A Hybrid TAM – Learning Analytics Framework for Predicting University Students' Adoption of Educational Technology

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Abstract. This study develops a hybrid analytical framework integrating the Technology Acceptance Model (TAM) with learning analytics indicators to explain university students' adoption of educational technology. While TAM emphasizes perceptual constructs such as perceived usefulness (PU) and perceived ease of use (PEOU), modern digital learning systems generate rich behavioral data that may also shape learners' adoption decisions. Data were collected from 162 undergraduate students using validated measurement scales for PU, PEOU, and behavioral intention (BI), together with self-reported learning analytics indicators including interaction frequency, time-on-task, and digital participation levels. Structural equation modeling was conducted using Python based SEM analysis. Results show that PU and PEOU significantly predict BI, consistent with classical TAM. Incorporating learning analytics indicators improves explanatory power, with hierarchical regression revealing an increase in R2 from 0.689 (TAM-only) to 0.739 in the hybrid model (ΔR2 = 0.050). Random Forest analysis further confirms the predictive importance of PU and learning analytics features. These findings demonstrate that behavioral engagement data substantially enhance students' technology adoption processes. The study contributes theoretically by integrating cognitive and behavioral perspectives of adoption, and offers practical implications for designing more engaging and data-informed digital learning environments.

Keywords: *Technology Acceptance Model; TAM; Learning Analytics; Educational Technology Adoption; Behavioral Intention; SEM; Random Forest*

1. Introduction

The rapid digitalization of higher education has accelerated the adoption of various educational technologies, including learning management systems, online assessment tools, and interactive digital platforms. As universities increasingly integrate technology into teaching and learning, understanding the determinants that influence students' willingness to adopt such systems has become a critical research priority. Traditional theoretical frameworks, particularly the Technology Acceptance Model (TAM), have been widely used to explain students' behavioural intention to use technology, emphasizing key perceptual constructs such as perceived usefulness (PU) and perceived ease of use (PEOU). These constructs have consistently been found to be strong predictors of users' attitudes and intentions across multiple educational contexts.

However, with the emergence of data-rich learning environments, contemporary digital systems now generate extensive behavioral data, often referred to as learning analytics. These data capture students' actual engagement and interaction patterns, such as platform usage frequency, time spent on tasks, and levels of digital participation. While TAM provides a cognitive perspective on technology adoption, it does not fully incorporate the behavioural dimension captured through learning analytics. As a result, an important theoretical gap persists regarding whether and how behavioural engagement data can strengthen or complement traditional perceptual beliefs in predicting technology adoption.

Addressing this gap, the present study proposes a hybrid framework that integrates TAM with learning analytics indicators to provide a more comprehensive explanation of university students' adoption of educational technology. By combining validated survey-based measurements with behavioural indicators, this study examines whether learning analytics can enhance the predictive power of the traditional TAM structure. The integration of cognitive and behavioural perspectives may offer a more holistic understanding of technology adoption in modern digital learning environments.

To achieve this objective, data were collected from 162 undergraduate students, and multiple analytical methods were applied, including structural equation modelling (SEM), hierarchical regression, and Random Forest analysis for robustness. The results demonstrate that incorporating learning analytics indicators improves prediction accuracy, offering both theoretical and practical contributions for designing data-informed educational technologies and engagement strategies.

2. Literature Review

2.1. Technology Acceptance Model (TAM)

The Technology Acceptance Model (TAM) has served as one of the most influential theoretical frameworks for explaining users' adoption of information systems. Originally developed to account for behavioural intention in relation to technology use, TAM posits that perceived usefulness (PU) and perceived ease of use (PEOU) shape users' acceptance decisions. Numerous empirical studies in educational contexts have validated this structure, consistently showing that PU is the strongest predictor of behavioural intention [5, 7]. Similarly, PEOU has been shown to influence both PU and students' adoption behaviours, particularly in digital and online learning settings [16].

TAM has been widely applied in higher education to understand the adoption of learning management systems, digital assessment tools, and e-learning platforms. Systematic reviews highlight that TAM remains robust across diverse educational technologies, though limited by its reliance on self-reported perceptions rather than behavioural evidence [1, 11]. This conceptual gap has motivated researchers to explore extensions of TAM, including the integration of contextual and behavioural variables.

2.2. Learning Analytics and Student Engagement

Learning analytics (LA) has emerged as a data-driven approach that leverages students' interaction data to understand and improve learning processes. Engagement indicators such as interaction frequency, time-on-task, and participation patterns provide objective evidence of students' actual behavior within digital learning environments [9, 15]. These indicators offer insights into learner engagement, self-regulation, and academic performance, complementing traditional survey-based methods.

