IJEMST International Journal of Education in Mathematics, Science and Technology

www.ijemst.net

What Drives Coding Adoption in Mathematics Teacher Education? Insights from an Extended UTAUT Model

Zeynep Gül Dertli [1 *], Nezihe Korkmaz [2], Elif Boran [3], Sena Uludağ [4], Bahadır Yıldız [5]

[1] Istanbul Aydın University, Turkiye, 0000-0002-4750-5343
[2] Çukurova University, Turkiye, 0000-0002-1284-0483
[3] Çukurova University, Turkiye, 0009-0001-9187-1463
[4] Uludağ University, Turkiye, 0009-0005-1549-8723
[5] Hacettepe University, Turkiye, 0000-0003-4816-3071
* Corresponding author: Zeynep Gül Dertli (zeynepdertli@aydin.edu.tr)

Article Info

Article History

Received:
21 June 2025

Revised:
5 October 2025

Accepted:
10 December 2025

Published:
1 March 2026

Keywords

Coding in education
Technology acceptance
Pre-service mathematics teachers
UTAUT
Hedonic motivation

Abstract

This study investigates the factors influencing pre-service mathematics teachers' intentions to integrate coding into their instructional practices, using the Unified Theory of Acceptance and Use of Technology (UTAUT) as its theoretical foundation. While coding is widely recognized as a crucial digital competency, its effective integration into mathematics education depends on various motivational and contextual variables. The study was conducted with 334 pre-service mathematics teachers from seven universities in Turkey. Data were collected using the Coding Usage Intention Scale, developed based on the UTAUT model and extended with additional variables: self-efficacy, perceived learning opportunities, and hedonic motivation. Structural Equation Modeling (SEM) was employed to test the proposed model. The results revealed that hedonic motivation was the most significant predictor of coding intention ($\beta = 0.646$, $p < .001$). Other significant predictors included performance expectancy, social influence, self-efficacy, and perceived learning opportunities. In contrast, effort expectancy and facilitating conditions did not have statistically significant effects. The overall model demonstrated good fit indices, supporting the validity of the proposed framework. These findings highlight the importance of both cognitive and affective factors in shaping pre-service teachers' willingness to adopt coding in education. The study offers theoretical and practical implications for teacher education programs, suggesting that increasing enjoyment, competence, and pedagogical awareness around coding may enhance its adoption in mathematics instruction.

Citation: Dertli, Z. G., Korkmaz, N., Boran, E., Uludağ, S., & Yıldız, B. (2026). What drives coding adoption in mathematics teacher education? Insights from an Extended UTAUT Model. *International Journal of Education in Mathematics, Science and Technology (IJEMST), 14*(2), 369-391. https://doi.org/10.46328/ijemst.5143

Introduction

In the evolving landscape of 21st-century education, coding has rapidly transitioned from a specialized technical skill to a foundational component of digital literacy. As a core concept of computer science, coding not only facilitates computational thinking but also supports essential cognitive, metacognitive, and socio-emotional skills such as logical reasoning, problem-solving, creativity, and collaboration (Chen et al., 2017; Fessakis et al., 2013; Gim, 2021). Increasingly, it is being positioned as a new form of literacy—on par with reading and mathematics—for today's learners (Metin et al., 2023; Sulistyaningtyas et al., 2020).

Coding has particular relevance for mathematics education. Research indicates that when learners engage in coding, they are not only practicing algorithmic thinking but also constructing and representing mathematical relationships, experimenting with variables, and exploring patterns (Calao et al., 2015; Gadanidis, 2015). This alignment between mathematical reasoning and computational structures offers unique opportunities to enhance the learning of abstract mathematical concepts. As shown in prior studies, coding can serve as a pedagogical bridge to facilitate conceptual understanding in topics such as geometry, algebra, and measurement (Solin, 2017; Welch et al., 2022). It is thus no coincidence that Gadanidis (2015) described coding as a "Trojan Horse" for reforming mathematics education—an entry point to deeper and more engaging mathematical learning.

Despite the educational benefits of coding, its successful implementation in classrooms depends largely on the knowledge, skills, and beliefs of teachers. As Liu et al. (2010) argue, integrating novel instructional approaches such as coding requires not only technical competence but also pedagogical confidence. Particularly among pre-service teachers, the adoption of educational technologies is influenced by a range of personal, contextual, and motivational factors (Dawson, 2008; Kay, 2006). Previous research has found that teachers often perceive their students to be more digitally competent than themselves, which may exacerbate technology avoidance and decrease confidence in implementing coding-related activities (Rich et al., 2019; Tondeur et al., 2012).

In this context, understanding the determinants of pre-service teachers' intentions to integrate coding into their teaching is vital for the design of effective teacher education programs. The present study approaches this issue using the Unified Theory of Acceptance and Use of Technology (UTAUT), a comprehensive framework developed by Venkatesh et al. (2003) that synthesizes elements from eight established acceptance models. UTAUT identifies four primary constructs that influence behavioral intention and technology use: performance expectancy, effort expectancy, social influence, and facilitating conditions. These constructs have been widely validated across various educational and organizational contexts.

However, UTAUT is not a static model. It can be extended by incorporating additional variables to account for context-specific determinants (Granić, 2023). In the context of teacher education and coding adoption, research has highlighted the relevance of several supplementary constructs:

- Self-Efficacy, defined as individuals' beliefs in their capabilities to execute tasks (Bandura, 1991), has been shown to influence teachers' confidence in applying technology in instructional settings (Hatlevik, 2017; Kundu et al., 2021).

- Perceived Learning Opportunities refer to the degree to which teachers believe that technology enhances pedagogical innovation and student engagement (Hermita et al., 2023).
- Hedonic Motivation, as introduced in UTAUT2 (Venkatesh et al., 2012), captures the intrinsic enjoyment associated with using a technology. Recent studies suggest that emotional gratification, not just utility, plays a crucial role in educational technology acceptance (Gunasinghe et al., 2019; Gyamfi, 2021).

This study builds an extended UTAUT model by integrating these three additional variables—Self-Efficacy, Perceived Learning Opportunities, and Hedonic Motivation—to explore their effect on Behavioral Intention to use coding. The conceptual model is illustrated in Figure 1, outlining the hypothesized paths among constructs.

