INTERNATIONAL JOURNAL OF ACADEMIC RESEARCH IN BUSINESS & SOCIAL SCIENCES
Vol 13, Issue 10, (2023) E-ISSN: 2222-6990

Adoption of an Educational-Animated Video to Enhance Learning

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To Link this Article: http://dx.doi.org/10.6007/IJARBSS/v13-i10/18873 DOI:10.6007/IJARBSS/v13-i10/18873
Published Date: *19 October, 2023*

Abstract
The adoption of innovative educational tools has become imperative to meet the evolving needs of learners in this rapid technology era. This study explores the factors influencing the adoption of animated videos as an educational tool to enhance the learning. The research is grounded in the integration of two essential frameworks: Task-Technology Fit (TTF) and the Technology Acceptance Model (TAM). A sample size of 155 participants underwent rigorous analysis employing Structural Equation Modeling (SEM). This analytical approach allowed for a comprehensive examination of the relationships among variables and the identification of critical factors impacting the adoption of animated videos in education.
Keywords: Animated Videos, Adoption, Learning, Technology Acceptance Model, Task-Technology Fit

Introduction

In the ever-evolving landscape of education, innovative tools and techniques continue to reshape the way students learn and instructors teach. One such transformative educational approach that has gained substantial attention and recognition is the utilization of educational-animated videos. These videos harness the power of visual storytelling, graphics, and animation to enhance the learning experience, engage students, and facilitate deeper comprehension of complex concepts. Illustrations of cartoon animation can provide a fun experience of learning, draw attention, build interest by getting rid of boredom and develop imaginative power. It can stimulate learners to think critically in formulating their points of view. Students can learn the concept correctly and retain the information in the brain. Cartoons also make them enjoy the learning process without realizing it (Srinivasalu, 2016). Educational-animated videos are a dynamic medium that merges the principles of multimedia learning with the captivating allure of animation. They offer a range of benefits that contribute to improved learning outcomes. The adoption of animated videos as a pedagogical tool to enhance learning among the Generation Z cohort is a critical concern. This encapsulates the need to understand the factors influencing the adoption of animated videos in education, especially among the Generation Z demographic, and the potential benefits they bring to the learning process.

While recent research suggests that the integration of the Task Technology Fit (TTF) model and the Technology Acceptance Model (TAM) can provide valuable insights into the factors influencing the adoption of educational animated videos, there remains a need to comprehensively investigate the significant determinants and barriers that affect their adoption and impact on learning outcomes. Addressing this gap is essential to facilitate more effective and engaging learning experiences for today's digitally native learners.

According to Dishaw and Strong (1999), the utilization and acceptance of technology can be better understood through an integrated model that combines the Technology Acceptance Model (TAM) and the Task-Technology Fit (TTF) model, as opposed to examining each model separately. Several studies have examined the efficacy or value of animation on learning, but relatively few have examined its actual use among learners in higher institutions. Therefore, this study aims to gain a deeper understanding of the use of Educational-Animated Video to enhance learning.

Theoretical background and research hypotheses

Animation-based learning

Numerous studies have highlighted the benefits of using animation as an educational tool. Animation can facilitate comprehension of abstract or complex concepts by providing visual representations, promoting active learning, and catering to various learning styles (Mayer, 2017). Animation can be designed to manage cognitive load effectively by presenting information incrementally and aligning with learners' cognitive processes (Sweller et al., 2011). Studies have shown that well-designed animations can reduce extraneous cognitive load, thus freeing cognitive resources for deeper learning (Tindall-Ford et al., 2010). Despite its benefits, the adoption of animation in learning is not without challenges. Issues such as the potential for cognitive overload with poorly designed animations (Kalyuga et al., 2004) and the need for proper training and resources for educators to effectively integrate animation into the curriculum are noteworthy (Dalgarno & Lee, 2010). Moreover, the effectiveness of animation may vary depending on individual differences in learner preferences and prior knowledge (Moreno & Mayer, 2007). Research has consistently demonstrated that animation's ability to provide dynamic visual representations of complex concepts fosters improved comprehension (Tversky et al., 2002). By offering vivid visualizations and real-time demonstrations, animation transcends the limitations of traditional static materials, making abstract and intricate ideas more accessible to learners. Several studies have provided empirical evidence of the positive impact of animation-based learning on educational outcomes. For instance, a study by Chien and Chang (2012) found that students who were exposed to animation-based learning demonstrated higher levels of interest and improved cognitive load management. Additionally, research has shown that animation-based learning is particularly effective in science and mathematics education (Zhang et al., 2007).

