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Cognitive Engagement as a Mediator of Adaptive Learning Technology Effectiveness within an Integrated TAM-TTF and Cognitive Psychology Framework

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Abstract

The integration of adaptive learning technologies in digital education has intensified scholarly interest in understanding how such systems influence academic performance beyond mere adoption behavior. This study examines cognitive-driven learning as a mediating mechanism linking adaptive technology use to academic performance, drawing on an integrated framework combining the Technology Acceptance Model (TAM), Task-Technology Fit (TTF), and cognitive psychology perspectives. Using a quantitative design, Partial Least Squares Structural Equation Modeling (PLS-SEM) was applied to data collected from 70 participants across diverse age groups in digital learning environments. Five constructs were analyzed: Teaching Digital Model, Adaptive Technology Learning, Learning Environment, Driven Cognitive Psychology, and Performance Assessment, with bootstrapping (5,000 subsamples) employed to ensure validity and reliability. Findings reveal that adaptive technology learning significantly influences both learning environment configuration and academic performance; however, it does not independently activate cognitive processes, indicating that technological tools alone are insufficient without deliberate cognitive engagement strategies. Driven cognitive psychology emerged as the strongest predictor of academic performance, while teaching digital models primarily shaped the learning environment rather than directly affecting outcomes. These findings contribute a nuanced, cognitively grounded perspective that extends beyond conventional technology acceptance frameworks, underscoring that the effectiveness of adaptive learning depends fundamentally on the degree to which technologies facilitate meaningful cognitive engagement.

1. Introduction

The rapid proliferation of adaptive learning technologies has fundamentally transformed educational landscapes globally, with institutions investing heavily in digital learning infrastructure to enhance student outcomes (Falebita et al., 2025; Putri et al., 2025; Strielkowski et al., 2025; Sudirman et al., 2026a). Despite widespread adoption, the relationship between technological integration and improved academic performance remains inconsistent and poorly understood. While some studies demonstrate significant learning gains from adaptive technologies (du Plooy et al., 2024; Contrino et al., 2024; Sudirman et al., 2021), others report minimal or no impact on student outcomes, suggesting that technology alone is insufficient for enhancing learning effectiveness (Gligorea et al., 2023; Sudirman et al., 2026b). This inconsistency points to the need for deeper understanding of the underlying mechanisms through which adaptive technologies influence academic performance, particularly the cognitive processes that mediate technology-learning relationships.

Extensive research has explored technology adoption through the Technology Acceptance Model (TAM) and Task-Technology Fit (TTF) frameworks, establishing robust predictors of user acceptance and system utilization. Recent studies have successfully applied these models to educational contexts, demonstrating that perceived usefulness, ease of use, and task-technology alignment significantly influence students' intention to use learning technologies (Al-Adwan et al., 2023; Kemp et al., 2024). Furthermore, extended TAM models incorporating additional factors such as self-efficacy, social

influence, and cognitive engagement have shown enhanced explanatory power in predicting technology adoption (Trigueros-Preciado et al., 2024). Network analyses of technology acceptance factors reveal complex interconnections between technological, pedagogical, and psychological variables that influence teachers' and students' adoption behaviors (Galimova et al., 2024). However, these technology-centric approaches predominantly focus on adoption behaviors rather than examining the cognitive processes that mediate technology's impact on learning outcomes.

Parallel research streams in cognitive psychology have emphasized the critical role of metacognition, working memory, and cognitive load in determining learning effectiveness in digital environments. Studies demonstrate that the digital age has fundamentally altered how individuals process information, with technology serving as cognitive tools that extend human capabilities while simultaneously placing new demands on metacognitive regulation (Risko & Gilbert, 2023). Recent investigations reveal that digital learning environments significantly influence cognitive load distribution, with factors such as immersion, interactivity, and interface design affecting learners' cognitive resources allocation (Frederiksen et al., 2021). The Cognitive-Affective-Social Theory of Learning in digital Environments (CASTLE) proposes that social processes and emotional factors interact with cognitive mechanisms to influence learning outcomes in technology-mediated contexts (Fiorella & Mayer, 2021). Current developments in applied cognitive psychology continue to yield practical implications for improving digital learning, emphasizing the importance of understanding how cognitive processes adapt to technology-rich educational environments (Roediger & Pyc, 2024).

A critical gap exists in current literature regarding the integration of technology acceptance models with cognitive psychology theories in educational contexts. While TAM and TTF effectively predict technology adoption, they fail to explain the cognitive mechanisms through which accepted technologies influence learning outcomes. Recent attempts to address this limitation include extending TAM with metacognitive self-regulated learning constructs to understand AI tool adoption (Dahri et al., 2024) and integrating social cognitive theory with TAM to examine mobile learning effectiveness (Almogren & Aljammaz, 2022). However, these integration efforts remain fragmented and context-specific, lacking a comprehensive theoretical framework that systematically combines technology acceptance variables with cognitive psychology constructs. This theoretical fragmentation limits understanding of how adaptive learning technologies can be designed and implemented to optimize both user acceptance and cognitive engagement, ultimately constraining the development of evidence-based educational technology interventions (Zobeidi et al., 2023; Chen et al., 2025).

This study addresses the identified gap by developing and testing an integrated model that combines TAM-TTF frameworks with cognitive psychology theory to examine how cognitive-driven learning mediates the relationship between adaptive technology acceptance and academic performance. The research contributes to educational technology literature by providing empirical evidence of cognitive mediation mechanisms, offering theoretical advancement beyond traditional technology acceptance models. The study introduces a validated measurement instrument that captures multidimensional relationships between digital teaching models, adaptive technology learning, learning environments,

cognitive psychology drivers, and performance assessment outcomes. Practically, the findings inform instructional designers and educators about the necessity of incorporating cognitive engagement strategies alongside technological implementations, addressing the growing need for evidence-based approaches to educational technology integration (Abdullah et al., 2025; Alamri et al., 2024).