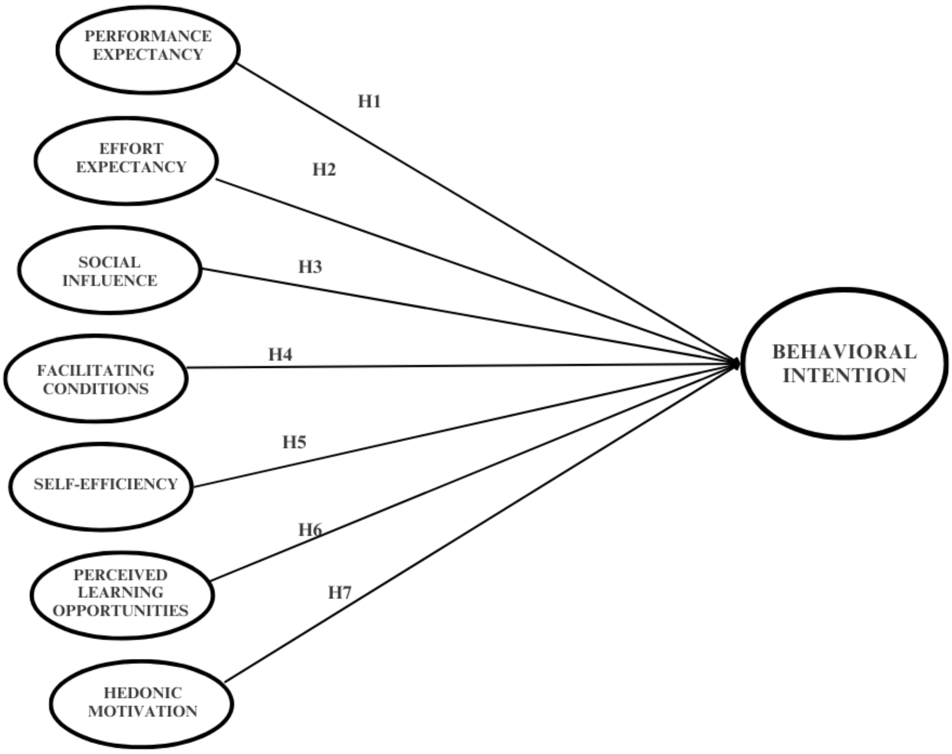

Figure 1. Proposed Coding Acceptance Model Based on Extended UTAUT Framework

The study aims to empirically test the following research hypotheses derived from the model:

- H1: Performance expectancy positively affects behavioral intention to use coding.
- H2: Effort expectancy positively affects behavioral intention to use coding.
- H3: Social influence positively affects behavioral intention to use coding.
- H4: Facilitating conditions positively affect behavioral intention to use coding.
- H5: Self-efficacy positively affects behavioral intention to use coding.
- H6: Perceived learning opportunities positively affect behavioral intention to use coding.
- H7: Hedonic motivation positively affects behavioral intention to use coding.

By investigating these hypotheses, the study contributes to the growing body of literature on digital technology integration in teacher education. More specifically, it offers a nuanced understanding of how cognitive, emotional, and contextual factors collectively shape mathematics teacher candidates' readiness to embed coding in their future classrooms.

Theoretical Framework

Coding in Education

Coding is defined as the process of developing applications through sets of instructions executed by a computer to solve problems, enable human-computer interaction, or accomplish specific tasks (Bers et al., 2019; Kalelioğlu et al., 2016). This definition highlights that coding is not merely a technical tool, but a skill that supports problem-solving and communication processes. Teaching children to code enables them to engage with digital technologies meaningfully, fostering their understanding of basic programming concepts and enhancing their digital literacy skills (Marsh et al., 2016; Sulistyaningtyas et al., 2020).

Because coding is the underlying structure of games and applications, it provides students with creative learning opportunities. For instance, through coding, students can design games, program robotic movements, and, in the process, develop their thinking and logical reasoning abilities (Chen et al., 2017; Romero et al., 2017). These activities not only support children's cognitive development but also allow them to comprehend and communicate using the language of coding (Lee, 2020). In this regard, coding activities contribute not only to individual learning but also to students' understanding of technology and their participation in creative problem-solving processes. Thus, coding has become not only a critical skill for navigating the digital era but also a pedagogical tool that supports students' cognitive development and logical reasoning processes.

Various computer technologies are used effectively in teaching, learning, and assessment processes in educational environments (Granić, 2023). Among these technologies, coding is gaining increasing attention in education due to its potential to improve student competencies, learning outcomes, and motivation (Calao et al., 2015). This potential stems not only from the innovative tools provided by technology but also from the pedagogical alignment of coding with mathematics and other disciplines. Gadanidis (2015) argues that coding functions as a "Trojan Horse" in mathematics education. According to Gadanidis, when young learners comprehend complex and abstract coding concepts—such as algorithms, loops, variables, and conditionals—they become more receptive to understanding similarly abstract and complex mathematical ideas. The shared logical structure between coding and mathematics creates a complementary relationship between the two domains. Consequently, coding, when integrated with mathematics instruction, enables students to establish connections between mathematical concepts and explore interrelations among them. This process not only improves students' mathematical achievement but also offers significant opportunities to close existing achievement gaps (Cheng, 2016; Gadanidis, 2015).

Numerous studies emphasizing the educational impact of coding confirm its critical role in developing mathematical skills. For example, Calao et al. (2015) found that students who received Scratch training were more successful in understanding mathematical processes. Similarly, Wang et al. (2014) demonstrated that Scratch has positive effects on problem-solving skills, learning motivation, and attitudes toward mathematics. Welch et al. (2022) found that robotic coding toys provided an effective context for developing measurement concepts during early childhood. Likewise, Solin (2017) suggested that the use of Python Turtle for visual coding and 3D modeling projects can highlight the creative and artistic aspects of mathematics. Solin and Roanes-Lozano (2020) stated that coding tools provide effective means for acquiring mathematical skills and standards such as understanding and solving problems, abstract thinking, higher-order reasoning, and modeling. These studies reveal the potential of coding and related technologies to help students acquire mathematical competencies more effectively. However, the integration of such technologies into teaching and learning processes depends not only on the technology itself but also on the role of teachers in these processes. As Teo (2011) emphasizes, the teacher is a key factor in the effective use of technology in education. Therefore, the adoption and successful implementation of technological tools in education are directly related to teachers' competencies, perceptions, and intentions.

Several factors contribute to teachers' limited use of technology. According to the literature, limited access to technology (Dawson, 2008; Staples et al., 2005), insufficient resources (Rich et al., 2019), lack of time (Rich et al., 2019; Wepner et al., 2003), teachers not feeling adequately prepared (Drent & Meelissen, 2008; Kay, 2006), and inflexible curricula (Staples et al., 2005) are among the main obstacles. Furthermore, many pre-service teachers lack the necessary knowledge and skills to use technology effectively in teaching and learning processes. Many teachers also believe that their students have greater digital competencies than they do (Rich et al., 2019; Tondeur et al., 2012; Yadav et al., 2016). This perception explains the lack of self-confidence among teachers and their struggles with pedagogical adaptation during technology integration. Particularly concerning coding, teachers' reluctance to use this specific technology in their classes is associated with additional factors. Research shows that teachers often find it difficult to relate coding to real-world applications and languages and lack confidence in identifying and correcting errors that arise during the coding process (Rich et al., 2019). These findings highlight both the pedagogical and technical challenges teachers face when integrating coding into instruction. In this context, scholars such as Brown et al. (2010), Hong et al. (2014), and Granić (2023) have proposed various theoretical perspectives to understand the acceptance and use of different technologies in teaching, learning, and assessment processes. One of these theoretical frameworks is the Technology Acceptance Model (TAM), which can serve as a basis for examining pre-service teachers' adoption of coding technologies.

Unified Theory of Acceptance and Use of Technology (UTAUT)

To investigate technology adoption in educational contexts, the Unified Theory of Acceptance and Use of Technology (UTAUT), developed by Venkatesh et al. (2003), provides a widely accepted theoretical foundation. Synthesizing elements from eight major models—including TAM, TRA, TPB, and SCT—UTAUT identifies four key constructs that influence behavioral intention and actual use:

- Performance Expectancy (PE): the degree to which an individual believes that using a technology will enhance their job performance.
- Effort Expectancy (EE): the ease associated with using the technology.
- Social Influence (SI): the extent to which individuals perceive that important others believe they should use the technology.
- Facilitating Conditions (FC): the belief that organizational and technical infrastructure exists to support usage.

