

Task–Technology Fit in Action: Understanding Learning–Task Alignment in Math Classes at Community Colleges

Jose Jonathan Gamez

Oscar Villalobos

Youngjin Lee

Kinshuk Kinshuk

Department of Learning Technologies

University of North Texas

United States

josegamez@my.unt.edu

oscarvillalobos@my.unt.edu

youngjin.lee@unt.edu

kinshuk@unt.edu

Abstract: This study examines task–technology alignment in gateway math courses at community colleges using the Task–Technology Fit (TTF) framework to better understand how learning platforms support the cognitive and procedural demands of mathematics instruction. Using survey data collected from students enrolled in introductory math courses across multiple instructional modalities, exploratory factor analysis (EFA) was conducted to evaluate the reliability and underlying structure of a Learning–Task Fit (LTF) construct. Results revealed a stable two-factor solution with strong internal consistency, indicating that students’ perceptions of technology effectiveness are closely tied to how well platforms support problem solving, practice, and assessment tasks. Hence, these findings extend existing TTF model into two-year college math settings and offer practical insight into how learning platforms can be designed and selected to better support student engagement and learning across all modalities.

Keywords: Technology Acceptance Model, Task–Technology Fit, Mathematics Education, Community Colleges, Exploratory Factor Analysis, Online Learning

Introduction

Task–technology alignment has become increasingly central in first-year math courses at community colleges, where instructional technologies are deeply embedded in problem solving, assessment, and feedback processes (Bany Mohammed et al., 2024; Davis, 1989; O’Dell & Sulastri, 2019). Despite widespread adoption of online learning platforms, students’ learning experiences vary substantially depending on how well technological tools support the cognitive and procedural demands of mathematical tasks (Dishaw & Strong, 1999; Goodhue & Thompson, 1995). In math classrooms, particularly those serving student populations at two-year institutions, misalignment between learning tasks and technology features can introduce friction that undermines engagement, persistence, and learning efficiency (Davis, 1989; O’Dell & Sulastri, 2019). Consequently, understanding task–technology fit (TTF) within math online learning environments offers a necessary lens for examining whether instructional technologies meaningfully support students’ learning processes rather than simply delivering content (Bany Mohammed et al., 2024; Goodhue & Thompson, 1995; Wang et al., 2022).

Purpose

The purpose of this study is to examine the validity and applicability of the TTF framework in gateway math courses by evaluating how well instructional technologies align with learning tasks and instructional demands (Bany Mohammed et al., 2024; Goodhue & Thompson, 1995). Moreover, this study seeks to assess whether task–technology alignment, instructional support features, and system usability collectively explain students’ learning experiences in technology-mediated math environments, an approach that responds to growing evidence linking

task–technology fit to academic learning performance in online settings (Bany Mohammed et al., 2024; Dishaw & Strong, 1999). Consequently, by applying exploratory factor analysis (EFA) to data collected from first-year math courses across all learning modalities, this study aims to strengthen empirical understanding of how task–technology alignment functions within community colleges, where such relationships remain underexamined in existing TTF research (Bany Mohammed et al., 2024; Goodhue & Thompson, 1995).

Research Questions

1. What is the underlying factor structure of the Learning–Task Fit construct in gateway mathematics courses at community colleges?
2. To what extent does the Learning–Task Fit instrument demonstrate acceptable levels of reliability and internal consistency in this context?
3. How can Learning–Task Fit help explain the alignment between educational technologies and the cognitive and procedural demands of mathematics learning tasks?

Literature Review

Research on technology use at two-year institutions consistently emphasizes that effective learning depends not only on access to instructional technologies but also on how well those technologies align with the tasks learners are expected to complete (Bany Mohammed et al., 2024; Goodhue & Thompson, 1995). Foundational work on the Task–Technology Fit (TTF) framework conceptualizes this alignment as the degree to which a technology supports task requirements, predicting improved performance and user outcomes when fit is achieved (Dishaw & Strong, 1999; Goodhue & Thompson, 1995). Subsequent studies have extended TTF to educational contexts, demonstrating that task–technology alignment influences learner engagement, perceived effectiveness, and instructional efficiency in online and blended environments (Bany Mohammed et al., 2024; Wang et al., 2022).

Research integrating TTF with instructional design perspectives suggests that technologies supporting cognitive processes, feedback approaches, and task sequencing are more likely to enhance learning outcomes, particularly in structured disciplines such as mathematics (Dishaw et al., 2006; Goodhue et al., 2019). Moreover, empirical research studies in online learning platforms further indicate that when instructional systems align with learners’ task demands, students report enhanced satisfaction and improved perceptions of instructional quality (Han & Yi, 2022; O’Dell & Sulastri, 2019). However, much of this literature focuses on four-year institutions, professional training environments, or generalized online learning contexts, with limited attention to community colleges (Bany Mohammed et al., 2024; Goodhue & Thompson, 1995; Wang et al., 2022).

