

Modeling the factors influencing the adoption of programming among 6th-grade students: An extended TAM-based SEM approach

Mai Thi Hoang¹ 
Hung Tran Van² 
Hoa Thi Nguyen³ 
Trung Tran⁴ 
Vu Nguyen Quoc⁵ 



¹Faculty of Mathematics and Information Technology, Hanoi Metropolitan University in Hanoi, Vietnam.
¹Email: tvhung@ued.udn.vn
^{2,3}The University of Danang, University of Science and Education, Danang, Vietnam.
³Email: htmai@hnm.edu.vn
³Email: thhoagaqs@gmail.com
⁴VNU University of Education, Vietnam National University, Hanoi, Vietnam.
⁴Email: trungt1978@gmail.com
⁵Dong Thap University, Vietnam.
⁵Email: nqvuu@dtu.edu.vn

Abstract

In the era of digital transformation and the rapid advancement of STEM education, integrating programming into secondary curricula has become a priority in Vietnam. However, there remains a critical gap in understanding the readiness and acceptance levels of 6th-grade students toward programming. This study aims to bridge this gap by examining the factors influencing the acceptance of programming learning among 6th-grade students in Da Nang City, utilizing an integrated theoretical framework based on the Technology Acceptance Model (TAM) and the Theory of Reasoned Action (TRA). A quantitative research design was employed, involving data collection from 599 6th-grade students via structured, five-point Likert-scale questionnaires. To ensure rigorous validation, the study utilized exploratory factor analysis (EFA), confirmatory factor analysis (CFA), and structural equation modeling (SEM). The results reveal that personal factors, the learning environment, and time management positively influence students’ intention to learn programming, with time management and the learning environment emerging as the most significant drivers. Conversely, family-related factors did not demonstrate a statistically significant impact. Notably, the study confirms that students’ intention to learn programming acts as a critical mediating variable that positively impacts their overall acceptance. These findings provide empirical evidence to guide the formulation of educational policies and instructional strategies for programming education. This research contributes to fostering computational thinking skills in the digital age, offering actionable recommendations for educators and policymakers.

Keywords: Da Nang City, Grade 6 middle school, Influencing factors, Learning programming, SEM, TAM.

Citation | Hoang, M. T., Van, H. T., Nguyen, H. T., Tran, T., & Quoc, V. N. (2026). Modeling the factors influencing the adoption of programming among 6th-grade students: An extended TAM-based SEM approach. *Journal of Education and E-Learning Research*, 13(4), 1–12. 10.20448/jeelr.v13i4.9400
History:
Received: 27 February 2026
Revised: 5 May 2026
Accepted: 29 May 2026
Published: 23 September 2026
Licensed: This work is licensed under a [Creative Commons Attribution 4.0 License](#) 
Publisher: Asian Online Journal Publishing Group

Funding: This research is funded by the Science and Technology Development Fund under grant number B2024-DN03-11.
Institutional Review Board Statement: This study was approved and conducted as part of a scientific research project at The University of Danang – University of Science and Education (UD-UED), in accordance with the university’s institutional research management regulations under [Decision No. 2298/QĐ-ĐHSP], dated [November 01, 2024]. Although UD-UED does not operate a formal Institutional Review Board (IRB), the study was approved as a registered research task in accordance with the university’s internal policies. All participants were informed of the voluntary nature of their participation and their right to withdraw from the study at any time without penalty. Informed consent was obtained from all participants prior to survey participation, and all collected data were anonymized to protect participants’ confidentiality.
Transparency: The authors confirm that the manuscript is an honest, accurate, and transparent account of the study; that no vital features of the study have been omitted; and that any discrepancies from the study as planned have been explained. This study followed all ethical practices during writing.
Competing Interests: The authors declare that they have no competing interests.
Authors’ Contributions: All authors contributed equally to the conception and design of the study. All authors have read and agreed to the published version of the manuscript.
Disclosure of AI Use: The authors used AI tools to assist with language refinement, including grammar and clarity. All outputs were carefully reviewed and revised by the authors to ensure accuracy and originality. The authors take full responsibility for the final content of the manuscript.

Contents

1. Introduction.....	2
2. Theoretical Framework	2
3. Theoretical Background and Hypothesis Development.....	4
4. Research Methodology.....	5
5. Research Results.....	6
6. Discussion	10
7. Conclusion.....	11
References	11

Contribution of this paper to the literature
This study is original in applying an integrated TAM and TRA model to analyze 6th-grade students' programming adoption in Da Nang, Vietnam. Unlike prior studies focusing on university or adult learners, this research fills a critical gap by providing empirical evidence within a specific K-12 educational context.

1. Introduction

Previous studies on technology adoption in education, particularly those based on the TAM and TRA models, have provided crucial evidence on the role of cognitive factors, such as perceived usefulness and perceived ease of use, in shaping behavioral intentions (Songkram, Chootongchai, Osuwan, Chuppunnarat, & Songkram, 2023). Many studies have expanded these models by incorporating contextual variables, such as the learning environment, family support, and personal characteristics, to explain learner behavior better (Choi & Lee, 2016). However, most studies focus on university students or adult learners, while middle school students especially sixth-grade students have not been adequately and systematically analyzed.

Furthermore, existing studies are often descriptive or only examine direct relationships, failing to fully consider the interaction between cognitive factors and context within the specific educational environment. In particular, in the Vietnamese context, the number of quantitative studies using combined theoretical models (TAM and TRA) to analyze students' programming learning behavior is limited, leading to a lack of empirical evidence for policy planning and curriculum design.

Building on these gaps, the current study has developed an integrated model based on TAM (Davis, 1989, 1993) and TRA, adding elements relevant to the local educational context to explain the programming learning intentions of 6th-grade students in Da Nang City. The study not only contributes theoretically by extending and validating the model in a new context but also provides practical value by offering a scientific basis for building an effective learning environment, aligned with the digital transformation trend in education.

In the rapidly evolving world of technology, countries need individuals with critical thinking and problem-solving skills, technological knowledge, leadership skills, flexibility, and adaptability. Alongside these skills, countries aspire for individuals to have computational thinking skills, including algorithms, necessary for problem-solving (Mills, Cope, Scholes, & Rowe, 2025; Usengül & Bahçeci, 2020; Wing, 2006). Computational thinking involves using algorithms to solve a given problem (Choi & Lee, 2016; Rao & Bhagat, 2024). The research delves into understanding the factors influencing the acceptance of programming education among 6th-grade students in secondary schools in Da Nang City, Vietnam. By analyzing and evaluating factors such as individual characteristics, family influence, learning environment, study time, and programming intention, the study aims to determine the extent of influence of each factor on the acceptance of programming education among 6th-grade students. The paper provides an overview of the current situation and challenges in implementing programming in education, along with specific recommendations based on research findings. Understanding these factors can help improve the effectiveness of programming instruction and create favorable conditions for students to develop essential skills in the digital age (Hair & Alamer, 2022; Songkram et al., 2023; Timotheou et al., 2023; Xu, Wang, & Wang, 2023). This research contributes to a general understanding of the impact of factors influencing the acceptance of programming education, thereby providing practical suggestions for educators and policymakers to enhance computer science education for students.

The study surveyed 599 6th-grade students in secondary schools in Da Nang City, Vietnam, with the aim of answering the following research questions:

- 1. Which factors influence the acceptance of programming education among 6th-grade students?
- 2. What is the extent of influence of each factor on the acceptance of programming education?