UTAUT has been validated across various domains, including education, and has demonstrated strong explanatory power for behavioral intention and usage behavior (Aliaño et al., 2019; Madani et al., 2023). In teacher education, it has been used to identify the perceived usefulness and ease of educational technologies, as well as the impact of peer and institutional support on technology adoption. However, researchers have increasingly noted that UTAUT's original formulation lacks constructs related to emotional engagement and internal motivation, both of which are particularly important in educational contexts and among younger technology users (Gyamfi, 2021; Gunasinghe et al., 2019). In response, various extensions of the model have been proposed.

Extending the UTAUT Model: Self-Efficacy, Learning Opportunities, and Hedonic Motivation

To capture a more holistic view of pre-service teachers' behavioral intention toward using coding, this study integrates three additional constructs into the UTAUT model: self-efficacy, perceived learning opportunities, and hedonic motivation.

Self-Efficacy. Self-efficacy refers to individuals' beliefs in their ability to execute a specific task successfully (Bandura, 1991). In the context of educational technology, teachers who feel confident in their capacity to use tools like coding environments are more likely to adopt them. Studies have shown a strong relationship between digital self-efficacy and technology integration in teaching (Hatlevik, 2017; Kundu et al., 2021). Since coding requires a combination of technical and pedagogical skills, self-efficacy plays a critical role in shaping teachers' willingness to use it.

Perceived Learning Opportunities. This construct represents the extent to which teachers believe that using a specific technology enhances students' learning experiences, enriches instructional strategies, and enables diverse approaches to teaching (Hermita et al., 2023). Coding, when perceived as a vehicle for creativity, collaboration, and differentiation, is more likely to be accepted by teachers. The belief that coding can foster deeper student engagement and develop 21st-century skills increases its perceived instructional value.

Hedonic Motivation. Hedonic motivation refers to the intrinsic enjoyment or pleasure derived from using a technology (Venkatesh et al., 2012). In learning environments, particularly among digital-native pre-service teachers, enjoyment significantly influences the decision to adopt new tools. Several studies confirm that emotional engagement is a key driver of voluntary technology use (Lee et al., 2015; Gyamfi, 2021). Teachers who find coding fun and exciting are more inclined to use it, even if it is perceived as challenging.

Method

Research Design

The purpose of this study is to measure pre-service teachers' intentions to use coding in mathematics education; therefore, it was deemed necessary to develop a new measurement tool appropriate for this research context. For this reason, the Unified Theory of Acceptance and Use of Technology (UTAUT) was used as the theoretical basis. UTAUT stands out as one of the most comprehensive and widely accepted models for explaining technology use intention and behavior. The model encompasses the key determinants of the technology adoption process, such as performance expectancy, effort expectancy, social influence, and facilitating conditions. These dimensions are directly related to understanding pre-service teachers' perceptions of using coding tools in classroom applications. However, considering the unique structure of mathematics education, additional constructs such as perceived learning opportunities and hedonic motivation have also been included in the model. Thus, the aim is to explain teacher candidates' intention to use coding in a more comprehensive way, both within a theoretically sound framework and with context-specific dimensions.

A quantitative research design was chosen to systematically examine the factors that influence pre-service teachers' intentions to use coding in their teaching practices. This design was selected because it allows for the identification of structural relationships between latent variables and the testing of theoretical assumptions with a large sample. A structural model was developed based on the UTAUT framework and its extensions.

Participants

The working group consisted of a total of 334 prospective mathematics teachers who volunteered from seven different universities in Turkey. An appropriate sampling method was chosen for this study because participants' voluntary participation in the study was fundamental. The inclusion of participants from different universities aimed to ensure both inter-institutional diversity and differences in class levels. The differences in participant numbers are entirely due to the principle of voluntariness. The distribution of participants by gender and year of study is presented in Table 1.

Table 1. Demographic Characteristics of Participants

Category	Group	Frequency (f)	Percentage (%)
Gender	Female	254	76.0
	Male	80	24.0
Year of Study	1st Year	88	26.3
	2nd Year	47	14.1
	3rd Year	109	32.6
	4th Year	90	26.9
University Enrolled	A	12	3.6
	B	120	35.9
	C	73	21.9
	D	77	23.1
	E	20	6.0
	F	25	7.5
	G	7	2.1

Category	Group	Frequency (f)	Percentage (%)
Participation in Coding Education/Projects	Yes	102	30.5
	No	232	69.5

Data Collection Tool

The data were collected using the "Coding Usage Intention Scale," which was developed by the researchers based on the UTAUT framework and extended constructs. The scale development process began with an item pool of 46 items based on an extensive literature review. After content validation by three field experts, the item pool was refined to 38 items.

During this refinement stage, each item was evaluated for clarity, relevance to the UTAUT constructs and extended variables, and alignment with the mathematics education context. Items that overlapped conceptually or displayed low item-total correlations (based on pilot data with a subset of participants) were removed or reworded. Where necessary, minor linguistic adjustments were made to ensure that terminology such as "coding," "digital literacy," or "mathematics instruction" reflected participants' day-to-day experiences. As this instrument was developed in Turkish, all final items were reviewed by bilingual experts to confirm that the scale's wording and theoretical intent would remain consistent if adapted for use in other languages. This approach helped ensure both face and content validity while facilitating potential future cross-cultural replications. In total, the final 38 items captured the primary constructs of performance expectancy, effort expectancy, social influence, facilitating conditions, self-efficacy, perceived learning opportunities, and hedonic motivation, along with behavioral intention.

Exploratory factor analysis (EFA) and confirmatory factor analysis (CFA) were applied to two separate groups. EFA was applied at the initial stage to explore the underlying factor structure of the newly developed scale without imposing a preconceived structure. This approach is particularly appropriate for newly developed instruments, as it allows researchers to empirically examine whether the observed items group together as theoretically expected. In this study, EFA was therefore employed to identify the latent constructs that emerged from the data and to ensure that the proposed items were meaningfully clustered under relevant factors.

A seven-factor structure was identified, consistent with the theoretical model. To confirm this structure, confirmatory factor analysis (CFA) was subsequently performed. Unlike EFA, which is exploratory in nature, CFA is a theory-driven approach used to test whether the factor structure fits the hypothesized model. Given that the scale was grounded in the UTAUT framework and extended constructs, CFA was necessary to verify whether the seven-factor solution obtained through EFA adequately represented the theoretical model.

In other words, CFA provided statistical evidence for construct validity by confirming the consistency between empirical findings and the proposed conceptual framework. Factor loadings obtained from the EFA are shown in Table 2.

Table 2. Factor Loadings

Item Code	1	2	3	4	5	6	7	8
pe1		0.712						
pe2		0.861						
pe3		0.598						
pe5		0.713						
pe6		0.737						
ee2						0.731		
ee3						0.886		
ee4						0.874		
fc1							0.739	
fc2							0.692	
fc3							0.379	
si2								0.535
si4								0.502
si8								0.590
se3					0.915			
se4					0.852			
se5					0.685			
hm1							0.520	
hm2							0.592	
hm3							0.600	
hm4							0.635	
hm5							0.582	
lo1	0.597							
lo2	0.563							
lo3	0.882							
lo4	0.857							
lo5	0.879							
bh3			0.768					
bh4			0.798					
bh5			0.782					
bh6			0.718					

Note. Extraction Method: Minimum Residual; Rotation Method: Oblimin. Total variance explained = 77.5%.