While there has been extensive study on the concepts of animation design and the benefits of animation for learning, there has been less discussion of its actual implementation in the education literature. Suki & Suki (2017) examined the determinants of students' behavioral intention to use animation and storytelling by applying the UTAUT model and found that performance expectancy played the most pertinent role as a determinant of students' behavioral intention to use animation and storytelling. Dajani & Abu Hegleh (2019) verified the factors that influence the students' behavior intention of animation usage by adapting the UTAUT2 model. They found that performance expectancy, students' innovativeness, learning value and effort expectancy were significant. Nevertheless, their primary emphasis was on the identification of exogenous elements that influence behavioral intention to adopt animation, rather than exploring the actual mechanisms of adoption in behavioral outcomes. This study aims to investigate the adoption behavior and process involved in the utilization of animation for educational purposes.

Technology Acceptance

Theories and models for gauging the success of IT adoption have been the subject of research in the field of information systems (IS). The IS success model, for instance, centres on user adoption and satisfaction with the system on the basis of system and information quality. The task technology fit model, on the other hand, evaluates IT based on how well it matches the needs of its target audience. The technology acceptance model is one of the most popular methods for predicting the spread of new technologies since it centers on the user's own evaluation of the technology's utility and simplicity. An integrated model of such theories and models has been used in this investigation of the widespread use of Educational-animated video to enhance learning.

TAM has its roots in the Theory of Reasoned Action (TRA) which sought to explain user intentions and behaviors. The Technology Acceptance Model (TAM) developed by Davis (1989), TAM posits that users' acceptance of technology is primarily influenced by two key factors: perceived usefulness (PU) and perceived ease of use (PEOU). Perceived usefulness refers to the user's belief that the technology will enhance their job performance, while perceived ease of use reflects the user's perception of how effortless it is to use the technology. TAM has been extensively validated and applied in various contexts (Davis, 1989). The user's disposition exhibits a propensity towards the behavioral desire to utilise or embrace the technology, thus impacting their actual usage behavior. The technology acceptance model is centered around the user's acceptance of technology, which is determined by their perceived of usefulness (PU) perceived ease of use (PEOU) (see to Figure 1). The use and examination of this phenomenon have been widely employed and rigorously evaluated in empirical investigations pertaining to the adoption of technology. This paper presents a proposed integrated model that expands upon the technology acceptance model by incorporating ideas of task-technology fit. In order to assess the acceptance of technology in the integrated model of animation adoption to enhance learning, we utilise the technology acceptance model proposed by Davis et al (1989) and present the following set of five hypotheses.

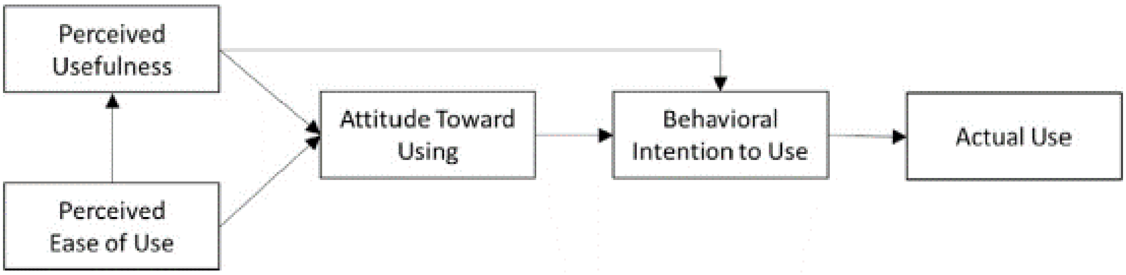

Figure 1: Technology acceptance model (Davis et al., 1989).

H1. Perceived ease of use will affect perceived usefulness in using Educational-Animated Video to Enhance Learning.
H2. Perceived usefulness will affect the intention to use Educational-Animated Video to Enhance Learning.
H3. Perceived usefulness will affect the attitude toward using Educational-Animated Video to Enhance Learning.
H4. Attitude toward use will affect the intention to use Educational-Animated Video to Enhance Learning.
H5. Intention to use will affect the actual use of Educational-Animated Video to Enhance Learning.

Task Technology Fit

The TTF model, introduced by Goodhue and Thompson in 1995, complements TAM by emphasizing the alignment between technology and specific tasks or job requirements. It suggests that the degree to which technology supports and fits with users' tasks significantly affects their performance and satisfaction. The authors present a theoretical model depicting the technology-to-performance link, as seen in Figure 2.

