



Exploring the intentions of science teacher candidates to implement computational thinking in their future classroom: A case study

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Abstract

The education system across countries is evolving as students and teachers are increasingly exposed to relevant technologies and innovative pedagogies through both plugged and unplugged activities to promote computational thinking. This paper examines the factors influencing preservice teachers' intentions to integrate computational thinking into their future teaching practices. A total of 164 preservice teachers from the University of Education in Southern Nigeria participated in the research. The analysis employed partial least squares structural equation modeling to explore the relationships among six latent variables identified in this study: perceived usefulness, ease of use, attitude toward computational thinking, behavioral control, subjective norm, and behavioral intention. The findings indicate that the proposed model explains 74.4% of the variance in preservice teachers' intentions to teach computational thinking in their classrooms. Additionally, the results demonstrate that attitude toward computational thinking, perceived behavioral control, ease of use, and usefulness significantly and positively influence preservice teachers' intentions to adopt computational thinking in their future educational practices. However, subjective norms did not significantly predict the intention of teacher candidates to apply computational thinking to their planned teaching practices. The authors discuss these results in the context of integrating computational thinking into educational settings and recommend directions for future research.

Keywords: Attitudes, Beliefs, Computational thinking, Intentions, Nigeria, Preservice teachers.

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Contribution of this paper to the literature

This study contributes to the existing literature on the teaching of computational thinking by preservice teachers in future classroom practices. It highlights the importance of improving teachers' attitudes and perceptions regarding the necessity of incorporating student perspectives to assess the effectiveness of technology utilization in universities. This study's conceptual model can forecast the effective and efficient acceptance and use of technology in online learning.

1. Introduction

In the current environment of rapid digital advancement and interconnectedness, the role of digital technology is pivotal across various sectors, underscoring the enhanced capabilities it provides and the corresponding necessity for computational thinking (CT). This recognition of CT's importance is primarily attributed to essential figures in computer science education. For instance, Wing (2006) regarded CT as the methodology for 'addressing problems, designing systems, and comprehending human behaviour through the lens of core computer science principles. The National Research Council (NRC) of the United States expands this definition, conceptualising CT as a comprehensive set of cognitive tools applicable to diverse challenges, extending beyond mere computing issues (National Research Council, 2010). Subsequently, the Computer Science Teachers Association (CSTA) and the International Society for Technology in Education (ISTE) articulated a practical interpretation of CT, describing it as a problem-solving methodology that necessitates structuring problems to use computers and other tools for organizing and analyzing data, representing information through models and simulations, automating solutions via systematic thinking, and discerning the most effective solutions (CSTA & ISTE, 2011). Although the definition of CT has remained elusive due to its application in various subjects and disciplines, conceptualizing CT beyond computer science is crucial for implementing it in schools. Computational thinking, in the context of this study, refers to the thought process applied when solving a problem, whether with or without digital technologies.

It is believed that teaching CT in schools offers several benefits, which include developing students' creativity, problem-solving abilities, programming proficiency, and analytical skills required to thrive in a technology-driven society (Chao, 2016; Noh & Lee, 2020; Saidin, Khalid, Martin, Kuppusamy, & Munusamy, 2021). Studies have shown that CT can enhance students' understanding of STEM subjects and teachers' self-efficacy in teaching science with educational robotics activities (Angeli & Jaipal-Jamani, 2018; Chao, 2016; Weintrop et al., 2016). Moreover, teaching robotics and coding in classrooms has enhanced students' CT skills (Angeli & Jaipal-Jamani, 2018; Noh & Lee, 2020). Exposing students to CT practices can develop their ability to analyze data, automate processes, and understand how various systems work (Cansu & Cansu, 2019; Weintrop et al., 2016). To emphasize the importance of CT, the Next Generation Science Standards (NGSS) in the United States categorized it as a fundamental practice in science and engineering education (National Research Council, 2012). Thus, incorporating CT in education can help students acquire the foundational computer science principles needed to solve problems effectively in different fields.

In countries like Nigeria, where many students find it difficult to understand introductory programming courses, (Agbo, Olaleye, Bower, & Oyelere, 2023), it is believed that teaching computational thinking (CT) concepts and practices in schools can help establish a strong foundation for computer science (CS) education. However, the successful implementation of CT in the country heavily depends on the methods employed by teachers. This highlights the crucial role teachers play in integrating CT practices and concepts into the classroom to improve students' learning outcomes and digital literacy (Barr & Stephenson, 2011; Dickes, Farris, & Sengupta, 2016; Kong, Lai, & Sun, 2020; Mouza, Yang, Pan, Ozden, & Pollock, 2017). Nonetheless, studies suggest that teachers often resist modifying their teaching methods and incorporating CT into their classrooms. This resistance may be due to obstacles such as insufficient preparation in previous teacher education programs to foster CT, particularly among preservice teachers. Additionally, factors like teachers' attitudes and engagement, self-efficacy, professional development capacity, available support, concerns, and collaboration with the broader computer science education community are also considered responsible for teachers' resistance to integrating CT in their classrooms (Bower et al., 2017; Kong et al., 2020). Given this context, it is assumed that teacher training programs that incorporate CT concepts, ideas, and practices into their curricula will enhance teachers' understanding and knowledge of CT. As teacher education programs increasingly focus on developing preservice teachers' CT skills and implementing measures to support them (Killen et al., 2023; McGinnis et al., 2020), it becomes essential to assess the readiness of preservice teachers to incorporate CT into their future teaching practices. Therefore, this study is framed around the research question:

- What are the critical determinants of preservice teachers' intentions toward integrating computational thinking in their future classroom practice?