As part of the reliability analysis, the overall Cronbach's α for the scale was calculated as .97, which indicates excellent internal consistency. Cronbach's α was selected because it is one of the most widely used indicators of internal consistency in scale development studies, providing information about the degree to which items measure the same underlying construct. According to Nunnally and Bernstein (1994), values above .70 are considered acceptable, values above .80 good, and values above .90 excellent. Therefore, the obtained value of .97 demonstrates that the items in this scale consistently measure the intended constructs. In addition, item–total correlations were examined to evaluate each item's contribution to the overall reliability of the scale. Item–total correlations above .50 are generally regarded as evidence that an item is strongly related to the overall construct and is functioning effectively (DeVellis & Thorpe, 2021). In this study, all items exceeded this threshold, which shows that each item contributed meaningfully to the internal consistency of the scale. Table 3 presents detailed reliability statistics for each item.

Table 3. Item Statistics

Factor	Code	Item	*Mean*	*SD*	*Item-Rest Correlation*
Performance Expectancy	pe1	Using coding as a teacher will increase the efficiency of my lessons.	3.63	1.10	0.782
	pe2	Using coding will allow me to deliver the learning outcomes in a shorter time.	3.58	1.06	0.770
	pe3	Coding in class will improve students' problem-solving skills.	3.73	1.04	0.719
	pe5	Coding helps students reach learning goals more easily.	3.70	1.05	0.799
	pe6	I believe I can convey topics better through coding.	3.54	1.07	0.785
Effort Expectancy	ee2	Coding tool content is understandable.	3.20	1.03	0.649
	ee3	The user guides of coding tools are sufficiently explanatory.	3.22	1.01	0.696
	ee4	The language used in coding tools is clear.	3.10	1.04	0.642
Facilitating Conditions	fc1	If the school has adequate resources, using coding will be easy.	3.69	1.09	0.772
	fc2	It is easier to use coding if students are equipped.	3.74	1.08	0.781
	fc3	Adequate internet access is necessary for coding use.	3.97	1.12	0.675
Social Influence	si2	I would be pleased if other teachers appreciated me for using coding.	3.80	1.15	0.519

Factor	Code	Item	*Mean*	*SD*	*Item-Rest Correlation*
	si4	I would be happy if my students enjoy math because of coding.	3.95	1.22	0.599
	si8	Coding use in math education is increasingly accepted.	3.59	1.08	0.789
Self-Efficacy	se3	I am confident in conveying learning outcomes via coding.	3.09	1.19	0.697
	se4	I think I will feel comfortable using coding in class.	3.22	1.12	0.756
	se5	I can help others with coding.	2.93	1.14	0.595
Hedonic Motivation	hm1	I enjoy using technology.	3.54	1.11	0.767
	hm2	I find coding fun.	3.49	1.13	0.746
	hm3	I will enjoy teaching more through coding.	3.54	1.13	0.756
	hm4	I find using coding in class exciting.	3.60	1.13	0.762
	hm5	Using coding will be an enjoyable experience.	3.59	1.13	0.774
Perceived Learning Opportunities	lo1	Coding tools help students develop higher-order thinking.	3.77	1.10	0.749
	lo2	Coding helps improve teamwork skills.	3.73	1.08	0.763
	lo3	Coding enhances digital literacy.	3.84	1.09	0.728
	lo4	Coding allows students to discover their interests.	3.81	1.10	0.734
	lo5	Coding offers various learning opportunities.	3.87	1.10	0.702
Behavioral Intention	bh3	I intend to develop coding-related projects as a teacher.	3.27	1.14	0.772
	bh4	I plan to continually update my coding knowledge.	3.40	1.14	0.729
	bh5	I feel determined to use coding in my future classes.	3.33	1.09	0.718
	bh6	I intend to join training programs on coding in education.	3.51	1.16	0.719

To assess construct reliability and convergent validity, Cronbach's α values and Average Variance Extracted (AVE) were calculated. Cronbach's α was used because it indicates the internal consistency of items within each construct, showing whether the items reliably measure the same underlying dimension. Values above .70 are considered acceptable, above .80 good, and above .90 excellent (Nunnally & Bernstein, 1994). Thus, high α values across all sub-dimensions demonstrate that each construct is measured with strong reliability.

In addition, AVE was calculated to evaluate convergent validity, which reflects the degree to which items of a given construct converge to measure the same theoretical concept. An AVE value above .50 suggests that the construct explains more than half of the variance of its indicators, which is regarded as an adequate level of convergent validity (Sarstedt et al., 2022; Hair et al., 2010). This criterion is widely accepted in structural equation modeling research because it confirms that the indicators have sufficient shared variance to represent their respective latent construct.

Table 4. Validity and Reliability Indices

Variable	*Cronbach's α*	*AVE*
Performance Expectancy	0.945	0.775
Effort Expectancy	0.921	0.798
Facilitating Conditions	0.903	0.768
Social Influence	0.888	0.746
Self-Efficacy	0.909	0.769
Hedonic Motivation	0.969	0.861
Perceived Learning Opportunities	0.969	0.864
Behavioral Intention	0.942	0.804

As shown in Table 4, all sub-dimensions of the scale exceeded the recommended thresholds for both Cronbach's α (.70) and AVE (.50), indicating that the constructs are not only internally consistent but also conceptually coherent. These results provide strong statistical support for the reliability and convergent validity of the measurement model.

Data Analysis

The data were analyzed using IBM SPSS 25 and AMOS 24 software. SPSS was used for preliminary analyses, including descriptive statistics, item analysis, and exploratory factor analysis, because it provides robust tools for handling large datasets and generating the initial evidence for reliability. AMOS was preferred for confirmatory factor analysis and structural equation modeling (SEM), as it enables the testing of complex models with multiple latent variables and is widely used in behavioral and educational research.

In this study, SEM was applied to evaluate the research model and test the proposed hypotheses. SEM was chosen because it allows for the simultaneous assessment of both the measurement model (the relationships between observed indicators and their latent constructs) and the structural model (the hypothesized causal relationships among latent constructs). This dual capacity makes SEM superior to traditional regression-based approaches when the goal is to test complex theoretical models grounded in multiple constructs (Hair et al., 2010). According to Hair et al. (2010), the SEM process consists of two key stages: (1) assessment of the measurement model and (2) assessment of the structural model. The measurement model was examined to ensure the validity and reliability of the constructs, which is crucial for confirming that the indicators accurately represent the intended latent variables. Once construct validity and reliability were established, the structural model was assessed to determine the strength and direction of the hypothesized relationships. This sequential approach was necessary to guarantee that any conclusions drawn about the relationships between constructs were based on sound and reliable measurement.

In the first stage, the measurement model was examined to determine the reliability and validity of the constructs. This involved reviewing factor loadings, item-total correlations, Cronbach's alpha coefficients, and average variance extracted (AVE) values. Following the criteria suggested by Hair et al. (2010), factor loadings of at least .50, preferably above .70, Cronbach's alpha coefficients above .70, and AVE values above .50 were considered acceptable indicators of construct quality. As shown in Tables 2, 3, and 4, all constructs in the study met these criteria, demonstrating sufficient construct reliability and convergent validity.

The second stage involved evaluating the structural model to determine the strength and direction of the relationships between the latent variables. Before conducting this analysis, statistical assumptions including normality, linearity, multicollinearity, and homoscedasticity were tested and found to be satisfied. The model's fit to the data was assessed using several indices: chi-square to degrees of freedom ratio (χ^2/df), root mean square error of approximation (RMSEA), comparative fit index (CFI), Tucker–Lewis index (TLI), and standardized root mean square residual (SRMR). The significance and effect sizes of the hypothesized paths were evaluated using standardized regression weights (β), standard errors, critical ratios (CR), and p-values. The results of these analyses are presented in the following section.