2. Theoretical Framework

2.1. Model TAM

The Technology Acceptance Model (TAM) provides a theoretical framework for explaining how individuals form intentions to adopt and use technological systems. It is designed not only to anticipate user behavior but also to offer a conceptual basis for understanding the factors that contribute to successful technology implementation. From a practical perspective, TAM supports practitioners in identifying appropriate strategies prior to system deployment. To fulfill these objectives, (Davis, 1989, 1993) developed TAM by introducing a set of intermediary mechanisms that link external system characteristics to actual usage behavior. Drawing on the Theory of Reasoned Action, the model adopts a psychological approach to explain how beliefs and attitudes influence user decisions. At the time of its introduction, this perspective represented a novel contribution to the information systems literature.

The next stage focuses on specifying the key constructs and validating measurement indicators that demonstrate strong associations with system usage behavior. Based on prior empirical studies in human behavior and information systems, researchers have developed and refined multi-item measurement scales to evaluate perceived usefulness and perceived ease of use. These constructs have been extensively tested and validated across different research contexts. Existing literature consistently indicates that these two factors play a central role in shaping users' acceptance of

technology (Johnson & Payne, 1985; Robey, 1979). From a behavioral perspective, individuals tend to make decisions by comparing the anticipated benefits of an action with the effort or cost required to perform it. Accordingly, the intention to use an information system is largely influenced by users' evaluation of its usefulness and the level of difficulty encountered during interaction (Davis, 1989).

The theoretical foundation of perceived usefulness can be traced to Bandura's concept of outcome expectancy, which reflects an individual's belief that a specific action will lead to desirable outcomes (Bandura, 1982; Robey, 1979). In contrast, perceived ease of use refers to the extent to which individuals believe that interacting with a system requires minimal effort (Davis, 1989). This construct is closely linked to the notion of self-efficacy, representing users' confidence in their ability to successfully perform tasks within a given system (Bandura, 1982; Davis, 1989).

Previous studies have also emphasized that self-efficacy is an important predictor of technology-related decision-making (Hill, Smith, & Mann, 1987). In addition, perceived ease of use shares conceptual similarities with the construct of complexity in innovation diffusion theory, where higher levels of perceived difficulty can hinder adoption. Complexity is typically defined as the degree to which an innovation is considered difficult to understand and apply (Roth, Ivanchenko, & Record, 2008). The reliability and validity of these constructs are commonly evaluated through their ability to predict self-reported system usage within organizational or educational contexts. Empirical evidence has demonstrated that these measurement scales exhibit strong psychometric properties. Furthermore, the robustness of the model is confirmed through significant relationships among perceived usefulness, perceived ease of use, behavioral intention, and actual system use (Davis, 1989).

The advancement of technology acceptance models and measurement frameworks has contributed significantly to both theoretical development and practical application. These models have enabled researchers to systematically examine user motivation and behavioral intention in adopting various information systems (Araújo & Casais, 2020; Gefen, Karahanna, & Straub, 2003). Previously, such evaluations were limited due to the absence of reliable and empirically validated measurement instruments. The introduction of well-defined constructs closely associated with actual usage behavior has improved the understanding of how system characteristics influence technology acceptance through both cognitive and emotional mechanisms.

In the context of information systems, acceptance extends beyond initial exposure and involves users' deliberate decisions to adopt, implement, and continuously use a system over time. This concept reflects an active and sustained commitment rather than a passive or reactive response. Over the past three decades, numerous theoretical models have been proposed to explain the complex interactions between individuals, technological systems, and environmental factors that shape user acceptance behavior. Among these, the TAM remains one of the most influential, widely validated, and practically applicable frameworks for analyzing technology adoption (Davis, 1989).

2.2. Intention to Behave is the Translation

Behavioral intention is commonly understood as an individual's willingness or preparedness to engage in a specific action and is widely regarded as the most immediate predictor of actual behavior. In the TRA, behavioral intention is determined by attitude toward the behavior and subjective norms. Perceived behavioral control is not a component of the TRA; it was introduced later in the Theory of Planned Behavior (TPB) to account for situations in which behavior may not be fully under volitional control (Ajzen, 1991).

According to the TRA, human behavior is primarily determined by the intention to act. This intention is shaped by two fundamental components: the individual's evaluation of the behavior (attitude) and the perceived expectations of significant others (subjective norms). The subsequent development of the TPB, rather than the TRA itself, added perceived behavioral control as a third determinant of behavioral intention and as a potential direct predictor of behavior when actual control is constrained (Ajzen, 1985, 1991). The relationship between intention and behavior has subsequently been operationalized and empirically tested in technology-acceptance research (Taylor & Todd, 1995). Figure 1 illustrates the TRA framework, in which attitude and subjective norms shape behavioral intention, which in turn predicts behavior.

Within this theoretical structure, the behavioral aspect represents the final stage of the cognitive-behavioral chain, shifting from a student's internal readiness to actual execution. According to the Theory of Reasoned Action (TRA), while behavioral intention serves as the core cognitive catalyst, it is the actual behavior manifested as the tangible engagement and perseverance in a task that solidifies technology adoption. In the context of early computer science education, this behavioral dimension transcends mere initial exposure to technology. It encompasses the students' active, persistent execution of programming tasks, regular classroom participation, and the long-term application of computational thinking skills to real-world problem-solving. Therefore, bridging the gap between a 6th-grade student's intention to learn and their practical, sustained engagement in programming tasks is vital to understanding the complete cycle of programming acceptance.

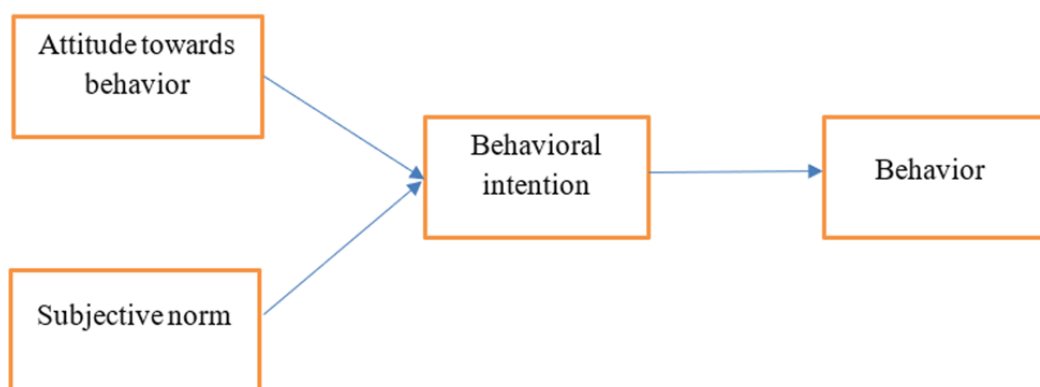


Figure 1. Theory of reasoned action (TRA) framework.

Source: Fishbein and Ajzen (1975).

2.3. Proposed Model

Therefore, the authors have chosen the TAM and the TRA as the theoretical framework for the study on the acceptance of programming education, justified by its proven effectiveness in research across various fields. As the interest in programming education continues to grow, applying TAM helps to better understand the influencing factors on 6th-grade students regarding programming education. In this study, evaluating the factors influencing 6th-grade students in programming education is crucial. For the individual aspect of students, analyzing the factors of the learning environment, time, and family in programming education is indispensable. This research can provide detailed insights into these factors and their impact on the programming learning process of 6th-grade students. Meanwhile, the factors directly influencing the intention to accept programming learning (ITA) also play a significant role, as they can provide information about the goals and expectations of 6th-grade students in accepting programming education (Bagozzi, 2007).

Applying research on the factors influencing the acceptance of programming education helps us understand more about the family, learning environment, time, and the students' themselves, thereby providing directions for improvement and optimization of the teaching process.

