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Estimating Predictive Power of Digital Technology in Improving Science Learning Outcomes of Secondary School Students

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Keywords

presage-process-product model, pls-sem, usage of e-content, development of e-content, science learning outcomes

Abstract

This study maps systemic variables onto an adapted Presage-Process-Product (3Ps) model using Partial Least Squares Structural Equation Modeling PLS-SEM to examine 15 structural pathways linking Science Learning Outcomes (LO) in secondary schools. Ten pathways were statistically significant. The Use of e-content (UE) was the strongest predictor of LO (Total Effect = .457; direct β = .346; indirect via Behavioural Intention (BI) β = .362). Upstream inputs like Teacher Deployment (TD) and Learning Interventions (LI) showed no direct link to LO. However, Development of e-content (DE) (Total Effect = .224) and LI (Total Effect = .265) predicted LO primarily when mediated by UE and BI, confirming a complex multi-indirect framework. Furthermore, Cross-Validated Predictive Ability Testing (CVPAT) confirmed its out-of-sample predictive power, showing a significant reduction in forecasting error.

Introduction

Empirical evidence demonstrates that digital technology has a heterogeneous impact on learning outcomes, often taking a non-linear, inverse U-shaped form (Rodrigues & Biagi, 2017). While studies by Lewin et al. (2019) underscore positive learning outcomes, a concurrent body of literature documents negligible or even detrimental effects on learning outcomes (Bau & Das, 2020; Moin & Singh, 2026; Petko et al., 2017). These incongruities suggest that critical human factors—including teachers' Behavioural Intention (BI)—moderate the nexus between technology and learning outcomes (Organisation for Economic Co-operation and Development, 2024)

Despite marginal improvements in foundational literacy, Science Learning Outcomes (LO) in Bihar consistently fall below national averages, particularly at the secondary level. Although infrastructure has expanded, Bihar remains at the bottom of the School Education Quality Index (NITI Aayog, 2019), trailing states such as Kerala and Tamil Nadu. Data from the National Achievement Survey (NCERT, 2022) corroborate this systemic underperformance, revealing profound proficiency gaps; specifically, a majority of Grade 10 students fail to achieve basic competency in science and social science. Although Grade 9 students demonstrate moderate proficiency—achieving success rates of 40% in LO and 37% in mathematics—these figures remain symptomatic of a broader national deficiency in higher-order problem-solving and scientific application (National Council of Educational Research and Training, 2025). Research suggests that traditional input-based policies, such as infrastructure expansion and teacher credentials, have limited impact on achievement (Hanushek, 2020). Even with school

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integration under the National Education Policy (Ministry of Human Resource Development, 2020), many government secondary schools still lack specialised science teachers. State-led digitisation and the deployment of specialist teachers have had little effect on LO. While teachers have created various e-learning platforms and offline tools, institutional hurdles continue to stifle their adoption in the classroom.

Conceptual Model of Digital Technology

This proposed conceptual framework posits that digital technology is associated with LO through a complex network of constructs (Figure 1). Grounded in the Unified Theory of Acceptance and Use of Technology (Venkatesh et al., 2016), the Technology Acceptance Model (Davis, 1989), and Self-Determination Theory (Han et al., 2018), this conceptual model integrates seven core dimensions: Digital Technology (DT), Innovation (IN), Development of e-content (DE), Use of e-content (UE), Learning Interventions (LI), Teacher Deployment (TD), and Behavioural Intention (BI). Central to this model is the role of the teacher; professional digital competence and positive dispositional factors foster the BI needed for teachers to use resources (Chandra, 2023, 2024). This conceptual linkage aligns with the Expectation-Confirmation Model (Bhattacherjee, 2001), in which perceived usefulness and ease of use drive the BI. This study adapts the Presage-Process-Product Model (Biggs et al., 2001) to conceptualise the educational production function. Teacher deployment serves as the presage variable, representing structural and systemic environmental inputs. These inputs shape process dynamics—namely, LI and targeted pedagogical strategies (development and use of e-content). Ultimately, these dynamics predict the product, measured by LO. This model posits that TD improves LO mainly through the delivery of quality LI. Furthermore, the framework acknowledges a non-linear relationship in technological intensity. While low-intensity users in developing countries derive significant marginal gains, high-intensity users often reach a plateau of diminishing returns (Haleem et al., 2022). Consistent with Blömeke et al. (2015) and Yang and Kaiser (2023), this model posits a bidirectional synergy between teacher competence and situational practice, suggesting that the structural validity of these interrelated constructs can be rigorously evaluated using PLS-SEM (Hair et al., 2022).