Given the theoretical framework and identified research gaps, this study addresses the following research questions: (1) How do adaptive technology learning characteristics influence students' cognitive psychology engagement and academic performance? (2) What is the mediating role of cognitive-driven learning in the relationship between technology acceptance and performance outcomes? (3) To what extent do teaching digital models and learning environments contribute to the technology-cognition-performance pathway? (4) How can the integrated TAM-TTF-cognitive psychology model inform the design of more effective adaptive learning interventions?

2. Methods

2.1 Research Design

This study employed a quantitative research approach using a cross-sectional survey design to examine the relationships between teaching digital models, adaptive technology learning, learning environment, driven cognitive psychology, and performance assessment. The research utilized Partial Least Squares Structural Equation Modeling (PLS-SEM) to test the proposed integrated model combining TAM, TTF, and cognitive psychology theories. PLS-SEM was selected over covariance-based SEM due to its suitability for exploratory research, ability to handle non-normal data distributions, and effectiveness in modeling complex relationships with reflective measurement models (Hair et al., 2019). The research design follows a predictive modeling approach, focusing on theory development and the identification of key driver constructs rather than theory confirmation.

The study adopts a positivist paradigm, assuming that relationships between constructs can be objectively measured and analyzed through statistical methods. The cross-sectional design allows for the examination of relationships between variables at a single point in time, which is appropriate for understanding the current state of technology-mediated learning processes. The quantitative approach enables the testing of hypothesized relationships derived from established theoretical frameworks while allowing for the integration of multiple theoretical perspectives into a unified model.

2.2 Research Participants

The target population comprised university students engaged in digital learning environments across various academic disciplines. Participants were selected using purposive sampling to ensure they had sufficient experience with adaptive learning technologies and digital teaching methods. The sample consisted of 70 participants, meeting the minimum sample size requirements for PLS-SEM analysis as recommended by Hair et al. (2017), which suggests a minimum of 10 observations per predictor variable in the most complex regression equation.

The demographic profile of participants included 25 male participants (35.7%) and 45 female participants (64.3%), representing a diverse gender distribution. Age distribution was categorized as follows: 19 participants (27.1%) under 30 years old, 22 participants (31.4%) between 30–40 years old, and 29 participants (41.5%) over 40 years old. This age diversity ensures representation across different generational cohorts with varying levels of technology familiarity and learning preferences.

Inclusion criteria required participants to: (1) be currently enrolled in higher education programs, (2) have at least six months of experience using digital learning platforms, (3) be actively engaged in courses incorporating adaptive learning technologies, and (4) provide informed consent for participation. Exclusion criteria included participants with less than six months of digital learning experience and those unable to complete the survey due to language barriers or technical constraints.

2.3 Data Collection Techniques

Data collection was conducted through a structured online questionnaire administered via a secure survey platform. The questionnaire was developed based on established scales from previous studies, adapted to fit the specific context of this research. All constructs were measured using reflective indicators on a 7-point Likert scale ranging from “strongly disagree” (1) to “strongly agree” (7). The instrument was designed to capture five main constructs through multiple dimensions and indicators as detailed in Table 1. Each construct was operationalized through specific dimensions that comprehensively covered the theoretical domains under investigation.

Table 1
Dimensions and Indicators of the Questionnaire

No	Dimensions	Indicators
1	Teaching Digital Models	- Development of interactive content - Application of tutorials - Online interaction - Virtual classroom management - Digital feedback
2	Learning Environment	- Availability of learning facilities - Conducive learning atmosphere - Support for educational technology - Collaborative discussion spaces - Independent learning zones (creativity)
3	Adaptive Technology Learning	- Ease of use of learning technologies (TAM – Perceived Ease of Use) - Alignment of technology features with learning needs (TTF – Task Fit) - Perceived usefulness of technology for learning improvement (TAM – Perceived Usefulness) - Comfort and flexibility in technology usage (TTF – Flexibility) - Intention to continuously use learning technologies (TAM – Behavioral Intention to Use)
4	Driven Cognitive Psychology	- Conceptual understanding ability - Cognitive schema development - Critical thinking skills - Logical reasoning - Metacognition - Learning strategies
5	Performance Assessment	- Academic achievement - Mastery of learning competencies - Subject matter mastery - Cognitive competence - Portfolio development

No	Dimensions	Indicators
		- Practical skills

The study operationalized five key constructs to comprehensively capture the dynamics of adaptive learning systems. The Teaching Digital Models construct focused on instructors' utilization of digital technologies, emphasizing interactive content, tutorial-based approaches, online interactions, classroom management, and digital feedback. The Learning Environment construct examined contextual factors such as learning facilities, conducive atmosphere, institutional support for technology integration, collaborative spaces, and provisions for independent learning. The Adaptive Technology Learning construct integrated the TAM and TTF frameworks, measuring perceived ease of use, perceived usefulness, behavioral intention to use, task-technology fit, and flexibility. Meanwhile, the Driven Cognitive Psychology construct covered cognitive processes including conceptual understanding, schema development, critical thinking, logical reasoning, metacognition, and learning strategies. Lastly, the Performance Assessment construct evaluated learning outcomes across academic achievement, competency mastery, subject-specific knowledge, cognitive skills, portfolio assessment, and practical performance. Altogether, these constructs were represented by 85 items adapted from established scales in educational technology and cognitive psychology, ensuring both theoretical grounding and contextual relevance.

To ensure validity and reliability, all measurement scales underwent rigorous expert review by specialists in educational technology, cognitive psychology, and psychometrics, who assessed item clarity, construct relevance, and theoretical alignment. Pilot testing with 15 participants further refined the instrument for comprehensibility, completion time, and response quality. The questionnaire was then administered electronically via institutional learning management systems and direct email, accompanied by detailed instructions and technical support. Data quality was maintained through attention checks, validation of response patterns, and automatic timestamping of responses. Participants completed the survey in approximately 25–30 minutes, with options to pause and resume, while reminder notifications were distributed strategically over a four-week period to enhance response rates without causing fatigue.