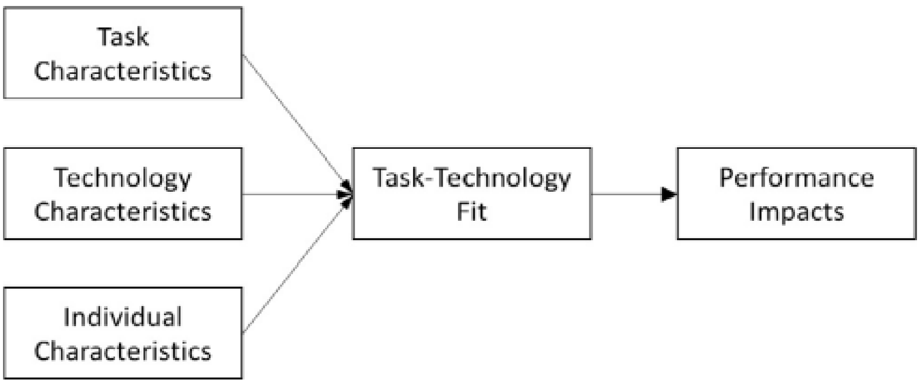

Figure 2: Theories of fit in the technology-to-performance chain (Goodhue & Thompson, 1995)

According to the proposition put forth by Goodhue and Thompson (1995), the antecedents of task technology fit can be attributed to the dynamic interactions that occur among the task, technology, and individual. In the context of our integrated model, the incorporation of technology is based on the theoretical framework of fit in the technology-to-performance chain, as established by (Goodhue and Thompson, 1995). Previous research on task technology fit has largely neglected the inclusion and examination of individual variables. The suggested model does not incorporate task characteristics due to the simplicity of the task involving the usage of Educational-Animated Video to Enhance Learning. As a result, there may be limited changes to assess in terms of complexity, non-routineness, or interdependence. Therefore, the present study formulates and examines the following hypothesis within our research framework.

H6. Technology characteristics will positively affect the fit of using Educational-Animated Video to Enhance Learning.

Integration of theories of technology acceptance and task technology fit

The integration of the Technology Acceptance Model (TAM) and the Task-Technology Fit (TTF) model has emerged as a comprehensive framework for understanding technology adoption and usage in various domains. Dishaw and Strong (1999) applied an integrated model to examine the factors affecting user acceptance of enterprise resource planning (ERP) systems, highlighting the importance of both perceived usefulness and task alignment.

In their study, Dishaw and Strong (1999) put forth a comprehensive model that builds upon the Technology Acceptance Model (TAM) by incorporating task-technology fit characteristics. Through empirical testing, they determined that the integrated model offers a higher degree of explanatory capability compared to either model in isolation. Lederer, Maupin, Sena, and Zhuang (2000) put out an integrated model that expanded upon the technological acceptance model by incorporating information quality, a significant determinant in the IS success model. This model was subsequently empirically examined within the context of web site adoption. In a more recent study, Yen et al (2010) undertook the task of adapting and conducting empirical testing on the integrated model for wireless technology adoption inside organisational contexts. Previous studies in the field of IT adoption have put forth and examined integrated models in order to enhance explanatory capabilities and get a deeper understanding of IT adoption across various contexts. To construct a comprehensive framework for the adoption of multimedia technology, we used concepts derived from previous studies on the acceptance of technology and the alignment of technology with tasks. Dishaw and Strong (1999) put up a theoretical proposition regarding a robust correlation between fit and perceived usefulness. However, their empirical findings were unexpected as they did not see a statistically significant relationship. Yen et al (2010) conducted additional research on the integrated model, specifically examining the direct relationship between fit and perceived usefulness. However, their findings did not yield statistically significant results. However, the task technology fit research provides theoretical support for this notion, since it suggests that performance outcomes are influenced by a combination of efficiency, effectiveness, and quality (Goodhue & Thompson, 1995). These outcomes are commonly referred to as usefulness in the Technology Acceptance Model (TAM). This study aims to examine the impact of fit on perceived usefulness by integrating the Technology Acceptance Model (TAM) and the Task-Technology Fit (TTF) framework. The following hypotheses are proposed.

H7. Task technology fit will positively affect perceived usefulness in using Educational-Animated Video to Enhance Learning.

In their study, Mathieson and Keil (1998) conducted a laboratory experiment with the aim of examining the association between task technology fit and perceived ease of use. Their findings indicated that neither task nor technology individually determines perceived ease of use. However, they observed that the interaction between task and technology, known as task technology fit, significantly influences perceived ease of use. The findings of the study align with previous research that indicates a correlation between inadequate task technology fit and a decrease in perceived usefulness (Keil et al., 1995). According to Dishaw and Strong (1999), it was also discovered that when there is a strong alignment between the technology and the task at hand, user tend to perceive the technology as easy to use for the task. Therefore, the present study puts out the subsequent hypothesis regarding the integration of Technology Acceptance Model (TAM) and Task-Technology Fit (TTF).

