if teachers perceive AI as complex or irrelevant to their teaching practices, their attitudes may be pessimistic, reducing their readiness to adopt AI (Mnguni, 2024; Sanusi et al., 2024). Subjective norms refer to the perceived social pressures to perform or not perform a particular behavior. In AI integration, normative beliefs involve the expectations of other roleplayers such as school administrators, colleagues, and students. If teachers believe their peers and supervisors expect them to use AI and value its implementation, they are more likely to develop a stronger intention to adopt AI technologies (Ajzen, 1991; Lawrence & Tar, 2018). Supportive professional communities and collaborative environments can transform these normative beliefs and encourage teachers to align with these expectations (Celik, 2023). Perceived behavioral control pertains to the perceived ease or difficulty of performing the behavior, influenced by control beliefs about the presence of facilitating or hindering factors. For teachers, control beliefs may include access to AI resources, professional development opportunities, and technical support (Ajzen, 1991). If teachers feel confident in their ability to use AI and perceive they have the necessary resources and skills, their perceived behavioral control is high, positively impacting their behavioral intentions to integrate AI into their teaching (Mnguni, 2024).

Therefore, teacher readiness to integrate AI into science teaching can be influenced by their attitudes toward AI, perceived social pressures, and confidence in managing AI tools. Enhancing these components through targeted interventions can increase the likelihood of successful AI integration in educational practices.

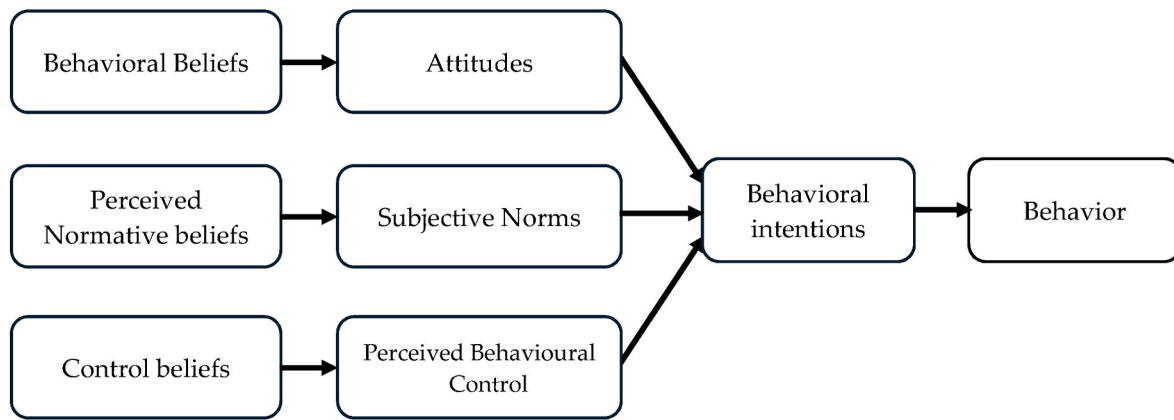


Fig. 1. The theory of planned behavior (Ajzen, 2006).

3. Methodology

3.1. Research approach

We adopted a positivist research paradigm, emphasizing objective reality and quantifiable observations. A quantitative approach (Creswell, 2014) was utilized to systematically investigate pre-service science teachers' behavioral intentions toward AI integration. This approach is suitable for generating reliable and generalizable data for informing effective teacher training programs. A non-experimental comparative descriptive survey design was employed. This design is ideal for identifying and describing patterns among variables without manipulating the study environment, thereby facilitating a direct comparison of behavioral intentions between pre-service science teachers in South Africa and Thailand (Mertens, 2015). This design was chosen to capture the natural variations in attitudes, subjective norms, and perceived behavioral control as described by the TPB.

3.2. Sampling strategy and sample description

A non-random, purposeful, and convenience sampling strategy was used to select participants. This approach ensures the inclusion of individuals most representative of the study's focus areas while acknowledging the limitations of sampling bias. The sample comprised final-year students pursuing Bachelor of Education degrees with majors in science subjects (i.e., Life Sciences, Natural Sciences, and Physical Sciences) from South African University ($n = 97$, response rate 26.6%) and Thailand University in Thailand ($n = 95$, response rate 41.3%). These students are training to teach in the Further Education and Training (FET) phase (grades 10–12). Thailand University and South African University (pseudonyms used for ethical reasons) were selected for this research due to their prominence in teacher education in their regions. Thailand University has extensive teacher training programs and is an educational hub in Thailand. Similarly, South African University offers comprehensive teacher education programs, enabling a diverse, comparative analysis of pre-service teachers' intentions toward AI integration in education across different cultural and educational contexts.