2.4 Data Analysis

Data analysis was carried out using SmartPLS 4.0.9 software, following the two-stage procedure outlined by Anderson and Gerbing (1988), which involved assessing both the measurement model (outer model) and the structural model (inner model). The measurement model evaluation focused on convergent validity, internal consistency reliability, and discriminant validity. Convergent validity was established through factor loadings (≥ 0.70), Average Variance Extracted (AVE ≥ 0.50), and Composite Reliability (CR ≥ 0.70), while internal consistency was confirmed using Cronbach's Alpha and CR values (≥ 0.70). Discriminant validity was assessed through the Fornell-Larcker criterion and Heterotrait-Monotrait (HTMT) ratio, with HTMT values below 0.90 indicating satisfactory results. Indicators with low

factor loadings or high cross-loadings were systematically removed to enhance reliability and discriminant validity.

The structural model assessment examined path coefficients, coefficient of determination (R^2), effect sizes (f^2), and predictive relevance (Q^2). Bootstrapping with 5,000 subsamples was conducted to test the significance of path coefficients using t-statistics and confidence intervals at a 5% significance level. R^2 values were interpreted based on Cohen's (1988) guidelines (0.02 = small, 0.13 = medium, 0.26 = large), while effect sizes were categorized as small (0.02), medium (0.15), and large (0.35). Predictive relevance was confirmed through Stone-Geisser Q^2 values exceeding zero. Data preparation steps included handling missing responses through listwise deletion (< 5%), assessing skewness and kurtosis for normality (with non-normal data acceptable in PLS-SEM), and evaluating multicollinearity using Variance Inflation Factor (VIF < 5.0).

3. Results

The analysis of the integrated TAM-TTF-cognitive psychology model proceeded through systematic evaluation of the measurement model followed by structural model assessment using PLS-SEM methodology. The measurement model demonstrates robust psychometric properties with all five constructs achieving satisfactory reliability and convergent validity thresholds, though discriminant validity concerns emerge between certain construct pairs, particularly Learning Environment and Teaching Digital Model. The structural model reveals a complex pattern of relationships where technology-related constructs show strong direct effects on learning environments and performance outcomes, while the hypothesized cognitive mediation pathways demonstrate weaker empirical support. The model explains substantial variance in Learning Environment (80.8%) and Performance Assessment (76.4%), with moderate explanatory power for Driven Cognitive Psychology (56.0%), indicating that the integrated framework captures key mechanisms in technology-mediated learning while highlighting limitations in cognitive activation processes. The following sections present detailed analyses of construct reliability and validity, discriminant validity assessments, explanatory power evaluation, hypothesis testing results, and effect size determinations that collectively reveal both the strengths and limitations of the proposed theoretical integration.

Table 2
Construct Reliability & Validity

Construct	No.	Cronbach's Alpha (α)	ρ_A	CR	AVE	Decision
Teaching Digital Model	16	0.930	0.931	0.941	0.591	Reliable/Valid
Learning Environment	15	0.932	0.934	0.943	0.650	Reliable/Valid
Adaptive Technology Learning	16	0.959	0.961	0.964	0.656	Reliable/Valid
Driven Cognitive Psychology	22	0.945	0.949	0.952	0.606	Reliable/Valid
Performance Assessment	16	0.910	0.913	0.927	0.614	Reliable/Valid
Note: General criteria: α ≥ 0.70; CR ≥ 0.70; AVE ≥ 0.50						

The construct reliability and validity assessment demonstrate (See Table 2) that all five constructs in the measurement model achieve excellent psychometric properties, surpassing the established threshold criteria of α ≥ 0.70, CR ≥ 0.70, and AVE ≥ 0.50. Internal consistency reliability, measured through Cronbach's Alpha, ranges from 0.910 (Performance Assessment) to 0.959 (Adaptive Technology Learning), indicating high reliability across all constructs, while the ρ_A values consistently align with Cronbach's Alpha coefficients, confirming stable internal consistency. Composite Reliability values range from 0.927 to 0.964, demonstrating robust construct reliability, with Adaptive Technology Learning exhibiting the highest reliability (CR = 0.964) followed by Learning Environment (CR = 0.943). Convergent validity, assessed through Average Variance Extracted, shows satisfactory results across all constructs, with values ranging from 0.591 (Teaching Digital Model) to 0.656 (Adaptive Technology Learning), indicating that each construct explains more than half of the variance in its respective indicators. The consistently high reliability and validity coefficients across all constructs confirm that the measurement model is psychometrically sound and suitable for subsequent structural model analysis, with Adaptive Technology Learning demonstrating the strongest measurement properties and Teaching Digital Model showing the lowest but still acceptable AVE value.

The PLS-SEM structural model diagram (Fig. 1) illustrates the complex relationships among the five key constructs in the integrated technology-cognition-performance framework, revealing significant direct and indirect pathways that explain substantial variance in the endogenous variables. The model demonstrates that Teaching Digital Model serves as a foundational construct with the strongest direct effect on Learning Environment (β = 0.518), while showing weaker direct relationships with Driven Cognitive Psychology (β = 0.240) and Performance Assessment (β = 0.096). Adaptive Technology Learning emerges as a critical driver with significant direct effects on all three endogenous constructs: Learning Environment (β = 0.420), Performance Assessment (β = 0.406), and Driven Cognitive Psychology (β = 0.374). The model reveals that Driven Cognitive Psychology functions as a powerful mediator with the strongest direct effect on Performance Assessment (β = 0.449), while Learning

Environment shows a relatively weak direct effect on cognitive processes (β = 0.173). The R^2 values indicate that the model explains substantial variance in Learning Environment (80.8%), Performance Assessment (76.4%), and moderate variance in Driven Cognitive Psychology (56.0%), suggesting that the integrated framework successfully captures the key mechanisms through which technology acceptance and environmental factors influence cognitive engagement and ultimately academic performance. The factor loadings displayed for each indicator (ranging from approximately 0.7 to 0.9 across constructs) confirm adequate measurement model quality, supporting the validity of the structural relationships identified in this comprehensive model of technology-mediated learning.