2. A Review of Related Literature

2.1. Computational Thinking (Nigerian Context)

Computational thinking (CT) is an essential competency for the modern workplace and a fundamental skill for everyone (Azhar, 2024). However, research indicates that Africa, including its higher education institutions (HEIs), lags in promoting CT education, underscoring the need to adopt CT in African institutions to enhance students' problem-solving skills (Tshukudu et al., 2023). Countries like Nigeria face unique challenges and opportunities in integrating CT into their school curricula. These challenges include, but are not limited to, a lack of infrastructure (Agbo, Oyelere, Suhonen, & Laine, 2021), a significant gap in teacher training (Kennedy, Udoetuk, & Ufot, 2017), and limited integration of CT within the national curriculum. Although there is a strong emphasis on the necessity of embedding CT in the national curriculum to enhance students' problem-solving skills, the integration of CT into Nigerian schools is still in its early stages (Agbo et al., 2021), with most initiatives being sporadic and localized. However, promising developments are emerging. Previous studies indicate that Nigerian education stakeholders are becoming aware of the importance of CT. Unplugged activities have proven beneficial in both K-12 and higher education contexts. Unplugged activities are manipulative methods to foster CT without reliance on digital devices. Incorporating unplugged activities in teaching CT has been identified as critical in contexts like Nigeria, where access to digital resources is often limited (Nuhu, Adedokun-Shittu, & Shittu, 2018; Nuhu, Adedokun-Shittu,

Asiyanbola, & Ajani, 2023). Nigerian teachers welcome unplugged activities as they benefit students and help teachers integrate them into classroom teaching. For example, recent studies within the country are beginning to focus on the use of unplugged activities to teach binary concepts in secondary school mathematics (Nuhu et al., 2023) and novice undergraduate computer science students (Nannim, Mosia, Ezema, & Egara, 2026). Emembolu, Emembolu, Umechukwu, Sulaiman, and Aderinwale (2020) also showed how researchers in the country used Scratch programming through a TeachAKid2Code program to enhance teachers' abilities to integrate CT into STEM education.

Recent findings on teaching CT in Nigeria also show that higher education institutions are increasingly utilizing CT to address the learning challenges in programming education. For instance, a study by Oladipo and Ibrahim (2018) demonstrated how the self-teaching CodeEazee system was developed to teach Python programming and CT to undergraduate students. Additionally, findings from a mixed-methods study by Agbo et al. (2021) revealed that engaging students in collaboratively designing mini-games in an online environment enhanced their understanding and application of CT concepts. They also observed that understanding CT concepts increases students' motivation and problem-solving skills. Building on their earlier research, Agbo et al. (2023) examined how mini-games developed in immersive virtual reality (IVR) environments (iThinkSmart) improve students' learning experiences and CT skills.

Based on the above discussions, there is clear evidence that CT is essential, as it utilizes fundamental concepts in computer science (CS) education to enhance students' knowledge of programming (Agbo et al., 2023). Nevertheless, efforts to formally integrate CT education into the Nigerian school curriculum still lag behind those of other countries, such as Canada, the United Kingdom, the United States, and South Africa. While the United Kingdom has embedded CT within its national curriculum since 2014, Nigeria is only now recognizing its importance. Nonetheless, the rapid rise of mobile technology and the increasing awareness of CT among educational stakeholders offer a promising outlook for Nigeria's progress in this area.

3. Conceptual Framework and Research Hypothesis Development

This study examines the important factors that influence preservice teachers' intentions to integrate computational thinking (CT) into their future classrooms by combining two primary theories: the Theory of Planned Behaviour (TPB) and the Technology Acceptance Model (TAM). Using the TPB, formerly known as the Theory of Reasoned Action (Fishbein & Ajzen, 1975), this study explores preservice teachers' various intentions and anticipated behaviors in incorporating CT into their future teaching practices. According to the TPB, an individual's decision to perform an action is influenced by their attitude towards the action, their perceived behavioral control, and social pressures. The TAM has been expanded to better understand and predict individuals' behaviors in specific contexts, particularly regarding the adoption of new information technologies. Researchers utilized this model to examine how and why individuals adopt new technologies, focusing on perceptions, acceptance levels, and attitudes of potential practitioners. These attitudes are shaped by their beliefs about technology's usefulness and ease of use. Davis (1989) described perceived usefulness (PU) as the conviction that utilizing a system enhances job performance, while perceived ease of use (PEOU) refers to the belief that engaging with a system requires minimal effort. Understanding these factors is essential for developing strategies to promote the integration of CT in educational settings, as they influence teachers' willingness and readiness to adopt new pedagogical tools and methods.

Using the Theory of Planned Behavior (TPB) and Technology Acceptance Model (TAM) enables the assessment of motivational factors and anticipated outcomes from preservice teachers' intended actions or plans to incorporate Computational Thinking (CT) into their future teaching practices. The two theories describe a sequence of causal relationships between an individual's perceptions regarding the use of a system and its actual implementation. In Nigeria, many teachers' reliance on traditional lecture methods could limit their confidence and motivation to implement CT-based activities. Thus, teachers' willingness to integrate CT into classrooms becomes crucial for developing students' problem-solving skills. Researchers are employing the TPB and TAM to explore the determinants affecting teachers' decisions and better understand the barriers and facilitators of CT integration. Insights derived from these investigations will be helpful to assist researchers in formulating effective strategies to facilitate the incorporation of CT within the Nigerian educational framework.

