Research Square

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Modeling Artificial Intelligence Tool Adoption in Mathematics Teacher Education: A TAM-Based Structural Equation Modeling

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Abstract

The role of Artificial Intelligence (AI) in the education of mathematics teachers is going to become an innovative phenomenon in the rapidly changing world of education. Nonetheless, the pre-service educators do not uniformly embrace AI tools, which makes it necessary to conduct a more nuanced study of the factors that may influence this adoption. The study employs an augmented Technology Acceptance Model (TAM) to simulate AI adoption intentions among 268 pre-service mathematics teacher educators in Patna, India. This model is based on the major constructs of the TAM, including Perceived Usefulness (PU), Perceived Ease of Use (PEOU), Attitude Towards Use (ATU), and Behavioural Intention (BI), with two key external variables, i.e., Technological Self-Efficacy (TSE) and Facilitating Conditions (FC). The validity of the measurement model was determined through the Confirmatory Factor Analysis (CFA), followed by testing the hypotheses using the Maximum Likelihood Estimation.

The results highlight that PU had a strong influence on both PEOU and ATU, whereas PEOU had a positive influence on ATU, which validates the significant TAM relations. However, the direct impact of TSE and FC was relatively low, which indicates the complex combination of the impacts of technological belief systems and contextual enablers. The fit indices of all models were more than the standard threshold (e.g., CFI = 1.000, RMSEA = 0.000), which validates the robustness of the model. The findings can provide an empirical base for policymakers and educators who want to introduce AI preparedness into teacher training, and the Technology Acceptance Model adds theoretical value in AI-enhanced learning environments.

INTRODUCTION

Artificial Intelligence (AI) in teaching and learning has become a growing focus of research and institutional interest, especially within the mathematics teacher education community. Also, the AI tools, such as Intelligent tutoring systems, automated assessment engines, and adaptive learning platforms, redefine the mode of introducing, practicing, and strengthening mathematical concepts in classes (Holmes et al., 2019; Zawacki-Richter et al., 2019). However, such types of tools not only supplement pedagogical activities but also provide personalized support and intellectual feedback that follow individual learner paths (Luckin & Holmes, 2016). Yet, despite these developments, the adoption and continuous use of AI technologies among pre-service mathematics teachers remain inconsistent, primarily due to the differences in perception, digital readiness, and institutional support (Ifinedo, 2012; Moroianu et al., 2023).

Thus, a strong theoretical framework is essential for understanding the backgrounds of AI adoption in teacher education. Against this backdrop, the Technology Acceptance Model (TAM), proposed by Davis (1989) has become a strong theoretical background in exploring user acceptance of emerging technologies. According to TAM, there are two cognitive beliefs, including Perceived Usefulness (PU) and Perceived Ease of Use (PEOU), that influence users' attitudes towards technology, which ultimately determine their Behavioural Intention (BI) to use it. Over the years, the model has been tested in a variety of technological settings and modified to fit in different population groups such as teachers, students, and administrators (Scherer et al., 2019; Teo, 2011; Venkatesh & Davis, 2000).

AI tools offer distinct opportunities in the context of mathematics education, where abstract thinking and conceptual clarity are paramount. As an example, intelligent learning environments have the capability to render abstract mathematical procedures visible and provide instantaneous adaptive feedback, which increases the effectiveness of instructions and engagement of learners (Moroianu et al., 2023). Nevertheless, the effective adoption in pre-service teacher education depends on how future teachers believe and integrate these technologies into their ways of pedagogy(Yuen et al., 2003).

To incorporate TAM within the realm of AI in mathematics teacher education, researchers have suggested including external variables that ensure the socio-cognitive and infrastructural aspects of technology utilization. Technological Self-Efficacy (TSE) is one of such constructs, describing an individual's belief in his or her capacity to effectively use digital tools (Compeau & Higgins, 1995a). As multiple studies have discovered, Technological Self-Efficacy (TSE) has a direct impact on both Perceived Usefulness (PU) and Perceived Ease of Use (PEOU), which makes it a decisive factor in the formation of digital adoption attitudes(Holden & Rada, 2011; Jensen et al., 2021). Even in teacher training contexts, self-efficacy not only

influences whether educators believe they can use AI but also their willingness to experiment pedagogically with it (Holmes et al., 2019).