3.1 Discriminant Validity-Fornell-Larcker

Discriminant validity was assessed using the Fornell-Larcker criterion, which requires that the square root of the AVE for each construct exceeds its correlations with all other constructs in the model. As presented in Table 3, the diagonal values representing the square root of AVE for each construct are greater than the corresponding inter-construct correlation coefficients, confirming adequate discriminant validity across all five constructs.

Table 3
Discriminant Validity-Fornell-Larcker

Adaptive Technology Learning (ATL)	**ATL**	**DCP**	**LE**	**PA**	**TDM**
	0.810				
Driven Cognitive Psychology (DCP)	0.722	0.779			
Learning Environment (LE)	0.853	0.700	0.806		
Performance Assessment (PA)	0.810	0.809	0.752	0.784	
Teaching Digital Model (TDM)	0.837	0.703	0.869	0.751	0.769

The Fornell-Larcker discriminant validity Table 3 reveals significant concerns regarding the distinctiveness of the constructs, as several construct pairs violate the fundamental criterion that the square root of Average Variance Extracted (diagonal values) should exceed all correlations with other constructs (off-diagonal values). Most notably, the correlation between Learning Environment and Teaching Digital Model (0.869) substantially exceeds both constructs' AVE values (0.806 and 0.769 respectively), indicating problematic overlap between these constructs. Additionally, Adaptive Technology Learning shows high correlations with Learning Environment (0.853) and Teaching Digital Model (0.837) that exceed its AVE of 0.810, while Performance Assessment demonstrates correlations with both Adaptive Technology Learning (0.810) and Driven Cognitive Psychology (0.809) that surpass its AVE of 0.784. These violations suggest that respondents may have difficulty distinguishing between certain constructs, particularly Learning Environment and Teaching Digital Model, which could indicate conceptual overlap, similar item wording, or the need for better construct differentiation. While the study acknowledges these limitations and provides theoretical justification for maintaining separate

constructs, these discriminant validity issues represent a notable weakness in the measurement model that could affect the interpretation of structural relationships and the overall validity of the findings.

Table 4
Discriminant Validity-HTMT Ratio

Construct Pair	HTMT	Threshold	Decision
Adaptive Technology Learning-Driven Cognitive Psychology	0.743	0.90	Satisfied
Adaptive Technology Learning-Learning Environment	0.898	0.90	Satisfied
Adaptive Technology Learning-Performance Assessment	0.857	0.90	Satisfied
Adaptive Technology Learning-Teaching Digital Model	0.880	0.90	Satisfied
Driven Cognitive Psychology-Learning Environment	0.733	0.90	Satisfied
Driven Cognitive Psychology-Performance Assessment	0.867	0.90	Satisfied
Driven Cognitive Psychology-Teaching Digital Model	0.734	0.90	Satisfied
Learning Environment-Performance Assessment	0.813	0.90	Satisfied
Learning Environment-Teaching Digital Model	0.929	0.90	Invalid
Performance Assessment- Teaching Digital Model	0.811	0.90	Satisfied

The HTMT discriminant validity assessment (Table 4) reveals a mixed pattern of results that largely corroborates the concerns identified in the Fornell-Larcker analysis, with nine out of ten construct pairs satisfying the discriminant validity criterion while one critical violation undermines the overall measurement model integrity. The majority of construct pairs demonstrate acceptable discriminant validity with HTMT values ranging from 0.733 (Driven Cognitive Psychology-Learning Environment) to 0.880 (Adaptive Technology Learning-Teaching Digital Model), all falling below the conservative 0.90 threshold. However, the Learning Environment-Teaching Digital Model pair exhibits a problematic HTMT value of 0.929, which exceeds the established threshold and confirms the discriminant validity issues previously identified through the Fornell-Larcker criterion. This violation is particularly concerning because it represents the same construct pair that showed the highest correlation (0.869) in the previous analysis, suggesting a consistent pattern of conceptual overlap between these two constructs. Additionally, while technically satisfying the criterion, several construct pairs show relatively high HTMT values approaching the threshold, including Adaptive Technology Learning-Learning Environment (0.898) and Adaptive Technology Learning-Teaching Digital Model (0.880), indicating potential areas of concern that warrant careful interpretation. The consistent violation of discriminant validity between Learning Environment and Teaching Digital Model across both assessment methods suggests that these constructs may be measuring overlapping phenomena, potentially due to similar item content, respondent perception similarities, or genuine conceptual overlap that challenges the theoretical distinction maintained by the researchers.

3.2 Validation Stage

The validation stage assessed the predictive power of the structural model through the Coefficient of Determination (R^2) and Adjusted R^2, which indicate the proportion of variance in each endogenous construct explained by its respective predictor variables. Table 5 demonstrates that the model exhibits strong predictive accuracy for Learning Environment ($R^2 = 0.808$) and Performance Assessment ($R^2 = 0.764$), while Driven Cognitive Psychology reflects a moderate level of explanatory power ($R^2 = 0.560$), collectively confirming the overall robustness of the proposed model.

Table 5

Coefficient of Determination (R^2) & Adjusted R^2

Endogenous Construct	**R^2**	**Adjusted R^2**	**Category**
Driven Cognitive Psychology	0.560	0.540	Moderate
Learning Environment	0.808	0.802	Strong
Performance Assessment	0.764	0.754	Strong
Note: interpretation guide (rule-of-thumb, social science contexts): = 0.25 weak; = 0.50 moderate; = 0.75 strong.			