H8. Task technology fit will positively affect perceived ease of use in Educational-Animated Video to Enhance Learning.
Figure 3 depicts a conceptual framework illustrating the suggested integrated model of Educational-Animated Video to enhance learning.

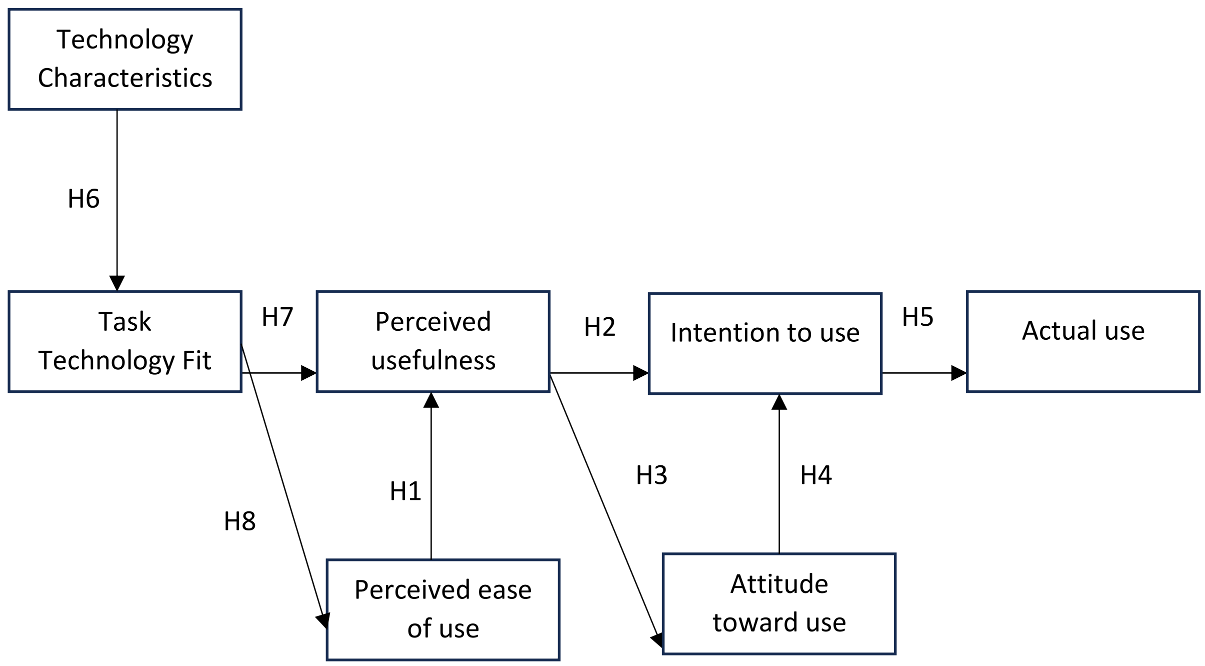

Figure 3: Proposed integrated model for adoption of Educational-Animated Video to enhance learning

Research Methodology
To gather the necessary data, convenience sampling was utilized. This involved students who are enrolled in the subject Economics from the Faculty of Business Management at University Technology MARA. The questionnaire was distributed to 155 students through an online survey Google form among students who specifically experienced using an animation video during an Economics class. In addition, five weeks before the final examination, the instructors have prepared an application that consists of an animation video for every

subtopic in the syllabus for revision. We considered all the students who had experienced watching an educational animated video before the surveys were collected.

The survey instrument utilized in this study was derived from prior research conducted by (Davis, 1989; Klopping and McKinney, 2004; Mathieson and Keil, 1998; Park and Raven, 2015; Park, et al., 2019). The construct of technological characteristics was operationalized through the utilization of questions that evaluate the quality of technology. The fit notion was operationalized by measuring user perceptions of fit. The constructs of ease of use, usefulness, attitude, intention to use, and actual usage were derived from the existing body of literature on the Technology Acceptance Model (TAM) and incorporated into the study. The concluding survey comprises two demographic inquiries and twenty-nine Likert-type items (1 = strongly disagree, 2 = disagree, 3 = neutral, 4 = agree, 5 = strongly agree).

Table 1 shows the key aspects of the demographic structure of respondents most of the respondents are female (75.5%) and male is 38% out of 155 sample size. The versions 27 statistical software SPSS and Amos 28 were used for testing. Microsoft Excel was used to update the collected data. A useable dataset for Amos was then prepared by transferring the data to SPSS, where question-based variables were created, along with mean values, standard deviations, and Cronbach's alpha. Table 2 displays descriptive statistics for each variable. All variables have Cronbach's alpha values higher than 0.70, the threshold for statistical significance (Taber, 2018).

