

Confirmatory Factor Analysis of the Extended Technology Acceptance Model in Online Gateway Courses at Community Colleges

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Abstract: Many community college students face challenges staying engaged in math courses across all modalities, where homework systems serve as the main source of practice and feedback. The Technology Acceptance Model provides a strong framework for understanding how students form beliefs about technology by emphasizing their perceptions of usefulness and ease of use. Hence, building upon earlier exploratory analysis, this study applied Confirmatory Factor Analysis to validate the Extended Technology Acceptance Model among community college students enrolled in gateway math courses, incorporating the constructs of Perceived Usefulness, Perceived Ease of Use, and Educational Support to explain how instructional and environmental supports influence technology acceptance. Using a new sample of 300 students, the analysis showed strong model fit with significant factor loadings across all constructs. Two items with low loadings were removed from the Educational Support construct, which improved coherence and overall model performance while maintaining acceptable internal consistency. Thus, findings confirm the reliability of the Extended Technology Acceptance Model and emphasize the importance of contextual and instructional supports in fostering engagement with online mathematics systems.

Keywords: Extended Technology Acceptance Model, Mathematics Education, Community Colleges, Confirmatory Factor Analysis, Online Learning

Introduction

Online homework platforms have become a central component of instruction in gateway math courses at community colleges, serving as primary tools for practice, feedback, and assessment across all modalities (Zogheib et al., 2015). Consequently, students' continued use of these systems depends not only on access but also on how learners perceive their usefulness, ease of use, and the instructional support available to navigate technology-mediated coursework (Davis, 1989; O'Dell & Sulastri, 2019). Moreover, the Technology Acceptance Model (TAM), a framework that explains adoption through perceived usefulness (PU) and perceived ease of use (PEU), has been widely used to examine student engagement with educational technologies, while extended versions of the model emphasize contextual and instructional factors captured through Educational Support (EdS) (Noh et al., 2021; Türkyılmaz, 2023; Zogheib et al., 2015). Therefore, the present study employs Confirmatory Factor Analysis (CFA), an approach that rigorously tests measurement structure, to validate the Extended TAM framework within the context of first-year math coursework at community colleges (Brown, 2015; Kline, 2023).

Purpose

The purpose of this study is to confirm the factor structure of the Extended TAM Model (TAM) by examining the relationships among PU, PEU, and EdS constructs using CFA in gateway math coursework at community colleges (Davis, 1989; Brown, 2015). Moreover, CFA is employed to evaluate whether the measurement model identified through prior exploratory factor analysis (EFA) demonstrates adequate construct validity, reliability, and overall model fit within an independent sample of students, an approach that strengthens confidence in the stability of the instrument (Kline, 2023; MacCallum et al., 1999). Consequently, validating the Extended TAM through CFA provides empirical support for the inclusion of instructional support factors when examining student acceptance of online homework systems across multiple course modalities in community college instruction (Noh et al., 2021; Türkylmaz, 2023; Zogheib et al., 2015).

Research Questions

RQ1: To what extent does the Extended Technology Acceptance Model (TAM), consisting of *Perceived Usefulness* (PU), *Perceived Ease of Use* (PEU), and *Educational Support* (EdS), demonstrate an acceptable model fit when tested through Confirmatory Factor Analysis (CFA) among community college students enrolled in gateway mathematics courses?

RQ2: Do the observed items load significantly onto their respective latent constructs (PU, PEU, and EdS), confirming the convergent and discriminant validity of the Extended TAM framework?

RQ3: Does the inclusion of the *Educational Support* (EdS) construct improve the overall model fit and internal consistency compared to the traditional two-factor TAM structure?

Literature Review

Research on technology acceptance in educational settings has consistently emphasized the importance of understanding how learners form perceptions about technologies designed for learning at community colleges, particularly in environments where online tools structure most learning activities (Albelbisi et al., 2024; Davis, 1989; O'Dell & Sulastri, 2019). Additionally, the TAM Model has served as a foundational framework for examining how PU and PEU influence students' willingness to engage with learning platforms, including online homework systems used in math classes in higher institutions (Çelik & Yeşilyurt, 2013; Zogheib et al., 2015). Moreover, studies conducted across institutions of higher education have shown that when students perceive learning tools as helpful and manageable, engagement and sustained use are more likely to occur, particularly in skill-intensive courses such as mathematics (Han & Sa, 2022; Sallam et al., 2023).