3.1. Attitude Toward the Use of Computational Thinking

The drive to integrate CT into educational curricula has emphasized the need to equip preservice teachers with CT skills and tools through dedicated courses and subject-specific methodologies (Yadav, Good, Voogt, & Fisser, 2017). As the integration of CT gains momentum, attitudes toward this concept become crucial, as they influence how effectively preservice teachers adopt and teach CT in classrooms. As Fishbein and Ajzen (2010) explained, attitude is "an evaluation of performing a future behavior in terms of favor or disfavor, good or bad, like or dislike." Prior research has demonstrated that their attitudes might significantly influence preservice teachers' intentions to teach CT. However, Yzer (2013) noted that attitude could be cognitive in terms of perception or affective regarding whether a behavior is enjoyed. It has also been noted that teachers' attitudes towards CT play a significant role in their willingness to implement CT in STEM education (Cutumisu & Guo, 2019; Günbatar & Bakırcı, 2019). Thus, teachers with positive attitudes towards CT are more likely to incorporate these skills into their future classrooms, highlighting the critical link between attitude and implementation, as also supported by Ateşkan and Hart (2021). Moreover, evidence suggests that attitudes toward CT significantly influence the development of CT skills (Cutumisu, Adams, Glanfield, Yuen, & Lu, 2022).

This reinforces the notion that fostering a positive attitude towards CT during teacher education can enhance preservice teachers' skills and confidence in applying these concepts effectively. Similarly, Powers, Musgrove, Brown, and Azhar (2020) support this view, suggesting that a robust understanding of CT can lead to a more positive attitude and greater intention to use CT in teaching. However, other studies present a more nuanced picture. Zha, Jin, Moore, and Gaston (2020) reported no significant change in students' attitudes when CT was integrated into a flipped Educational Technology module, suggesting that the mode of integration and the context of the intervention can significantly impact its effectiveness. Additionally, Fessakis and Prantsoudi (2019) highlighted that existing

preconceptions about CT could lead to negative attitudes, posing a barrier to its integration. These studies collectively suggest that while positive attitudes towards CT are crucial for its successful adoption, the way CT is taught and the pre-existing beliefs of preservice teachers also play significant roles in its adoption. This implies that teacher education programs must provide comprehensive CT training and address and reshape negative preconceptions to effectively prepare future teachers for incorporating CT into their classrooms.

3.2. Perceived Ease of Use of Computational Thinking Concepts and Practices

Perceived ease of use (PEOU) within the Technology Acceptance Model (TAM) corresponds with the broader concept of technological competence, which is characterized as the capability to effectively manage a diverse array of technology applications for various purposes (Teo, Fan, & Du, 2015). For this research, PEOU pertains to the extent to which preservice teachers perceive that acquiring and applying CT concepts and practices will require minimal effort (Davis, 1989). People use technology when they think they can effectively navigate it. Kaya, Newley, Yesilyurt, and Deniz (2020) studies demonstrated that targeted interventions could enhance preservice teachers' beliefs in their ability to use CT effectively in elementary science lessons. Earlier, Kalogiannakis and Papadakis (2017) highlighted the effectiveness of user-friendly educational tools, such as ScratchJr, in obtaining strong acceptance and enhancing confidence among preservice teachers in teaching CT concepts. ScratchJr's intuitive interface and engaging approach make it a valuable resource for teachers so that they can introduce complex CT ideas in a more accessible and enjoyable manner. In another study, Tankiz and Atman Uslu (2023) found that building preservice teachers' computational skills and self-efficacy using educational games in a block-based programming environment significantly impacted their perceptions of CT and self-efficacy (SE) in teaching CT. In addition, Çiftçi and Topçu (2023) found that 68 early childhood preservice teachers developed CT teaching self-efficacy beliefs when exposed to CT-integrated STEM education.

3.3. Perceived Usefulness of Computational Thinking

Within the TAM framework, Davis (1989) characterizes perceived usefulness (PU) as the strength of an individual's belief that utilizing a specific technology will enhance their job performance. He emphasized the importance of PU as a crucial factor influencing the adoption of technology. Accordingly, perceived ease of use (PEOU) relates to PU, and both factors predict technology acceptance (Davis, 1989). Thus, a preservice teacher's perception of the ease of using CT tools will enhance their PU, which may, in turn, influence their intention to incorporate CT skills in the classroom.

There is a lack of literature on preservice teachers' PU of CT in various contexts. However, researchers have emphasized the importance of understanding these dynamics in different contexts of interest. Hashim and Husnin (2019) found a positive correlation between teachers' attitudes, perception of usability (PU), and behavioral intention to use CT skills in their teaching. Similarly, Abdullah, Ward, and Ahmed (2016) explored the behavioral intention of 242 undergraduates to accept e-portfolios for learning and found that PU and PEOU were determinants of their behavioral intention. Therefore, it is important to understand these dynamics within the educational context. Venkatesh and Bala (2008) extended TAM to incorporate subjective norms, image, job relevance, output quality, and results that influence PEOU and PU. This highlights the complexities and multifaceted nature of technology acceptance among teachers. Given these findings, improving preservice teachers' PEOU can directly impact their PU, which may be important in determining their behavioral intention to use CT skills in their future teaching.