Findings

Measurement Model Evaluation

To assess the model's fit to the data, several goodness-of-fit indices were examined. According to Byrne (2012), Hoyle (2012), and Kline (2010), acceptable model fit is indicated when the relative chi-square (χ^2/df) is less than 3, the Comparative Fit Index (CFI) is greater than 0.90, the Root Mean Square Error of Approximation (RMSEA) is less than 0.08, the Tucker–Lewis Index (TLI) is greater than 0.90, and the Standardized Root Mean Square Residual (SRMR) is less than 0.10. As shown in Table 5, the model met all these criteria, suggesting good overall fit.

Table 5. Model Fit Indices

CFI	*TLI*	χ^2	*df*	*p*	*SRMR*	*RMSEA*	*RMSEA p*
0.953	0.946	1022	406	< .001	0.034	0.067	< .001

Structural Model Evaluation

This study hypothesized that performance expectancy, effort expectancy, social influence, facilitating conditions, self-efficacy, perceived learning opportunities, and hedonic motivation would be significant predictors of pre-service mathematics teachers' behavioral intention to use coding. A path analysis was conducted to test the hypotheses based on the proposed structural model. Figure 2 displays the path diagram and model results retrieved from Jamovi.

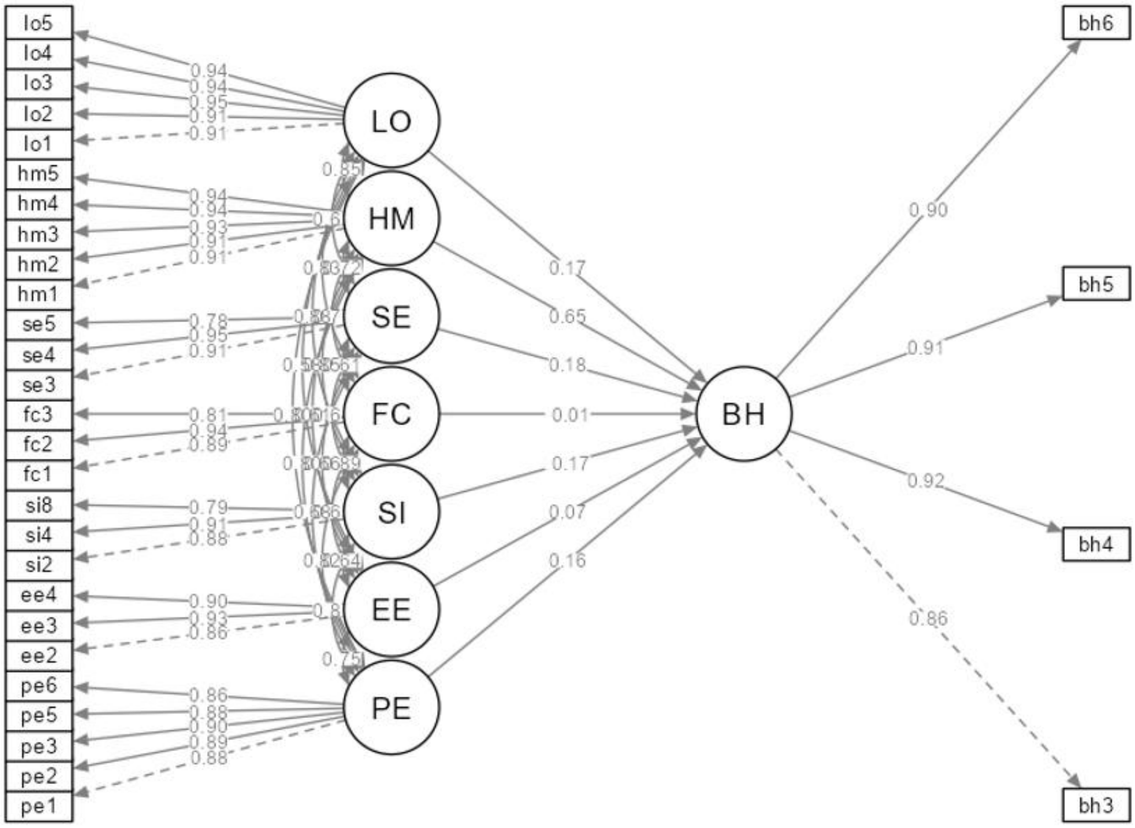

Figure 1. Path Diagram and Model Results

The results revealed that performance expectancy (PE) significantly predicted behavioral intention (BH), supporting Hypothesis 1. However, no significant relationship was found between effort expectancy (EE) and behavioral intention, leading to the rejection of Hypothesis 2. Social influence (SI) had a statistically significant effect on behavioral intention, thus supporting Hypothesis 3. In contrast, the relationship between facilitating conditions (FC) and behavioral intention was not significant, and therefore Hypothesis 4 was not supported.

A significant positive effect was observed between self-efficacy (SE) and behavioral intention, confirming Hypothesis 5. Similarly, perceived learning opportunities (LO) and hedonic motivation (HM) were found to have significant positive effects on behavioral intention, supporting Hypotheses 6 and 7. Table 6 presents the path coefficients, standard errors, critical ratios, significance levels, and the outcome of each hypothesis test.

According to the analysis results, the strongest predictor of behavioral intention was hedonic motivation (β =

0.6462, $p < .001$). While other variables such as performance expectancy ($\beta = 0.1636$, $p < .001$), social influence ($\beta = 0.1674$, $p < .001$), self-efficacy ($\beta = 0.1828$, $p < .001$), and perceived learning opportunities ($\beta = 0.1701$, $p < .001$) had smaller standardized effects, they still contributed significantly to behavioral intention. In contrast, the effects of facilitating conditions ($\beta = 0.0134$, $p = 0.198$) and effort expectancy ($\beta = 0.0725$, $p = 0.181$) were not statistically significant, even though their direction was positive.

Table 6. Results of Structural Equation Modelling Analysis

Hypothesis	Path	Estimate	*SE*	*β*	*z*	*p*	Result
H1	PE → BH	0.1860	0.0567	0.1636	3.412	< .001	Supported
H2	EE → BH	0.0807	0.0604	0.0725	1.336	0.181	Not Supported
H3	SI → BH	0.1653	0.0294	0.1674	1.991	< .001	Supported
H4	FC → BH	0.0135	0.0872	0.0134	1.286	0.198	Not Supported
H5	SE → BH	0.1741	0.0464	0.1828	2.336	< .001	Supported
H6	LO → BH	0.1952	0.0487	0.1701	2.098	< .001	Supported
H7	HM → BH	0.6238	0.0582	0.6462	7.978	< .001	Supported

Discussion

This study employed an extended Unified Theory of Acceptance and Use of Technology (UTAUT) model to examine the factors influencing pre-service mathematics teachers' intentions to integrate coding into their classroom practices. In addition to the original UTAUT constructs, the model included self-efficacy, perceived learning opportunities, and hedonic motivation—dimensions that emphasize both affective and pedagogical aspects of technology acceptance. Structural equation modeling results indicated that this augmented framework offers substantial explanatory power for understanding behavioral intentions toward coding usage.

A particularly salient finding is that hedonic motivation emerged as the strongest predictor of behavioral intention. This result corroborates previous research (Gyamfi, 2021; Venkatesh et al., 2012), which underscores the importance of emotional engagement, enjoyment, and intrinsic interest in the adoption of new technologies. Pre-service teachers who perceive coding as exciting and pleasurable are more inclined to incorporate it into their future teaching. This underscores the need for teacher education programs to offer playful, creative, and hands-on learning opportunities that stimulate curiosity and foster sustained motivation toward digital tools.