More recent research has extended TAM by incorporating contextual and support-related factors that shape how learners interact with educational technologies beyond individual perceptions alone (Noh et al., 2021; Türkylmaz, 2023). In particular, constructs related to facilitating conditions, instructional guidance, and motivational support have been shown to influence technology use by reducing barriers and reinforcing students' confidence in navigating digital learning environments (Mailizar et al., 2021; Yunus et al., 2022). Within mathematics education, these support mechanisms are especially salient, as students often rely on structured feedback, system guidance, and institutional resources when completing online assignments that require procedural accuracy and sustained effort (Zogheib et al., 2015). Consequently, the inclusion of Educational Support (EdS) within extended TAM frameworks reflects growing recognition that acceptance is shaped not only by usability and usefulness, but also by the learning conditions surrounding technology use (Doğan & Balkaya, 2023; Noh et al., 2021).

Methodologically, much of the existing TAM-based research in education has relied on EFA or structural modeling approaches applied within the modality of choice, often emphasizing initial instrument development rather than rigorous confirmation of measurement structures (Comrey & Lee, 2013; MacCallum et al., 1999). Although CFA has increasingly been used to validate TAM extensions in areas such as mobile learning, online assessment, and emerging educational technologies, relatively few studies have applied CFA to extended TAM models within math courses at community colleges, particularly across multiple instructional modalities (Brown, 2015; Kline, 2023;

Nurahmasari et al., 2023). As a result, limited empirical evidence exists confirming whether extended TAM constructs, including support-related dimensions, function as stable and distinct factors within this population.

Taken together, prior research highlights the theoretical value of extended TAM frameworks while revealing a gap in confirmatory validation within first-year math coursework at two-year institutions, where online homework systems play a central instructional role across face-to-face, hybrid, and online platforms (Zogheib et al., 2015; Noh et al., 2021). Accordingly, the present study addresses this gap by applying CFA to validate the Extended TAM measurement model, providing empirical evidence for its structural integrity and supporting its use in future research examining student engagement and technology acceptance in first-year math learning environments across all modalities at two-year colleges (Brown, 2015; Kline, 2023).

Methods

CFA was conducted using survey responses from 300 students enrolled in gateway math courses at a community college in Houston, Texas, where participation was voluntary and responses were collected anonymously following approval from the institution's Institutional Review Board (IRB) in accordance with established ethical research practices (Comrey & Lee, 2013; MacCallum et al., 1999).

Additionally, several demographic indicators were collected to provide descriptive context for the participant sample. Age distribution indicated that 260 students (86.7%) were between 18–24 years old, 32 students (10.7%) were between 25–34, and 6 students (2.0%) were between 35–44, while one participant (0.3%) reported ages 45–54 and one participant (0.3%) reported 65 years or older, with no participants reporting ages 55–64. Furthermore, gender responses indicated that 170 participants (56.7%) identified as female, 128 participants (42.7%) identified as male, and two participants (0.7%) selected another option or preferred not to disclose their gender identity. Moreover, course modality responses showed that 221 students (73.7%) were enrolled in online courses, 62 students (20.7%) were enrolled in face-to-face courses, and 17 students (5.7%) were enrolled in hybrid courses combining online and face to face instruction.

Furthermore, the survey included items measuring TAM constructs PU, PEU, and EdS, with the EdS construct drawing from FC and BI items identified during prior EFA, and the survey items used to operationalize these constructs are provided in Appendix A (Davis, 1989; Türkyılmaz, 2023; Zogheib et al., 2015). Subsequently, CFA was conducted using Jamovi version 2.7 with the SEMlj module, which implements the lavaan package within the R environment to estimate latent variable models (Gallucci & Jentschke, 2021; Rosseel, 2023; The Jamovi Project, 2024).