3.4. Perceived Behavioral Control

Behavioral intention is the extent to which a person plans to behave in a specific way in the future (Teo et al., 2015). The Theory of Planned Behaviour (TPB) provides a conceptual framework for understanding human behavior in a specific context. In TPB, an individual's attitudes influence their intentions, which subsequently predict their behaviors (Fishbein & Ajzen, 2010). Supporting this, Dong, Li, Sun, and Liu (2024) observed a positive association between preservice teachers' CT ability and influencing factors such as attitudes, emotions, self-efficacy, interest, and will (behavioral control). However, there appears to be a scarcity of literature on preservice teachers' perception of behavioral control; however, the TPB explains this concept. Drawing on the TRA and TPB, Muchsini, Siswandari, Gunarhadi, and Wiranto (2022) found that perceived control positively influences the intention to implement CT. Similarly, Alqahtani, Hall, Leventhal, and Argila (2022) reported an intervention study where preservice teachers' exposure to robotics teaching changed their intention to use robots. This suggests that preservice teachers' perception of the ease and usefulness of CT will determine the extent to which they integrate CT into their teaching.

3.5. Subjective Norm

The TPB and the TAM lay the groundwork for understanding the concept of subjective norm, which refers to the perceived social pressures that influence a person's decision to engage in specific behaviors or tasks (Fishbein & Ajzen, 1975). This concept is based on individuals' interpretations of significant others' (colleagues, close peers, friends, professors, or university management) expectations for their behavior Teo and Milutinovic (2015). Therefore, teachers' perceptions that their friends or colleagues use new technology can influence their behavior and intention to use it, despite their attitude towards it. Supporting this assertion, Huang, Teo, and Zhou (2020) demonstrated that Chinese students' intentions were strongly influenced by their perceived ease of use (PEOU) and subjective norms, which subsequently strengthened their views on the usefulness of internet-based technologies. Gurer (2021) concurred, identifying subjective norms as a critical predictor of the intention to adopt technology, among other factors. Muchsini et al. (2022) also supported the idea that subjective norms, attitudes, and perceived behavioral control would strongly influence pre-service teachers' incorporation of computational thinking (CT) into spreadsheet learning, as observed in a study of college students. Similarly, Watson and Rockinson-Szapkiw (2021) noted that preservice teachers occupy an important position among students, enabling them to gauge the perspectives of their teachers, colleagues, parents, and future students. Thus, subjective norms based on external factors influence preservice teachers' intention to use CT within a broader social context. This study, therefore, hypothesizes that the perceived social pressures and expectations from both current and future educational environments will significantly

impact preservice teachers' intentions to utilize CT. Figure 1 depicts the conceptual model derived from the studies reviewed in the prior discussion.

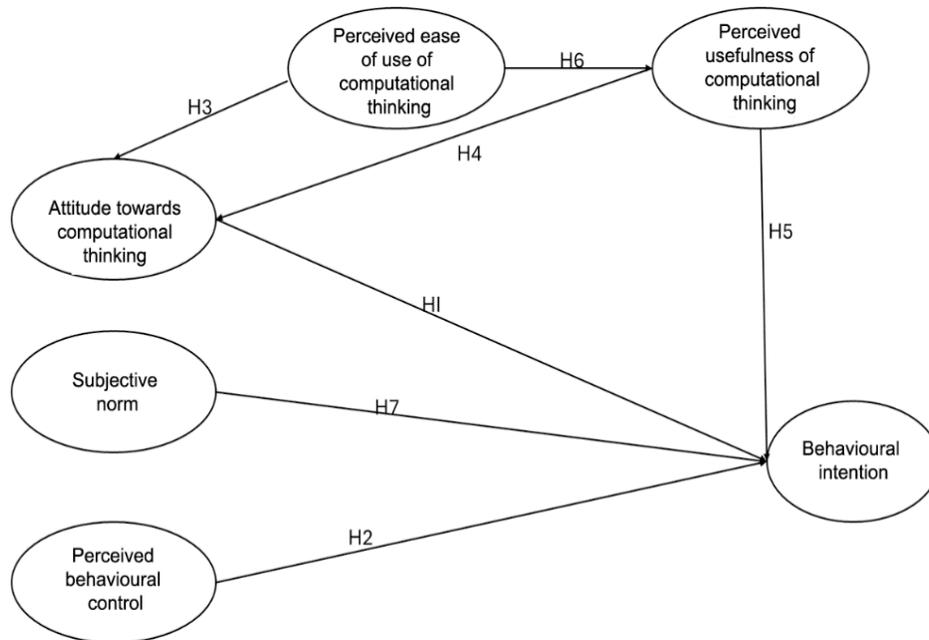


Figure 1. Proposed structural model of the study.

In line with the hypothetical framework in Figure 1, the following hypotheses were stated.