Recent studies have demonstrated that LA can enhance predictive modelling of learning outcomes and behavioural intention. For instance, behavioural log data have been successfully used to predict persistence, performance, and technology adoption tendencies [4, 12]. Despite these advantages, the existing literature shows limited integration of LA into theoretical acceptance models, leaving a gap in understanding how behavioural engagement interacts with perceptual beliefs such as PU and PEOU.

2.3. Towards a Hybrid TAM – Learning Analytics Framework

As educational technologies increasingly incorporate real-time learning analytics dashboards and behavioural indicators, researchers have called for hybrid frameworks that integrate cognitive and behavioural perspectives. Extending TAM with LA indicators may offer a more comprehensive explanation of students' adoption of digital learning tools. Prior work has suggested that behavioural engagement can reinforce perceived usefulness and shape learners' motivation to adopt educational technologies [1, 16].

Building on this conceptual direction, the present study proposes and empirically tests a hybrid TAM–Learning Analytics framework. By combining validated TAM constructs with behavioural engagement indicators, this integrated approach aims to enhance predictive power and address the theoretical limitations of perception-only models identified in prior reviews [6, 11].

3. Methodology

3.1. Model Specification

The analytical framework combines a covariance-based structural equation model (SEM), hierarchical regression, and machine-learning estimation. Let the full parameter vector be:

$$\theta = (\lambda, \beta, \Phi, \Theta\varepsilon)$$

where λ denotes the vector of factor loadings, β the structural coefficients, Φ the latent covariance matrix, and $\Theta\varepsilon$ the measurement error variances [2, 10].

3.1.1 Measurement Model

Let the p-dimensional observed indicator vector be:

$$x = \Lambda\eta + \varepsilon$$

$$E[\varepsilon] = 0, \qquad Cov(\varepsilon) = \Theta\varepsilon.$$

$$PU: \quad \begin{pmatrix} PU1 \\ PU2 \\ PU3 \end{pmatrix} = \begin{pmatrix} \lambda_1 \\ \lambda_2 \\ \lambda_3 \end{pmatrix} PU + \varepsilon_{PU},$$

$$PEOU: \quad \begin{pmatrix} PEOU1 \\ PEOU2 \\ PEOU3 \end{pmatrix} = \begin{pmatrix} \lambda_4 \\ \lambda_5 \\ \lambda_6 \end{pmatrix} PEOU + \varepsilon_{PEOU},$$

$$BI: \quad \begin{pmatrix} BI1 \\ BI2 \\ BI3 \end{pmatrix} = \begin{pmatrix} \lambda_7 \\ \lambda_8 \\ \lambda_9 \end{pmatrix} BI + \varepsilon_{BI},$$

$$LA: \quad \begin{pmatrix} LA1 \\ LA2 \\ LA3 \end{pmatrix} = \begin{pmatrix} \lambda_{10} \\ \lambda_{11} \\ \lambda_{12} \end{pmatrix} LA + \varepsilon_{LA}.$$

where: $x \in \mathrm{R}^{12}$ (four constructs, three indicators each), Λ is a 12×4 loading matrix, $\eta = (\mathrm{PU}, \mathrm{PEOU}, \mathrm{BI}, \mathrm{LA})'$ is the latent vector, ε is the vector of measurement errors, assumed to satisfy.

Explicitly, the measurement equations are:

The measurement specification follows standard reflective SEM practice in educational and learning analytics research, where each latent construct is operationalized by multiple indicators and the implied covariance structure is modelled via Λ, Φ and $\Theta\varepsilon$ [13, 14,15]. The model-implied covariance matrix is: This analytical process is visualized in Figure 1, which outlines the full workflow of the Hybrid TAM-Learning Analytics framework.