Moreover, the Diagonally Weighted Least Squares (DWLS) estimation method was applied to accommodate the ordinal structure of Likert type survey responses, an estimation approach recommended for CFA involving categorical educational data (Abd-El-Fattah, 2010; Brown, 2015; Epskamp, 2022; Kline, 2023). Finally, model evaluation relied on multiple goodness of fit indices, including the Comparative Fit Index (CFI), Tucker Lewis Index (TLI), Standardized Root Mean Square Residual (SRMR), and Root Mean Square Error of Approximation (RMSEA), to determine the adequacy of the proposed extended TAM measurement model (Abd-El-Fattah, 2010; Brown, 2015; Kline, 2023; R Core Team, 2024).

Results

Exploratory Factor Analysis

EFA was first conducted using a sample of 300 students to examine the underlying structure of the extended TAM constructs prior to implementing CFA, where the Principal component analysis with varimax rotation and Kaiser normalization supported a clear three-factor solution corresponding to PU, PEU, and EdS, with eigenvalues greater than 1.0 and a cumulative variance explained of approximately 66% (R Core Team, 2024; Watkins, 2021). Moreover, inspection of the scree plot indicated a distinct elbow after the third component, reinforcing retention of the three-factor structure. Additionally, rotated factor loadings demonstrated strong and theoretically consistent item clustering, with all retained items loading above recommended thresholds and minimal cross-loadings, indicating satisfactory construct separation and alignment with the proposed extended TAM framework, as shown in Figure 1.

Figure 1. Rotated Component Matrix for Exploratory Factor Analysis

Rotated Component Matrix^a

	Component		
	1	2	3
TAM21PEU	.826		
TAM18PEU	.809		
TAM19PEU	.808		
TAM16PEU	.793		
TAM17PEU	.754		
TAM20PEU	.749		
TAM13PU		.851	
TAM14PU		.834	
TAM11PU		.799	
TAM15PU		.778	
TAM12PU		.777	
TAM10PU		.692	
TAM27FC			.823
TAM24FC			.682
TAM25FC			.644
TAM26FC			.566
TAM29BI			.556

Extraction Method: Principal Component Analysis.

Rotation Method: Varimax with Kaiser Normalization.

a. Rotation converged in 5 iterations.

Confirmatory Factor Analysis

Following the exploratory phase, CFA was conducted on the sample of 300 participants to validate the three-factor measurement model identified in the EFA. Moreover, results indicated that all observed indicators loaded significantly onto their respective latent constructs, with standardized factor loadings ranging from acceptable to strong magnitudes ($p < .001$), providing evidence of convergent validity. Furthermore, latent factor covariances were statistically significant, suggesting theoretically meaningful relationships among PU, PEU, and EdS while maintaining construct distinctiveness. Hence, overall model fit indices indicated an acceptable to good fit (CFI = .943, TLI = .930, SRMR = .062, RMSEA = .069), supporting the adequacy of the proposed extended TAM measurement model. Standardized factor loadings and model fit indices are summarized in Table 1, and the final CFA measurement model is visually represented in Figure 2.

Table 1. Confirmatory Factor Analysis Standardized Loadings and Model Fit Indices (N = 300)

Latent Construct	Indicator	Standardized Loading (β)	SE	z	p
Perceived Usefulness (PU)	TAM10PU	.653	.051	12.09	< .001
	TAM11PU	.813	.041	16.49	< .001