- *H₁: Attitude significantly predicts behavioral intention.*
- *H₂: Perceived behavioral control significantly predicts behavioral intention.*
- *H₃: PEOU of CT significantly predicts PST attitude towards CT.*
- *H₄: PU of CT significantly predicts PST's attitude towards CT.*
- *H₅: PU of CT concepts and practices significantly predict PST's behavioral intention to integrate CT in their future classroom practice.*
- *H₆: PU of CT significantly predicts the PEOU of CT concepts and practices.*
- *H₇: Subjective norm significantly predicts PST's behavioral intention.*

4. Method

This research employs a cross-sectional survey design to investigate the reasons behind preservice teachers' intentions to incorporate CT into their prospective teaching practices. Based on the combination of the TAM and the TPB used as a conceptual framework in this study, an empirical study was undertaken in Nigeria as part of a larger project that explored how to support teachers' integration of CT in science classrooms. Approval for this study was granted on 19 February 2024 by the Ethics Committee of the University of Johannesburg, South Africa, with an institutional clearance number SEM 1-2024-021.

4.1. Study Participants

The participants were undergraduate students enrolled in the Bachelor of Computer Science Education program for the 2023/2024 academic year at Lagos State University of Education, Nigeria. All students completed an introductory programming course in their first semester. One hundred sixty-four preservice teachers filled out the online questionnaire, and all responses were deemed sufficient for further analysis. The sample comprised 67.8% males and 32.2% females (Table 1). Most participants were second-year (63.4%) and first-year undergraduate students (36.6%).

Table 1. Respondent demographic.

Variables	Group	Frequency	Percentage
Gender	Male	111	67.7
	Female	53	32.3
Age	15 - 20	97	59.1
	21 - 25	60	36.6
	26 - 30	6	3.7
	31 and above	1	0.6
Year of study	1 st year	60	36.6
	2 nd year	104	63.4

4.2. Instrumentation and Data Collection

The instruments used in this study were based on questions adapted from Yadav, Mayfield, Zhou, Hambrusch, and Korb (2014); Bower et al. (2017) and Ling, Saibin, Labadin, and Aziz (2017). The questions were closed-ended with a 5-point Likert scale. Two academic experts in science and technology education validated the questionnaire, and their feedback was used to refine the items for clarity (Fraenkel, Wallen, & Hyun, 2012). The survey was then electronically shared with preservice teachers enrolled in a computer science module at the Lagos State University of Education, which remained open for a period of three months. Ethical guidelines were followed, and participants provided informed consent after being informed about the study's purpose and procedures. Many were motivated to

participate in the study because of the prospect of contributing to improvements in their CT education course and future teaching practices.

The final survey consisted of three sections. The first four questions collected demographic information about preservice teachers (PSTs), including age, gender, year of study, and past workshops, trainings, seminars, or classes related to computer science, technology, or computer programming. The second section included 11 open-ended questions that explored PST awareness and understanding of CT, which are not reported in this study. The third part included six constructs with 33 adapted items. The section contained items selected from the TAM (PU and PEU) and the TPB (attitude, subjective norm, perceived behavioral control, and intention), measured on a five-point Likert scale (1 = “strongly disagree” and 5 = “strongly agree”). The perceived behavioral control construct scale ranged from (1 = “Never” to 5 = “Always”). The scale distribution of the retained items included a PU scale of five items, a PEU scale of six items, a CT attitude scale of four items, a subjective norm scale of four items, a perceived behavioral control scale of nine items, and a behavioral intention scale of five items. The adapted items were deemed appropriate for preservice teachers within the context of this study based on their reliability and convergent validity, as shown in Table 2. Thus, the sample included preservice teachers who had received training in CT concepts and practices.

4.3. Data Analysis

The data for this study were pre-analyzed using IBM SPSS version 26 for screening and descriptive statistics, including means and frequencies. Missing values, accounting for only 0.7% of the dataset (7 indicators out of 164 responses), were replaced with the mean of valid values, which was well within the acceptable 5% threshold (Dong & Peng, 2013; Hair et al., 2021). With a skewness <3 and kurtosis <10, the statistics complied with univariate normality thresholds (Kline, 2015).

The researchers analyzed the data using least squares structural equation modeling (PLS-SEM) with SmartPLS4 software, which was chosen for its suitability with small sample sizes and non-normal data (Hair, Hult, Ringle, & Sarstedt, 2022). Partial least squares structural equation modeling (PLS-SEM) comprises two key components: the measurement model, which assesses the validity and reliability of constructs, and the structural model, which examines the relationships between latent variables (Ringle, Wende, & Becker, 2022). The analysis explored the factors influencing preservice teachers' intentions to incorporate CT into their teaching, using path model analysis to determine the significance and strength of proposed relationships.

5. Results

In determining preservice teachers' intentions to incorporate CT into their future classroom practice, participants' responses are presented by evaluating the model using the two-step approach recommended by Hair et al. (2022), which is discussed in the following section.

5.1. Measurement Model Assessment

The measurement model was assessed using the PLS algorithm to evaluate indicator and latent variable reliability, internal consistency (Cronbach's alpha and composite reliability), and construct validity. Convergent validity was measured by determining the average variance extracted (AVE), cross-loading, and the HTMT criterion. The reliability analysis reveals that factor loadings exceed the critical value of 0.60, with all loadings above 0.70, confirming acceptable item reliability as recommended by Hair et al. (2022). According to the common guideline, the construct explains more than 50% of the variance in the indicator, demonstrating acceptable item reliability. Cronbach's alpha and composite reliability values exceeded 0.7, indicating strong reliability and internal consistency (Hair et al., 2022; Kline, 2015). Additionally, AVE values were above 0.5, demonstrating good convergent validity (see Table 2), while Appendix A provides details of the questions used in the online questionnaire.

Table 2. Validity and reliability of the construct.