Despite the central role of gateway math courses in community college degree pathways, there remains a lack of empirical research exploring task–technology alignment within these courses across instructional modalities. Hence, existing TTF studies rarely address the specific cognitive and procedural demands of introductory college math coursework, nor do they adequately capture how instructional technologies support problem-solving, practice, and assessment tasks in these settings (Goodhue & Thompson, 1995; Wang et al., 2022). Consequently, a gap persists in understanding how task–technology fit operates within community college math courses across all modalities, a gap this study seeks to address through exploratory factor analysis (Bany Mohammed et al., 2024; Goodhue & Thompson, 1995).

Methods

This study used a quantitative survey to explore how tasks and technology align in gateway math courses at a local community college, applying both the TAM and Task–Technology Fit (TTF) models (Bany Mohammed et al., 2024; Goodhue & Thompson, 1995). Hence, to ensure representation of all teaching formats, data were collected from students in introductory math classes across face-to-face, hybrid, and online modalities (Goodhue & Thompson, 1995; Wang et al., 2022). The final dataset consisted of responses from 134 students, and participant demographic characteristics are summarized in Table 1.

Table 1. Participant Demographic Characteristics

Demographics	Category	n	Percent
Age Group	18–24	117	87.3
	25–34	13	9.7
	35–44	4	3.0
Gender	Male	46	34.3
	Female	86	64.2
Course Modality	Face-to-face	19	14.2
	Online	106	79.1
	Hybrid	9	6.7

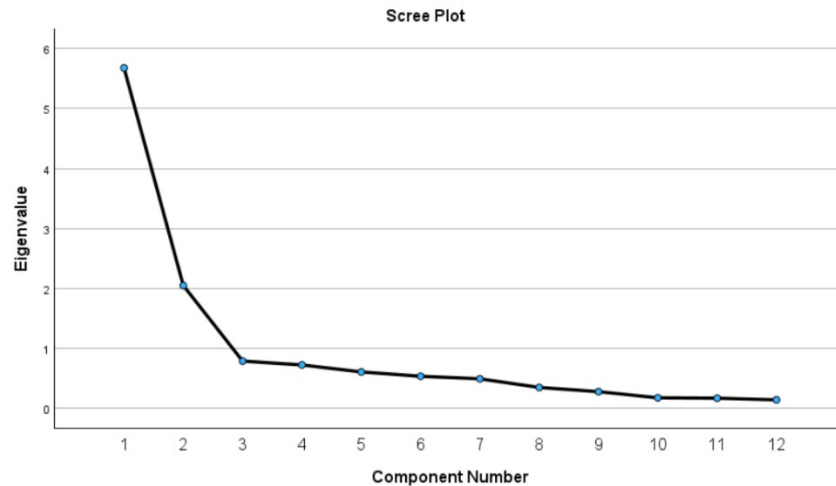
The survey included questions from established TTF measures about task and technology traits, as well as how instructional technologies fit course tasks (Dishaw & Strong, 1999; Goodhue et al., 2019). EFA with principal component extraction and varimax rotation was used to examine the tool's factor structure and match questions to TTF concepts, a common approach in early validation studies (Dishaw et al., 2006; Wang et al., 2022). Internal consistency was checked with Cronbach's alpha to ensure each factor's reliability before analysis (Goodhue & Thompson, 1995). Hence, the analysis enabled a focused examination of task–technology alignment in gateway math courses and proved appropriate for exploratory studies in community colleges.

Results

An EFA was conducted on the combined LTF and TAM – PU items to examine their underlying factor structure. Prior to factor extraction, assumptions related to sampling adequacy and factorability were evaluated. The Kaiser–Meyer–Olkin (KMO) measure of sampling adequacy was .867, indicating a meritorious level of shared variance among items, and Bartlett's test of sphericity was statistically significant, $\chi^2(66) = 987.714$, $p < .001$. Collectively, these results support the appropriateness of the correlation matrix for factor analysis and justify proceeding with factor extraction (DeVellis, 2016; Goodhue & Thompson, 1995).

Eigenvalue analysis indicated a two-factor solution with eigenvalues greater than 1.00. The first component accounted for 47.33% of the total variance, while the second component explained an additional 17.08% of the variance. Together, the two factors explained 64.41% of the total variance, exceeding commonly accepted thresholds for explanatory adequacy in educational and social science research (DeVellis, 2016; Goodhue & Thompson, 1995). Moreover, the scree plot revealed a clear point of inflection after the second component, further supporting the retention of a two-factor solution, as shown in Figure 1.