Meanwhile, Facilitating Conditions (FC) have equally been identified as important antecedents of technology use behaviour. Some of the conditions that should be facilitated include access to technical infrastructure, administrative facilitation, and access to professional development (Venkatesh & Davis, 2000) Contextual factors in teacher education settings, such as the presence of curriculum reform and institutional resistance, may co-exist, wherein facilitating conditions can be both a prerequisite and a limiting factor to the use of AI tools(Alraimi et al., 2015; Ifinedo, 2012). Indicatively, the absence of instructional alignment or inadequate technical support can discourage even the most technologically proficient teacher candidates from working with AI applications in mathematics classrooms.

Although some past researchers have used TAM to study the different educational technologies (e.g., e-learning systems, mobile-based learning, or learning management systems), little research has used it to examine AI-specific tools in mathematics teacher education(Scherer et al., 2019; Tondeur et al., 2017). In addition, the relationship between the TAM constructs and other predictors, including TSE and FC, should be empirically established to maintain contextual integrity. Indeed, according to Zawacki-Richter et al. (2019), the effective implementation of AI in higher education requires not only technological advances but also the psychological preparedness of educators and their access to structures.

Due to these gaps, the current study aims to develop and empirically examine a structural model of TAM with extensions comprising TSE and FC to gain insights into the behavioural intention of pre-service mathematics teachers to adopt AI tools. The study aligns with the convergence of technology acceptance theory, mathematics pedagogy, and teacher training, thereby filling an urgent gap in the provision of evidence-based models to guide educational technology policy and practice.

TECHNOLOGY ACCEPTANCE MODEL (TAM)

The Technology Acceptance Model (TAM) was developed by Davis (1989) as a theoretical framework for predicting and explaining the acceptance and usage of technology by individuals. It holds that two major cognitive beliefs; Perceived Usefulness (PU), which refers to the extent to which an individual believes that the use of a certain system would improve job performance, and Perceived Ease of Use (PEOU), which is the extent to which an individual believes that using the system would not be accompanied by any effort, directly affect Attitude Towards Use (ATU) of the user and subsequently Behavioural Intention (BI) to use the technology. TAM has been broadly tested and stretched over time in education and organizational settings, which confirms its strength and applicability (Venkatesh & Davis, 2000). Although PU has a significant influence on BI by way of affecting ATU, PEOU indirectly influences BI by way of influencing PU and ATU. The ease of the model, its generalizability, and the accuracy of its predictions have established it as a prevailing model in the study of technology adoption, even in other fields like e-learning, mobile apps, and smart educational tools (Scherer et al., 2019; Tondeur et al., 2017). Its flexibility also enables the inclusion of external factors like Technological Self-Efficacy and Facilitating Conditions to be incorporated, making it more contextually applicable in research such as AI adoption in teacher education.

The objectives of the study are:

1. To study the direct and indirect relationship among PU, PEOU, ATU, BI, TSE, and FC using Structural Equation Modeling (SEM).
2. To test the mediation effects within the model for the influence of Perceived Usefulness (PU) on the relationship between Technological Self-Efficacy (TSE) and Attitude Toward Use (ATU).
3. To suggest the pedagogical implications for mathematics teacher educators and policymakers, which aim to integrate AI into instructional frameworks.

HYPOTHESES OF THE STUDY

1. Technological Self-Efficacy significantly influences Perceived Usefulness.
2. Facilitating Conditions significantly influence Behavioural Intention to Use.
3. Perceived Usefulness significantly influences Perceived Ease of Use.
4. Behavioural Intention to Use significantly influences Perceived Ease of Use.
5. Perceived Usefulness significantly influences Attitude Towards Use.
6. Perceived Ease of Use significantly influences Attitude Towards Use.

METHODOLOGY

This study employed a quantitative, cross-sectional research design, which is grounded in the theoretical framework of Structural Equation Modeling (SEM) to investigate the structural relationships among latent constructs that influence the adoption of artificial intelligence (AI) tools in mathematics teacher education. The model was designed around an extended Technology Acceptance Model (TAM), which integrates the variables such as Technological Self-Efficacy (TSE), Facilitating Conditions (FC), Perceived Usefulness (PU), Perceived Ease of Use (PEOU), Attitude Towards Use (ATU), and Behavioural Intention to Use (BI). The sample of the study consists of 268 pre-service teacher educators who were enrolled in teacher education institutions across the Patna district of Bihar, India. The Purposive sampling technique was used to ensure representation from various institutional types and academic streams. Participation was voluntary, and informed consent was obtained from all respondents in accordance with ethical research standards.