Item number	Factor loadings	Cronbach's alpha	Composite reliability	Average variance extracted (AVE)
1. Attitude towards CT		0.908	0.936	0.785
1.1.	0.803			
1.2	0.917			
1.3	0.889			
1.4	0.929			
2. Subjective norm		0.863	0.907	0.709
2.1.	0.809			
2.2	0.883			
2.3	0.850			
2.4	0.825			
3. Perceived ease of use		0.875	0.906	0.617
3.1.	0.847			
3.2	.0739			
3.3	0.860			
3.4	0.770			
3.5	0.743			
3.6	0.743			
4. Behavioural intention		0.888	0.918	0.692
4.1	0.838			
4.2	0.852			
4.3.	0.885			
4.4	0.828			
4.5.	0.752			

Item number	Factor loadings	Cronbach's alpha	Composite reliability	Average variance extracted (AVE)
5. Perceived usefulness		0.928	0.946	0.777
5.1	0.852			
5.2	0.873			
5.3	0.908			
5.4	0.907			
5.5	0.868			
6. Perceived behavioral control		0.919	0.932	0.580
6.1	0.731			
6.2	0.771			
6.3	0.738			
6.4	0.840			
6.5	0.796			
6.6	0.756			
6.7	0.735			
6.8	0.708			
6.9	0.721			

Findings from the measurement model show that 31 items retained have factor loadings (see Table 2). Discriminant validity was confirmed using the Fornell-Larcker criterion and HTMT, with HTMT values below 0.90 (Henseler, Hubona, & Ray, 2016). The square root of the AVE for each construct exceeded its correlations with other constructs (Table 3), and HTMT values ranged from 0.4 to 0.8, indicating distinct latent variables with minimal cross-correlation (Table 4). These findings confirm that the measurement items effectively represent the intended latent constructs.

Table 3. Discriminant validity test (Fornell-Larcker).

Constructs	ATT	BI	PBC	PEU	PU	SN
ATT	0.886					
BI	0.742	0.832				
PBC	0.392	0.516	0.761			
PEU	0.734	0.745	0.464	0.785		
PU	0.749	0.827	0.447	0.782	0.882	
SN	0.480	0.584	0.590	0.524	0.565	0.842

Table 4. Heterotrait-Monotrait (HTMT) Ratio of Correlations.

Constructs	ATT	BI	PBC	PEU	PU	SN
ATT	0.886					
BI	0.742					
PBC	0.392	0.562				
PEU	0.734	0.855	0.506			
PU	0.749	0.809	0.478	0.863		
SN	0.480	0.665	0.665	0.601	0.629	

5.2. Structural Model Evaluation

All constructs evaluated had Variance Inflation Factor (VIF) values below 5, indicating no multicollinearity. The Standardized Root Mean Square Residual (SRMR), which measures the average discrepancy between the observed covariance matrix and the covariance matrix implied by the model, was 0.070, below the 0.08 threshold, indicating a good model fit (Henseler et al., 2016). The Normed Fit Index (NFI), which assessed the overall model's suitability, was 0.800, slightly below the 0.9 benchmark, which is not significantly different (Bentler & Bonett, 1980). Overall, the model demonstrated a satisfactory fit with the observed data, with collinearity and model fit results summarized in Table 5.

Table 5. Collinearity analysis and model fit.

Dimension correlation	VIF	Model fit
ATT -> BI	2.312	SRMR=0.070
PBC -> BI	1.584	NFI=0.800
PEU -> ATT	2.578	
PEU -> PU	1.000	
PU -> ATT	2.578	
PU -> BI	2.631	
SN -> BI	1.865	

The hypothesized structural model illustrates the constructs and their path relationships, which were later examined using the accelerated bootstrapping technique, involving 5000 subsamples across multiple iterations (Hair et al., 2021). The model verification is explained by the hypothesized correlations among the constructs, represented by the path coefficient and the coefficient of determination (R^2). Path coefficients, ranging from -1 to +1, indicate the strength and direction of relationships, with values near +1 signifying strong positive associations and those near -1 indicating strong negative associations (Hair et al., 2022). The statistical significance ($p < 0.05$) of the path coefficients, along with T-statistics and p-values, is detailed in Table 6. Figure 2 visually represents the developed PLS-SEM model.