Table 1
Demographic structure of respondents

Respondents' Demographic Frequency			**%**
Gender	Male	38	24.5
	Female	117	75.5
Age	18 to 20	150	96.8
	21 to 23	4	2.6
	24 to 26	1	0.6

Table 2
Descriptive statistics

Variables	**Mean**	**Standard deviation**	**Cronbach's α**
TC	20.20	3.268	0.934
FIT	20.46	2.838	0.907
PU	20.16	3.044	0.924
PEOU	20.27	3.115	0.935
ATT	11.54	2.117	0.914
LV	11.91	1.813	0.894
IU	5.818	2.412	0.910
ACT	8.04	1.258	0.861

The internal consistent reliability of the measures utilized in this investigation is therefore acceptable (Sakaran, 1992). This shows a positive perception of using educational-animated videos among the students.

Analysis of Results
Measurement Model
To verify the measurement models, Confirmatory Factor Analysis (CFA) was computed using AMOS. Factor loadings were checked for each item as part of the confirmatory factor analysis, and one item (ACT3) was deleted due to low factor loadings (0.50). The model's overall goodness of fit was assessed using model-fit measures such as CMIN/df, GFI, CFI, TLI, SRMR, and RMSEA. All values met the recommended threshold acceptance levels (Ullman, 2001; Hu and Bentler, 1998, Bentler, 1990) except for GFI is marginally fit. The GFI measures have been criticized for being outdated in recent years due to their sensitivity and bias (Sharma et al, 2005). This indicates that the model is adequately constructed, and that the data fit the model. Table 3 provides a comprehensive summary of fit indices values and recommended values.

Table 3
CFA Statistics of Model Fit

Fit Indices	Recommended Value	Sources	Obtained Value
CMIN ($\chi 2$/df)	3-5	Less than 2 (Ullman, 2001) to 5 (Shumacker & Lomax, 2004)	1.922
GFI	>0.90	Hair et al (2010)	0.782
CFI	>0.90	Bentler, 1990	0.928
TLI	>0.90	Bentler, 1990	0.917
SRMR	<0.80	Hu and Bentler, 1998	0.043
RMSEA	<0.80	Hu and Bentler, 1998	0.077

Construct Reliability was assessed using Cronbach's Alpha and Composite Reliability. Cronbach's Alpha, we calculated using SPSS and shown in table 2 above. Cronbach Alpha for each construct in the study was found over the required limit of 0.70 (Nunnally and Bernstein, 1994). Composite reliabilities ranged from 0.727 to 0.931, above the 0.70 benchmark (Hair et al., 2010). Hence, construct reliability was established for each construct in the study (Table 4).

The convergent validity of scale items was estimated using the Average Variance Extracted (Fornell & Larcker,1981). The average variance-extracted values were above the threshold value of 0.50 (Fornell & Larcker, 1981). Therefore, the scales used for the present study have the required convergent validity (Table 4).

Table 4
Analysis of item loadings and reliability

Construct	Item	Loadings	Composite Reliability	AVE
Technology Characteristics	TC1	**0.819**	**0.931**	**0.73**
	TC2	**0.858**		
	TC3	**0.867**		
	TC4	**0.844**		
	TC5	**0.881**		
Fit	FIT1	**0.812**	**0.896**	**0.63**
	FIT2	**0.76**		
	FIT3	**0.748**		
	FIT4	**0.831**		
	FIT5	**0.826**		
Perceived Usefulness	PU1	**0.807**	**0.918**	**0.69**
	PU2	**0.825**		
	PU3	**0.786**		
	PU4	**0.868**		
	PU5	**0.87**		
Perceived Ease of Use	PEOU1	**0.846**	**0.94**	**0.76**
	PEOU2	**0.858**		
	PEOU3	**0.922**		
	PEOU4	**0.839**		
	PEOU5	**0.886**		
Attitude	ATT1	**0.848**	**0.916**	**0.77**
	ATT2	**0.921**		
	ATT3	**0.885**		
Intention to Use	IU1	**0.817**	**0.882**	**0.7**
	IU2	**0.863**		
	IU3	**0.853**		
Actual Use	ACT1	**0.869**	**0.727**	**0.73**
	ACT2	**0.869**		

To determine the distinctiveness of the constructs, discriminant validity is established. It demonstrates that the constructs in the study have their own distinct identities and are not overly connected with other factors (Bagozzi et al., 1991). Discriminant validity in the study was assessed using Heterotrait-Monotrait (HTMT) Ratio. All ratios were less than the required limit of 0.85 using the strict HTMT criterion and less than 0.90 using the liberal HTMT criterion for constructs intention to use, actual use, perceived to use and task technology fit (Table 5). Henseler et al (2015) propose a threshold value of 0.90 for structural models with constructs that are conceptually very similar. When constructs are conceptually more distinct, a lower, more conservative, threshold value is suggested, such as 0.85 (Henseler et al., 2015). He also mentions in his study, that the construct of the technology acceptance model such as intention to use and actual use are difficult to distinguish empirically (Henseler et al., 2015).