Instrumentation

A pre-designed, psychometrically validated questionnaire based on well-established sources was used to collect data on the six latent variables. Each construct was defined using several indicators on a five-point Likert scale, with options for strongly disagree and strongly agree. Expert validation of the instrument was conducted to assess its content validity, internal consistency, and clarity. Cronbach's Alpha was used to assess the reliability of the **AI Tool Adoption Perception Scale**, consisting of 36 statements, which yielded a coefficient of **0.869**.

Ethical Consideration

Ethical permission was obtained from the relevant institutional review board prior to data collection. The respondents were informed that their answers would remain confidential and anonymous, that it was a totally voluntary exercise, and that he/she could withdraw at any point in the research.

RESULT & DISCUSSION

Figure 1 shows the first Confirmatory Factor Analysis (CFA) model, which represents the hypothesised latent constructs-Perceived Usefulness (PU), Perceived Ease of Use (PEOU), Attitude Towards Use (ATU), Behavioural Intention to Use (BI), Technological Self-Efficacy (TSE), and Facilitating Conditions (FC) with their corresponding observed variables. Although the model attained an initial adequate structure of identifying latent constructs, some factor loadings and modification indices suggested a possible measurement overlap and cross-loadings. Such restrictions prompted the following refinement stage to guarantee the improved representation and interpretability of the latent dimensions (Hair et al., 2013).

The adjusted CFA model is displayed in Fig. 2 and indicates that the factor loadings and the removal of cross-loadings have been substantially improved, as well as the construct reliability. The final model is consistent with good practices in structural validation, which provides evidence of the strong measurement model. The iteration not only increased the statistical adequacy but also the theoretical integrity through the strengthening of the special role of each indicator to its latent construct (Fornell & Larcker, 1981; Hair et al., 2013).

Table 1
Reliability and Convergent Validity

Variables/Constructs	Items	Standardized Factor Loadings	Composite Reliability	Average Variance Extracted	Maximum Shared Variance
PERCEIVED USEFULNESS	**PU 1**	.707	0.906	0.618	0.367
	PU 2	.830			
	PU 3	.892			
	PU 4	.752			
	PU 5	.796			
	PU 6	.724			
PERCEIVED EASE OF USE	**PEOU 1**	.721	0.907	0.621	0.133
	PEOU 2	.888			
	PEOU 3	.795			
	PEOU 4	.796			
	PEOU 5	.746			
	PEOU 6	.773			
ATTITUDE TOWARDS USE	**ATU 1**	.841	0.941	0.698	0367
	ATU 2	.888			
	ATU 3	.866			
	ATU 4	.891			
	ATU 5	.836			
	ATU 6	.790			
	ATU 7	.721			
BEHAVIOURAL INTENTION TO USE	**BI 1**	.712	0.882	0.602	0.125
	BI 2	.888			
	BI 3	.843			
	BI 4	.629			
	BI 5	.780			
TECHNOLOGICAL SELF-EFFICACY	**TSE 1**	.590	0.836	0.510	0.045
	TSE 2	.820			
	TSE 3	.609			
	TSE 4	.736			

Model Fitness: X^2**=** 1.565, X^2/df = 1.565, df = 509, RMESA=.046, RMR=.035, GFI=.854, CFI=.953, RFI=.868, IFI=.953

Variables/Constructs	Items	Standardized Factor Loadings	Composite Reliability	Average Variance Extracted	Maximum Shared Variance
	TSE 5	.784			
FACILITATING CONDITIONS	**FC 1**	.653	0.889	0.620	0.125
	FC 2	.682			
	FC 3	.799			
	FC 4	.901			
	FC 5	.870			
Model Fitness: X^2**=** 1.565, X^2/df = 1.565, df = 509, RMESA=.046, RMR=.035, GFI=.854, CFI=.953, RFI=.868, IFI=.953					

Table 1 shows the reliability and convergent validity of every construct. All Constructs' Composite Reliability (CR) values are above the suggested value (0.70), and the values ranged between 0.836 (TSE) and 0.941 (ATU), depicting that the internal consistency is excellent (Kline, 1999). The values of Average Variance Extracted (AVE) are also higher than 0.50, which indicates that each construct achieves a considerable amount of variance in its indicators (Fornell & Larcker, 1981). The standardized factor loadings of certain constructs, including PU, PEOU, and ATU, are particularly high (> 0.70), indicating that these variables can be suitable and consistent measures for gauging AI adoption in educational settings.