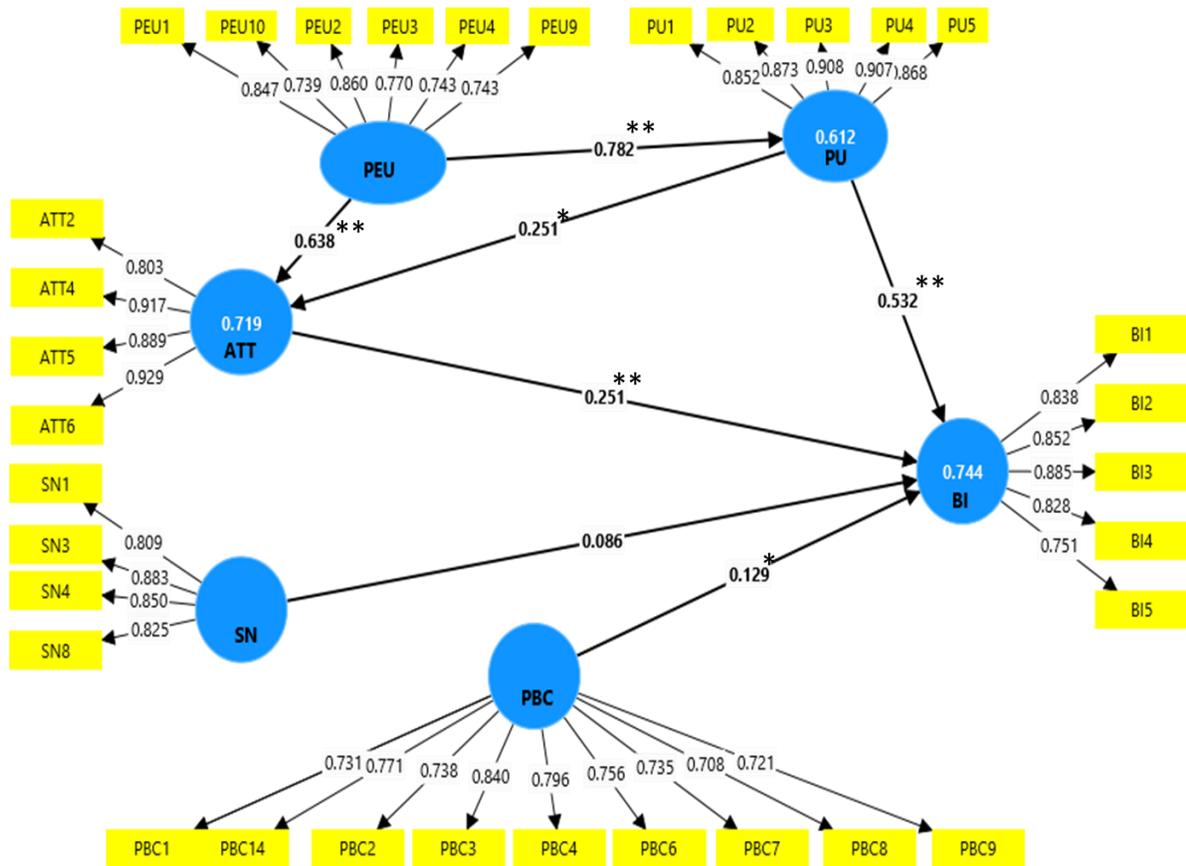


Figure 2. Empirical Structural Model (Path) and Measurement of Preservice Teachers' Behavioral Intention to Implement Computational Thinking Based on Standardized Coefficients.

Table 6. Standardized path coefficient for the tested model.

Hypothesis	Path links	Path coefficient (β)	Sample mean	Standard deviation	T Statistics	P values	F ² effect size	Remarks
H1	ATT -> BI	0.251	0.246	0.060	4.209	0.000	0.107	Accepted
H2	PBC -> BI	0.129	0.141	0.061	2.121	0.034	0.041	Accepted
H3	PEU -> ATT	0.638	0.624	0.093	6.848	0.000	0.561	Accepted
H4	PU -> ATT	0.251	0.262	0.101	2.477	0.013	0.087	Accepted
H5	PU -> BI	0.532	0.524	0.076	6.962	0.000	0.420	Accepted
H6	PU -> PEU	0.782	0.782	0.056	14.03	0.000	1.578	Accepted
H7	SN -> BI	0.086	0.089	0.068	1.255	0.210	0.015	Not accepted

The proposed model included seven hypotheses (Figure 1), with results detailed in Table 6. However, the data in Table 6 indicate that the path coefficients of all the direct and hypothesized relationships reached a significant level, confirming that H1, H2, H3, H4, H5, and H6 in this study are valid, except for H7, which is not valid. Furthermore, the explanatory power of the structural model was assessed using the coefficient of determination (R^2) with a value of 0.744, indicating that 74.4% of the variance in behavioral intention is explained by PU, subjective norm, attitude towards CT, and perceived behavioral control (Chin, 1998). Additionally, the findings suggest that a 71.9% change in preservice teachers' attitudes towards CT is attributed to their PEOU and the usefulness of CT. In comparison, their PEOU of CT explains 61.2% of preservice teachers' PU of CT.

The contribution of the independent variables to the R^2 of preservice teachers' behavioral intention (dependent variable) was measured using Cohen (1988) guidelines for assessing effect size (f^2). According to the guideline, an f^2 value exceeding 0.02 indicates a small effect size, an f^2 value above 0.15 indicates a moderate effect size, and an f^2 greater than 0.35 indicates a large effect size. Results in Table 5 show that attitude towards CT ($f^2 = 0.107$), perceived behavioral control ($f^2 = 0.041$), and PU ($f^2 = 0.087$) have a negligible impact on behavioral intention, while subjective norms have no impact.

The findings of this research also show direct and indirect relationships between the latent variables and behavioral intention. A direct effect occurs when two variables are directly linked, while the combination of coefficients along the path determines an indirect effect. The combined influence of both direct and indirect effects signifies the total effect. Upon further examination, it is uncovered that PEOU of CT ($\beta = 0.626$, $t = 8.528$; $p = 0.000$) and PU ($\beta = 0.063$, $t = 2.137$; $p = 0.033$) both exert a significant indirect influence on behavioral intention, while PEOU significantly influences attitude towards CT indirectly ($\beta = 0.196$, $t = 2.237$; $p = 0.025$). A detailed breakdown of the direct and indirect effects of various factors on behavioral intention and attitude is shown in the Appendices.