The coefficient of determination analysis (Table 5) demonstrates that the proposed integrated model exhibits strong to moderate explanatory power across the three endogenous constructs, with notable variations in the model's ability to predict different outcome variables. Learning Environment achieves the highest explanatory power with an R^2 of 0.808 (adjusted $R^2 = 0.802$), indicating that approximately 81% of the variance in learning environment quality is explained by the predictor constructs, primarily Teaching Digital Model and Adaptive Technology Learning, representing a strong effect according to Cohen's (1988) benchmarks. Performance Assessment shows similarly robust predictive capability with an R^2 of 0.764 (adjusted $R^2 = 0.754$), suggesting that roughly 76% of the variance in academic performance outcomes is accounted for by the combined effects of adaptive technology learning, driven cognitive psychology, teaching digital models, and learning environment factors. In contrast, Driven Cognitive Psychology exhibits moderate explanatory power with an R^2 of 0.560 (adjusted $R^2 = 0.540$), indicating that 56% of the variance in cognitive psychological processes is explained by the predictor variables, which while statistically meaningful, suggests the presence of additional unmeasured factors that influence cognitive engagement in digital learning environments. The minimal differences between R^2 and adjusted R^2 values across all constructs (ranging from 0.006 to 0.020) indicate that the model complexity is appropriate and that the explanatory power is not artificially inflated by the inclusion of numerous predictors, supporting the model's parsimony and statistical robustness.

Table 6
Path Coefficients & Hypothesis Testing (Bootstrap)

Hypothesized Path	(β)	t-stat	p-value	97.5%	Decision
Adaptive Technology Learning-> Driven Cognitive Psychology	0.374	1.879	0.060	0.383	Rejected
Adaptive Technology Learning-> Learning Environment	0.420	3.907	0.000	0.383	Accepted
Adaptive Technology Learning-> Performance Assessment	0.406	3.538	0.000	0.383	Accepted
Driven Cognitive Psychology-> Performance Assessment	0.449	5.080	0.000	0.383	Accepted
Learning Environment-> Driven Cognitive Psychology	0.173	0.837	0.403	0.383	Rejected
Teaching Digital Model-> Driven Cognitive Psychology	0.240	1.294	0.196	0.383	Rejected
Teaching Digital Model-> Learning Environment	0.518	4.734	0.000	0.383	Accepted
Teaching Digital Model-> Performance Assessment	0.096	0.764	0.445	0.383	Rejected

The path analysis results (Table 6) reveal a complex pattern of relationships where Adaptive Technology Learning demonstrates significant direct effects on both Learning Environment and Performance Assessment, indicating that technology integration enhances learning contexts and academic outcomes simultaneously, while notably failing to activate Driven Cognitive Psychology processes, suggesting that mere technology availability is insufficient to stimulate deeper cognitive engagement. Driven Cognitive Psychology emerges as the strongest predictor of Performance Assessment, confirming that when cognitive processes such as critical thinking, metacognition, and reasoning are effectively activated, academic performance improves substantially, positioning cognition as the central mediator between learning processes and outcomes. Teaching Digital Models primarily influence Learning Environment rather than directly affecting performance or cognitive processes, functioning as foundational infrastructure that creates supportive learning ecosystems but requires additional mechanisms to translate into cognitive activation and performance gains. This pattern demonstrates that optimal performance assessment outcomes cannot be achieved through any single factor alone but require the integrated functioning of adaptive technology (providing direct performance benefits), cognitive psychology (serving as the primary performance driver), and digital teaching models (establishing conducive learning environments), conveying the critical message that effective modern instructional design must simultaneously integrate technological, cognitive, and environmental factors to achieve meaningful educational outcomes.

This bootstrapping results diagram (Fig. 2) displays the statistical significance of all structural paths and indicator loadings through t-statistics values, revealing a mixed pattern of significant and non-significant relationships within the integrated model. The diagram shows that several key structural paths achieve statistical significance with t-values exceeding the critical threshold of 1.96 ($p < 0.05$), most notably the path from Teaching Digital Model to Learning Environment (t = 4.734), Driven Cognitive Psychology to Performance Assessment (t = 5.080), Adaptive Technology Learning to Learning Environment (t = 3.907), and Adaptive Technology Learning to Performance Assessment (t = 3.538). However, critical weaknesses emerge in the cognitive engagement pathways, where Teaching Digital Model to Driven Cognitive Psychology shows a non-significant relationship (t = 1.294), Adaptive Technology Learning to Driven Cognitive Psychology demonstrates marginal significance (t = 1.879), and Learning Environment to Driven Cognitive Psychology exhibits a particularly weak non-significant relationship (t = 0.837). The indicator t-statistics displayed on the measurement model components show generally robust factor loadings, with most values ranging from approximately 2.0 to over 28.0, indicating that the majority of indicators load significantly on their respective constructs, though some weaker loadings are evident particularly in certain constructs. This pattern of results suggests that while the model successfully explains direct technology-performance relationships and environmental factors, the hypothesized pathways through cognitive psychological processes are not well-supported empirically, indicating that the integration of cognitive psychology constructs may not function as theoretically proposed in this particular educational technology context.

Table 7

Effect Size (f^2) between construct

Predictor	**Target**	**f^2**	**Category**
Adaptive Technology Learning	Driven Cognitive Psychology	0.075	Small
Adaptive Technology Learning	Learning Environment	0.276	Medium
Adaptive Technology Learning	Performance Assessment	0.186	Medium
Driven Cognitive Psychology	Performance Assessment	0.381	Large
Learning Environment	Driven Cognitive Psychology	0.013	Small
Teaching Digital Model	Driven Cognitive Psychology	0.028	Small
Teaching Digital Model	Learning Environment	0.420	Large
Teaching Digital Model	Performance Assessment	0.011	Small
Cohen's (1988) guidelines: 0.02–0.14 = small; 0.15–0.34 = medium; ≥ 0.35 = large			