Based on the TAM and the TRA, the paper proposes a research model as depicted in Figure 2. Figure 2 presents the proposed research model, which integrates the TAM and the TRA to examine the factors influencing 6th-grade students' intention to learn programming. It illustrates the hypothesized relationships between independent variables specifically family, personal, learning environment, and time factors and the dependent variable representing students' acceptance of programming education. Acceptance of programming (PA) serves as the dependent variable in this research, reflecting a student's active commitment to adopting programming knowledge for daily life and future endeavors. Unlike a passive reaction, PA denotes a sustained and deliberate decision to utilize programming skills. The study demonstrates that this acceptance is positively influenced by the intention to accept programming learning (ITA). By effectively managing critical variables such as the learning environment, personal factors, and time allocation educators and policymakers can significantly enhance students' PA, thereby promoting the development of vital computational thinking skills in the digital age.

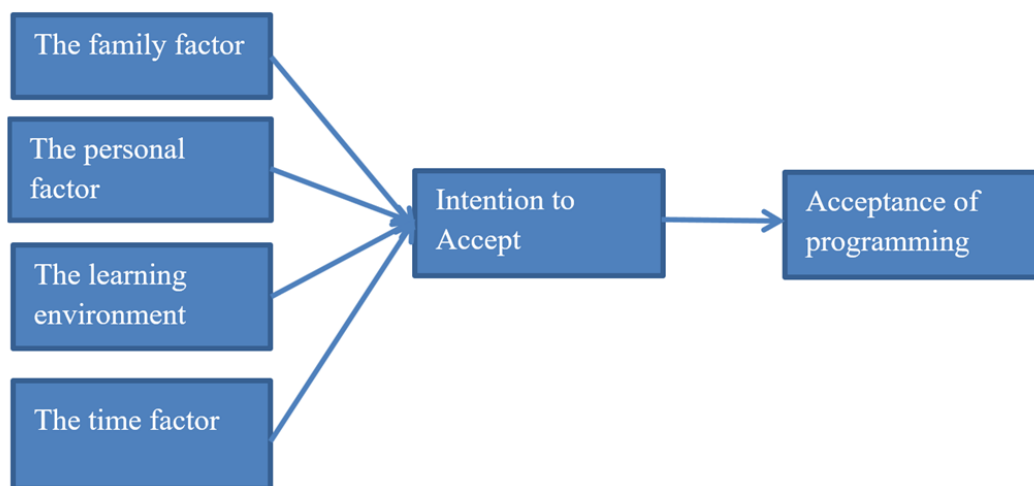


Figure 2. Proposed research model.

3. Theoretical Background and Hypothesis Development

3.1. Family Factor (FF)

Family plays a crucial role in shaping students' awareness and interest in learning programming. Support from parents and the expectations set by the family (Kong, 2023) can both influence students' programming learning. Previous research has shown that active involvement of parents in the learning process can create encouragement and positively impact students' knowledge acquisition. Family, as the primary building block for the existence of society and for maintaining its sustainability, is equally important for the education system (Đurišić & Bunijevac, 2017). The family's attitude towards school plays an important role in shaping the emotional and behavioral development of students, as well as their perception, orientation, and skill development (Popa, 2020).

From these analyses, we propose two observed variables to analyze the family factor (FF). Firstly, family support for your involvement in programming activities outside of school hours (FF1) focuses on examining how this model influences students' programming learning and whether it yields the desired results. Secondly, material conditions (FF2) relate to the family's provisions for students to practice and review programming at home to enhance their knowledge and programming skills for learning purposes. Therefore, we hypothesize that:

H₁: The family factor directly influences the intention to accept programming learning in 6th grade.

3.2. The Personal Factor (TPF)

The personal factor is analyzed through four observed variables. Firstly, problem-solving ability through programming (TPF1) focuses on assessing whether individuals possess the necessary skills to effectively solve problems through programming. This variable examines the suitability of individuals to engage in programming learning. The study suggests that learning programming runs parallel with problem-solving skills. Secondly, self-learning and autonomy (TPF2) are related to the student's ability to self-study and be autonomous in the learning process, assessing the extent to which the programming subject requires self-learning and autonomy from the student. According to Bishop and Verleger (2013), the ability to develop self-motivation and interest in learning is the motivation for teachers to change and update teaching methods (Boonma & Swatevacharkul, 2020). Thirdly, the student's desire and passion for technology (TPF3) refer to whether the student intends to learn programming to pursue their passion for technology. Finally, patience (TPF4) addresses the student's ability to overcome challenges in learning programming, as learning programming can sometimes involve a lot of information and the learning

process can be challenging. The student's ability to patiently explore and overcome these challenges in the learning process is crucial (Kadar, Wahab, Othman, Shamsuddin, & Mahlan, 2021). Therefore, we hypothesize that:

H₁: The self-factor has a direct impact on the intention to accept programming learning of 6th-grade students.

3.3. Learning Environmental Factors (LEF)

The learning environment at school greatly influences students' acceptance of programming education (Nwokedi, 2023). Support from teachers, peers, and the school's facilities can create favorable or challenging conditions for programming learning. Schools with integrated programming education programs and adequate facilities may encourage students' interest and participation. Additionally, peers play an important role in providing support and encouragement to students in the programming learning process.

From this observation, we identify and propose 3 variables to study the environmental learning factors. Firstly, the infrastructure (ELF1) is crucial in the programming learning process of students at school, influencing the effectiveness and quality of programming education for both general students and sixth graders in particular Ahmed, Taha, Alneel, and Gaffar (2018). Secondly, teacher support (ELF2) refers to the assistance provided by teachers in explaining learning difficulties to students (Inês, Pacheco, Abelha, & Seabra, 2022). Lastly, the level of support and encouragement from peers and classmates regarding students' learning of programming (ELF3) during the school years, peer relationships directly influence students' learning, especially for students in the 6th grade (Shanti, Janssens, & Setiadi, 2021).

Through the 3 observed variables, we propose:

H₂: The factor of the learning environment directly influences the intention to accept programming learning of 6th-grade students.

3.4. Time Factor (TF)

The time factor is related to how students manage their time for programming study. Study schedules, hobbies, and extracurricular activities can all influence students' ability and intention to learn programming. Having a fixed study schedule and allocating time wisely between study and other activities can help students create an effective learning environment and facilitate programming learning. We propose 3 observed variables for this factor. First, the study schedule at school (TF1) is intended to investigate the amount of time students spend studying at school if additional programming during the learning process is accommodated and has a significant impact on accepting programming. Second, the time spent on extracurricular programming activities (TF2) accepting programming is a continuous learning process that requires continuous practice and knowledge enhancement, so spending time on extracurricular activities to enhance programming knowledge is also a major issue. Finally, the time spent on programming study at home (TF3) aims to support the author in assessing their own review frequency to ensure that future studies are tailored to students' needs (Islam, Sheikh, Fatima, & Alvi, 2019).

Our research team proposes:

H₃: The factor of time directly influences the intention to accept programming learning of 6th-grade students.

3.5. Intention to Accept Programming Learning (ITA)

Intention to use is related to the student's intention to apply programming knowledge in their daily life and future endeavors. The interest and awareness of the applicability of programming can influence the level of acceptance and commitment of students to programming learning. Students who intend to use programming knowledge to solve everyday problems or pursue a career in the field of information technology may tend to be more engaged and committed to accepting programming learning. The author's team proposes 4 observed variables to analyze the intention to learn programming factor, with the first being pre-planning (ITA1) (Ajzen, 1991). The second variable, programming learning intention (ITA2), expectancy to learn programming (ITA3), Willingness to explore programming in the near future (ITA4). This study referenced and utilized a synthesized behavioral intention scale from various research works by different authors (Guo, Du, & Zheng, 2023; Koç, Altun, & Yüksel, 2022; Oberländer, Beinicke, & Bipp, 2020; Taylor & Todd, 1995; Yisa & Orji, 2024). This scale has been validated through experimental studies in many places and various fields worldwide. However, for this study conducted in Vietnam, the authors kept the core content of each variable in the scale and made adjustments to the wording to fit the context. Therefore, the research team proposes:

H₅: The intention to accept programming learning positively and directly influences programming acceptance among 6th-grade students.