Perceived learning opportunities also significantly affected behavioral intention. When teacher candidates recognize coding's potential to promote deeper learning, problem-solving, and creativity, they are more likely to adopt it. This outcome supports the view that coding should be presented not solely as a technical skill but as a pedagogical instrument capable of enriching the teaching and learning process (Hermita et al., 2023; Rich et al., 2019).

The present study further underscores the role of self-efficacy in technology adoption. Congruent with Bandura's (1991) theoretical framework, teacher candidates who feel competent and confident about applying coding in instructional contexts demonstrate stronger intentions to use it. This suggests that enhanced peer collaboration, mentorship, and hands-on training within teacher preparation programs could bolster self-efficacy beliefs, thereby promoting greater technology integration in classroom settings.

The findings also validate performance expectancy and social influence as relevant predictors, aligning with well-documented UTAUT research (Teo, 2011; Aliaño et al., 2019). Teachers who anticipate improved instructional effectiveness through coding, and who receive positive reinforcement from peers or institutional actors, are more inclined toward technology adoption.

By contrast, effort expectancy and facilitating conditions showed no statistically significant effect on behavioral intention in this sample. Considering that pre-service teachers—often conceptualized as "digital natives"—may already feel at ease with learning new technologies, the perceived ease of use might hold diminished salience. Similarly, because they have yet to enter the professional workforce, their perceptions of institutional infrastructure and support remain relatively abstract, thereby attenuating the impact of facilitating conditions.

It is worth noting that although effort expectancy and facilitating conditions were not statistically significant in this study, these findings should be interpreted within the specific context of pre-service teacher candidates. While digital-native preservice teachers may perceive less need for institutional support or easy-to-use features during their training, these factors could gain prominence once they assume full teaching responsibilities. For instance, when they become in-service teachers, real-world constraints such as limited infrastructure, classroom management demands, and administrative support may heighten awareness of how technical ease-of-use and institutional facilitation influence coding integration. Future research could therefore explore whether effort expectancy and facilitating conditions become more substantial predictors of coding adoption among teachers who have accumulated professional experience or face more complex resource environments.

Overall, the findings imply that affective and pedagogical determinants—particularly hedonic motivation, perceived learning opportunities, and self-efficacy—can overshadow traditional UTAUT variables in shaping pre-service mathematics teachers' intentions to utilize coding. These results emphasize that teacher educators must look beyond purely utilitarian or functional considerations, and instead promote motivational, enjoyable, and instructionally meaningful learning experiences to foster robust technology integration.

Conclusion

This research aimed to identify the determinants of pre-service mathematics teachers' intention to integrate coding into their instructional practices, utilizing an extended UTAUT framework. Besides the original constructs (performance expectancy, effort expectancy, social influence, and facilitating conditions), the model incorporated self-efficacy, perceived learning opportunities, and hedonic motivation to capture more nuanced motivational and pedagogical factors.

The structural equation modeling results revealed that hedonic motivation stands out as the most influential predictor of behavioral intention, indicating that enjoyment and intrinsic engagement play pivotal roles in shaping acceptance of new technologies among future educators. Moreover, perceived learning opportunities and self-efficacy emerged as critical factors, highlighting how beliefs in coding's pedagogical value and one's own competence can substantially increase one's willingness to use such tools. The study also confirms a moderate but significant role for performance expectancy and social influence, demonstrating that teachers' perceptions of usefulness and the encouragement received from peers or mentors are relevant to coding adoption. However, effort expectancy and facilitating conditions did not yield significant effects, suggesting that, for digital-native pre-service teachers, institutional support and ease of use may currently be less decisive in determining usage intentions.

Taken together, these findings underscore a shift in how future educators perceive coding—no longer simply as a technical add-on but as an enjoyable and pedagogically beneficial practice that enriches mathematics instruction. Teacher education programs should therefore prioritize hands-on, collaborative, and engaging learning experiences that enhance both competencies and positive attitudes toward coding, ultimately aiding the integration of computational thinking skills into the mathematics curriculum.

Recommendations

The findings of this study provide important implications for teacher education, curriculum design, and educational policy, particularly in relation to integrating coding into mathematics instruction. First, the dominant role of hedonic motivation suggests that teacher training programs should not only focus on the technical or pedagogical aspects of coding but also seek to enhance enjoyment and personal engagement. Coding activities should be designed to be stimulating, creative, and playful, allowing teacher candidates to experience firsthand the joy and satisfaction that can be derived from developing digital projects. Providing authentic and student-centered coding tasks can help pre-service teachers see coding not as an abstract technical skill, but as a meaningful instructional tool that enhances both teaching and learning.

Second, the strong effects of perceived learning opportunities and self-efficacy underscore the importance of helping future teachers understand the pedagogical value of coding and feel competent in its use. Teacher education programs should offer structured opportunities to explore how coding supports student learning, collaboration, and problem-solving in mathematics. Embedding coding into methods courses, model lessons, and teaching practicums can foster both pedagogical awareness and instructional confidence. Opportunities for collaborative work and mentoring can further enhance pre-service teachers' self-efficacy and willingness to innovate.

Third, while performance expectancy and social influence were found to have moderate effects, these constructs still play a supporting role. Educators and teacher educators should highlight real-world applications and success stories of coding in mathematics classrooms to reinforce its instructional relevance. Additionally, cultivating a positive culture of innovation among teacher educators, school mentors, and peers may encourage teacher candidates to adopt new practices more readily.

On the other hand, the non-significant findings for effort expectancy and facilitating conditions should not be dismissed. These factors may become more salient once teachers enter professional contexts where institutional support and ease of use can vary greatly. Therefore, in-service training and school-level support systems should still address infrastructure, time management, and usability issues to ensure sustained implementation of coding initiatives.

In light of these findings, teacher education programs are encouraged to adopt a multidimensional approach that couples technical training with emotional engagement, pedagogical depth, and accessible real-world examples. One practical strategy is to design short teaching simulations or microteaching sessions where pre-service teachers integrate coding tasks into lessons on geometry, algebra, or data analysis. Additionally, collaborative lesson-planning workshops could invite candidates to co-develop interdisciplinary projects that merge coding with mathematics problem-solving, thus allowing them to experience firsthand how computational thinking amplifies learning outcomes. Another tangible recommendation is to curate model lesson plans or code repositories—organized by mathematics topics or grade levels—that can guide instructors who are new to technology-supported pedagogy. Throughout these efforts, teacher educators and mentors should offer formative feedback on both the pedagogical and technical aspects of coding-based instruction, ensuring that future educators graduate with the confidence, skill set, and enthusiasm to implement coding effectively. Complementing these program-level initiatives, policy makers could reinforce the integration of coding into national curricula and professional development frameworks, acknowledging that enjoyment, competence, and supportive school environments are instrumental in sustaining technology adoption in mathematics classrooms.

Limitations and Future Research Directions

Despite offering valuable insights, this study's conclusions must be interpreted in light of several limitations, which also point to directions for further inquiry. One limitation is that all participants were pre-service mathematics teachers from seven universities in Turkey, restricting the generalizability of the findings to other contexts, disciplines, or in-service educators. While this setting offers useful insights into a particular educational and cultural environment, it also means that broader cross-cultural differences in teacher education and technology acceptance remain unexamined. In countries with differing policy frameworks, curriculum standards, or digital readiness levels, the relative influence of UTAUT constructs and additional factors (e.g., self-efficacy, hedonic motivation) may vary considerably. Future research could include more diverse samples—such as experienced teachers or participants from varied cultural settings—to determine whether the patterns identified here hold consistent beyond the current population. Such cross-cultural explorations would likewise shed light on how shared or differing values, resource availability, and pedagogical traditions affect the integration of coding in mathematics education.