Table 2
Discriminant Validity

PERCEIVED USEFULNESS	PERCEIVED USEFULNESS	ATTITUDE TOWARDS USE	PERCEIVED EASE OF USE	BEHAVIOURAL INTENTION TO USE	TECHNOLOGICAL SELF-EFFICACY	FACILITATING CONDITIONS
	0.786					
ATTITUDE TOWARDS USE	0.605	**0.835**				
PERCEIVED EASE OF USE	0.326	0.364	**0.788**			
BEHAVIOURAL INTENTION TO USE	-0.076	-0.024	0.048	**0.776**		
TECHNOLOGICAL SELF-EFFICACY	0.083	0.066	0.061	0.053	**0.714**	
FACILITATING CONDITIONS	0.038	0.021	0.009	0.354	0.211	**0.787**

To determine discriminant validity, the Fornell-Larcker criterion was used, as shown in Table 2. In both cases, the diagonal elements (square roots of AVEs) exceed the inter-construct correlations, which statistically demonstrate that the constructs are sufficiently differentiated from one another. Although there is a moderate correlation between PU and ATU (r = 0.605), both are discriminant and independent. Also, TSE and FC show weak associations with core TAM constructs, which suggests that their influence may be indirect or contextually bound within teacher education settings (Fornell & Larcker, 1981).

Figure 3: The conceptual model is based on TAM and includes six constructs and directional paths, which are hypothesized. This diagram operationalises the theoretical framework and presents the assumed causal associations among technological self-efficacy, facilitating conditions, perceived usefulness, ease of use, attitude, and behavioural intention. Its visual display gives a structural review that is of importance in regard to empirical validation (Venkatesh & Davis, 2000).

Figure 4 illustrates the result of the final measurement model after refinement. Each latent construct's indicators are related to the observed variables in terms of standardized loading coefficients. The visual inspection of simplicity and homogeneity of loadings (> 0.70 in the majority of paths) confirms the convergent validity of the model and corresponds to the psychometric expectations in SEM (Sarstedt et al., 2017). This model served as the empirical foundation for testing the hypothesis and estimating the path coefficient.

Table 3
Regression Weights

Hypotheses	Paths	Estimate	S.E.	C.R.	P	Remarks
H1	Technological Self-Efficacy> Perceived Usefulness	.056	.037	1.527	**.127**	**H1 Not Supported**
H2	Facilitating Conditions >Behavioural Intention to Use	.285	.042	6.832	***	**H2 Not Supported**
H3	Perceived Usefulness > Perceived Ease of Use	.485	.077	6.320	***	**H3 Supported**
H4	Behavioural Intention to Use> Perceived Ease of Use	.091	.064	1.432	**.152**	**H4 Not Supported**
H5	Perceived Usefulness> Attitude Towards Use	.532	.045	11.869	***	**H5 Supported**
H6	Perceived Ease of Use >Attitude Towards Use	.127	.033	3.839	***	**H6 Supported**
***** indicates p < .001, ** indicates p < .01, * indicates p < .05**						

Table 3 illustrates the results of structural hypothesis testing. The statistical support was given to three out of six hypotheses. PU had a strong and positive effect on both ATU (β = 0.532, p < .001) and PEOU (β = 0.485, p < .001), which concurs with the past studies that indicate PU as a fundamental predictor of attitudinal responses in TAM (Venkatesh & Davis, 2000). PEOU had a positive influence on ATU (β = 0.127, p < .001) as well. TSE, on the other hand, was not a significant Predictor of PU (β = 0.056, p > .05), a result that contradicts Compeau and Higgins (1995), who highlighted the influence of self-efficacy on the development of utility perceptions. On the same note, BI had no significant influence on PEOU (β = 0.091, p > .05), implying that behavioural intent, singularly, does not convert into perceived usability.