3.3. Data collection

Data were collected using an online survey administered between January and May 2024. The survey instrument was a structured closed-ended questionnaire organized into sections capturing different dimensions of the TPB, namely, Attitudes, Behavioural Beliefs, Subjective Norms, Normative Beliefs, Perceived Behavioural Control, Control Beliefs, and Behavioural Intentions as recommended in the literature (Ajzen, 2006; Fishbein & Ajzen, 2010). Biographical data were also

collected. Science and teacher education experts reviewed the instrument to assess face, content, and criterion-based validity. A pilot survey was conducted with a group similar to the main study participants. The feedback received from the pilot survey led to several refinements:

- Some items were reworded for clarity based on feedback indicating that specific terms and phrases were ambiguous or difficult to understand. For example, technical jargon was simplified to ensure comprehensibility for all respondents.
- Several items were shortened to reduce survey fatigue. Feedback indicated that the original survey length could discourage complete responses.
- The Likert scale options were revised to provide a more balanced range of responses. Some respondents in the pilot survey indicated that the original scale did not adequately capture their sentiments.
- Some items were deemed irrelevant or redundant and were subsequently removed. The feedback helped to streamline the survey, focusing on the most pertinent aspects of the TPB components.

The final instrument had 35 closed-ended items probing Attitudes, Behavioural Beliefs, Subjective Norms, Normative Beliefs, Perceived Behavioural Control, Control Beliefs, and Behavioural Intentions (Table 1).

3.4. Data analysis

Descriptive statistics were used to identify patterns and trends within the data, providing an overview of the distribution, central tendency, and variability of responses. The reliability of the survey instrument was assessed using Cronbach's Alpha, which measures internal consistency. High Cronbach's Alpha values indicate that the items within each construct consistently measure the same underlying concept, ensuring the instrument's reliability. Exploratory Factor Analysis was employed to determine the underlying structure of the measured variables and whether the items aligned with the anticipated components as proposed by the TPB. Data in this research were ordinal, and normal distribution could not be assumed. Consequently, Spearman's correlation analysis was conducted to evaluate construct validity, confirming that the instrument accurately measures the theoretical constructs it is intended to assess. Relatedly, Mann-Whitney U tests were employed to compare responses between the two universities. This non-parametric test was deemed ideal for comparing differences between independent groups when the dependent variable is ordinal or not normally distributed, providing insights into differences in perceptions and intentions. Ordinal Logistic Regression was also used to identify predictors of behavioral intentions, modeling relationships between multiple independent variables and an ordinal dependent variable. This analysis is appropriate for understanding how attitudes, subjective norms, and

Table 1

Example items used to measure behavioral intentions for integrating AI in science education^a.

Construct	Item
Attitude	Integrating AI in teaching and learning science would be beneficial to the school.
	Integrating AI in teaching and learning science would be beneficial to my students.
Behavioural Beliefs	Integrating AI in teaching and learning science would make me a better teacher.
	Integrating AI in teaching and learning science would enhance learners' understanding of complex scientific concepts.
Subjective Norms	My colleagues would approve of me integrating AI in teaching science.
	My learners would approve of my integrating AI into teaching science.
Normative Beliefs	My colleagues believe that I should integrate AI into teaching science.
	My learners believe that I should integrate AI into teaching science.
Perceived Behavioural Control	I am confident I can successfully integrate AI into teaching science.
	I have the necessary skills to integrate AI into teaching science.
Control Beliefs	I have control over the technological infrastructure and support necessary for integrating AI into teaching science.
	I can overcome any technical challenges that may arise when integrating AI into teaching science.
Behavioral Intention	I intend to incorporate AI tools into my science teaching practices.
	I intend to use AI tools to develop assessment tools for my science teaching.

^a A complete list of items is provided in Appendix 1.

perceived behavioral control influence behavioral intention levels. These comprehensive analyses provided robust insights into the factors influencing AI integration intentions among pre-service science teachers in diverse educational contexts, ensuring the findings are reliable, valid, and applicable across different settings.

4. Results

4.1. Instrument validity and reliability

4.1.1. Spearman correlation coefficients between TPB constructs

The construct validity of the survey instrument in measuring the constructs of the TPB was determined through Spearman correlation (Table 2) because the data collected from the TPB constructs were ordinal, and normal distribution could not be assumed. Spearman correlation is ideal for assessing the strength and direction of monotonic relationships between two variables when data do not meet parametric assumptions, ensuring reliable validation of the constructs. (Huang et al., 2024; Ragamin et al., 2024). The TPB posits specific relationships among its constructs to predict behavior (Conner & Sparks, 2005). In

Table 2

Spearman Correlation coefficients between TPB constructs.

Constructs	1	2	3	4	5	6
1. Attitudes						
2. Behavioural Beliefs	.144					
3. Subjective Norms	.109	.459				
4. Normative Beliefs	.160 ^a	.234	.353			
5. Perceived Behavioural Control	.145	.217	.226	.452		
6. Control Beliefs	.153 ^a	.218	.332	.340	.329	
7. Behavioral Intention	.158 ^a	.331	.144	.171 ^a	.149 ^a	.159 ^a

Correlation is significant at the 0.01 level (2-tailed).

^a Correlation is significant at the 0.05 level (2-tailed).

this regard, behavioral beliefs correlate highly with attitudes toward the behavior. Normative beliefs correlate with subjective norms, and control beliefs correlate with perceived behavioral control. Additionally, attitudes, subjective norms, and perceived behavioral control all correlate with behavioral intentions. These correlations support the predictive validity of TPB, linking beliefs to intentions and, ultimately, to behavior. Therefore, significant positive correlations between TPB constructs of the survey instrument would provide evidence that these constructs are related as theoretically predicted by the TPB, thereby supporting the instrument's construct validity.