4. Research Methodology

4.1. Data Collection and Participants

This study investigates the intention of 6th-grade students in Da Nang City, Vietnam, to engage in programming learning, based on a sample of 599 students from various junior high schools. In addition to examining students' behavioral intentions, the research seeks to provide deeper insights into the applicability of the TAM and the TRA within the local educational context. The research sample consists of 599 6th-grade students currently enrolled in lower secondary schools in Da Nang City. Data collection was conducted over a one-month period, from March 1 to April 1, 2024, using structured survey questionnaires administered directly at the participating schools.

4.2. Method

The first part of the questionnaire was designed to collect demographic information about students, including basic characteristics such as age, gender, and grade level. The second part of the questionnaire uses a 5-point Likert scale, with level 1 representing the highest and level 5 the lowest. Analysis results show that all scales in the research model achieve high reliability, with Cronbach's Alpha (Bonett & Wright, 2015) exceeding the acceptable threshold (> 0.7). This confirms the internal consistency and reliability of the measurement tools used in the study.

4.3. Data Analysis

The collected data were processed and analyzed using SPSS ("Statistical Package for the Social Sciences") software according to appropriate statistical analysis procedures. In the first step, the study evaluated the measurement model by assessing the reliability of the scales within the factor groups in the proposed model. Next, an exploratory factor analysis (EFA) was performed to determine the structure of the observed variables, and regression models were constructed to test their relationships. In addition, AMOS 22 was used to model and test the theoretical structure based on the TAM and TRA. This tool enables the analysis of relationships in highly complex linear structural models. The analysis results provide detailed quantitative indicators for each observed variable and factor, thereby supporting the clarification of the research objectives. At the same time, these results contribute to a deeper understanding of sixth-grade students' intentions to learn programming and the extent to which various factors influence their decision-making.

5. Research Results

5.1. Sample Description

The study was conducted through actual surveys with 755 students, and after data processing, the appropriate number of responses was 599 surveys from secondary schools in Da Nang City. All participating students completed the survey, accounting for 100%. Regarding the school locations, 29.41% of students attended schools in Cam Le district, 44.12% in Hoa Vang district, and 42.77% in Ngu Hanh Son district.

5.2. Reliability Test of the Scale

To test the scale's reliability, the study used two main indicators: Cronbach's Alpha and the Corrected Item–Total Correlation (CITC). According to Hair, Black, Babin, and Anderson (2019), a scale is considered reliable when its Cronbach's Alpha value is greater than or equal to 0.7. Similarly, according to Tzafilkou, Perifanou, and Economides (2022), each observed variable is considered appropriate when its CITC coefficient reaches 0.3 or higher, reflecting the degree of correlation of that variable with the other variables within the same factor (Tzafilkou et al., 2022). A higher CITC value indicates a stronger correlation between the observed variable and the scale's structure, thereby contributing to the scale's overall reliability. Data analysis using IBM SPSS Statistics 27 software shows that all observed variables have CITC coefficients exceeding 0.3 (Rahman & Muktadir, 2021), indicating reliability. In addition, all model factors have Cronbach's Alpha coefficients ranging from 0.750 to 0.847, meeting the acceptance criteria set by Bonett and Wright (2015). The detailed Cronbach's Alpha values for each factor are presented in Table 1.

Table 1. Reliability.

Factor	Cronbach's Alpha
Family factor (FF)	0.777
The personal factor (TPF)	0.847
Learning environment factor (LEF)	0.774
Time factor (TF)	0.768
Intention to Accept (ITA)	0.831
Programming acceptance (PA)	0.750

5.3. Results EFA

To evaluate the scale's validity, the study conducted an EFA to examine the relationships among observed variables within the entire model. The goal of this method is to identify variables that are likely to load multiple different factors or that do not fit the original theoretical structure (Hair et al., 2019). The criteria used in the EFA analysis include: the Kaiser-Meyer-Olkin (KMO) coefficient, Bartlett's test of sphericity, Eigenvalues, total variance extracted, and factor loadings. The results presented in Table 2 show that the KMO coefficient reached 0.737 (> 0.5), indicating that the data are suitable for factor analysis. Simultaneously, the Bartlett test has a significance level of Sig = 0.000 (< 0.05), indicating that the observed variables are correlated in the overall data. Therefore, the application of EFA in this study is entirely appropriate (Sürücü, Maslakçi, & Sesen, 2022).

Table 2. KMO and Bartlett's test.

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		0.737
Bartlett's Test of Sphericity	Approx. Chi-Square	4490.262
	df	171
	Sig.	0.000

In EFA analysis, the Eigenvalue is used as a key criterion to determine the number of factors to extract. The analysis results show that 6 factors were identified, with all Eigenvalues greater than 1. This indicates that these 6 factors best represent and summarize the information of the 19 observed variables included in the analysis. Therefore, all 6 factors were retained for subsequent analysis steps. Furthermore, the total extracted variance reached 58.362% (exceeding the 50% threshold), indicating that the extracted factors explain 58.362% of the variation in the observed variables in the model. This is an appropriate level of explanation in social science research. During the factor rotation process, the Promax method was used, with a minimum factor loading of 0.5 to ensure strong correlations between the observed variables and the representative factors. The results in Table 3 show that variables with the same theoretical nature focus on the same set of factors, indicating good convergence. At the same time, the rotated matrix also shows a clear separation between the groups of variables, with each group represented in separate columns, reflecting the distinction between the model's factors (Hair et al., 2019).

Table 3. Pattern Matrix^a.

Factor	1	2	3	4	5	6
TPF1	0.854					
TPF2	0.766					
TPF3	0.744					
TPF4	0.681					
ITA1		0.825				
ITA2		0.799				
ITA3		0.764				
ITA4		0.618				
LEF1			0.896			
LEF2			0.701			
LEF3			0.587			
TF1				0.927		
TF2				0.664		
TF3				0.625		
PA1					0.874	
PA2					0.659	
PA3					0.598	
FF1						0.805
FF2						0.794

Extraction Method: Principal Axis Factoring.
Rotation Method: Promax with Kaiser Normalization.

Note: a. Rotation converged in 6 iterations.

After conducting EFA, the observed variables within each scale showed no problematic cross-loadings. Therefore, the authors retained six constructs: four exogenous predictors—Family Factor (FF), The Personal Factor (TPF), Learning Environmental Factors (LEF), and Time Factor (TF)—together with Intention to Accept Programming Learning (ITA) and Programming Acceptance (PA).

5.4. Results of the Multiple Linear Regression Analysis

After completing the EFA, the independent and dependent variables were included in a multiple linear regression model to test the hypothesized relationships. To assess the model's fit, the F-test was used with the null hypothesis H0: R² = 0. The results presented in Table 4 show a Sig value of 0.001 (< 0.05), allowing the null hypothesis H0 to be rejected. This demonstrates that the coefficient of determination R² is statistically significant, confirming that the constructed regression model fits the study data.

Table 4. ANOVA Table on Model Fit.

ANOVA ^a						
Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	43.883	5	8.777	21.024	0.000 ^b
	Residual	247.549	593	0.417		
	Total	291.432	598			

Note: a. Dependent Variable: PA
b. Predictors: (Constant), TF, FF, ITA, LEF, TPF

The test results in Table 5 show that all five independent variables in the regression model have a positive linear relationship with students' decision to learn programming. The correlation coefficient R is 0.388, while the adjusted coefficient of determination (Adjusted R²) is 0.143. This indicates that the model variables explain approximately 14.3% of the variation in intention to use. In addition, the Durbin–Watson (DW) index was used to check for first-order autocorrelation in the residuals. The DW value is 1.654, within the acceptable range of 1.5 to 2.5, indicating that the model does not violate the autocorrelation assumption, ensuring the reliability of the regression results.