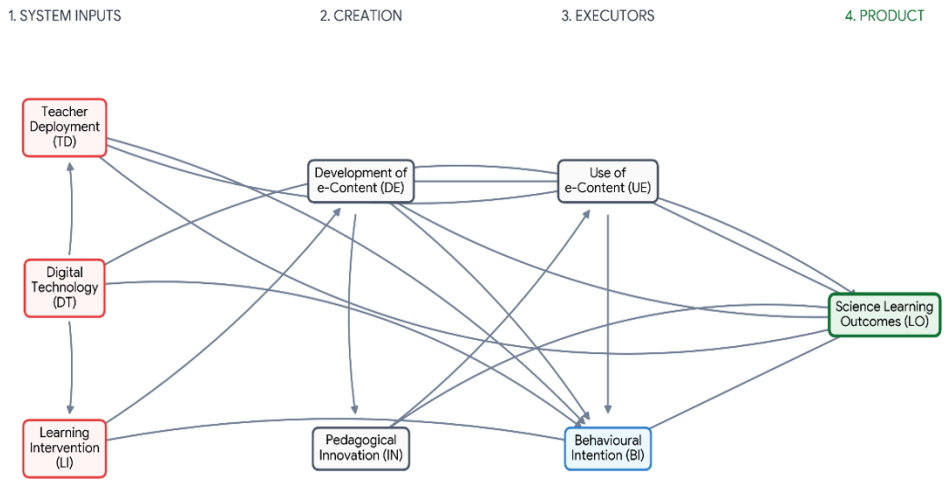

Figure 1: **Conceptual linkage between constructs**

Background to the Study

Despite significant growth in school access and infrastructure, learning outcomes in core subjects failed to meet required standards, indicating that school resources and traditional teaching methods have had a limited role in performance (Hanushek, 2020). Data reveal significant subject variation in the learning performance of Grade 10 students (NCERT, 2022). While 44% of students performed at a basic level in mathematics, that figure dropped to between 16 and 19% for science, english, and social science. Furthermore, approximately 76% of students in science and 68% in social science secured marks below the basic level, suggesting a critical need for subject-specific interventions to improve Learning Outcomes (NCERT, 2022). The recent *PARAKH Rashtriya Sarvekshan* on LO highlighted gaps in mathematics, language, science, and social science across Grades 3, 6, and 9 (NCERT, 2025). In Grade 9, students in Bihar demonstrated moderate performance in science and mathematics, while average performance in language remained low.

Research Objectives

1. To examine the relationship between Digital Resources and LO.
2. To ascertain the relationship between TD, BI and LO.

Hypotheses

Hypothesis 1: Teacher Deployment (TD) indirectly predicts Science Learning Outcomes (LO) through Behavioural Intention (BI).

Hypothesis 2: Innovation (IN) in teaching practices mediates the relationship between the Development of e-content (DE) and the Use of e-content (UE).

Hypothesis 3: Learning Interventions (LI) link to Science Learning Outcomes (LO) indirectly by predicting teachers' Behavioural Intention (BI).

Hypothesis 4: The Use of e-content (UE) mediates the relationship between Innovation (IN) and Science Learning Outcomes (LO).

Methods

Participants

The study utilised a two-stage sampling design. Twelve of the 38 districts in Bihar were randomly selected using randomisation software. Twelve state-run rural secondary schools were randomly selected from each district using the UDISE Plus (2024-25) framework (Ministry of Education, 2025). Data were collected from 297 science teachers across 144 schools. Each school had two or more independent science sections, with one teacher exclusively teaching a section. Science marks were operationalised as the aggregated average marks of students in each science section. To test the assumption of independence, Intraclass Correlation Coefficients (ICC) were computed for student marks across the 297 science sections nested within 144 schools. The ICC was < .05, indicating that 5% of the variance in student marks was attributable to between-section differences. This is the conventional threshold for negligible clustering. An additional ICC was calculated at the school level and was also below .05, supporting the treatment of classes as independent units. The design effect was 1.05, well below 2.0. Hence, the clustering effect was ignored. Both predictor and outcome variables were conceptualised and measured at the section level. The sample size was validated for PLS-SEM (P min = 0.11–0.20, *p*

< .05) using the Inverse Square Root Method (Kock & Hadaya, 2018). The study sample comprised teachers aged 34 to 44.5 with two to nine years of teaching experience. While all participants held professional teaching degrees (BEd or MEd), 87% were science graduates, and 67% demonstrated digital proficiency through laptop ownership and familiarity with software. Additionally, 13% of the cohort possessed either a postgraduate degree in a science discipline or a diploma in computer science.

Instruments

Digital Technology Scale (DTS)

To ensure contextual relevance, the Digital Technology Scale was developed by adapting items from the existing literature (Chandra, 2023; Venkatesh et al., 2016). Content validity was assessed by a panel of experts from the State Council of Education Research and Training (SCERT), Patna. The final instrument comprised 22 items across seven constructs: digital technology (3), development of e-content (3), e-content use (4), innovation (4), teacher deployment (2), learning intervention (3), and behavioural intention (3). It was administered on a five-point interval scale; its structural properties were further validated through Confirmatory Composite Analysis, as shown in Tables 1-3.