The effect size (f^2) analysis (see Table 7) reveals substantial heterogeneity in the practical significance of relationships within the model, with only two pathways demonstrating large effect sizes while most relationships exhibit small to negligible practical impact. Teaching Digital Model exerts the strongest influence on Learning Environment with a large effect size ($f^2 = 0.420$), indicating that digital teaching

approaches substantially impact the quality of the learning environment, followed by Driven Cognitive Psychology's large effect on Performance Assessment ($f^2 = 0.381$), confirming that cognitive processes are practically significant predictors of academic outcomes. Adaptive Technology Learning shows moderate effect sizes on both Learning Environment ($f^2 = 0.276$) and Performance Assessment ($f^2 = 0.186$), suggesting meaningful but moderate practical significance in these relationships. However, the model reveals concerning weaknesses in cognitive engagement pathways, where most relationships targeting Driven Cognitive Psychology exhibit negligible effect sizes: Learning Environment ($f^2 = 0.013$), Teaching Digital Model ($f^2 = 0.028$), and Adaptive Technology Learning ($f^2 = 0.075$) all demonstrate small effects, indicating that these predictors have minimal practical impact on cognitive psychological processes. Similarly, Teaching Digital Model's direct effect on Performance Assessment shows negligible practical significance ($f^2 = 0.011$), suggesting that digital teaching methods primarily influence performance through indirect pathways rather than direct impact. This pattern indicates that while the model identifies some statistically significant relationships, many lack practical significance, particularly in activating cognitive processes that the theoretical framework suggests should be central mediators in technology-enhanced learning.

4. Discussion

The findings of this study provide important insights into the complex relationships between technology acceptance, environmental factors, and cognitive processes in digital learning contexts, while revealing both convergent and divergent patterns compared to existing literature. The integrated model successfully explains substantial variance in learning outcomes ($R^2 = 0.764$) and learning environments ($R^2 = 0.808$), demonstrating that the combination of TAM-TTF frameworks with cognitive psychology theory offers meaningful predictive power for understanding technology-mediated learning. However, the moderate explanatory power for cognitive psychological processes ($R^2 = 0.560$) and the rejection of several cognitive engagement hypotheses indicate limitations in how these theoretical frameworks integrate in practice.

The strong direct effects of Adaptive Technology Learning on both Learning Environment ($\beta = 0.420$, $p < 0.001$) and Performance Assessment ($\beta = 0.406$, $p < 0.001$) align well with recent meta-analytical evidence demonstrating that adaptive learning technologies consistently enhance student engagement and academic performance across various educational contexts (du Plooy et al., 2024; Strielkowski et al., 2025). This finding corroborates Contrino et al.'s (2024) experimental results showing significant improvements in student performance when incorporating adaptive learning strategies in both online and face-to-face education. The substantial effect sizes observed ($f^2 = 0.186$ to 0.276) provide practical evidence supporting García-Martínez et al. (2023) conclusion that adaptive learning technologies lead to higher pass rates and improved student retention compared to traditional teaching methods.

However, the failure to establish significant pathways from Adaptive Technology Learning to Driven Cognitive Psychology ($\beta = 0.374$, $\rho = 0.060$) presents a notable departure from theoretical expectations and some empirical findings. This contrasts with recent research by Mejeh and Rehm (2024), who

demonstrated that adaptive learning technologies enhanced with natural language processing successfully support self-regulated learning and cognitive processes. Similarly, the non-significant relationship contradicts findings from cognitive load theory research, where AI-driven adaptive learning systems have been shown to improve learning efficacy through dynamic cognitive load management and personalized instruction based on real-time neurophysiological data (Ackermann et al., 2025). The disconnect suggests that mere availability of adaptive technology is insufficient to activate deeper cognitive processes, requiring additional pedagogical interventions or design considerations.

The strong predictive relationship between Driven Cognitive Psychology and Performance Assessment ($\beta = 0.449$, $f^2 = 0.381$) strongly supports recent findings emphasizing the mediating role of cognitive engagement in technology-enhanced learning. This aligns with Liang et al.'s (2023) discovery that cognitive engagement serves as a serial mediator between AI interaction and learning achievement and supports the broader literature demonstrating that self-efficacy and cognitive engagement are crucial determinants of academic success in digital environments. The large effect size ($f^2 = 0.381$) provides robust evidence for the centrality of cognitive processes in determining learning outcomes, consistent with educational neuroscience research showing significant effects of cognitive engagement on learning performance ($\beta = 0.38$ to 0.42) in adaptive learning contexts. Furthermore, Rauhun et al. (2025) identified that low conceptual understanding in students is a multi-dimensional phenomenon encompassing cognitive, affective, and motivational barriers — further affirming that cognitive engagement cannot be reduced to technology use alone, but requires comprehensive pedagogical support.

From a theoretical perspective, the study reveals both support for and challenges to established frameworks. The strong support for TAM-based relationships (Technology Acceptance → Performance outcomes) aligns with extensive meta-analytical evidence confirming TAM validity across educational contexts, where perceived usefulness and ease of use consistently predict technology adoption and learning outcomes (Al-Adwan et al., 2023; Kemp et al., 2024). The integration of TTF theory through task-technology alignment measures further strengthens the theoretical foundation, supporting Alamri et al.'s (2024) findings that compatibility and task-technology fit significantly influence educational technology effectiveness.

However, the weak cognitive engagement pathways challenge the theoretical assumption that technology acceptance automatically translates into cognitive activation. This finding suggests limitations in current theoretical integration approaches, particularly the assumption that TAM and cognitive psychology theories operate through straightforward mediational pathways. Recent advances in educational neuroscience and AI-driven learning indicate that cognitive activation requires more sophisticated mechanisms than traditional technology acceptance models propose (Ackermann et al., 2025). The small effect sizes for cognitive engagement pathways ($f^2 = 0.013$ to 0.075) suggest that additional theoretical frameworks may be needed to explain how technology acceptance translates into meaningful cognitive engagement.

The discriminant validity issues between Learning Environment and Teaching Digital Model (HTMT = 0.929) highlight potential theoretical overlap that challenges the distinctiveness of environmental and instructional factors in digital learning contexts. This finding suggests that in technology-rich educational environments, the boundaries between teaching methods and learning environments may be more fluid than traditional educational theories propose, supporting recent calls for more integrated theoretical approaches to technology-mediated learning (Radif, 2024; Palacios-Hidalago & Huertas-Abril, 2025).