Table 5. Results of multiple linear regression.

Model Summary ^b					
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	0.388 ^a	0.151	0.143	0.646	1.654

Note: a. Predictors: (Constant), TF, FF, ITA, LEF, TPF
b. Dependent Variable: PA

To assess the statistical significance of the regression coefficients, the study used a t-test with the null hypothesis H0: the regression coefficient for the independent variable Xi is 0. The results presented in Table 6 show that four independent variables, TF, FF, LEF, and TPF, have Sig values < 0.05, indicating that these variables are statistically significant and directly affect the dependent variable PA. Conversely, the variable ITA has a Sig value greater than 0.05, indicating that it does not have a significant impact on PA and plays only a supporting role in the research model (Ye & Liu, 2023).

In addition, the results in Table 6 show that all four predictors (FF, TPF, LEF, and TF) have positive standardized regression coefficients (Beta), indicating positive associations with PA. The time factor (TF) has the strongest effect ($\beta = 0.323$), followed by the learning environment factor (LEF; $\beta = 0.219$), the personal factor (TPF; $\beta = 0.173$), and the family factor (FF; $\beta = 0.077$). All VIF values are below 2, indicating that multicollinearity is not a concern in this regression model (Akinwande, Dikko, & Samson, 2015; Hair et al., 2019).

Table 6. Regression coefficients of independent variable.

Coefficients ^a								
Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
		B	Std. Error	Beta			Tolerance	VIF
1	(Constant)	0.777	0.251		3.097	0.002		
	FF	0.066	0.032	0.077	2.034	0.042	0.991	1.009
	TPF	0.163	0.039	0.173	4.203	0.000	0.849	1.178
	LEF	0.197	0.037	0.219	5.341	0.000	0.849	1.177
	ITA	-0.041	0.033	-0.049	-1.241	0.215	0.907	1.103
	TF	0.295	0.036	0.323	8.122	0.000	0.907	1.102

Note: a. Dependent Variable: PA.

Based on the regression coefficients (Beta), the author constructs the standardized regression equation as follows:
 $PA = 0.323 * TF + 0.219 * LEF + 0.173 * TPF + 0.077 * FF + \varepsilon \quad (1)$

5.5. CFA Analysis Results

After completing the exploratory factor analysis (EFA), the study proceeded with confirmatory factor analysis (CFA) to test the established scale structure. In CFA, the basic assumption is that the observed variables are appropriately allocated to their respective factors. To assess the model's fit, the study examined the internal consistency of the factors and the relationships among the latent structures (Kline, 2016).

The analysis results showed that all model fit indicators met the acceptable threshold. Specifically, the Chi-square/df value = 3.960 (≤ 5) indicates a good fit; the CFI = 0.907 (≥ 0.9) reflects a good fit; and the TLI = 0.884 remains within the acceptable range. Moreover, RMSEA = 0.007 (≤ 0.08) indicates a small approximate error. These results demonstrate that the measurement model fits the initially proposed factor structure (Goretzko, Siemund, & Sterner, 2024). After assessing the overall fit of the CFA model, the study further examines the quality of the observed variables in the measurement model to identify suitable variables and those to be removed if necessary. This assessment is based on the results from the two tables, Regression Weights and Standardized Regression Weights. Regarding p-values, the results in Table 7 show that all observed variables have p-values < 0.05 , indicating that they are statistically significant in the model and contribute positively to the scale structure.

Table 7. Unstandardized Regression Weights for the CFA Measurement Model.

Observed Variables	Path	Latent Factor	Estimate	S.E.	C.R.	P
TPF3	<---	TPF	1.000			
TPF1	<---	TPF	0.724	0.038	18.956	0.000
TPF4	<---	TPF	0.902	0.044	20.563	0.000
TPF2	<---	TPF	0.712	0.042	16.866	0.000
ITA1	<---	ITA	1.000			
ITA2	<---	ITA	1.006	0.050	20.140	0.000
ITA3	<---	ITA	1.067	0.057	18.763	0.000
ITA4	<---	ITA	0.740	0.052	14.269	0.000
LEF1	<---	LEF	1.000			
LEF2	<---	LEF	0.888	0.058	15.313	0.000
LEF3	<---	LEF	0.745	0.054	13.758	0.000
TF1	<---	TF	1.000			
TF3	<---	TF	0.655	0.044	14.797	0.000
TF2	<---	TF	0.674	0.050	13.457	0.000
PA1	<---	PA	1.000			
PA2	<---	PA	0.800	0.061	13.180	0.000
PA3	<---	PA	0.829	0.062	13.356	0.000
FF1	<---	FF	1.000			
FF2	<---	FF	1.605	0.546	2.940	0.003

Next, standardized regression weights were used to assess the contribution of the observed variables to the latent factors. The results presented in Table 8 show that all observed variables have standardized regression weights in the "Estimate" column greater than 0.5, with many exceeding 0.7. This indicates that the observed variables can well explain the corresponding latent factors and meet the scale's convergence requirements (Jung & Park, 2018).

Table 8. Standardized Regression Weights for the CFA Measurement Model.

Observed Variables	Path	Latent Factor	Estimate
TPF3	<---	TPF	0.854
TPF1	<---	TPF	0.733
TPF4	<---	TPF	0.788
TPF2	<---	TPF	0.665
ITA1	<---	ITA	0.814
ITA2	<---	ITA	0.821
ITA3	<---	ITA	0.757
ITA4	<---	ITA	0.593

Observed Variables	Path	Latent Factor	Estimate
LEF1	<---	LEF	0.824
LEF2	<---	LEF	0.750
LEF3	<---	LEF	0.631
TF1	<---	TF	0.955
TF3	<---	TF	0.668
TF2	<---	TF	0.596
PA1	<---	PA	0.810
PA2	<---	PA	0.656
PA3	<---	PA	0.672
FF1	<---	FF	0.629
FF2	<---	FF	1.010

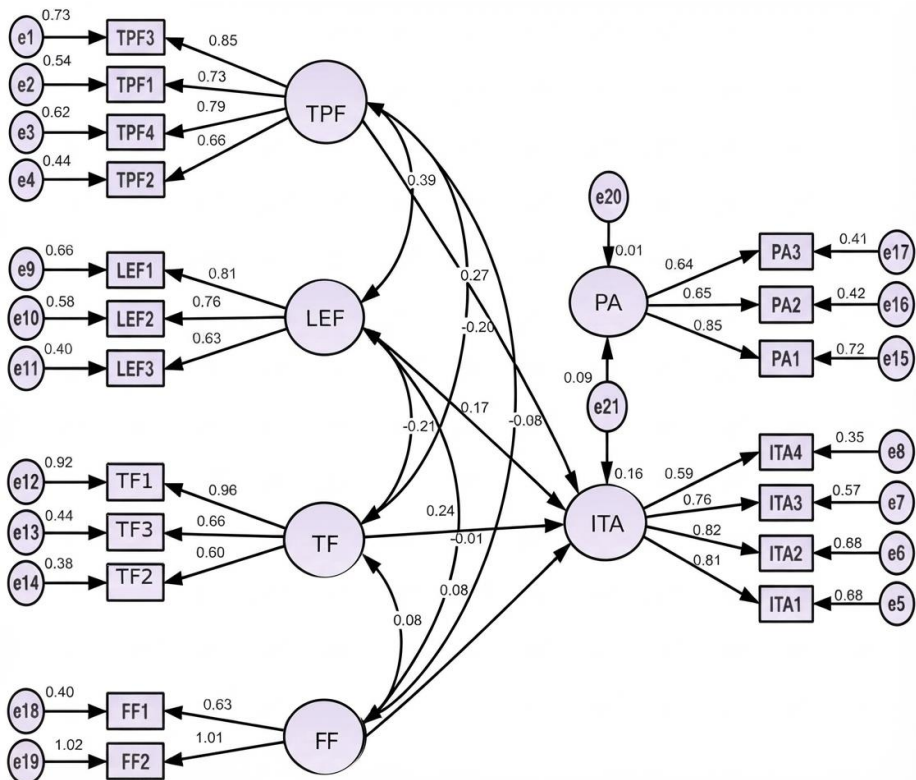


Figure 3. Linear structural equation modeling (SEM) Model.