6. Discussion

Rapid technological advancement has created a global demand for individuals skilled in using computational tools, which are now essential across various industries. Given the increasing demand for a workforce with these skills, especially in rapidly digitalizing countries like Nigeria, teaching CT in schools has become essential. Thus, this research investigates the behavioral intentions of preservice science teachers from a Nigerian university regarding their intent to incorporate CT into their classroom instruction. In the structural model of this study, seven hypotheses were established. The study hypothesized relationships between preservice teachers' intentions to teach CT and three factors: their attitudes toward teaching it, their perception of its use, and their belief in their ability to

successfully implement CT strategies in their classrooms. The study's findings showed that attitude, PU, PEOU, and perceived behavioral control significantly affected preservice teachers' intentions to teach CT in their classroom instruction. This study supports the findings of previous studies (e.g., (Hashim & Husnin, 2019; Muchsini et al., 2022)) and confirms the positive role of attitudes on intentions to implement CT into their teaching (Hashim & Husnin, 2019; Muchsini et al., 2022).

The data analysis revealed that preservice teachers' attitudes significantly influence their intentions to incorporate computational thinking (CT) into their teaching practices. Their prior computer experience and training may have motivated them to participate in this study Abdulkareem and Lennon (2025). The most significant influence on their teaching attitudes was their ability to use CT concepts and practices. These findings support the conceptual framework that users' perceptions influence their attitudes and intentions (Davis, 1989; Songkram et al., 2024). Preservice teachers' willingness to use CT may also depend on their views on its usefulness and ease; their positive views of CT may lead them to use it in their teaching, while their understanding of CT and their perceptions of its efficacy and ease may affect their attitude (Munoz Del et al., 2019). Perceived behavioral control was also identified as another predictor of preservice teachers' intent to teach CT, with a significant direct effect. Therefore, preservice teachers with strong self-efficacy in applying CT concepts and principles are more inclined to teach them in their future classrooms (Yadav et al., 2014).

Research indicates that skills, resources, and social learning significantly influence a teacher's behavioral intention to implement specific teaching practices, confirming previous findings on behavioral intentions (Demir, 2010; Hardin-Fanning & Ricks, 2017). These factors, coupled with infrastructure and colleague support, can significantly influence a teacher's perceived ability to integrate CT into their classroom. Therefore, the widespread lack of adequate infrastructure and resources in many Nigerian schools could lead preservice teachers to perceive the integration of CT in their future classrooms as difficult. However, the observed positive intentions of preservice teachers suggest that other factors, such as their skills, motivation, and peer support, may have mitigated the negative impact of resource constraints. In contrast, subjective norms (social pressure or expectations from others) did not significantly influence the intentions of preservice teachers to integrate and teach CT in their future classrooms. This unexpected finding may be due to lecturers' prevailing preference for traditional teaching methods over innovative approaches, such as CT. Additionally, the social pressure to conform to established school norms may have further discouraged preservice teachers from expressing strong intentions to integrate CT into their teaching practices (Agbo et al., 2023).

7. Conclusion

This study was analyzed using the TPB and TAM frameworks, and the analysis of the structural model shows that all the formulated assumptions exhibited significant direct and indirect relationships, except for subjective norm. Hence, the results showed that participants believe that their attitude towards CT, perceived behavioral control, perceived usefulness, and perceived ease of use of CT concepts and practices will influence how they integrate CT into their future classroom practice. This implies that the effective integration of CT in future classroom practice by preservice teachers can only be possible if they have the right attitude and perceptions. However, these attitudes and perceptions can only evolve if preservice teachers are provided with the proper support and exposure to professional training on CT.

8. Implications and Recommendations

Incorporating computational thinking into school curricula, teachers can teach pupils to solve problems, model real-world situations, and make informed decisions. This method helps students develop analytical and structured thinking skills to create unique plans and solutions that benefit society (Pérez & Ladino, 2021). In light of this, teacher education programs should incorporate CT pedagogy across multiple courses and topic areas to equip preservice teachers with the confidence and skills necessary to teach CT. These training programs should also provide preservice teachers with realistic materials for CT integration. Examples include hands-on CT activities (both plugged and unplugged), ready-made lesson plans, online tutorials, and mentorship programs. Preservice teachers should practice CT through micro-teaching or simulated classroom experiences with coaching and feedback to enhance confidence and skills. All these resources can contribute to improving preservice teachers' positive attitudes and perceptions towards integrating CT into their future classrooms, making them feel more confident in their ability to implement it and fostering their sense of control over their behavior. Additionally, there is a need to update educational policies and curricula to incorporate a variety of activities that support the development of students' CT skills in the learning process.

9. Limitation

Nevertheless, this investigation is not devoid of specific limitations. A prominent issue is that the findings are derived from self-reported data provided by preservice teachers, which introduces the possibility that participants may have offered responses they perceived to be socially desirable. This potential source of bias constitutes a risk to the integrity of our conclusions. Subsequent research endeavors could employ interview methodologies and observational techniques to evaluate how the intentions of preservice teachers transition into tangible classroom practices over time. Additionally, the study's focus on preservice teachers from a single department within one university is another limitation. Consequently, the findings cannot be generalized to all preservice teachers in Nigeria or even to those within the same university where the research took place. Therefore, a longitudinal study that includes multiple universities and diverse data collection methods could be planned to broaden the scope of the research and provide a depth of insight into the intention and actual practice of CT among preservice teachers in Nigeria.

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