$$\sum(\theta) = \Lambda\Phi\Lambda' + \Theta\varepsilon$$

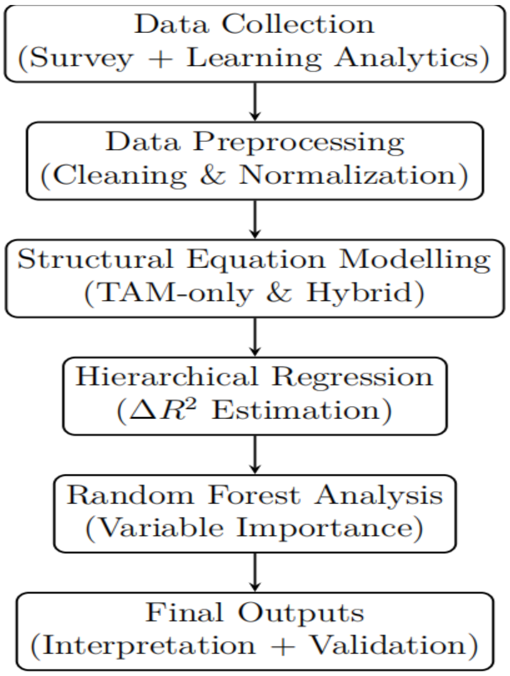

Figure 1: Workflow of the Hybrid TAM–Learning Analytics Analytical Framework

3.1.2 Structural Model

Let the structural model be:

$$\eta = B\eta + \zeta$$

where B is a 4×4 coefficient matrix with zeros on the diagonal, and ζ is the vector of structural disturbances.

TAM-only model.

$$PU = \beta 1 PEOU + \zeta 1,$$

$$BI = \beta 2 PU + \beta 3 PEOU + \zeta 2.$$

In matrix form:

$$B_{TAM} = \begin{pmatrix} 0 & \beta_1 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ \beta_3 & \beta_2 & 0 & 0 \\ 0 & 0 & 0 & 0 \end{pmatrix}.$$

This specification is consistent with recent TAM-based SEM studies in digital and mobile learning, where PEOU is treated as an antecedent of PU and both jointly predict behavioural intention [8, 14].

Hybrid TAM–Learning Analytics model.

The hybrid extension incorporates LA → PU and LA → BI:

$$PU = \beta 1PEOU + \beta 4LA + \zeta 3,$$

$$BI = \beta 2PU + \beta 3PEOU + \beta 5LA + \zeta 4.$$

Matrix representation:

$$B_{Hybrid} = \begin{pmatrix} 0 & \beta_1 & 0 & \beta_4 \\ 0 & 0 & 0 & 0 \\ \beta_3 & \beta_2 & 0 & \beta_5 \\ 0 & 0 & 0 & 0 \end{pmatrix}.$$

Integrating behavioural engagement into the structural component reflects the increasing use of learning analytics variables as additional predictors in technology adoption research, especially when combining TAM constructs with log- or self-reported usage measures [10, 13].

3.1.3 SEM Estimation

The SEM minimizes the discrepancy between the sample covariance matrix S and model-implied $\Sigma(\theta)$ using the maximum likelihood (ML) fit function:

$$FML(\theta) = log\left|\sum(\theta)\right| + trS\sum(\theta) - 1 - log|S| - p$$

The first-order condition is:

$$\frac{\partial F_{ML}}{\partial \theta} = 0$$

which is solved iteratively using quasi-Newton algorithms, as is standard in covariance-based SEM implementations in the social and behavioural sciences [2, 10]. The gradient is:

$$\frac{\partial F}{\partial \theta_j} = \mathrm{tr}\left[(\Sigma^{-1} - \Sigma^{-1}S\Sigma^{-1})\frac{\partial \Sigma}{\partial \theta_j}\right]$$

3.2 Hierarchical Regression

For robustness and incremental explanatory power, behavioural intention BI is regressed on TAM variables first, then LA indicators, following standard two-step hierarchical procedures that quantify the added variance explained by new blocks of predictors [2, 13].

$$\text{Model 1:} \qquad BI = \alpha 0 + \alpha 1PU + \alpha 2PEOU + u.$$

$$\text{Model 2:} \qquad BI = \alpha 0 + \alpha 1PU + \alpha 2PEOU + \gamma 1LA1 + \gamma 2LA2 + \gamma 3LA3 + u.$$

The variance increase is measured by:

$$\Delta R2 = R2Model\,2 - R2Model\,1$$

An F-test evaluates statistical significance:

$$F = \frac{(R_2^2 - R_1^2)/k}{(1 - R_2^2)/(n - m - 1)}$$

which is commonly used to assess whether behavioural or learning analytics variables provide statistically meaningful incremental explanatory power over traditional perceptual measures [8, 14].