Table 5
Factor Correlations

	TC	FIT	PU	PEOU	ATT	IU	ACT
TC							
FIT	0.69						
PU	0.75	0.88					
PEOU	0.73	0.82	0.88				
ATT	0.53	0.74	0.78	0.69			
IU	0.65	0.74	0.84	0.82	0.79		
ACT	0.61	0.80	0.87	0.83	0.78	0.87	

Structural Model

Subsequently, the structural model (Figure 4) was subjected to testing. In the structural equation model (SEM) examined, several path coefficients were estimated to understand the relationships among the latent constructs. These path coefficients represent the strength and direction of the associations between the variables. The findings presented in Table 6 demonstrate that the suggested model has provided support for all eight hypothesized direct paths. All five paths in the technology acceptance model are significant. The path from PEOU to PU is significant (β = 0.419, SE = 0.102, CR = 3.633, p < .001), supporting H1. The path from PU to IU is significant (β = 0.692, SE = 0.096, CR = 7.148, p < .001), supporting H2. The path from PU to ATT is significant (β = 0.791, SE = 0.097, CR = 9.484, p < .001), supporting H3. The path from ATT to IU is significant (β = 0.280, SE = 0.070, CR = 3.422, p < .001), supporting H4. The path from IU to ACT is highly significant (β = 0.925, SE = 0.088, CR = 11.410, p < .001), supporting H5. For the path in the theories of task technology fit is significant, with the path from TC to FIT highly significant (β = 0.777, SE = 0.079, CR = 8.929, p < .001), supporting H6. The last two paths for integrating the TAM and the theories of task technology fit are also significant. The path from FIT to PU is significant (β = 0.562, SE = 0.123, CR = 4.607, p < .001), supporting H7. The path from FIT to PEOU is perfectly significant (β = 0.884, SE = 0.098, CR = 10.199, p < .001) thus supporting H8.

Examining the variance explained, the R^2 value, of the final dependent construct, allows one to assess the explanatory power of a research model. The results indicate that the predictor variables exhibit varying degrees of explanatory power, ranging from moderate to strong. The R^2 score for the actual use in the proposed model was 0.857, suggesting that the research model accounted for 85.7% of the variance in the dependent variable. It is higher than other integrated models in which the R^2 value of actual use was 0.51 (Dishaw & Strong, 1999), and 0.55 (Park et al., 2019). The R^2 for the key constructs that integrate TAM and the theories of task technology is also higher than prior research. R^2 value for perceived usefulness 0.909 is substantially high compared to Park et al. (2019), 0.67, while for R^2 value for perceived ease of use is 0.781 higher than another integrated model 0.41 (Park et al., 2019).