The moderate success in explaining cognitive psychological processes suggests that integrating cognitive psychology with technology acceptance models requires more nuanced approaches than simple additive frameworks. While the study demonstrates that cognitive processes are strong predictors of learning outcomes when activated, the pathways to cognitive activation remain unclear. This aligns with recent research emphasizing that successful adaptive learning implementation requires deliberate cognitive engagement strategies rather than relying solely on technological sophistication (Alamri et al., 2024; Mejeh & Rehm, 2024). This is consistent with Putri and Cahyanti (2024), who found that while technology applications support procedural problem-solving, excessive reliance on such tools may actually impede deeper cognitive engagement, underscoring the need for intentional instructional design.

The findings suggest that future theoretical development should focus on identifying the specific conditions under which technology acceptance translates into cognitive engagement, rather than assuming automatic mediation. Recent advances in AI-driven personalization and real-time cognitive load management (Ackermann et al., 2025) indicate that effective cognitive activation may require more sophisticated technological and pedagogical interventions than traditional adaptive learning approaches provide. This points toward the need for hybrid theoretical frameworks that better account for the complexity of cognitive processes in technology-mediated learning environments, supporting recent calls for more integrated approaches to educational technology research (Bearman et al., 2024; Holmes & Miao, 2023).

5. Conclusion

This study successfully developed and tested an integrated model combining Technology Acceptance Model (TAM), Task-Technology Fit (TTF), and cognitive psychology theory to examine how adaptive learning technologies influence academic performance. Using PLS-SEM methodology with 70 participants, the research revealed a critical finding that challenges conventional assumptions in educational technology: adaptive technology learning does not directly activate cognitive psychological processes ($\beta = 0.374$, $p = 0.060$), despite showing strong direct effects on learning environment ($\beta = 0.420$, $p < 0.001$) and performance assessment ($\beta = 0.406$, $p < 0.001$). The model demonstrated strong explanatory power for Learning Environment ($R^2 = 80.8\%$) and Performance Assessment ($R^2 = 76.4\%$), while Driven Cognitive Psychology emerged as the strongest predictor of academic performance ($\beta =$

0.449, $f^2 = 0.381$), confirming that cognitive processes are central mediators in learning outcomes when effectively activated.

The findings have profound implications for educational technology implementation, demonstrating that technological sophistication alone is insufficient without deliberate cognitive engagement strategies. The research challenges the prevalent assumption that technology adoption automatically leads to enhanced learning outcomes, instead revealing that adaptive technologies primarily influence performance through environmental enhancement and direct benefits rather than cognitive activation. This suggests that successful educational technology integration requires the orchestrated combination of technological tools, supportive learning environments, and explicit pedagogical approaches designed to foster cognitive engagement. For practitioners, the study emphasizes that optimal learning outcomes in digital environments depend not merely on technological adoption but on the skillful integration of adaptive technologies with cognitive science principles and evidence-based instructional strategies that deliberately activate metacognitive processes, critical thinking, and self-regulated learning.

Declarations

Author Contributions

Suci Nurhayati: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Writing – original draft, Writing – review & editing

Tommy Tanu Wijaya: Methodology, Writing – review & editing

Sudirman Sudirman: Data curation, Formal analysis, Writing – review & editing

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Clinical Trial Number

Clinical trial number: not applicable.

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Data Availability Statement

The data that support the findings of this study are available from the corresponding author upon reasonable request.

Disclosure Statement

The authors declare no conflict of interest. This research was conducted independently without any influence from commercial entities or technology vendors that could potentially bias the findings.

Ethics Approval

This study was approved by the Research and Community Service Institute (LPPM) of Universitas Terbuka with ethical approval number B/932/UN31.LPPM/PT.01.04/2025. All participants provided informed consent prior to their participation in the study.

Consent to Participate

Informed consent was obtained from all participants involved in the study.