Figure 1. Scree Plot for Exploratory Factor Analysis



A varimax rotation was applied to enhance the interpretability of the factor structure, and the rotated solution produced a clear and conceptually coherent pattern of loadings. Items associated with PU loaded strongly on the first factor, with standardized loadings ranging from .706 to .901. Items representing learning-task fit loaded primarily on the second factor, with loadings ranging from .617 to .795. Cross-loading was minimal, and all retained items exceeded the .60 threshold commonly used to indicate practical significance, as seen in Figure 2.

Figure 2. Rotated Component Matrix

Rotated Component Matrix ^a		
	Component	
	1	2
Q13_TAM_PU_	.901	
Q15_TAM_PU_	.897	
Q17_TAM_PU_	.857	
Q16_TAM_PU_	.845	
Q14_TAM_PU_	.818	
Q12_TAM_PU_	.706	
Q11_TTF_LF		.795
Q9_TTF_LF		.785
Q8_TTF_LF		.703
Q7_TTF_LF		.700
Q10_TTF_LF		.631
Q6_TTF_LF		.617

Extraction Method: Principal Component Analysis.
Rotation Method: Varimax with Kaiser Normalization. ^a

a. Rotation converged in 3 iterations.

Discussion

The findings provide strong empirical support for the LTF construct as a reliable and theoretically grounded framework for understanding how educational technologies support mathematics at community colleges, particularly within first-year level coursework. Moreover, consistent with the TTF theoretical framework, an

approach that emphasizes alignment between system capabilities and task demands, the two-factor structure and strong internal consistency suggest that students evaluate technology effectiveness largely through its ability to support the cognitive and procedural requirements of learning tasks rather than through isolated system features alone (Dishaw & Strong, 1999; Goodhue & Thompson, 1995). Additionally, the results align with prior research integrating TTF with TAM frameworks, which demonstrates that task alignment strengthens perceived usefulness and engagement by grounding user perceptions in actual learning activities (Davis, 1989; Marikyan & Papagiannidis, 2023; Wang et al., 2022). Consequently, the findings extend existing Task–Technology Fit theory and empirical work into introductory math courses at two-year institutions, an area that remains underrepresented in the literature despite its importance for student success and course completion (Countermaun & Zientek, 2021; Newell & Sabawi, 2023). Finally, these findings reinforce the importance of designing and selecting learning technologies that align with structured reasoning and problem-solving demands, an implication that supports both theoretical refinement of TTF in educational settings and practical decision-making for institutions seeking to improve student engagement and learning outcomes across all learning modalities (Davis, 1989; Marikyan & Papagiannidis, 2023).

Limitations and Future Research

Despite these contributions, several limitations should be acknowledged. First, the study relied on a survey from a local community college that measured constructs associated with the students' perceptions of task–technology alignment rather than direct measures of learning performance or achievement (Goodhue & Thompson, 1995). Consequently, future research should extend this work by examining group differences using approaches such as independent-samples *t* tests and analysis of variance (ANOVA) to explore whether LTF varies across demographic characteristics and learning modalities, as well as by integrating confidence-related constructs from the Computer Attitude Questionnaire (CAQ) and core and extended Technology Acceptance Model (TAM) constructs, including PU, PEU, facilitating conditions (FC), and behavioral intention (BI), through correlational analyses and confirmatory factor analysis (CFA) within a unified measurement framework (Davis, 1989; Dishaw & Strong, 1999; Goodhue & Thompson, 1995; Wang et al., 2022).

Conclusions

This study contributes to the growing body of research examining how learning technologies function within gateway math courses at community colleges by empirically validating the LTF construct through EFA (Dishaw & Strong, 1999; Goodhue & Thompson, 1995). Moreover, consistent with the TTF framework, an approach that emphasizes alignment between task demands and technology support, the findings suggest that students evaluate learning tools primarily based on how well those tools support math problem-solving and learning processes rather than on standalone system features or technical capabilities (Bany Mohammed et al., 2024; Wang et al., 2022). Additionally, these findings highlight the importance of selecting and designing learning technologies that align with structured cognitive demands, an implication that is especially relevant for institutions serving diverse student populations across face-to-face, hybrid, and online formats (O'Dell & Sulastri, 2019). Hence, by extending TTF research into introductory math courses at community colleges, this study offers practical guidance for instructional design decisions and institutional technology adoption aimed at improving student learning experiences and course outcomes (Dishaw et al., 2006; Goodhue & Thompson, 1995).