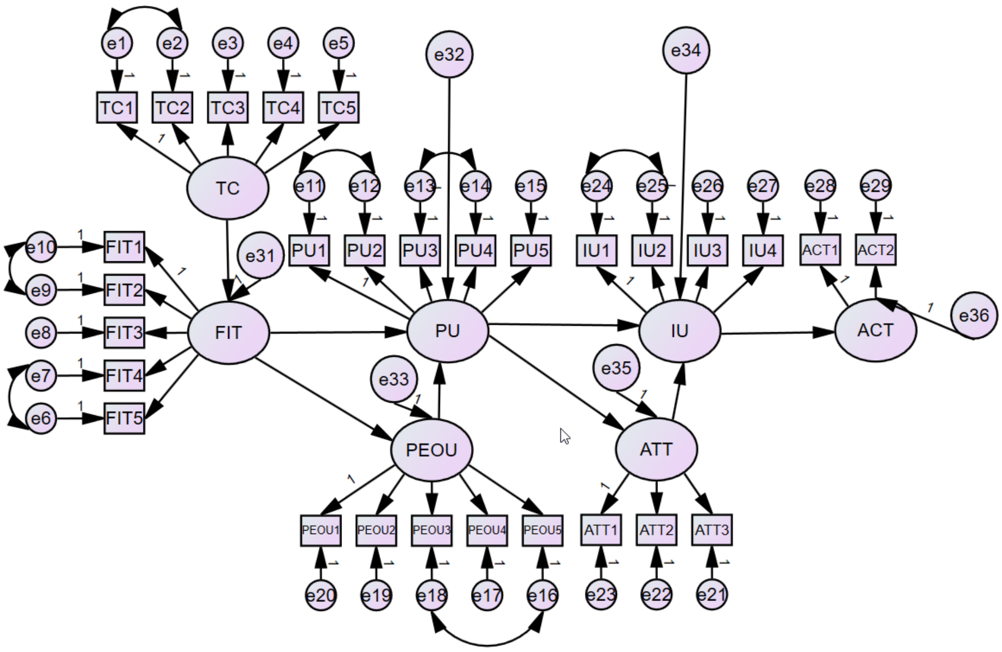

Figure 4: Structural Model

Table 6
Results of Path Tests

Path			Estimate	S.E.	C.R.	P-value	Decision
FIT	<---	TC	.777	.079	8.929	***	Supported
PEOU	<---	FIT	.884	.098	10.199	***	Supported
PU	<---	FIT	.562	.123	4.607	***	Supported
PU	<---	PEOU	.419	.102	3.633	***	Supported
ATT	<---	PU	.791	.097	9.484	***	Supported
IU	<---	PU	.692	.096	7.148	***	Supported
IU	<---	ATT	.280	.070	3.422	***	Supported
ACT	<---	IU	.925	.088	11.410	***	Supported

Conclusion

Based on the results of the structural equation model, it is evident that the paths between these constructs are highly significant, indicating robust relationships among them. To further enhance the understanding and applicability of these findings, it is recommended to conduct additional analyses or investigations to explore the underlying mechanisms and practical implications of these relationships in the context of specific research or application areas. Furthermore, these findings underscore the importance of task-technology fit in influencing users' perceptions and behaviors related to technology adoption and use. A well-fitting technology that is perceived as easy to use and useful can positively influence users' attitudes and intentions to use, ultimately leading to actual usage. This has significant implications for the design and implementation of technology in various contexts, emphasizing the need to prioritize alignment with users' tasks and to enhance technology acceptance and utilization. Further research could focus on identifying potential mediators or moderators that may influence these relationships and examining their impact on educational or practical outcomes. Additionally, considering the significance of these relationships, practitioners and educators may find it beneficial to prioritize strategies that leverage these constructs to optimize learning or operational processes. The findings also reveal substantial variability explained by the predictor variables in the model. The implications of these findings suggest the importance of these predictor variables in understanding and predicting the observed outcomes in the structural equation model. These insights provide valuable information for researchers and practitioners seeking to comprehend and model the complex relationships between these constructs, particularly in the context of structural equation modeling.

References

Bentler, P. M. (1990). Comparative fit indexes in structural models. *Psychological bulletin*, *107*(2), 238.

Collier, J. E. (2020). *Applied structural equation modeling using AMOS: Basic to advanced techniques*. Routledge.

Chien, T. H., & Chang, C. C. (2012). Research and development of an animation teaching system for students' learning interest and cognitive loads. Computers & Education, 58(1), 243-252.

Clark, R. C., & Mayer, R. E. (2016). E-learning and the Science of Instruction: Proven Guidelines for Consumers and Designers of Multimedia Learning (4th ed.). Wiley.

Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. MIS Quarterly, 13(3), 319-340.

Dalgarno, B., & Lee, M. J. (2010). What are the learning affordances of 3-D virtual environments? British Journal of Educational Technology, 41(1), 10-32.

Dajani, D., & Abu Hegleh, A. S. (2019). Behavior intention of animation usage among university students. Heliyon, 5(10), e02536. https://doi.org/10.1016/j.heliyon.2019.e02536

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

Fornell, C., & Larcker, D. F. (1981). Structural equation models with unobservable variables and measurement error: Algebra and statistics.

Srinivasalu, G. N. (2016). Using Cartoons as Effective Tools in Teaching Learning Process of Social Science. Scholarly Research Journal for Interdisciplinary Studies. 3(23), 1898-1905.

Goodhue, D. L., & Thompson, R. L. (1995). Task-Technology Fit and Individual Performance. *MIS Quarterly*, *19*(2), 213–236. https://doi.org/10.2307/249689

Henseler, J., Ringle, C. M., & Sarstedt, M. (2015). A new criterion for assessing discriminant validity in variance-based structural equation modeling. Journal of the Academy of Marketing Science, 43(1), 115–135.

Hu, L. T., & Bentler, P. M. (1998). Fit indices in covariance structure modeling: Sensitivity to under parameterized model misspecification. *Psychological methods*, *3*(4), 424.

Kline, R. B. (2011). Principles and practice of structural equation modeling (3rd ed.). The Guilford Press.

Keil, M., Beranek, P., & Konsynski, B. (1995). Usefulness and ease of use: Field study evidence regarding task considerations. Decision Support Systems, 13(1), 75-91. https://doi.org/10.1016/0167-9236(94)E0032-M.