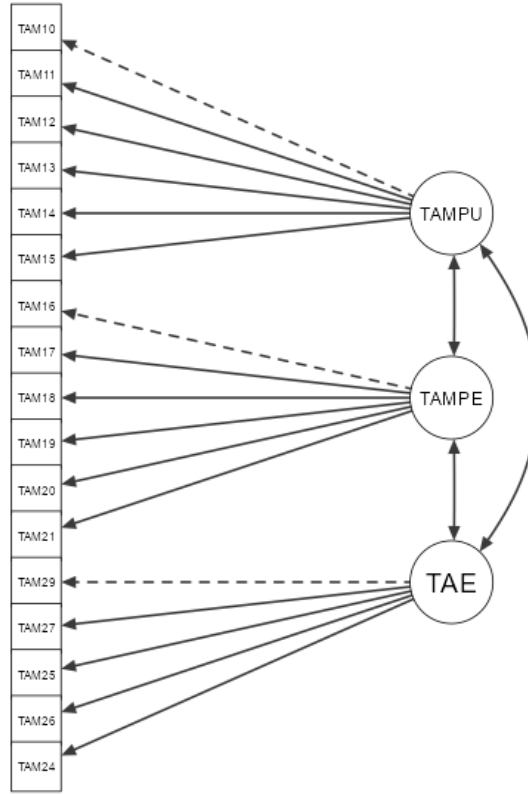
Latent Construct	Indicator	Standardized Loading (β)	SE	z	p
Perceived Ease of Use (PEU)	TAM12PU	.794	.044	15.77	< .001
	TAM13PU	.846	.041	17.49	< .001
	TAM14PU	.823	.040	16.80	< .001
	TAM15PU	.763	.042	14.92	< .001
	TAM16PEU	.735	.049	14.37	< .001
	TAM17PEU	.726	.045	14.13	< .001
	TAM18PEU	.827	.041	16.85	< .001
	TAM19PEU	.882	.041	18.82	< .001
	TAM20PEU	.801	.044	16.11	< .001
	TAM21PEU	.856	.043	17.92	< .001
Educational Support (EdS)	TAM24FC	.707	.046	12.63	< .001
	TAM25FC	.649	.046	11.37	< .001
	TAM26FC	.725	.047	13.40	< .001
	TAM27FC	.520	.044	8.81	< .001
	TAM28BI	.626	.048	10.83	< .001
	TAM29BI	.513	.047	8.54	< .001

Model Fit Indices

Fit Index	Value
χ^2 (df = 126)	305.00, p < .001
CFI	.943
TLI	.930
SRMR	.062
RMSEA	.069
RMSEA 90% CI	[.059, .078]

Note. PU = perceived usefulness; PEU = perceived ease of use; EdS = educational support. All reported values are standardized factor loadings. All factor loadings were statistically significant at $p < .001$. Model fit was evaluated using commonly accepted thresholds for confirmatory factor analysis.

Figure 2. Confirmatory Factor Analysis Path Diagram for the Extended TAM Model



Note. The figure presents the confirmatory factor analysis (CFA) path diagram for the extended Technology Acceptance Model, including perceived usefulness (PU), perceived ease of use (PEU), and educational support (EdS). Additionally, the rectangles represent observed indicators and circles represent latent constructs. Moreover, single-headed arrows indicate standardized factor loadings, all of which were statistically significant at $p < .001$, while double-headed arrows represent correlations among latent constructs. Dashed paths denote fixed or constrained parameters specified for model identification.

Discussion

The findings from EFA and CFA collectively support a stable three-factor structure for the extended TAM in first-year math coursework at two-year colleges, a structure that integrates PU, PEU, and EdS as distinct yet related constructs (Davis, 1989; DeVellis, 2016). Additionally, the consistency between the EFA results and the CFA model fit indices suggests that the proposed measurement model adequately represents how students evaluate instructional technologies used in mathematics learning environments, an outcome that aligns with prior validation efforts of TAM-based instruments in gateway math classes at community colleges (Han & Sa, 2022; Sallam et al., 2023). Consequently, the observed correlations among latent constructs indicate that ease of use and educational support are more closely associated with student confidence-related perceptions than perceived usefulness alone, a pattern that reinforces concerns raised in prior research regarding the limited role of usefulness in explaining affective responses to technology in cognitively demanding courses such as mathematics (Zogheib et al., 2015; O'Dell & Sulastri, 2019). Finally, these findings suggest that while perceived usefulness may influence students' valuation of instructional technologies, sustained confidence and engagement in entry-level math courses appear to be more strongly shaped by usability and perceived instructional support, an implication that highlights the importance of teaching-design choices when implementing technology across all learning modalities (Çelik & Yeşilyurt, 2013; Noh et al., 2021).

Limitations

Several limitations should be considered when interpreting these findings. First, the study relied on a survey administered at a local community college, which may reflect perceptual biases rather than direct measures of student behavior or performance.