Figure 3 illustrates the Linear SEM model, which visualizes the hypothesized structural relationships among the research constructs. It maps the integrated theoretical framework based on the TAM and the TRA, depicting the directional paths and influences of independent variables such as personal factors, the learning environment, time, and family on students' intention to learn programming and their ultimate acceptance of programming education.

5.6. SEM Model Testing Results

At the 5% significance level, the results in Table 9 show that the path from FF to ITA is positive but not statistically significant ($B = 0.104$, $p = 0.072$); therefore, H1 is not supported. In contrast, TPF ($B = 0.263$, $p < 0.001$), LEF ($B = 0.174$, $p = 0.002$), and TF ($B = 0.215$, $p < 0.001$) have significant positive effects on ITA, supporting H2, H3, and H4, respectively. ITA also has a significant positive effect on PA ($B = 0.091$, $p = 0.045$), supporting H5. Thus, the structural model indicates that TPF, LEF, and TF predict ITA, while ITA predicts PA; it does not indicate that ITA affects TPF (Calonico, Cattaneo, & Titunik, 2014).

Table 9. Unstandardized Regression Weights for the SEM Structural Model.

Observed Variables	Path	Latent Factor	Estimate	S.E.	C.R.	P
ITA	<---	TPF	0.263	0.050	5.216	0.000
ITA	<---	LEF	0.174	0.055	3.170	0.002
ITA	<---	TF	0.215	0.043	5.015	0.000
ITA	<---	FF	0.104	0.058	1.799	0.072
PA	<---	ITA	0.091	0.046	2.004	0.045
TPF3	<---	TPF	1.000			
TPF1	<---	TPF	0.723	0.038	18.927	0.000
TPF4	<---	TPF	0.902	0.044	20.559	0.000
TPF2	<---	TPF	0.708	0.042	16.775	0.000
ITA1	<---	ITA	1.000			
ITA2	<---	ITA	1.013	0.050	20.064	0.000
ITA3	<---	ITA	1.074	0.057	18.702	0.000
ITA4	<---	ITA	0.743	0.052	14.210	0.000
LEF1	<---	LEF	1.000			

Observed Variables	Path	Latent Factor	Estimate	S.E.	C.R.	P
LEF2	<---	LEF	0.913	0.061	14.981	0.000
LEF3	<---	LEF	0.761	0.056	13.630	0.000
TF1	<---	TF	1.000			
TF3	<---	TF	0.646	0.048	13.558	0.000
TF2	<---	TF	0.675	0.053	12.647	0.000
PA1	<---	PA	1.000			
PA2	<---	PA	0.756	0.064	11.734	0.000
PA3	<---	PA	0.757	0.065	11.695	0.000
FF1	<---	FF	1.000			
FF2	<---	FF	1.600	0.638	2.507	0.012

Table 10 presents the standardized regression weights. Among the significant predictors of ITA, TPF has the strongest standardized effect ($\beta = 0.271$), followed by TF ($\beta = 0.238$) and LEF ($\beta = 0.170$). The standardized effect of FF on ITA is smaller ($\beta = 0.075$) and is not statistically significant (Nieminen, Lehtiniemi, Vähäkangas, Huusko, & Rautio, 2013).

Table 10. Standardized Regression Weights for the SEM Structural Model.

Observed Variables	Path	Latent Factor	Estimate
ITA	<---	TPF	0.271
ITA	<---	LEF	0.170
ITA	<---	TF	0.238
ITA	<---	FF	0.075
PA	<---	ITA	0.100
TPF3	<---	TPF	0.855
TPF1	<---	TPF	0.732
TPF4	<---	TPF	0.789
TPF2	<---	TPF	0.662
ITA1	<---	ITA	0.811
ITA2	<---	ITA	0.822
ITA3	<---	ITA	0.757
ITA4	<---	ITA	0.592
LEF1	<---	LEF	0.811
LEF2	<---	LEF	0.759
LEF3	<---	LEF	0.635
TF1	<---	TF	0.959
TF3	<---	TF	0.662
TF2	<---	TF	0.599
PA1	<---	PA	0.846
PA2	<---	PA	0.646
PA3	<---	PA	0.640
FF1	<---	FF	0.630
FF2	<---	FF	1.008

Finally, Squared Multiple Correlations were examined to assess the model’s coefficients of determination. As reported in Table 11, the R^2 value for ITA is 0.158, indicating that FF, TPF, LEF, and TF jointly explain 15.8% of the variance in ITA. The R^2 value for PA is 0.010, indicating that ITA explains 1.0% of the variance in PA (Kwan & Chan, 2014).

Table 11. Squared Multiple Correlations.

Construct	R^2
ITA	0.158
PA	0.010

6. Discussion

The findings show that FF has a positive but statistically nonsignificant effect on ITA ($\beta = 0.075$, $p = 0.072$); therefore, H1 is not supported. This result suggests that, in this sample, family support and material conditions alone do not significantly predict students’ intention to accept programming learning, although family involvement remains educationally relevant (Gonzalez-DeHass, Willems, Powers, & Musgrove, 2022).

The results show that personal factors significantly influence intention to accept programming learning, supporting Hypothesis 2. This finding is consistent with recent studies showing that self-efficacy and learner-related beliefs are central predictors of students’ behavioural intention in technology-supported learning environments (Songkram et al., 2023). It is also aligned with evidence that computational thinking is positively associated with programming self-efficacy, with growth mindset playing an important mediating role in strengthening students’ confidence and readiness to engage in programming-related tasks (Wang et al., 2024).

The positive impact of LEF on ITA provides corresponding support for Hypothesis 3. Some previous studies have also indicated similar findings. This suggests that the learning environment is indispensable for fostering students' passion for learning in a particular field, such as programming in this study (An & Guo, 2024).

According to the findings, TF directly affects ITA in programming education, thus confirming Hypothesis 4. TF not only influences the effectiveness of programming education but also plays a crucial role in determining students' learning experiences in the classroom (Lee, Lin, Wang, Chang, & Huang, 2023). To promote programming education for 6th-grade students, balancing time between subjects, homework assignments, and extracurricular activities is highly essential.

Lastly, ITA has a positive and statistically significant effect on PA ($\beta = 0.100$, $p = 0.045$), supporting H5. This finding indicates that stronger intention to accept programming learning is associated with greater programming acceptance among 6th-grade students. Accordingly, interventions that strengthen students' personal readiness, learning environment, and time management may indirectly promote programming acceptance through ITA (Giday & Perumal, 2024; Ni & Cheung, 2023; Songkram et al., 2023).

7. Conclusion

The survey results clarify the relationships among family, personal, learning-environment, and time factors, ITA, and PA among 6th-grade students. FF does not significantly predict ITA, whereas TPF, LEF, and TF have significant positive effects on ITA. These findings highlight the importance of students' personal readiness, a supportive learning environment, and appropriate time allocation in strengthening their intention to accept programming learning.