The Spearman correlation coefficients in Table 2 validate the survey instrument within the TPB framework. The positive correlation between Attitudes and Behavioral Intentions ($\rho = .158, p < .05$) suggests that favorable attitudes toward AI integration increase intentions to integrate AI in teaching, consistent with TPB. Behavioral Beliefs significantly correlate with Behavioral Intentions ($\rho = .331, p < .01$), indicating their strong influence. Subjective Norms, while showing a statistically insignificant correlation with Behavioral Intentions ($\rho = .144$), significantly correlate with Normative Beliefs ($\rho = .353, p < .01$) and Perceived Behavioral Control ($\rho = .226, p < .01$), as posited by the TPB. Normative Beliefs significantly correlate with Behavioral Intentions ($\rho = .171, p < .05$) and other constructs, supporting the impact of perceived social pressures. Perceived Behavioral Control correlates with Behavioral Intentions ($\rho = .149, p < .05$), indicating that perceived ease or difficulty of integration influences intentions. Control Beliefs also significantly correlate with Behavioral Intentions ($\rho = .159, p < .05$) and other constructs, emphasizing their role in forming intentions. These correlations confirm the instrument's convergent and discriminant validity by demonstrating the interrelationships among TPB constructs as theoretically predicted.

4.1.2. Exploratory Factor Analysis

An Exploratory Factor Analysis (EFA) was conducted using Principal Component Analysis (PCA) with Varimax rotation to further validate the constructs within the TPB framework (Table 3). The analysis aimed to identify the measured variables' underlying structure and assess whether the items loaded onto the expected components as theorized by the TPB.

The KMO measure of sampling adequacy was .839, indicating that the sample size is adequate for conducting factor analysis, suggesting that the correlations between the items are sufficient for identifying a structure among the variables (Table 3). Bartlett's Test of Sphericity yielded a significant result (approx. $\chi^2 = 4050.11, p < .001$), confirming that the correlations among the items were strong enough for factor analysis. The significant result from Bartlett's test indicates that the observed correlation matrix is not an identity matrix, further supporting the suitability of the data for factor analysis.

The factor analysis revealed that seven factors had eigenvalues greater than 1, accounting for 72.15% of the total variance (Table 4). This indicates that these factors explain a substantial portion of the variability in the dataset. The first component explained 28.56% of the variance, while the second and third components explained 11.54% and 9.84%, respectively. The cumulative variance explained by the first five components reached 63.52%, indicating the importance of these factors in understanding the underlying structure of the Theory of Planned Behavior (TPB) constructs related to AI integration in education.

As shown in Table 5, the factor loadings and communalities from the

Table 3

Kaiser-Meyer-Olkin measure and Bartlett's test for assessing the suitability of factor analysis.

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.839
Bartlett's Test of Sphericity	Approx. Chi-Square	4050.112
	df	496
	Sig.	<.001

Table 4

Total variance explained by extracted factors.

Component	Initial Eigenvalues	% of Variance	Cumulative %
1	9.140	28.562	28.562
2	3.692	11.537	40.099
3	3.147	9.836	49.935
4	2.419	7.558	57.493
5	1.927	6.022	63.516
6	1.492	4.663	68.179
7	1.269	3.967	72.146

rotated component matrix identified seven components related to teachers' behavioral intentions for integrating AI in science education. These components align with the TPB constructs, representing different aspects of behavioral intentions, perceived behavioral control, attitudes, and subjective norms. The communalities, indicating the variance in each variable explained by the extracted factors, ranged from 0.510 to 0.856, demonstrating that the extracted factors explain a significant portion of the variance in these items. Three items with communalities less than 0.3 were removed. Three items (PBC1, PBC2, and PBC3) cross-loaded between components 1 and 7. Despite this cross-loading, these items were retained based on their high communalities and literature, which suggests that cross-loading may reflect the complex interconnected relationship between the constructs of the TPB (McGlade et al., 2012). This view is supported by Khanjari et al. (2023), who found a positive correlation between behavioral beliefs and PBC, suggesting that when participants believe in the benefits of behavior, their perceived control over the behavior increases. This decision was also consistent with Molina et al. (2020), who argue that the assumption of zero cross-loadings may yield misleading results in instances where

complex relationships exist among constructs. The failure to account for cross-loadings can inflate factor correlations, leading to an inaccurate representation of the constructs involved (Marsh et al., 2010). Therefore, retaining the observed items helps capture the nuanced influence of PBC on teachers' intentions, as control-related beliefs can affect behavioral intentions indirectly through their impact on outcome expectations.

The Rotated Component Matrix analysis (Table 5) confirms the validity of core TPB constructs in the context of AI integration in science education. Key findings include strong loadings for Behavioral Intentions, with items like item BI1 (I intend to incorporate AI tools into my science teaching practices) (.811), reflecting teachers' future-oriented commitment. Similarly, Subjective Norms loadings, such as item SN1 (My colleagues believe I should integrate AI into teaching and learning science.) (.788), indicate that social expectations significantly influence intentions. Attitudes toward AI integration are also highly positive, as seen in items like item A2 (Integrating AI in teaching and learning science would be beneficial to my students) (.911). Additionally, Control Beliefs show high loadings, such as item CB1 (I have control over the technological infrastructure and support necessary for integrating AI in teaching and learning science) (.899), suggesting that teachers feel empowered to overcome challenges. Together, these components explain over 72% of the variance, demonstrating the predictive power of the TPB in understanding teachers' intentions to adopt AI in teaching.