Table 4
Model Fit Indexes

FIT INDEX	VALUE	RECOMMENDED THRESHOLD	INTERPRETATION
Chi-square/df **(CMIN/DF)**	**.546**	< 3.00	**Acceptable Fit**
Root Mean Square Error of Approximation **(RMSEA)**	**0.000**	< 0.06	**Good Fit**
Comparative Fit Index **(CFI)**	**1.000**	> 0.95	**Excellent Fit**
Tucker-Lewis Index **(TLI)**	**1.028**	> 0.95	**Excellent Fit**
Incremental Fit Index **(IFI)**	**1.014**	> 0.90	**Excellent Fit**
Goodness of Fit Index **(GFI)**	**0.995**	> 0.90	**Excellent Fit**
Adjusted Goodness of Fit Index **(AGFI)**	**0.986**	> 0.85	**Excellent Fit**
Root Mean Square Residual **(RMR)**	**0.010**	< 0.05	**Excellent Fit**
Normed Fit Index **(NFI)**	**0.983**	> 0.90	**Good Fit**
Parsimony Normed Fit Index **(PNFI)**	**0.524**	> 0.50	**Good Parsimony**
Parsimony Comparative Fit Index **(PCFI)**	**0.533**	> 0.50	**Good Parsimony**
Model Fitness: X^2/df=.546, RMESA = 0.000, CFI=.1.000, TLI = 1.028, AGFI = 0.986, and RMR = 0.010			

Table 4 presents model fit indices, all of which surpass the conventional thresholds. The model exhibits exceptional goodness-of-fit with RMSEA = 0.000, CFI = 1.000, TLI = 1.028, and RMR = 0.010. These results indicate that the hypothesized model accurately represents the observed data structure. These indices confirm the model's statistical adequacy and conceptual integrity (Hu & Bentler, 1999), strengthening the theoretical assumptions included in TAM.

Mediation Testing:

Table 5
Mediation Analysis

Hypotheses	Path	Total Effects	Direct Effects	Indirect Effects	Remarks
H7	TSE > PU > ATU	.033	.000	.033	Hypothesis not supported since indirect effects are not statistically significant.
***** indicates p < .001, ** indicates p < .01, * indicates p < .05**					

Table 5 represents the mediation analysis for the pathway TSE - PU - ATU. The indirect effect was not found to be significant. Although the total effect was positive (0.033), but it was very small, which implies that PU does not mediate the relationship between TSE and ATU. This result is contrary to Holden and Rada (2011), who reported that self-efficacy had an indirect effect on attitude, which was mediated by perceived usability. The non-significant mediation effect between the construct suggests that in the context of mathematics teacher training, self-efficacy may not be sufficient to influence attitudinal shifts without direct usability experiences or contextual support structures.

CONCLUSION

The study empirically tested an Extended Technology Acceptance Model (TAM) to investigate pre-service mathematics teacher educators for AI tool adoption factors. The result indicated that Perceived Usefulness (PU) and Perceived Ease of Use (PEOU) had significant positive effects on the Attitude Towards Use (ATU), which was consistent with the previous TAM-based studies(Davis, 1989; Venkatesh & Davis, 2000). Nevertheless, Technological Self-Efficacy (TSE) and Facilitating

Conditions (FC) showed little direct effect, which indicates that the belief in own abilities and the supports provided by the environment do not carry predictive value of the adoption unless their experiential value is explicit. This finding contrasts with earlier claims made by Compeau and Higgins (1995), a factor that indicates contextual specificity of technology adoption in teacher education. The study contributes to theory by confirming the predictive validity of the central TAM constructs and determining the understated influence of the external variables. Excellent fit indices of the model (e.g., RMSEA = 0.000; CFI = 1.000) indicate the structural soundness, and the model can be utilized to inform the incorporation of AI in pedagogical training models. The results provide a solid foundation for institutional-level interventions that can target the development of digital readiness and acceptance of AI among prospective mathematics teachers.

IMPLICATIONS

The results of the present study have significant implications for policymakers, curriculum developers, and teacher education institutions that significantly incorporate Artificial Intelligence (AI) in mathematics education. The validated structural model demonstrates the significance of Perceived Usefulness and Perceived Ease of Use as the determinants of attitude and behavioural intention towards the adoption of AI tools among pre-service teachers, which indicates that teacher education programs should focus on practical training and must show practical instructional advantages of AI. Moreover, the role of Technological Self-Efficacy and Facilitating Conditions emphasizes an urgent necessity to improve an institutional support system, which encompasses stable infrastructure, technical support, and ongoing professional training. These insights promote the idea of a two-fold strategy of enhancing AI readiness, which is based on both reinforcing internal belief systems (via competence-building initiatives) and optimizing external settings. Finally, the study will provide a theoretically substantiated and empirically approved conceptualization that can be used in the strategic deployment of AI technologies in teacher education and thus empower future mathematics teachers to have the confidence and ability to use AI to innovate teaching.