References

- Abdekhoda, M., Dehnad, A., & Zarei, J. (2022). Factors influencing adoption of e-learning in healthcare: Integration of UTAUT and TTF model. *BMC Medical Informatics and Decision Making*, 22(1), 327. <https://doi.org/10.1186/s12911-022-02060-9>
- Alwadain A, Fati SM, Ali K, Ali RF (2024). Correction: From theory to practice: An integrated TTF-UTAUT study on electric vehicle adoption behavior. *PLoS ONE* 19(7): e0306761. <https://doi.org/10.1371/journal.pone.0306761>

- Bany Mohammed, A., Maqableh, M., Qasim, D., & AlJawazneh, F. (2024). *Exploring the factors influencing academic learning performance using online learning systems*. *Heliyon*, *10*(12), e32584. <https://doi.org/10.1016/j.heliyon.2024.e32584>
- Counterman, C., & Zientek, L. R. (2021). An investigation of differences in student success and persistence rates by course modality. *European Journal of Science and Mathematics Education*, *9*(3), 110–124. <https://doi.org/10.30935/scimath/10976>
- 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>
- 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>
- DeVellis, R. F. (2016). *Scale development: Theory and applications* (4th ed.). Sage.
- Dishaw, M. T., & Strong, D. M. (1999). Extending the technology acceptance model with task–technology fit constructs. *Information & Management*, *36*(1), 9–21. [https://doi.org/10.1016/S0378-7206\(98\)00101-3](https://doi.org/10.1016/S0378-7206(98)00101-3)
- Dishaw, M., Strong, D., & Bandy, D. B. (1999). Developing a general method to assess task-technology fit. *AMCIS 1999 Proceedings*, 211. <http://aisel.aisnet.org/amcis1999/211>
- Ebnehoseini, Z., Tabesh, H., Deghatipour, A., & Tara, M. (2022). Development an extended-information success system model (ISSM) based on nurses' point of view for hospital EHRs: a combined framework and questionnaire. *BMC Medical Informatics and Decision Making*, *22*(1), 71. <https://doi.org/10.1186/s12911-022-01800-1>
- 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>
- Goodhue, D. L., & Thompson, R. L. (1995). Task-technology fit and individual performance. *MIS Quarterly*, 213–236. <https://www.jstor.org/stable/249689>
- Marikyan, D., & Papagiannidis, S. (2023). Technology acceptance in higher education. *Education and Information Technologies*, *28*, 945–964. <http://open.ncl.ac.uk/>
- Newell, M. A., & Sabawi, O. (2023). Faculty success or student success? Factors that contribute to community college students' success in college-level math. *Journal of Applied Research in the Community College*, *30*(1), 5–29. <https://www.ingentaconnect.com/content/montezuma/jarcc/2023/00000030/00000001/art00002>
- O'Dell, J., & Sulastri, F. (2019). Technology acceptance and engagement in learning. *Journal of Educational Technology*. <https://doi.org/10.5281/zenodo.3375176>
- Sungur Gül, K., & Ateş, H. (2023). An examination of the effect of technology-based STEM education training in the framework of technology acceptance model. *Education and Information Technologies*, *28*(7), 8761–8787. <https://doi.org/10.1007/s10639-022-11539-x>

- Wang, F., Wijaya, T. T., Habibi, A., & Liu, Y. (2022). Predictors influencing urban and rural area students to use tablet computers as learning tools: Combination of UTAUT and TTF models. *Sustainability*, 14(21), 13965. <https://doi.org/10.3390/su142113965>
- Wang, J., Guo, L., Gao, J. Q., & Zhao, H. (2024). How to build better environments that reinforce adaptation of online learning?—Evidence from a large-scale empirical survey of Chinese universities. *Education and Information Technologies*, 29(14), 1–23. <https://doi.org/10.1007/s10639-024-12556-8>
- Zigurs, I., & Buckland, B. K. (1998). A theory of task/technology fit and group support systems effectiveness. *MIS Quarterly*, 313–334. <https://www.jstor.org/stable/249668>

Appendix A

Task–Technology Fit (TTF) and 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.

Task–Technology Fit (TTF) Items (Learning-Fit)

- Q6. The educational math tools fit my typical learning workflow.
- Q7. The educational math tools provide sufficient detail for my learning tasks.
- Q8. The educational math tools allow me to reach important learning resources quickly.
- Q9. The educational math tools are easy to navigate and use.
- Q10. The educational math tools operate consistently without frequent errors.
- Q11. The educational math tools present learning-related information in an understandable format.

Technology Acceptance Model (TAM) Items

Perceived Usefulness (PU)

- Q12. Using educational math tools in my math class would enable me to complete assignments more quickly.
- Q13. Using educational math tools would improve my performance in this course.
- Q14. Using educational math tools in my math class would increase my productivity.
- Q15. Using educational math tools would enhance my effectiveness in this course.
- Q16. Using educational math tools would make it easier to succeed in my math class.
- Q17. I would find educational math tools useful for my studies.