Kalyuga, S., Chandler, P., & Sweller, J. (2004). When redundant on-screen text in multimedia technical instruction can interfere with learning. Human Factors: The Journal of the Human Factors and Ergonomics Society, 46(3), 567-581.

Klopping, I. M., & McKinney, E. M. (2004). Extending the technology acceptance model and the task-technology fit model to consumer e-commerce. Information Technology, Learning, and Performance Journal, 22(1), 35–48.

Khedekar, R. S., & Peters, G. B. (2013). Fit between task requirements and system features: A replication study. Journal of Computer Information Systems, 54(4), 70-78.

Lin, H. C., Hsieh, Y. H., & Pi, S. M. (2010). Effects of animated instructional materials on students' achievement and attitudes. Computers & Education, 55(2), 722-733.

Lim, J., Kim, Y., Chen, J. V., & Ryder, C. (2008). Extending the task-technology fit model with self-efficacy constructs. AMCIS 2008 Proceedings, 285.

Lederer, A. L., Maupin, D. J., Sena, M. P., & Zhuang, Y. (2000). The technology acceptance model and the World Wide Web. Decision Support Systems, 29(3), 269–282.

Legris, P., Ingham, J., & Collerette, P. (2003). Why do people use information technology? A critical review of the technology acceptance model. Information & Management, 40(3), 191-204.

Mayer, R. E. (2017). Using multimedia for e-learning. Journal of Computer Assisted Learning, 33(5), 403-423.

Mayer, R. E. (2009). Multimedia Learning (2nd ed.). Cambridge University Press.

Moreno, R., & Mayer, R. E. (2007). Interactive multimodal learning environments. Educational Psychology Review, 19(3), 309-326.

Mathieson, K., & Keil, M. (1998). Beyond the interface: Ease of use and task/technology fit. Information & Management, 34(4), 221–230.

Nunnally, J. C., and Bernstein, I. H. (1994) The Assessment of Reliability. Psychometric Theory, 3, 248-292.

Park, C., & Raven, A. (2015). Information quality as a determinant of task-technology fit in using communication technology for simple task. Issues in Information Systems, 16(1), 189–199.

Park, C., Kim, D. G., Cho, S., & Han, H. J. (2019, March). Adoption of multimedia technology for learning and gender difference. *Computers in Human Behavior*, *92*, 288–296. https://doi.org/10.1016/j.chb.2018.11.029

Ullman, J. B. (2001). Structural equation modeling. In B. G. Tabachnick & L. S. Fidell (2001). Using Multivariate Statistics (4th ed& pp 653- 771). Needham Heights, MA: Allyn & Bacon.

Spanjers, I. A. E., Wouters, P., van Gog, T., & van Merriënboer, J. J. G. (2011). An expertise reversal effect of segmentation in learning from animated worked-out examples. Computers in Human Behavior, 27(1), 46-52.

Sharma, S., Mukherjee, S., Kumar, A., and Dillon, W. R. (2005), "A simulation study to investigate the use of cutoff values for assessing model fit in covariance structure models," Journal of Business Research, 58 (1), 935-43.

Sweller, J., Ayres, P., & Kalyuga, S. (2011). Cognitive load theory. Springer.

Suki, N. M., & Suki, N. M. (2017). Determining students' behavioural intention to use animation and storytelling applying the UTAUT model: The moderating roles of gender and experience level. The International Journal of Management Education, 15(3), 528–538. https://doi.org/10.1016/j.ijme.2017.10.002

Taber, K. S. (2018) The use of cronbach's alpha when developing and reporting research instruments in science education. Res Sci Educ 48:1273–1296.

Tindall-Ford, S., Chandler, P., & Sweller, J. (2010). When two sensory modes are better than one. Journal of Experimental Psychology: Applied, 16(2), 163-181.

Tversky, B., Morrison, J. B., & Betrancourt, M. (2002). Animation: Can it facilitate? International Journal of Human-Computer Studies, 57(4), 247-262.

Sekaran, U. (1992). Research Methods for Business: A Skill-Building Approach. New York: John Wiley & Sons, Inc.

Yen, D. C., Wu, C.-S., Cheng, F.-F., & Huang, Y.-W. (2010). Determinants of users' intention to adopt wireless technology: An empirical study by integrating TTF with TAM. Computers in Human Behavior, 26(5), 906–915.

Zhang, D., Zhou, L., Briggs, R. O., & Nunamaker Jr, J. F. (2006). Instructional video in e-learning: Assessing the impact of interactive video on learning effectiveness. Information & Management, 43(1), 15-27.