Furthermore, the study's results also indicate that ITA positively impacts PA - acceptance of programming learning. This underscores the significance of students' passion and confidence in the learning process, while highlighting the importance of considering family, personal, time, and learning environment factors to optimize the programming learning process for 6th-grade students. This represents a significant step forward in better understanding the factors influencing the intention to learn programming at a young age, and it may provide specific directions for educational policies and strategies to support the development of programming skills at the school level (Chen, Nguyen, Yan, & Dow, 2020; Mills et al., 2025).

This study makes a significant contribution in both theoretical and practical aspects. Theoretically, the paper expands the TAM by integrating elements from TRA theory, thereby constructing an analytical framework suitable for the context of general education. Notably, the study is one of the few works focusing on 6th-grade students and helps clarify the mechanisms underlying the formation of the intention to learn programming at an early age. In practice, the research results provide scientific evidence to help schools and teachers design effective learning environments that promote the teaching and learning of programming in the context of digital transformation.

References

- Ahmed, Y., Taha, M. H., Alneel, S., & Gaffar, A. M. (2018). Evaluation of the learning environment and the perceived weakness of the curriculum: Student perspective. *International Journal of Research in Medical Sciences*, 7(1), 165–173. <https://doi.org/10.18203/2320-6012.ijrms20185374>
- Ajzen, I. (1985). From intentions to actions: A theory of planned behavior. In J. Kuhl & J. Beckmann (Eds.), *Action control: From cognition to behavior* (pp. 11–39). Berlin, Germany: Springer-Verlag. https://doi.org/10.1007/978-3-642-69746-3_2
- Ajzen, I. (1991). The theory of planned behavior. *Organizational Behavior and Human Decision Processes*, 50(2), 179–211. [https://doi.org/10.1016/0749-5978\(91\)90020-T](https://doi.org/10.1016/0749-5978(91)90020-T)
- Akinwande, M. O., Dikko, H. G., & Samson, A. (2015). Variance inflation factor: As a condition for the inclusion of suppressor variable(s) in regression analysis. *Open Journal of Statistics*, 5(7), 754–767. <https://doi.org/10.4236/ojs.2015.57075>
- An, F., & Guo, J. (2024). Does students' perceived peer support facilitate their deeper learning? The chain mediating role of computer self-efficacy and perceived classroom mastery goal structure. *Education and Information Technologies*, 29(7), 9013–9036. <https://doi.org/10.1007/s10639-023-12193-7>
- Araújo, T., & Casais, B. (2020). *Customer acceptance of shopping-assistant chatbots*. Paper presented at the Proceedings of the International Conference on E-Commerce and Web Technologies, Springer.
- Bagozzi, R. P. (2007). The legacy of the technology acceptance model and a proposal for a paradigm shift. *Journal of the Association for Information Systems*, 8(4), 244–254. <https://doi.org/10.17705/1jais.00122>
- Bandura, A. (1982). Self-efficacy mechanism in human agency. *American Psychologist*, 37(2), 122–147. <https://doi.org/10.1037/0003-066X.37.2.122>
- Bishop, J., & Verleger, M. A. (2013). *The flipped classroom: A survey of the research*. Paper presented at the 2013 ASEE Annual Conference & Exposition Proceedings, Atlanta, GA.
- Bonett, D. G., & Wright, T. A. (2015). Cronbach's alpha reliability: Interval estimation, hypothesis testing, and sample size planning. *Journal of Organizational Behavior*, 36(1), 3–15. <https://doi.org/10.1002/job.1960>
- Boonma, N., & Swatevacharkul, R. (2020). The effect of autonomous learning process on learner autonomy of English public speaking students. *Indonesian Journal of Applied Linguistics*, 10(1), 194–205. <https://doi.org/10.17509/ijal.v10i1.25037>
- Calonico, S., Cattaneo, M. D., & Titiunik, R. (2014). Robust nonparametric confidence intervals for regression-discontinuity designs. *Econometrica*, 82(6), 2295–2326. <https://doi.org/10.3982/ECTA11757>
- Chen, H.-M., Nguyen, B.-A., Yan, Y.-X., & Dow, C.-R. (2020). Analysis of learning behavior in an automated programming assessment environment: A code quality perspective. *IEEE Access*, 8, 167341–167354. <https://doi.org/10.1109/ACCESS.2020.3024102>
- Choi, E., & Lee, J. (2016). Investigating the relationship of target language proficiency and self-efficacy among nonnative EFL teachers. *System*, 58, 49–63. <https://doi.org/10.1016/j.system.2016.02.010>
- Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly*, 13(3), 319–340. <https://doi.org/10.2307/249008>
- Davis, F. D. (1993). User acceptance of information technology: System characteristics, user perceptions and behavioral impacts. *International Journal of Man-Machine Studies*, 38(3), 475–487. <https://doi.org/10.1006/imms.1993.1022>
- Đuričić, M., & Bunijevac, M. (2017). Parental involvement as a important factor for successful education. *Center for Educational Policy Studies Journal*, 7(3), 137–153. <https://doi.org/10.26529/cepsj.291>
- Fishbein, M., & Ajzen, I. (1975). *Belief, attitude, intention, and behavior: An introduction to theory and research*. Reading, MA: Addison-Wesley Pub Co.
- Gefen, D., Karahanna, E., & Straub, D. W. (2003). Trust and TAM in online shopping: An integrated model. *MIS Quarterly*, 27(1), 51–90. <https://doi.org/10.2307/30036519>
- Giday, D. G., & Perumal, E. (2024). Students' perception of attending online learning sessions post-pandemic. *Social Sciences & Humanities Open*, 9, 100755. <https://doi.org/10.1016/j.ssaho.2023.100755>