Conclusion

In conclusion, the present study provides empirical support for an extended TAM Model that integrates PU, PEU, and EdS as distinct yet interrelated dimensions of technology acceptance in introductory math courses at community colleges (Davis, 1989; DeVellis, 2016; Zou et al., 2025). Moreover, the combined EFA and CFA demonstrate that the proposed three-factor structure is psychometrically sound, with strong factor loadings and acceptable model fit indices, reinforcing prior validation efforts of TAM-based instruments in educational settings (Davis, 1989; Kline, 2023). Additionally, the inclusion of the EdS construct highlights the importance of instructional design and institutional scaffolding in shaping student experiences with learning technologies, particularly in mathematically demanding courses that are gateway and challenging at two-year colleges (Noh et al., 2021; Sallam et al., 2023). Collectively, these findings extend existing technology acceptance research by offering a validated measurement framework that can inform future studies examining student engagement, persistence, and technology that assist instruction across multiple modalities in community college (Çelik & Yeşilyurt, 2013; Zogheib et al., 2015).

References

- Abd-El-Fattah, S. M. (2010). Structural equation modeling with AMOS: basic concepts, applications and programming. *Journal of applied quantitative methods*, 5(2), 365-368.
- Albelbisi, N. A., Al-Adwan, A. S., Habibi, A., & Rasool, S. (2024). The relationship between students' attitudes toward online homework and mathematics anxiety. *International journal of mathematical education in science and technology*, 55(1), 4-22. <https://doi.org/10.1080/0020739X.2021.2023769>
- Brown, T. A. (2015). *Confirmatory factor analysis for applied research*. Guilford Publications.
- Çelik, V., & Yeşilyurt, E. (2013). Attitudes to technology, perceived computer self-efficacy, and computer anxiety as predictors of computer-supported education. *Computers & Education*, 60(1), 148-158. <https://doi.org/10.1016/j.compedu.2012.06.008>
- Comrey, A. L., & Lee, H. B. (2013). *A first course in factor analysis*. Psychology Press.
- 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>
- DeVellis, R. F. (2016). *Scale development: Theory and applications* (4th ed.). Sage.
- Doğan, F., & Balkaya, M. (2023). *Scale development and validation study on using YouTube as a learning environment in secondary education according to the technology acceptance model*. *African Educational Research Journal*, 11(1), 1-20. <https://doi.org/10.30918/AERJ.111.22.061>
- Epskamp, S. (2022). *semPlot: Path Diagrams and Visual Analysis of Various SEM Packages' Output*. [R package]. Retrieved from <https://cran.r-project.org/package=semPlot>.
- Gallucci, M., & Jentschke, S. (2021). SEMlj: jamovi SEM Analysis [Computer software].
- Kline, R. B. (2023). *Principles and practice of structural equation modeling*. Guilford Publications.
- Han, J. H., & Sa, H. J. (2022). Acceptance of and satisfaction with online educational classes through the technology acceptance model (TAM): The COVID-19 situation in Korea. *Asia Pacific Education Review*, 23(3), 403-415. <https://doi.org/10.1007/s12564-021-09716-7>
- MacCallum, R. C., Widaman, K. F., Zhang, S., & Hong, S. (1999). Sample size in factor analysis. *Psychological Methods*, 4(1), 84-99. <https://doi.org/10.1037/1082-989X.4.1.84>
- Mailizar, M., Almanthari, A., & Maulina, S. (2021). Examining teachers' behavioral intention to use E-learning in teaching of mathematics: An extended TAM model. *Contemporary educational technology*, 13(2), ep298. <https://doi.org/10.30935/cedtech/9709>
- Noh, N. H. M., Raju, R., Eri, Z. D., & Ishak, S. N. H. (2021). Extending the Technology Acceptance Model (TAM) to measure the students' acceptance of using digital tools during open and distance learning (ODL). *IOP Conference Series: Materials Science and Engineering*, 1176, 012037. <https://doi.org/10.1088/1757-899X/1176/1/012037>