Consent to Publish

NOT APPLICABLE

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Figures

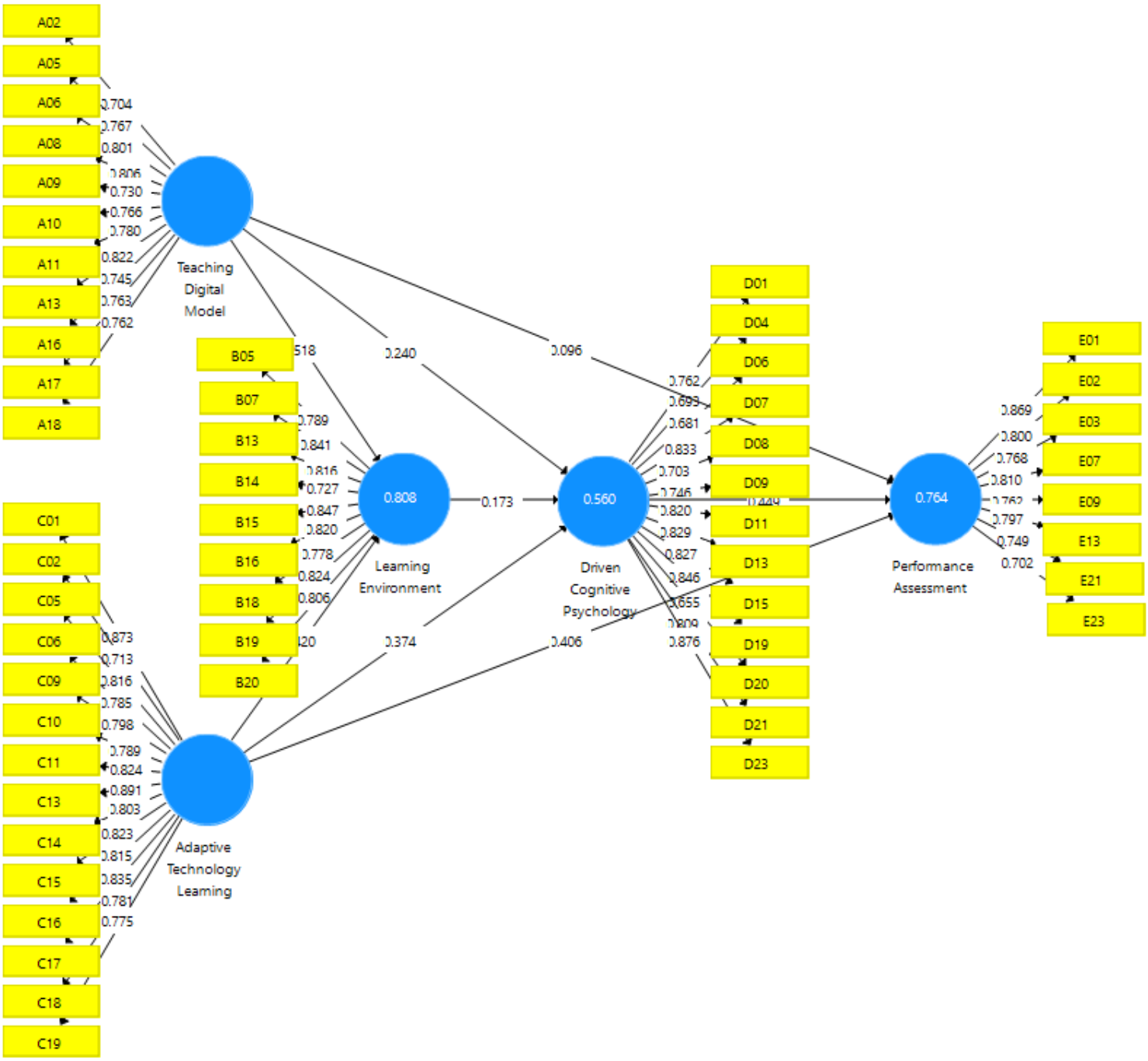


Figure 1

Run of PLS Algorithm

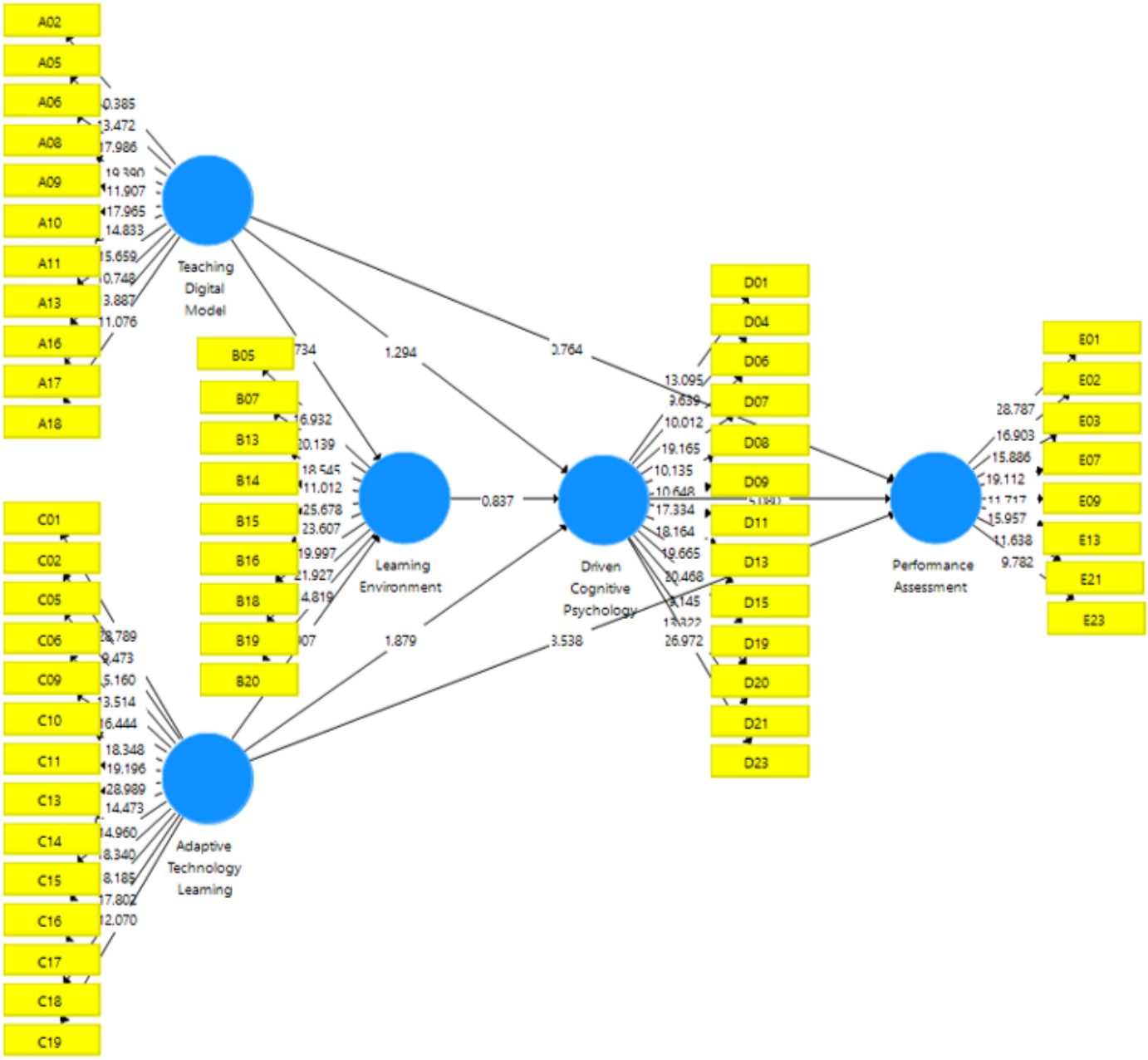


Figure 2

Run of Bootstrapping