- Gonzalez-DeHass, A. R., Willems, P. P., Powers, J. R., & Musgrove, A. T. (2022). Parental involvement in supporting students' digital learning. *Educational Psychologist*, 57(4), 281-294. <https://doi.org/10.1080/00461520.2022.2129647>
- Goretzko, D., Siemund, K., & Sterner, P. (2024). Evaluating model fit of measurement models in confirmatory factor analysis. *Educational and Psychological Measurement*, 84(1), 123-144. <https://doi.org/10.1177/00131644231163813>
- Guo, L., Du, J., & Zheng, Q. (2023). Understanding the evolution of cognitive engagement with interaction levels in online learning environments: Insights from learning analytics and epistemic network analysis. *Journal of Computer Assisted Learning*, 39(3), 984-1001. <https://doi.org/10.1111/jcal.12781>
- Hair, J., & Alamer, A. (2022). Partial least squares structural equation modeling (PLS-SEM) in second language and education research: Guidelines using an applied example. *Research Methods in Applied Linguistics*, 1(3), 100027. <https://doi.org/10.1016/j.rmal.2022.100027>
- Hair, J. J. F., Black, W. C., Babin, B. J., & Anderson, R. E. (2019). *Multivariate data analysis* (8th ed.). Boston, MA: Cengage Learning.
- Hill, T., Smith, N. D., & Mann, M. F. (1987). Role of efficacy expectations in predicting the decision to use advanced technologies: The case of computers. *Journal of Applied Psychology*, 72(2), 307-313. <https://doi.org/10.1037/0021-9010.72.2.307>
- Inês, H., Pacheco, J. A., Abelha, M., & Seabra, F. (2022). Teaching students with learning difficulties or disabilities: Regular education teachers' professional development and practices. *Education Sciences*, 12(10), 652. <https://doi.org/10.3390/educsci12100652>
- Islam, N., Sheikh, G. S., Fatima, R., & Alvi, F. (2019). A study of difficulties of students in learning programming. *Journal of Education & Social Sciences*, 7(2), 38-46. <https://doi.org/10.20547/jess0721907203>
- Johnson, E. J., & Payne, J. W. (1985). Effort and accuracy in choice. *Management Science*, 31(4), 395-414. <https://doi.org/10.1287/mnsc.31.4.395>
- Jung, S., & Park, J. (2018). Consistent partial least squares path modeling via regularization. *Frontiers in Psychology*, 9, 174. <https://doi.org/10.3389/fpsyg.2018.00174>
- Kadar, R., Wahab, N. A., Othman, J., Shamsuddin, M., & Mahlan, S. B. (2021). A study of difficulties in teaching and learning programming: A systematic literature review. *International Journal of Academic Research in Progressive Education and Development*, 10(3), 591-605. <https://doi.org/10.6007/IJARPED/v10-i3/11100>
- Kline, R. B. (2016). *Principles and practice of structural equation modeling* (4th ed.). New York: The Guilford Press.
- Koç, Ö., Altun, E., & Yüksel, H. G. (2022). Writing an expository text using augmented reality: Students' performance and perceptions. *Education and Information Technologies*, 27(1), 845-866. <https://doi.org/10.1007/s10639-021-10438-x>
- Kong, S. (2023). Parental support for students' music learning. In *Cultural Capital and Parental Involvement*. In (pp. 23-35). Singapore: Springer Nature.
- Kwan, J. L. Y., & Chan, W. (2014). Comparing squared multiple correlation coefficients using structural equation modeling. *Structural Equation Modeling: A Multidisciplinary Journal*, 21(2), 225-238. <https://doi.org/10.1080/10705511.2014.882673>
- Lee, H.-Y., Lin, C.-J., Wang, W.-S., Chang, W.-C., & Huang, Y.-M. (2023). Precision education via timely intervention in K-12 computer programming course to enhance programming skill and affective-domain learning objectives. *International Journal of STEM Education*, 10(1), 52. <https://doi.org/10.1186/s40594-023-00444-5>
- Mills, K. A., Cope, J., Scholes, L., & Rowe, L. (2025). Coding and computational thinking across the curriculum: A review of educational outcomes. *Review of Educational Research*, 95(3), 581-618. <https://doi.org/10.3102/00346543241241327>
- Ni, A., & Cheung, A. (2023). Understanding secondary students' continuance intention to adopt AI-powered intelligent tutoring system for English learning. *Education and Information Technologies*, 28(3), 3191-3216. <https://doi.org/10.1007/s10639-022-11305-z>
- Nieminen, P., Lehtiniemi, H., Vähäkangas, K., Huusko, A., & Rautio, A. (2013). Standardised regression coefficient as an effect size index in summarising findings in epidemiological studies. *Epidemiology, Biostatistics, and Public Health*, 10(4), 1-15.
- Nwokedi, B. F. C. (2023). Influence of classroom environment on the academic performance of students in English language. *International Journal of Advance Social Sciences and Education*, 1(4), 191-198.
- Oberländer, M., Beinicke, A., & Bipp, T. (2020). Digital competencies: A review of the literature and applications in the workplace. *Computers & Education*, 146, 103752. <https://doi.org/10.1016/j.compedu.2019.103752>
- Popa, E. M. (2020). Family climate and students attitude toward school: A systematic review. *SSRN Electronic Journal*, 1-23. <https://doi.org/10.2139/ssrn.3786066>
- Rahman, A., & Mukhtadir, M. G. (2021). SPSS: An imperative quantitative data analysis tool for social science research. *International Journal of Research and Innovation in Social Science*, 5(10), 300-302. <https://doi.org/10.47772/IJRISS.2021.51012>
- Rao, T. S. S., & Bhagat, K. K. (2024). Computational thinking for the digital age: A systematic review of tools, pedagogical strategies, and assessment practices. *Educational Technology Research and Development*, 72(4), 1893-1924. <https://doi.org/10.1007/s11423-024-10364-y>
- Robey, D. (1979). User attitudes and management information system use. *Academy of Management Journal*, 22(3), 527-538. <https://doi.org/10.5465/255742>
- Roth, V., Ivanchenko, V., & Record, N. (2008). Evaluating student response to WeBWoRK, a web-based homework delivery and grading system. *Computers & Education*, 50(4), 1462-1482. <https://doi.org/10.1016/j.compedu.2007.01.005>
- Shanti, T. I., Janssens, J. M. A. M., & Setiadi, B. (2021). Friends' support, motivation to learn, emotional adjustment, and academic performance among Indonesian first-year students. *Jurnal Psikologi*, 48(2), 67-82. <https://doi.org/10.22146/jpsi.34060>
- Songkram, N., Chootongchai, S., Osuwan, H., Chuppunnarat, Y., & Songkram, N. (2023). Students' adoption towards behavioral intention of digital learning platform. *Education and Information Technologies*, 28(9), 11655-11677. <https://doi.org/10.1007/s10639-023-11637-4>
- Sürücü, L., Maslakçi, A., & Sesen, H. (2022). Transformational leadership, job performance, self-efficacy, and leader support: Testing a moderated mediation model. *Baltic Journal of Management*, 17(4), 467-483. <https://doi.org/10.1108/BJM-08-2021-0306>
- Taylor, S., & Todd, P. (1995). Decomposition and crossover effects in the theory of planned behavior: A study of consumer adoption intentions. *International Journal of Research in Marketing*, 12(2), 137-155. [https://doi.org/10.1016/0167-8116\(94\)00019-K](https://doi.org/10.1016/0167-8116(94)00019-K)
- Timotheou, S., Miliou, O., Dimitriadis, Y., Sobrino, S. V., Giannoutsou, N., Cachia, R., . . . Ioannou, A. (2023). Impacts of digital technologies on education and factors influencing schools' digital capacity and transformation: A literature review. *Education and Information Technologies*, 28(6), 6695-6726. <https://doi.org/10.1007/s10639-022-11431-8>
- Tzafilkou, K., Perifanou, M., & Economides, A. A. (2022). Development and validation of students' digital competence scale (SDiCoS). *International Journal of Educational Technology in Higher Education*, 19(1), 30. <https://doi.org/10.1186/s41239-022-00330-0>
- Usengül, L., & Bahçeci, F. (2020). The effect of Lego Wedo 2.0 education on academic achievement and attitudes and computational thinking skills of learners toward science. *World Journal of Education*, 10(4), 83-93. <https://doi.org/10.5430/wje.v10n4p83>
- Wang, C., Lu, C., Chen, F., Liu, X., Zhao, Q., & Wang, S. (2024). Growth mindset mediates the relationship between computational thinking and programming self-efficacy. *Education and Information Technologies*, 29(16), 21331-21354. <https://doi.org/10.1007/s10639-024-12735-7>
- Wing, J. M. (2006). Computational thinking. *Communications of the ACM*, 49(3), 33-35. <https://doi.org/10.1145/1118178.1118215>
- Xu, E., Wang, W., & Wang, Q. (2023). A meta-analysis of the effectiveness of programming teaching in promoting K-12 students' computational thinking. *Education and Information Technologies*, 28(6), 6619-6644. <https://doi.org/10.1007/s10639-022-11445-2>
- Ye, T., & Liu, B. (2023). Uncertain significance test for regression coefficients with application to regional economic analysis. *Communications in Statistics - Theory and Methods*, 52(20), 7271-7288. <https://doi.org/10.1080/03610926.2022.2042562>
- Yisa, V., & Orji, R. (2024). Hidden desires, echoed distress: Dissecting Nigeria's sexting landscape and its ties to depression. *Computers in Human Behavior*, 161, 108420. <https://doi.org/10.1016/j.chb.2024.108420>