- Nurahmasari, M., Silfiah, S. N., & Pangaribuan, C. H. (2023). The intention to use digital banking services among Gen Z in Indonesia, based on the Technology Acceptance Model (TAM). *Jurnal Manajemen Dan Bisnis Madani*, 5(1), 15-31. <https://doi.org/10.51353/jmbm.v5i1.692>
- O'Dell, J., & Sulastrri, F. (2019). Technology acceptance and engagement in learning. *Journal of Educational Technology*. <https://doi.org/10.5281/zenodo.3375176>
- Rosseel, Y. (2023). lavaan: An R package for structural equation modeling. *Journal of Statistical Software*, 48(2), 1–36.
- R Core Team (2024). *R: A Language and environment for statistical computing*. (Version 4.4) [Computer software]. Retrieved from <https://cran.r-project.org>. (R packages retrieved from CRAN snapshot 2024-08-07).
- Sallam, M., Salim, N., Barakat, M., Al-Mahzoum, K., Al-Tammemi, A. B., Malaeb, D., Hallit, R., & Hallit, S. (2023). Validation of a Technology Acceptance Model-Based Scale (TAME-ChatGPT) on Health Students' Attitudes and Usage of ChatGPT in Jordan. *JMIR Preprints*. <https://doi.org/10.2196/preprints.48254>
- The Jamovi Project (2024). *jamovi*. (Version 2.6) [Computer Software]. Retrieved from <https://www.jamovi.org>.
- Türkyılmaz, S. (2023). Investigation of telemedicine services, an innovative and technology-based healthcare application, by using the extended Technology Acceptance Model (TAM2): An example from Turkey. *European Journal of Applied Sciences*, 11(1), 594–621. <https://doi.org/10.14738/aivp.111.14101>
- Watkins, M. W. (2021). *A step-by-step guide to exploratory factor analysis with SPSS*. Routledge. <https://doi.org/10.4324/9781003149347>
- Yunus, N. S. N. M., Hassan, H., Harun, H., Abdul Aziz, Z., & Mohd Noor, A. S. (2022). Factors affecting students' behavioral intention to use mobile learning: An empirical study using the extended technology acceptance model (TAM2). *Sustainability*, 14(20), 13261. <https://doi.org/10.3390/su142013261>
- Zou, B., Wang, C., Yan, Y., Du, X., & Ji, Y. (2025). Exploring English as a foreign language learners' adoption and utilization of ChatGPT for speaking practice through an extended technology acceptance model. *International Journal of Applied Linguistics*, 35(2), 689-704. <https://doi.org/10.1111/ijal.12658>
- Zogheib, B., Rabaa'i, A., Zogheib, S., & Elsheikh, A. (2015). University student perceptions of technology use in mathematics learning. *Journal of Information Technology Education: Research*, 14, 417–438. <http://www.jite.org/documents/Vol14/JITEv14ResearchP417-438Zogheib2039.pdf>

Appendix A

Technology Acceptance Model (TAM) Survey Items

Participants responded to the following items using a 5-point Likert scale ranging from 1 (Strongly Disagree) to 5 (Strongly Agree). Additionally, the term “**educational math tools**” refer to online homework systems such as MyLabMath, WebAssign, ALEKS, Connect, and MyOpenMath.

Perceived Usefulness (PU)

1. Using educational math tools in my math class would enable me to complete assignments more quickly.
2. Using educational math tools would improve my performance in this course.
3. Using educational math tools in my math class would increase my productivity.
4. Using educational math tools would enhance my effectiveness in this course.
5. Using educational math tools would make it easier to succeed in my math class.
6. I would find educational math tools useful for my studies.

Perceived Ease of Use (PEU)

7. Learning to operate educational math tools would be easy for me.
8. I would find it easy to get educational math tools to do what I need in my math class.
9. My interaction with educational math tools would be clear and understandable.
10. I would find educational math tools clear and understandable.
11. It would be easy for me to become skillful at using educational math tools.
12. I would find educational math tools easy to use.

Social Influence (SI)

- 13. In my math class, my instructor encourages the use of educational math tools.
- 14. Using educational math tools helps me stay engaged and motivated in my coursework.

Facilitating Conditions / Educational Support (EdS)

- 15. I have the resources necessary to use educational math tools.
- 16. I have access to the technical support I need to use educational math tools.
- 17. Educational math tools are compatible with other resources I use for my studies.
- 18. The use of educational math tools is supported by my instructor or school.

Behavioral Intention to Use (BI)

- 19. I intend to continue using educational math tools in the future.
- 20. I will use educational math tools regularly for my assignments.
- 21. I will recommend the use of educational math tools to others.