DECLARATIONS

FUNDING

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Author Contribution

V.K.R. conceived and designed the study, conducted data collection, performed data analysis using Structural Equation Modelling (SEM), interpreted the results, and prepared the original manuscript draft. M.T.V.N. supervised the research process, provided methodological guidance, reviewed the analysis, and critically revised the manuscript for important intellectual content. K.D. assisted in data collection, literature review, data organization, and manuscript editing. All authors reviewed, revised, and approved the final version of the manuscript.

Data Availability

Data will be shared as per requirement by the respected resource person.

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Figures

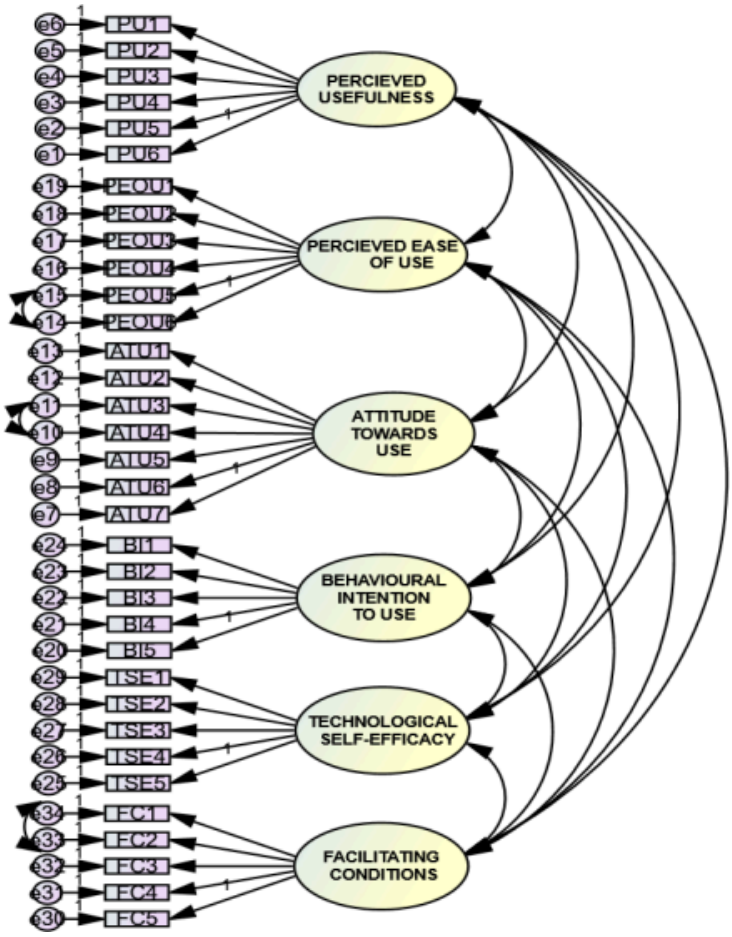


Figure 1

Initial CFA Model

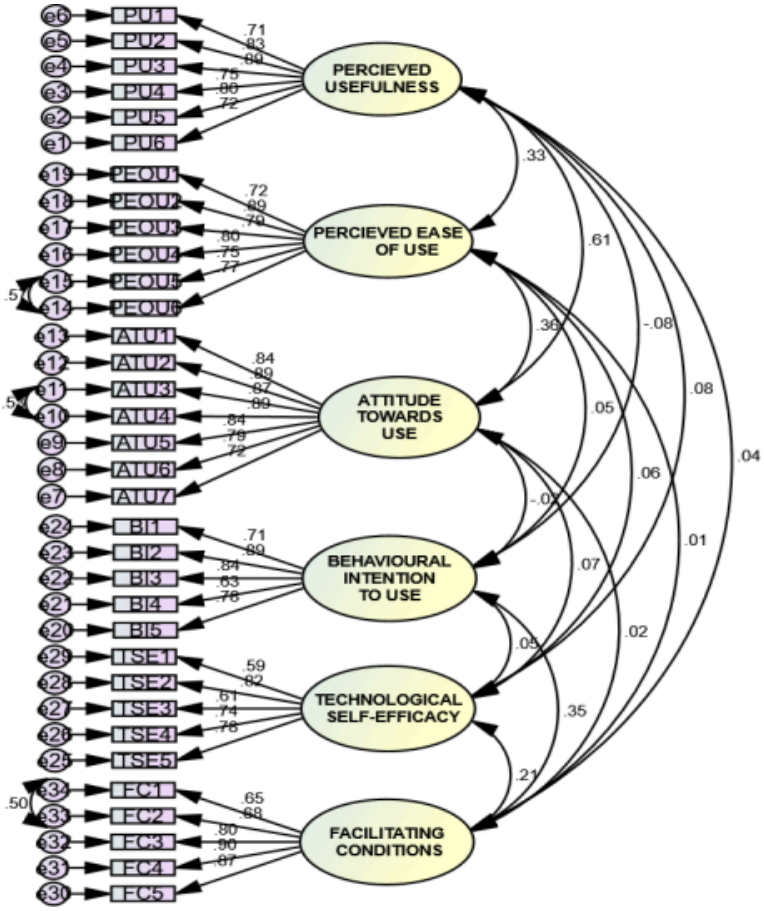


Figure 2

Final CFA Model

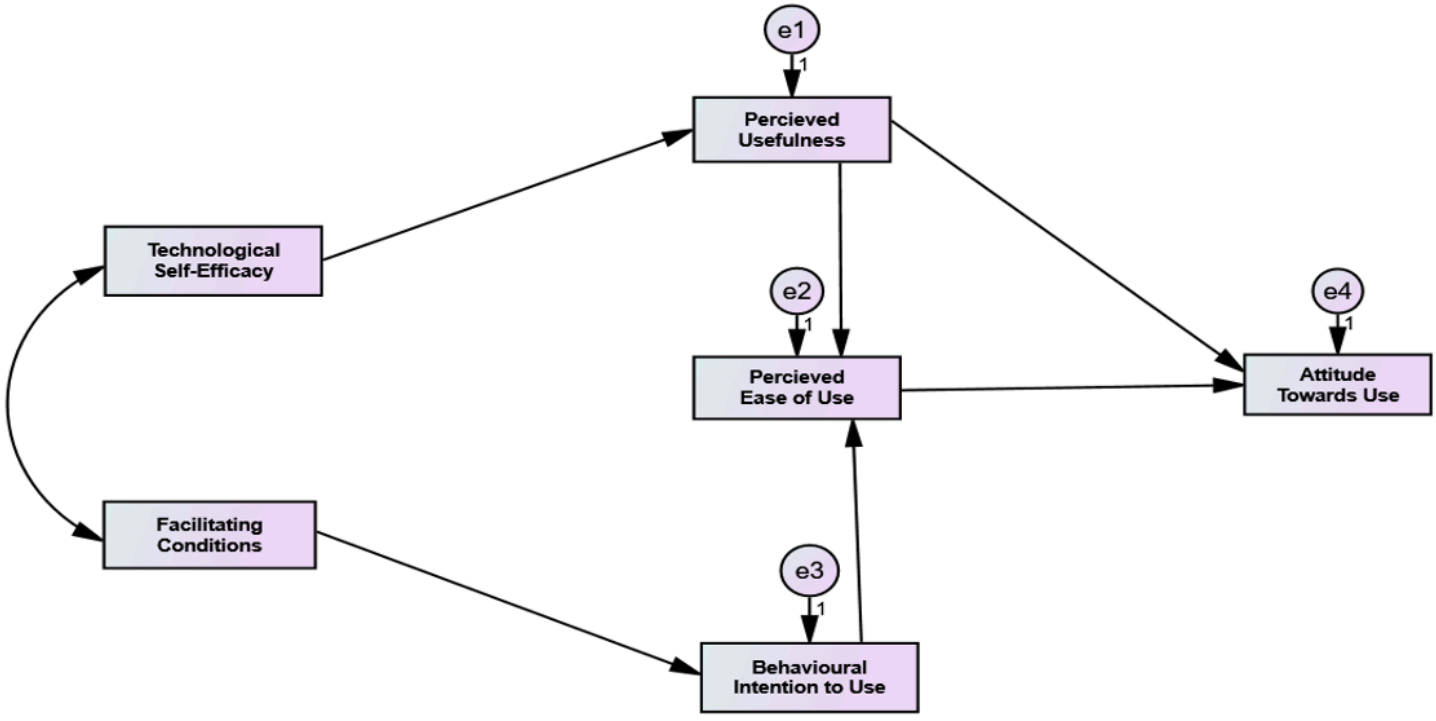


Figure 3

Proposed Structural Model for Hypothesis Testing

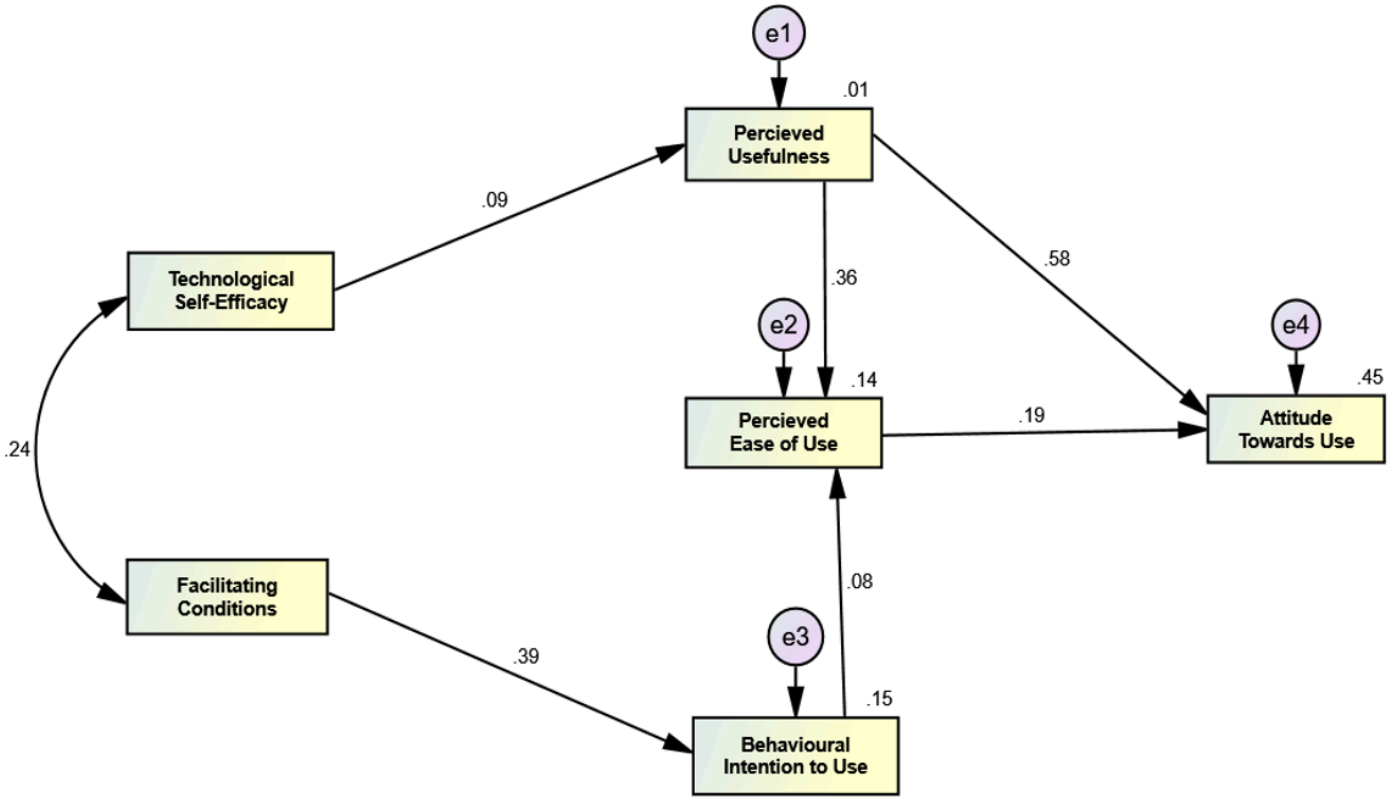


Figure 4

Measurement Model Result