4.1.3. Cronbach's alpha reliability analysis of the TPB scale components

As Boyko et al. (2011) suggested, Cronbach's alpha values were calculated for each construct rather than the whole instrument to assess each specific construct's internal consistency and reliability within the

Table 5

Rotated factor loadings and communalities for teachers' beliefs on AI integration in science education.

Item Codes ^a	Component							Communalities (extraction)
	1	2	3	4	5	6	7	
A1							.900	.853
A2							.911	.849
A3							.761	.623
BF1	.798							.671
BF2	.772							.697
BF3	.808							.695
BF4	.780							.703
BF5	.687							.592
PBC1	.491					.392		.510
PBC2	.602					.421		.599
PBC3						.815		.836
PBC4	.318					.819		.840
PBC5		.322				.766		.783
SN1					.788			.724
SN2					.789			.733
SN3					.815			.819
SN4					.740			.749
NB1				.532	.331			.531
NB2				.797				.723
NB3				.772				.669
NB4				.777				.711
NB5				.718				.576
CB1		.812						.743
CB2		.834						.749
CB3		.899						.856
CB4		.810						.719
CB5		.802						.709
BI1			.811					.800
BI2			.879					.847
BI3			.818					.756
BI4			.876					.839
BI5			.591	.325				.584

Extraction Method: Principal Component Analysis.

Rotation Method: Varimax with Kaiser Normalization.

^a Full items representing these codes are provided in Appendix 1.

TPB framework. Each construct (e.g., Attitudes, Behavioural Beliefs, Subjective Norms) represents a distinct theoretical domain that should be measured independently to ensure that the items within that construct consistently reflect the underlying concept. This approach allows for identifying any weaknesses or inconsistencies within individual constructs, thereby providing a more nuanced understanding of the instrument's reliability and ensuring the accuracy of the measurement of each specific construct.

Results indicated that the instrument is robust, as demonstrated by high Cronbach's alpha values for each construct (Table 6). These values exceed the commonly accepted threshold of .70, indicating strong internal consistency and reliability across all scales (Taber, 2018). However, we note the influence of sample size on the stability of these estimates. Considering a sample of 97 South African and 95 Thai participants, the reliability estimates should be interpreted cautiously, as smaller sample sizes can lead to less stable Cronbach's alpha values (Bujang et al., 2018). Despite this, the values suggest that the items within each construct consistently measure the intended theoretical constructs, thereby supporting the validity and dependability of the instrument in assessing pre-service science teachers' intentions toward AI integration. This view aligns with the literature (e.g., Bujang et al., 2018; Conroy, 2015), which suggests that smaller sample sizes can still provide reliable Cronbach's alpha estimates, provided that the scale items exhibit strong correlations.

4.2. A comparison of TPB constructs between South African University and Thailand University

An analysis was conducted to compare the percentage of favorable responses for each TPB construct between Thailand University and South African University (Fig. 2). Differences were observed in Control Beliefs and Normative Beliefs, where Thailand University students showed a notably higher favorable response (90.1%) compared to South African University (48.5%), indicating that students at Mahasarakham feel a greater sense of control over integrating AI into their teaching practices. Similarly, Normative Beliefs were higher at Thailand University (77.8%) than at South African University (55.7%), suggesting stronger perceived social pressures or expectations favoring AI integration at Mahasarakham.

Despite these differences, there were notable similarities in other constructs. Both universities exhibited favorable behavioral intentions toward AI integration, with Thailand University at 97.5% and South African University at 89.7%. Additionally, both institutions showed favorable responses in Attitudes, Subjective Norms, and Behavioural Beliefs, indicating favorable attitudes and beliefs toward AI integration. These findings highlight commonalities and context-specific differences in the perceptions and readiness of pre-service teachers to integrate AI into their teaching, reinforcing the instrument's reliability across diverse educational settings.

Further analysis was conducted to determine whether the differences in responses for TPB Constructs between Thailand University and South African University were statistically significant using the Mann-Whitney U Test. The results (Table 7) reveal significant differences and similarities between Thailand University and South African University regarding their TPB constructs. Specifically, significant differences were

observed in Subjective Norms ($p < .001$), Control Beliefs ($p < .001$), Behavioural Intention ($p = .003$), and Perceived Behavioural Control ($p = .018$), indicating that perceptions regarding social pressures, control over AI integration, and intentions to use AI differ substantially between the two universities. Additionally, Behavioural Beliefs showed a significant difference ($p = .027$), suggesting a variation in beliefs about the benefits of AI integration. In contrast, no significant differences were observed in Normative Beliefs ($p = .171$) and Attitudes ($p = .219$), indicating that students from both universities share similar normative expectations and favorable attitudes toward AI integration. These findings suggest that while students may share common attitudes and expectations regarding AI, their beliefs about control and the influence of social pressures diverge depending on the institutional context. These results underscore the variability in how different constructs of the TPB are perceived across cultural and institutional settings. Understanding these differences can help tailor teacher training programs that address teachers' specific needs in different regions.