3.3 Random Forest Model

Random Forest constructs K classification/regression trees $[1]^{k}_{k=1}$. The prediction is the ensemble average (regression) or majority vote (classification):

$$\hat{y} = \frac{1}{K}\sum_{k=1}^{K} T_k\,(x)$$

At each node t, a random subset of predictors m ≪ p is selected. For regression, splits minimize:

$$\Delta i(s_t) = i(t) {-}_{pL} i(t_L) {-}_{pR} i(t_R)$$

where i(t) is node impurity:

$$i(t) = \frac{1}{N_t}\sum_{i \in t} (\,y_i - \bar{y}_t)^2$$

Variable importance is the accumulated impurity decrease:

$$\mathrm{Imp}(X_j) = \sum_{k=1}^{K}\sum_{t \in T_k} \Delta\, i(s_t)\mathbb{I}(v(s_t) = X_j)$$

This formulation follows the original Random Forest framework for assessing variable importance via impurity reduction [4] and has been widely applied in predictive learning analytics and student performance modelling in recent Springer studies [3,15,10].

4. Results

As presented in Figure 2, the Hybrid TAM-Learning Analytics Structural Model illustrates the paths between latent constructs (PEOU, PU, BI, LA) and their corresponding coefficients.

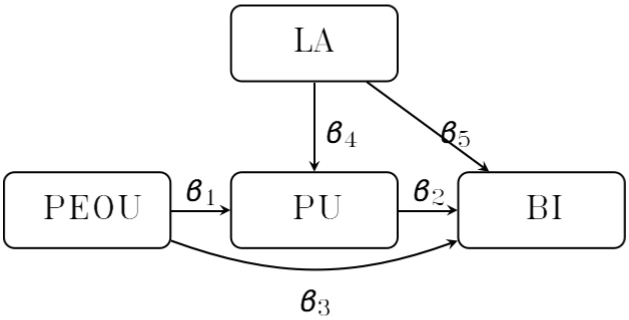

Figure 2. Hybrid TAM – Learning Analytics Structural Model.

4.1 Structural Equation Modelling

4.1.1 TAM-only Model

The initial structural equation model examined the traditional TAM structure consisting of PU, PEOU, and BI. The model demonstrated excellent fit to the data, with $\chi^2(24) = 17.02$, $p = 0.848$, RMSEA = 0.00, AIC = 41.85, and BIC = 113.11. These indices indicate that the TAM-only model adequately represents the relationships among the core perceptual constructs. Both PU and PEOU showed significant positive effects on behavioural intention, consistent with expectations for TAM-based analyses.

Table 1. SEM Model Fit Indices for TAM-only and Hybrid Models.

Model	χ2	df	p-value	RMSEA	AIC	BIC
TAM-only	17.0248	24	0.8476	0.000	41.8452	113.1114
Hybrid TAM–LA	48.2538	48	0.9920	0.000	59.5613	161.3701

4.1.2 Hybrid TAM–Learning Analytics Model

The second model incorporated three learning analytics indicators (interaction frequency, time-on-task, digital participation) as predictors of PU and BI. The hybrid model exhibited strong model fit, with $\chi2(48) = 48.25$, $p = 0.992$, AIC = 59.56, and BIC = 161.37. Although the AIC and BIC values increased due to the model's larger parameter set, the hybrid model improved explanatory power for BI. Learning analytics indicators demonstrated positive associations with both PU and BI, suggesting that higher behavioural engagement strengthens students' perceptions of usefulness and their intention to adopt educational technologies

4.2 Hierarchical Regression Analysis

To further assess the contribution of learning analytics indicators, a hierarchical regression analysis was conducted. In Step 1, the TAM-only predictors (PU and PEOU) accounted for R2 = 0.6892 of the variances in behavioural intention. In Step 2, the inclusion of learning analytics variables increased the explained variance to R2 = 0.7393. This represents an incremental increase of ΔR2 = 0.0500, indicating that learning analytics indicators provide meaningful additional predictive power beyond perceptual variables alone.

Table 2. Hierarchical Regression Results Predicting Behavioural Intention.

Model	R2	ΔR2
Step 1: TAM-only (PU, PEOU)	0.6892	—
Step 2: + Learning Analytics (LA1–LA3)	0.7393	0.0500

4.3 Random Forest Analysis

A Random Forest model was employed to evaluate the robustness of predictors and assess variable importance. The results showed that PU-related items were the strongest predictors of behavioural intention, with PU1 (0.3137) and PU2 (0.3031) ranking highest in importance. PEOU-related indicators demonstrated moderate importance, while learning analytics variables also contributed meaningfully, with LA2 (0.0604), LA3 (0.0414), and LA1 (0.0313) displaying comparable influence. These findings confirm that behavioural engagement indicators complement perceptual beliefs in predicting students' adoption decisions.