Another limitation concerns the cross-sectional nature of the research, given that the data were gathered at a single point in time. This design constrains our understanding of how teacher candidates' beliefs and behaviors evolve as they progress through their training or transition into in-service teaching. Future inquiries could employ longitudinal or follow-up approaches, examining shifts in coding attitudes and adoption patterns over multiple semesters or early years in the teaching profession. Additionally, a mixed-methods design that triangulates survey data with interviews, classroom observations, or lesson artifacts would yield a more nuanced portrayal of how cognitive and emotional factors jointly influence real-world instructional practices. Such studies could illuminate the interplay between pre-service experiences and on-the-job realities, ultimately providing deeper insights into how best to sustain coding adoption across different stages of a teaching career.

A further constraint lies in the exclusive reliance on quantitative data from self-report instruments. Surveys alone may not capture the depth and complexity of individuals' experiences and contextual nuances related to coding adoption. Mixed-methods approaches that incorporate interviews, focus groups, or classroom observations would yield more comprehensive accounts of the affective and cognitive dimensions shaping technology acceptance.

There is also the matter of coding environments and pedagogical strategies, which this study did not examine in detail. Although coding was broadly defined, differences between platforms such as Scratch, Python, or robotics kits, as well as distinct instructional designs, may each affect acceptance and usage behaviors in unique ways. Future research that compares or isolates specific approaches can thus refine understanding of how coding fits into the mathematics curriculum.

Facilitating conditions did not significantly predict behavioral intentions among pre-service teachers, possibly because they have not yet encountered the institutional realities of teaching, including limited resources, varying levels of administrative support, and time constraints. Studies focusing on in-service teachers at different career stages could clarify how real-world conditions interact with other factors in coding adoption. Although the present study successfully integrated factors like self-efficacy and hedonic motivation into the UTAUT framework, there remain other constructs that could shed further light on coding adoption in mathematics education. For instance, coding anxiety may inhibit teacher candidates who otherwise demonstrate high levels of technical proficiency or interest, while digital literacy could interact with perceived learning opportunities to amplify or diminish their effect on behavioral intention. Likewise, attitudes toward mathematics itself—particularly for pre-service educators who struggled with mathematical content—may shape how they view the integration of coding in the subject. Finally, future research could investigate interaction effects among existing variables. One intriguing question is whether elevated self-efficacy, for example, moderates the impact of performance expectancy, or whether high hedonic motivation compensates for low facilitating conditions. Incorporating these additional dimensions and examining possible moderating relationships would enrich the theoretical model and offer a more complete understanding of how various factors intersect to influence coding adoption.

The findings of this study reveal that pre-service teachers' intentions to use coding in mathematics education are influenced by both cognitive and affective factors. According to the findings, hedonic motivation is the strongest predictor. This indicates that coding should be presented in teacher education programs not only as a technical skill but also in a way that makes the learning process enjoyable and motivating. In this regard, it is recommended that teacher educators and program developers integrate coding into course content using more gamified, interactive, and student-centered approaches. In addition, performance expectations, social influence, self-efficacy, and perceived learning opportunities are also variables that significantly predict teacher candidates' intentions. Therefore, it would be beneficial for professional development programs to focus on strengthening teacher candidates' self-efficacy, increasing peer support, and emphasizing the pedagogical benefits of coding. Furthermore, providing more learning opportunities related to coding at universities and allowing teacher candidates to experience these opportunities will positively influence their intentions. In terms of research, it is recommended that studies conducted with different samples test the generalizability of the findings and that longitudinal studies examine changes in teacher candidates' coding usage intentions over time. Finally, additional variables beyond those included in the extended UTAUT model, such as coding anxiety or digital literacy levels, remain unexplored. Incorporating these psychological and contextual factors in future investigations would further enrich the understanding of how various constructs interact to influence coding integration in mathematics education.

References

Aliaño, Á. M., Hueros, A. M. D., Franco, M. D. G., & Aguaded, I. (2019). Mobile learning in university contexts based on the unified theory of acceptance and use of technology (UTAUT). *Journal of New Approaches in Educational Research, 8(1)*, 7–17. https://doi.org/10.7821/naer.2019.1.317

Bandura, A. (1991). Social cognitive theory of self-regulation. *Organizational Behavior and Human Decision Processes, 50*, 248–287.

Bers, M. U., González-González, C., & Armas-Torres, M. B. (2019). Coding as a playground: Promoting positive learning experiences in childhood classrooms. *Computers & Education, 138*, 130-145. https://doi.org/10.1016/j.compedu.2019.04.013

Brown, S. A., Dennis, A. R., & Venkatesh, V. (2010). Predicting collaboration technology use: Integrating technology adoption and collaboration research. *Journal of Management Information Systems, 27*(2), 9–54.

Byrne, B. M. (2012). *Structural equation modeling with Mplus: Basic concepts, applications, and programming*. Routledge.

Calao, L. A., Moreno-Le´on, J., Correa, H. E., & Robles, G. (2015). *Developing Mathematical Thinking with Scratch. Design for Teaching and Learning in a Networked World* (pp. 17-27). Springer International Publishing

Cheng, H. (April 16, 2016). *Programming Can Help Narrow Achievement Gap*.

Chen, G., Shen, J., Barth-Cohen, L., Jiang, S., Huang, X., & Eltoukhy, M. (2017). Assessing elementary students' computational thinking in everyday reasoning and robotics programming. *Computers & education*, *109*, 162-175. https://doi.org/10.1016/j.compedu.2017.03.001

Dawson, V. (2008). Use of information communication technology by early career science teachers in Western Australia. *International Journal of Science Education*, *30*(2), 203-219.

DeVellis, R. F., & Thorpe, C. T. (2021). *Scale development: Theory and applications*. Sage publications.

Drent, M. and Meelissen, M. (2008) Which factors obstruct or stimulate teacher educators to use ICT innovatively? *Computers & Education, 51*, 187-199. https://doi.org/10.1016/j.compedu.2007.05.001

Fessakis, G., Gouli, E. ve Mavroudi, E. (2013). Problem solving by 5–6 years old kindergarten children in a computer programming environment: A case study. *Computers & Education, 63*, 87-97. https://doi.org/10.1016/j.compedu.2012.11.016

Gadanidis, G. (2015). Coding as a Trojan Horse for mathematics education reform. *Journal of Computers in Mathematics and Science Teaching, 34*(2), 155-173.

Gim, N. G. (2021). Development of life skills program for primary school students: Focus on entry programming. *Computers*, *10*(5), 1–17. https://doi.org/10.3390/computers10050056

Granić, A. (2023). Technology Acceptance and Adoption in Education. In: Zawacki-Richter, O., Jung, I. (eds) *Handbook of Open, Distance and Digital Education* (p.183-197). Springer, Singapore. https://doi.org/10.1007/978-981-19-2080-6_11

Gunasinghe, A., Abd-Hamid, J., Khatibi, A., & Azam, S. F. (2019). Academicians' acceptance of online learning environments: A review of information system theories and models. *Global Journal of Computer Science and Technology, 39*, 31–39. https://doi.org/10.34257/GJCSTHVOL19IS1PG31.