4.3. Factors that affect behavioral intentions within groups

Ordinal logistic regression was conducted to assess the impact of various predictors—attitudes, behavioral beliefs, subjective norms, normative beliefs, perceived behavioral control, and control beliefs—on the likelihood that pre-service science teachers would express different levels of intention to integrate AI into their teaching practices (Table 8a–d). The analysis was conducted separately for Thailand University and South African University.

For Thailand University, the model fitting results suggest that the predictors significantly influenced behavioral intentions ($\chi^2(6) = 34.039$, $p < .001$), indicating that the predictors, as a group, explain a substantial amount of variance in the outcome variable (Table 8a). However, the South African University data did not show a statistically significant model ($\chi^2(6) = 4.252$, $p = .643$), suggesting that the predictors used in this model did not significantly explain the behavioral intentions of South African pre-service teachers.

The goodness-of-fit statistics (Table 8b) confirm that the model for Thailand University provided an adequate fit, with non-significant Pearson ($p = .797$) and deviance ($p = .950$) chi-square statistics. This indicates that the model fits the data well in Thailand University. For South African University, however, the Pearson chi-square was marginally significant ($p = .054$), indicating a borderline fit, while the deviance statistic suggested a reasonable fit ($p = .208$).

As shown in Table 8c, the model's explanatory power was substantial for Thailand University, as shown by Nagelkerke's $R^2 = .404$, Cox and Snell's $R^2 = .330$, and McFadden's $R^2 = .236$. These figures suggest that the predictors explained a meaningful portion of the variance in behavioral intentions at Thailand University. For South Africa, however, the model's explanatory power was minimal, indicating that the predictors had little to no explanatory power.

The parameter estimates in Table 8d suggest that for Thailand University, behavioral beliefs emerged as a significant positive predictor of behavioral intentions (Estimate = 2.595, SE = 0.607, Wald $\chi^2(1) = 18.264$, $p < .001$), indicating that stronger behavioral beliefs increase the likelihood of higher behavioral intentions. Attitudes were approaching significance (Estimate = 0.406, SE = 0.230, Wald $\chi^2(1) = 3.129$, $p = .077$), suggesting a possible influence on behavioral intentions. Normative beliefs were also close to significance (Estimate = 0.779, SE = 0.407, Wald $\chi^2(1) = 3.667$, $p = .056$). For the South African University, none of the predictors were statistically significant. The estimates for attitudes, behavioral beliefs, subjective norms, normative beliefs, perceived behavioral control, and control beliefs all had non-significant p-values, indicating that these factors did not substantially impact behavioral intentions in this group.

The parameter estimates (Table 8d) suggest that for Thailand University, behavioral beliefs were a significant positive predictor of behavioral intentions (Estimate = 2.392, SE = 0.548, Wald $\chi^2(1) =$

Table 6
Cronbach's alpha reliability analysis of the TPB scale components.

	Reliability	Number of items
Attitudes	.849	3
Behavioral Beliefs	.878	5
Subjective Norms	.886	4
Perceived Normative Beliefs	.842	5
Perceived Behavioral Control	.863	5
Control Beliefs	.917	5
Behavioural Intentions	.833	5

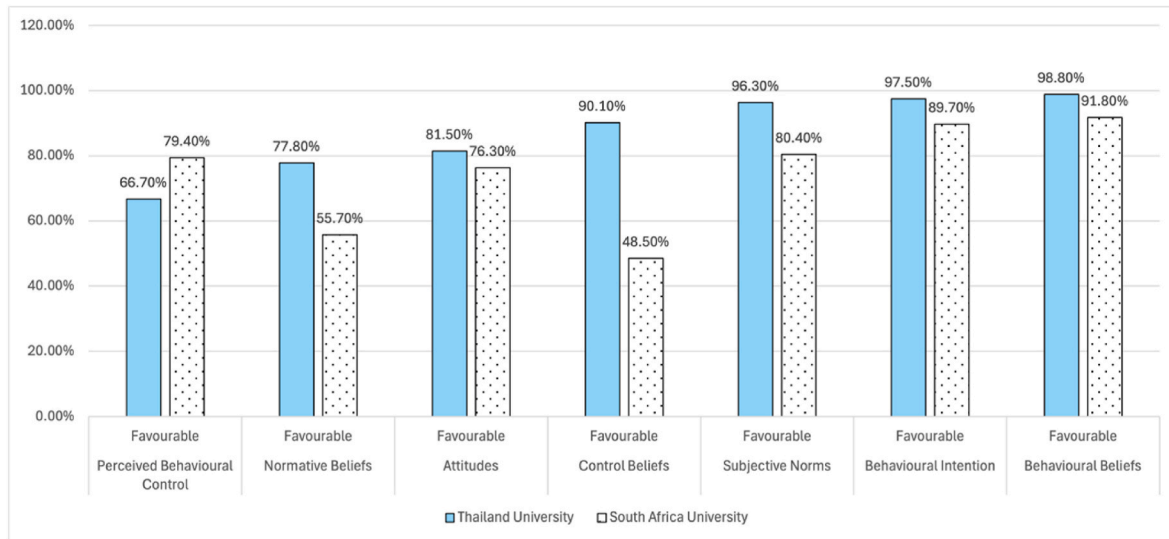


Fig. 2. Comparison of the proportion of participants reporting favorable responses for TPB Constructs between Thailand University and South African University. "Favorable" refers to positive evaluations or perceptions, such as supportive attitudes, beneficial social norms, or high confidence in one's ability to perform a behavior.