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Table 3. Random Forest Variable Importance Rankings.

Variable	Importance
PU1	0.3137
PU2	0.3031
PU3	0.0935
PEOU1	0.0759
LA2	0.0604
LA3	0.0414
PEOU2	0.0412
PEOU3	0.0396
LA1	0.0313

5. Discussion

The purpose of this study was to examine university students' adoption of educational technology by integrating perceptual constructs from the Technology Acceptance Model (TAM) with behavioural indicators derived from learning analytics. The findings demonstrate that while TAM variables remain strong predictors of behavioural intention, behavioural engagement indicators provide additional explanatory power, supporting the value of a hybrid cognitive–behavioural framework.

The TAM-only model exhibited excellent fit and confirmed the central role of perceived usefulness (PU) and perceived ease of use (PEOU) in shaping students' behavioural intention (BI). This aligns with the well-established understanding that students are more likely to adopt educational technologies when they perceive them as beneficial and easy to use. The strong loadings of PU-related items in both SEM and Random Forest analyses reinforce the importance of perceived performance benefits as the primary driver of adoption decisions.

The hybrid model that incorporated learning analytics indicators—interaction frequency, time-on-task, and digital participation—also demonstrated strong model fit. These behavioural variables positively influenced both PU and BI, indicating that students who engage more actively with digital learning environments tend to develop stronger perceptions of usefulness and higher adoption intentions. This finding suggests a reciprocal relationship between behavioural engagement and perceptual beliefs: students who use the technology more frequently are likely to appreciate its benefits more deeply, reinforcing their motivation to continue using it.

The hierarchical regression analysis further supports this interpretation. The increase in explained variance from R2 = 0.6892 in the TAM-only model to R2 = 0.7393 in the hybrid model indicates that behavioural indicators provide meaningful additional explanatory value. Although the incremental improvement of ΔR2 = 0.0500 is modest, it suggests that behavioural data can enrich traditional TAM based analyses by capturing dimensions of engagement not reflected in perceptual measures alone.

The Random Forest analysis provides additional support for the hybrid approach. While PU-related variables remained the strongest predictors, learning analytics indicators contributed non-trivial importance scores. This reinforces the notion that behavioural engagement is an essential component of students' technology adoption process. Even though perceptual constructs dominate, behavioural indicators enhance predictive robustness and provide complementary insights into students' actual usage patterns.

Overall, the results highlight the value of integrating cognitive and behavioural perspectives when analyzing technology adoption in higher education. While perceptual constructs remain central, behavioural data offer a more grounded and empirically rich understanding of how students interact with digital learning technologies. The findings underscore the importance of designing educational technologies that not only appear useful and easy to use but also actively promote behavioural engagement.

6. Conclusion

This study proposed and empirically tested a hybrid framework that integrates perceptual constructs from the Technology Acceptance Model (TAM) with behavioural indicators derived from learning analytics to explain university students' adoption of educational technology. Using structural equation modelling, hierarchical regression, and Random Forest analysis, the results consistently demonstrate that behavioural engagement indicators provide additional explanatory value beyond traditional perceptual constructs.

The TAM-only model confirmed the central role of perceived usefulness (PU) and perceived ease of use (PEOU) in shaping behavioural intention (BI), reinforcing the continued relevance of TAM in digital learning research. The hybrid model showed that learning analytics indicators—interaction frequency, time-on-task, and digital participation—positively influenced PU and BI, suggesting that behavioural engagement strengthens both perception formation and technology adoption decisions. The incremental increase in R2 and the variable importance rankings from the Random Forest model highlight the contribution of behavioural data to model robustness and predictive accuracy.

Theoretically, this study advances technology adoption research by demonstrating the value of integrating cognitive and behavioural perspectives. TAM provides a foundational understanding of users' perceptions, while learning analytics offers real-world behavioural evidence that enriches the analysis. Practically, the findings suggest that educational institutions can enhance students' adoption of digital learning technologies by designing systems that promote meaningful engagement, support sustained interaction, and provide clear performance benefits.

Future research may incorporate system-generated behavioural logs rather than self-re-ported indicators to further strengthen the measurement accuracy of learning analytics constructs. Additionally, examining the hybrid model across diverse educational contexts and technology types would enhance the generalizability of the findings. Overall, the present study provides a comprehensive framework that reflects the realities of modern digital learning environments and offers actionable insights for researchers, educators, and technology designers.

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