Gyamfi, S. A. (2021). Influencing factors of students' smartphones use for academic purposes: A developing country's perspective. *International Journal of Emerging Technologies in Learning (IJET)*, *16*(23), 233-246. https://doi.org/10.3991/ijet.v16i23.26675

Hair, J. F., Jr., Anderson, R. E., Tatham, R. L. and Black W. C. (2010),"Multivariate Data Analysis", 7th Edition. Englewood Cliffs, NJ: Prentice Hall.

Hatlevik, O. E. (2017). Examining the relationship between teachers' self-efficacy, their digital competence, strategies to evaluate information, and use of ICT at school. *Scandinavian Journal of Educational Research*, *61*(5), 555-567. https://doi.org/10.1080/00313831.2016.1172501

Hermita, N., Wijaya, T.T., Yusron, E., Abidin, Y., Alim, J.A. and Putra, Z.H. (2023) Extending unified theory of acceptance and use of technology to understand the acceptance of digital textbook for elementary School in Indonesia. *Frontiers in Education.8.* https://doi.org/10.3389/feduc.2023.958800

Hong, W., Chan, F. K. Y., Thong, J. Y. L., Chasalow, L., & Dhillon, G. (2014). A framework and guidelines for context-specific theorizing in information systems research. *Information Systems Research, 25*(1), 111–136.

Hoyle, R. H. (Ed.). (2012). *Handbook of structural equation modeling*. Guilford Publications.

Kalelioglu, F., Gulbahar, Y., & Kukul, V. (2016). A framework for computational thinking based on a systematic research review. *Baltic Journal of Modern Computing, 4*(3), 583-596.

Kay, R. H. (2006). Evaluating strategies used to incorporate technology into preservice education: A review of the literature. *Journal of research on technology in education*, *38*(4), 383-408.

Kline, R. B. (2010). *Principles and practice of structural equation modeling (3rd ed.)*. Guilford publications.

Kundu, A., Bej, T., & Dey, K. N. (2021). Investigating effects of self-efficacy and infrastructure on teachers' ICT use, an extension of UTAUT. *International Journal of Web-Based Learning and Teaching Technologies (IJWLTT), 16*(6), 1-21. http://doi.org/10.4018/IJWLTT.20211101.oa10

Lee, Y., Lee, J., & Hwang, Y. (2015). Relating motivation to information and communication technology acceptance: Self-determination theory perspective. *Computers in Human Behavior*, *51*, 418-428. https://doi.org/10.1016/j.chb.2015.05.021

Lee, J. (2020). Coding in early childhood. *Contemporary Issues in Early Childhood*, *21*(3), 266–269. https://doi.org/10.1177/1463949119846541

Liu, I.-F., Chen, M. C., Sun, Y. S., Wible, D., & Kuo, C.-H. (2010). Extending the TAM model to explore the factors that affect intention to use an online learning community. *Computers & Education, 54*(2), 600–610. https://doi.org/10.1016/j.compedu.2009.09.009

Madani, H., Adhikari, A. and Hodgdon, C. (2023). Understanding faculty acceptance of online teaching during the COVID-19 pandemic: A Saudi Arabian case study. *Journal of International Education in Business, 16*(2), 152-166. https://doi.org/10.1108/JIEB-12-2021-0109

Marsh, J., Plowman, L., Yamada-Rice, D., Bishop, J., & Scott, F. (2016). Digital play: A new classification. *Early Years, 36*(3), 242-253. https://doi.org/10.1080/09575146.2016.1167675

Metin, S., Basaran, M., & Kalyenci, D. (2023). Examining coding skills of five-year-old children. *Pedagogical Research, 8*(2), em0154. https://doi.org/10.29333/pr/12802

Nunnally J. C., Bernstein I. H. (1994). *Psychometric theory* (3rd ed.). New York, NY: McGraw-Hill.

Rich, P. J., Browning, S. F., Perkins, M., Shoop, T., Yoshikawa, E., & Belikov, O. M. (2019). Coding in K-8: International trends in teaching elementary/primary computing. *TechTrends*, *63*, 311-329. https://doi.org/10.1007/s11528-018-0295-4

Romero, M., Lepage, A., & Lille, B. (2017). Computational thinking development through creative programming in higher education. *International Journal of Educational Technology in Higher Education*, *14*, 1-15. https://doi.org/10.1186/s41239-017-0080-z

Sarstedt, M., Ringle, C. M., & Hair, J. F. (2021). Partial least squares structural equation modeling. In *Handbook of market research* (pp. 587-632). Cham: Springer International Publishing.

Solin, P. (2017). Bringing More STEAM to Mathematics Education. *International Journal for Technology in Mathematics Education*, *24*(4), 191-198.

Solin, P., & Roanes-Lozano, E. (2020). Using computer programming as an effective complement to mathematics education: experimenting with the standards for mathematics practice in a multidisciplinary environment for teaching and learning with technology in the 21st century. *International Journal for Technology in Mathematics Education*, *27*(3), 147-156.

Staples, A., Pugach, M. C., & Himes, D. J. (2005). Rethinking the technology integration challenge: Cases from three urban elementary schools. *Journal of Research on Technology in Education, 37*(3), 285–311. https://doi.org/10.1080/15391523.2005.10782438

Sulistyaningtyas, R. E., Yuliantoro, P., Astiyani, D., & Nugraheni, C. (2020). A literature review of coding for early childhood. In *Proceedings of the 2nd Borobudur International Symposium on Humanities and Social Sciences, BIS-HSS*. https://doi.org/10.4108/eai.18- 11-2020.2311709

Teo, T. (2011). Factors influencing teachers' intention to use technology: Model development and test. *Computers & Education, 57*(4), 2432-2440. https://doi.org/10.1016/j.compedu.2011.06.008

Tondeur, J., Van Braak, J., Sang, G., Voogt, J., Fisser, P., & Ottenbreit-Leftwich, A. (2012). Preparing pre-service teachers to integrate technology in education: A synthesis of qualitative evidence. *Computers&Education*, *59*(1),134-144. https://doi.org/10.1016/j.compedu.2011.10.009

Wang, H.-Y., Huang, I., & Hwang, G.-J. (2014). Effects of an integrated Scratch and project-based learning approach on the learning achievements of gifted students in computer courses. 2014 IIAI 3rd International Conference on Advanced Applied Informatics (pp. 382–387). IEEE. https://doi.org/10.1109/IIAI-AAI.2014.85

Welch, L. E., Shumway, J. F., Clarke-Midura, J., & Lee, V. R. (2022). Exploring measurement through coding: Children's conceptions of a dynamic linear unit with robot coding toys. Education Sciences, 12(2), 143.

Wepner, S. B., Ziomek, N., & Tao, L. (2003). Three teacher educators' perspectives about the shifting responsibilities of infusing technology into the curriculum. Action in Teacher Education, 24(4), 53-63. https://doi.org/10.1080/01626620.2003.10463279

Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. *MIS quarterly, 27*(3), 425-478. http://dx.doi.org/10.2307/30036540

Venkatesh, V., Thong, J. Y. L., Xu, X., (2012). Consumer acceptance and use of information technology: Extending the unified theory of acceptance and use of technology. *MIS Quarterly, 36*(1), 157-178. https://doi.org/10.2307/41410412

Yadav, A., Gretter, S., Hambrusch, S., & Sands, P. (2016). Expanding computer science education in schools: understanding teacher experiences and challenges. *Computer science education, 26*(4), 235-254. https://doi.org/10.1080/08993408.2016.1257418