Table 7

Mann-Whitney U test results for TPB constructs between the universities (df = 2).

Constructs	Test Statistic	Asymptotic Sig. (2-sided test)
Attitudes	1.230	0.219
Behavioural Beliefs	2.211	0.027
Subjective Norms	3.620	<.001
Normative Beliefs	1.370	0.171
Perceived Behavioural Control	2.366	0.018
Control Beliefs	6.111	<.001
Behavioral Intention	2.942	0.003

Table 8a

Model fitting information for ordinal logistic regression analysis.

University	Model	–2 Log Likelihood	Chi-Square	df	Sig.
Thailand University	Intercept	101.977			
	Final	67.938	34.039	6	<.001
South African University	Intercept	138.640			
	Final	134.389	4.252	6	.643

Table 8b

Goodness-of-fit statistics for ordinal logistic regression models.

University	Test	Chi-Square	df	Sig.
Thailand University	Pearson	56.292	66	.797
	Deviance	48.288	66	.950
South African University	Pearson	126.011	102	.054
	Deviance	113.379	102	.208

Table 8c

Pseudo R-square values for ordinal logistic regression models.

University	Cox and Snell R ²	Nagelkerke R ²	McFadden R ²
Thailand University	.330	.404	.236
South African University	.043	.051	.024

19.046, $p < .001$). This indicates that pre-service teachers with stronger behavioral beliefs are significantly more likely to express higher behavioral intentions to integrate AI into their teaching practices. Other

factors such as attitudes (Estimate = 0.148, SE = 0.194, Wald $\chi^2(1) = 0.588$, $p = .443$) and normative beliefs (Estimate = –0.023, SE = 0.318, Wald $\chi^2(1) = 0.005$, $p = .942$) did not reach statistical significance, suggesting that while behavioral beliefs play a dominant role, attitudes and normative beliefs do not strongly influence behavioral intentions in this group. For South African University, none of the predictors showed statistically significant effects. Behavioral beliefs (Estimate = 0.190, SE = 0.398, Wald $\chi^2(1) = 0.228$, $p = .633$), attitudes (Estimate = 0.176, SE = 0.147, Wald $\chi^2(1) = 1.434$, $p = .231$), subjective norms, normative beliefs, perceived behavioral control, and control beliefs all had non-significant p-values. This suggests that these factors did not meaningfully influence the behavioral intentions of South African pre-service teachers to integrate AI into their teaching. These findings point to the possibility that factors not included in this model may play a more prominent role in influencing behavioral intentions in the South African context.

5. Discussion

The study aimed to investigate the behavioral intentions of pre-service science teachers in South Africa and Thailand towards integrating AI into their teaching practices. The findings partially confirm the structure of the TPB, with favorable attitudes and behavioral beliefs significantly influencing behavioral intentions in the Thai sample but not in the South African sample. This was supported by high Cronbach's alpha values, indicating strong internal consistency across constructs. The EFA results further support the construct validity of the TPB framework, highlighting the importance of behavioral beliefs as a key predictor of AI integration intentions in Thailand. However, in South Africa, none of the TPB constructs significantly predicted behavioral intentions, including attitudes and social pressures. These findings align with Ayanwale et al. (2022) and Mnguni (2024) for the Thai context, where attitudes, social pressures, and control beliefs motivate teachers to adopt AI. However, the results suggest that additional contextual factors beyond TPB constructs may influence AI integration in South Africa.

Significant differences in subjective norms, or perceived social pressures, were observed between Thailand University and South African University, highlighting the importance of contextual factors in AI adoption. Participants at Thailand University reported more favorable subjective norms, suggesting that context-specific elements like

Table 8d
Parameter estimates for ordinal logistic regression (df = 1).

University of current study			Estimate	Std. Error	Wald	Sig.	95% Confidence Interval	
							Lower Bound	Upper Bound
Thailand University	Threshold	[Behavioural Intention = 1.00]	5.120	1.334	14.724	<.001	2.505	7.735
		[Behavioural Intention = 2.00]	8.833	1.582	31.176	<.001	5.733	11.934
	Location	Behavioural Beliefs	2.392	.548	19.046	<.001	1.318	3.466
		Perceived Behavioural Control	.000	.548	.000	1.000	−1.075	1.075
		Subjective Norms	.551	.360	2.345	.126	−.154	1.256
		Normative Beliefs	−.023	.318	.005	.942	−.646	.600
		Control Beliefs	.078	.451	.030	.862	−.805	.962
		Attitude	.148	.194	.588	.443	−.231	.528
		[Behavioural Intention = 1.00]	.070	.869	.007	.935	−1.633	1.774
		[Behavioural Intention = 2.00]	3.145	.949	10.972	<.001	1.284	5.006
South African University	Threshold	[Behavioural Intention = 1.00]	.070	.869	.007	.935	−1.633	1.774
		[Behavioural Intention = 2.00]	3.145	.949	10.972	<.001	1.284	5.006
	Location	Behavioural Beliefs	.190	.398	.228	.633	−.591	.971
		Perceived Behavioural Control	−.088	.387	.052	.820	−.847	.671
		Subjective Norms	−.248	.259	.917	.338	−.756	.260
		Normative Beliefs	.384	.327	1.383	.240	−.256	1.024
		Control Beliefs	.106	.206	.263	.608	−.298	.510
		Attitude	.176	.147	1.434	.231	−.112	.464

supportive professional communities and collaborative environments may transform normative beliefs, thereby encouraging AI adoption (Mhlongo et al., 2023; Nja, 2023; Nuangchalerm & Saregar, 2024). Additionally, the significant differences in perceived behavioral control between the two groups indicate that Thai participants felt more confident in integrating AI than their South African counterparts. While participants from both universities exhibited favorable behavioral intentions toward AI integration, the results showed that at Thailand University, behavioral beliefs significantly predicted higher behavioral intentions to integrate AI, with attitudes and normative beliefs also demonstrating influence. However, none of the TPB constructs significantly impacted behavioral intentions in South Africa.

We propose that context-specific factors may explain the observed differences in behavioral intentions to integrate AI in South Africa and Thailand. Factors such as resource availability, professional development, and institutional support have been shown to affect teachers' confidence in integrating technology into their teaching (Chai et al., 2021; Chatterjee & Bhattacharjee, 2020; Mhlongo et al., 2023). In South Africa, technology integration is often hindered by limited resources, a lack of skills, and insufficient institutional support (Gcabashe, 2024). These constraints contribute to lower confidence and reduced behavioral intentions to adopt AI in teaching practices (Mhlongo et al., 2023). In contrast, Thailand benefits from better access to technological resources and professional development opportunities for teachers, which likely explains Thai pre-service teachers' higher confidence and readiness to integrate AI. In this regard, Dipendra (2023) reports that 60%–93% of Thai teachers have access to professional development, online learning platforms, and qualified technical staff for integrating digital technologies. In South Africa, however, while 80% of schools report internet connectivity, "this connectivity is not ideal for teaching and learning" (DBE, 2023, p. 45), and 70% of schools lack reliable internet access for educational purposes (Malinga, 2022). Furthermore, in some South African provinces, fewer than 10% of schools have access to library or laboratory facilities (EFMS, 2024).

Moreover, educational policies and support systems in place may also account for the observed differences in AI integration readiness between South Africa and Thailand. Thailand's focus on digital literacy and educational reforms may provide a more supportive environment for AI integration, enhancing perceived behavioral control among teachers (Chatterjee & Bhattacharjee, 2020). Conversely, South Africa's ongoing struggle with educational inequality and inconsistent policy implementation may contribute to the lower readiness levels observed among its pre-service teachers (Mavuru & Ramaila, 2022; Mnguni, 2024; Shilenge & Ramaila, 2020). Additionally, cultural differences and societal attitudes towards technology may influence teachers' attitudes and subjective norms, affecting their readiness to adopt AI (Egbert et al.,

2002). In cultures that value technological innovation, such as Thailand, teachers may feel more encouraged and confident to integrate AI into their teaching practices (Følstad et al., 2018).

These contextual factors will likely affect teachers' intentions to adopt AI technologies in their teaching. This may also explain the observed lack of association between TPB constructs and behavioral intentions in South Africa. Other factors could include socioeconomic conditions, such as disparities in resources and infrastructure, and the influence of educational policies and reforms, which may overshadow individual attitudes, perceived behavioral control, and subjective norms. These external variables, which were not fully captured in the current study, likely have a more substantial impact on the intention to integrate AI in teaching. This finding supports critiques of the TPB (e.g., Barber, 2011), who argue that it oversimplifies human behavior by focusing primarily on rational decision-making while neglecting emotional, habitual, and unconscious influences. Furthermore, critics contend that the TPB does not adequately account for external variables, such as socioeconomic status or environmental constraints, which can significantly influence behavior (Si et al., 2019). Therefore, further research is needed to investigate these external determinants, including systemic socioeconomic issues and policy implementation barriers, to fully understand AI integration readiness in contexts like South Africa.

6. Implications of the study findings

Our findings have important implications for teacher training and educational policy concerning integrating AI into teaching. The results show that behavioral beliefs, attitudes, and subjective norms influence pre-service teachers' behavioral intentions toward AI integration, especially in Thailand. However, the lack of significance in these factors for South African teachers highlights the need for more targeted interventions in resource-constrained contexts (Ayanwale et al., 2022; Mnguni, 2024). To effectively integrate AI, teacher training programs must focus on building technological proficiency and pedagogical content knowledge. These programs should address teachers' confidence and perceptions of AI's usefulness in countries like South Africa, where resource disparities hinder readiness (Chai et al., 2021; Mhlongo et al., 2023). Creating supportive professional communities can also enhance subjective norms, motivating teachers to adopt AI by providing collaborative and peer support (Celik, 2023). Educational policies must also prioritize providing access to AI tools, continuous professional development, and technical support to foster teachers' confidence and perceived control over AI use (Chatterjee & Bhattacharjee, 2020). Policymakers should address infrastructural concerns and ensure equitable resource distribution in underserved regions (Chen et al., 2020).

While the study's findings are important, further research is required

to explore the nuances related to the constructs of the TPB and their impact on the integration of AI in science teaching. Future research should explore these factors in more diverse educational contexts to validate and extend these findings. Additionally, longitudinal studies are needed to examine how the behavioral intentions of pre-service teachers translate into actual classroom practices over time. Our study’s limitations, including its reliance on self-reported data and the focus on two specific educational contexts, suggest the need for more comprehensive approaches. Mixed-methods research incorporating qualitative insights could provide a deeper understanding of teachers’ underlying motivations and challenges. Furthermore, expanding the research to include in-service teachers and different educational systems could offer a more holistic view of AI integration in education (Celik, 2023; Chai et al., 2021; Zhang, 2023). Addressing these gaps will improve the generalizability and applicability of the findings.

7. Conclusion

The research aimed to investigate the behavioral intentions of pre-service science teachers in South Africa and Thailand towards integrating AI into their teaching practices. The study confirmed that favorable attitudes, supportive subjective norms, and high perceived behavioral control predict AI integration intentions significantly. Notably, Thai pre-service teachers exhibited stronger favorable norms and perceived control than their South African counterparts, highlighting the influence of contextual factors. These findings emphasize the need for targeted teacher training programs and supportive educational policies to enhance AI readiness, particularly in resource-constrained settings. Future research should expand to diverse contexts and employ mixed-methods approaches to deepen understanding and generalizability.

CRedit authorship contribution statement

Lindelani Mnguni: Writing – original draft, Resources, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Prasart Nuangchalerm:** Writing – review & editing, Investigation, Conceptualization. **R. Ahmad Zaky El Islami:** Investigation, Conceptualization. **Doras Sibanda:** Investigation, Conceptualization. **Indah Juwita Sari:** Investigation, Conceptualization. **Moleboheng Ramulumo:** Investigation, Conceptualization.

Informed consent

All participants involved in the study provided informed written

consent.

Ethical approval

This research project received ethical approval from the South African University (Ref 2023 RPC 040 and Ref 2023/07/05/90291786/25/AM). All participants gave informed consent, and their privacy rights were strictly observed. The data can be obtained upon reasonable request from the corresponding author.

Data availability and sharing policy

The ethical clearance conditions of the research do not permit data sharing.

Declaration of generative AI and AI-assisted technologies in the writing process

During the preparation of this work, the author(s) used ChatGPT, Grammarly, and Recite to refine drafts, improve language clarity, organize complex concepts, and edit references. After using these tools, the authors reviewed and edited the content as needed and take full responsibility for the content of the publication.

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Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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During the preparation of this work, the author used ChatGPT and Grammarly to revise sentences and Recite to revise references. After using these tools, the authors reviewed and edited the content as needed and take full responsibility for the publication’s content.

Appendix 1

Item code	Item used in the questionnaire
A1	Integrating AI in teaching and learning science would be beneficial to the school.
A2	Integrating AI in teaching and learning science would be beneficial to my students.
A3	Integrating AI in teaching and learning science would be beneficial to my colleagues.
BF1	Integrating AI in teaching and learning science would make me a better teacher.
BF2	Integrating AI in teaching and learning science would enhance learners’ understanding of complex scientific concepts.
BF3	Integrating AI in teaching and learning science would improve students’ problem-solving and critical-thinking skills.
BF4	Integrating AI in teaching and learning science would increase students’ interest and motivation to learn science.
BF5	Integrating AI in teaching and learning science would facilitate student engagement and active participation.
PBC1	My colleagues would approve of me integrating AI in teaching and learning science.
PBC2	My learners would approve of my integrating AI into teaching and learning science.
PBC3	My school principal would approve of me integrating AI in teaching and learning science.
PBC4	My head of department would approve of me integrating AI in teaching and learning science.
PBC5	The Department of Basic Education would approve of me integrating AI in teaching and learning science.
SN1	My colleagues believe that I should integrate AI into teaching and learning science.
SN2	My learners believe that I should integrate AI into teaching and learning science.

(continued on next page)

(continued)

Item code	Item used in the questionnaire
SN3	My school principal believes that I should integrate AI into teaching and learning science.
SN4	The Department of Basic Education believes that I should integrate AI into teaching and learning science.
NB1	I am confident that I can successfully integrate AI into teaching and learning science.
NB2	I have the necessary skills to integrate AI into teaching and learning science.
NB3	I have the necessary training to integrate AI into teaching and learning science.
NB4	I have the necessary support and resources to effectively integrate AI into teaching and learning science.
NB5	I feel confident in my ability to integrate AI into teaching and learning science.
CB1	I believe that I have control over the resources and materials required to effectively integrate AI into science education.
CB2	I feel confident in my ability to adapt and customize AI-based instructional tools to suit my science classroom's specific needs and goals.
CB3	I have control over the technological infrastructure and support necessary for integrating AI in teaching and learning science.
CB4	I can overcome any technical challenges that may arise when integrating AI into teaching and learning science.
CB5	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.
BI1	I intend to incorporate AI tools into my science teaching practices.
BI2	I intend to use AI tools to develop assessment tools for my science teaching.
BI3	I plan to attend professional development workshops to help me integrate AI into science teaching.
BI4	I intend to work with my colleagues to integrate AI into science teaching.
BI5	I intend to use AI tools to plan my science lessons.

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