Science Learning Outcomes Measure (LOM)

This was measured as the aggregated average of the marks of students enrolled in each science section.

Data Analysis

Given the negligible clustering and the class-level nature of both the independent and dependent variables, the data were analysed at the class level using SmartPLS (Version 4.0).

Ethical Consideration

As the state lacked a functioning ethics approval committee, the Education Secretary of the Department of Education (Government of Bihar) granted administrative clearance for this data collection. Headmasters and teachers provided voluntary consent before data collection, and the research team maintained strict anonymity and confidentiality for all participants.

Results

The measurement model analysis provided the scale's properties, while the structural model analysis identified a pattern of relationships among the variables.

Measurement Model Analysis

A Confirmatory Composite Analysis was performed to verify the hypothesised relationships among exogenous constructs. Tables 1–4 report factor loadings, reliability, validity, and the correlation matrix. The loadings for each indicator of the construct were all above .72. The internal consistency reliability (ICR) of the scale exceeded .83. The squared root average variance extracted (AVE) was more than .80 in all cases and was higher than the squared loadings of each indicator (> .71), indicating convergent validity of the scale (Table 4). The pattern of loadings and cross-loadings supported the internal consistency (Table 1). The HTMT was analysed to assess the discriminant validity of each factor (Table 3). On average, the HTMT ratio was below .90, confirming the scale's discriminant validity.

The SmartPLS-SEM measurement model confirms high reliability and validity for seven constructs—BI, DE, DT, TD, IN, LO and UE—with factor loadings exceeding .72 and ICRs above .83. To evaluate the structural integrity of the structural model and ensure that the

estimated path coefficients were not distorted by multi-collinearity, Variance Inflation Factors (VIFs) were systematically examined for all structural regression blocks. The assessment reveals a highly stable model layout, with all structural dimensions falling well below the conservative threshold of 3.3 recommended by Hair et al. (2022) to rule out structural vulnerabilities.

Table 1: Confirmatory Composite Analysis: Partial Least Squares Loadings and Cross-Loadings

Construct		Factor 1	Factor 2	Factor 3	Factor 4	Factor 5	Factor 6	Factor 7
Digital technology	DT 1	.85						
(DT)	DT 2	.83						
	DT 3	.81						
	IN 1		.79					
Innovation (IN)	IN 2		.83					
	IN 3		.84					
	IN 4		.77					
Development of e-content (DE)	DE 1			.81				
	DE 2			.78				
	DE 3			.76				
	UE 1				.80			
Use of e-content (UE)	UE 2				.79			
	UE 3				.82			
	UE 4				.85	.24		
Learning Interventions (LI)	LI 1					.86		
	LI 2					.82		
	LI 3					.79		
Teacher Deployment	TD 1						.72	
(TD)	TD 2						.74	
Behavioural Intention	BI 1							.85
(BI)	BI 2							.83
	BI 3							.81

Note. Only significant loadings of each factor are shown.

Table 2: Composite Reliabilities and Convergent Validity of the Scale

Construct	Cronbach's Alpha	Composite Reliability (rho a)	Composite Reliability (CR)	Average Extracted Variance
Behavioural Intention	.84	.85	.89	.76
Digital Technology	.85	.86	.85	.73
Innovation	.80	.83	.87	.78
Development of e-content	.71	.75	.83	.73
Use of e-content	.87	.88	.89	.80
Learning Interventions	.71	.75	.83	.74
Teacher Deployment	.82	.82	.89	.74
Learning Outcomes	.75	.76	.84	.76

Table 3: Discriminant Validity of the Scale

Latent Construct	BI	DT	IN	DE	UE	LI	TD	LO
Behavioural Intention	-							
Digital Technology	.81	-						
Innovation	.76	.78	-					
Development of e-content	.71	.77	.81	-				
Use of e-content	.75	.80	.73	.72	-			
Learning Interventions	.73	.70	.66	.67	.69	-		
Teacher Deployment	.81	.82	.79	.76	.77	.75	-	
Learning Outcomes	.59	.65	.61	.64	.60	.63	.62	-

Correlation Matrix

The correlational analysis (Table 4) informs the research objectives, highlighting the pathways to learning outcomes. These correlations suggest that learning success depends on a triad of creative pedagogy (DE, UE, and LI), adequate staffing (TD), and psychological readiness (BI), rather than on a single factor. The analysis revealed a synergy between DT and the DE content ($r = .49$, $p < .001$). The role of human capital was also articulated through the central position of BI. By showing robust links to TD and IN ($r = .41$, $p < .001$), BI served as the "cognitive pivot" of the model. This was further validated by a significant relationship between TD and the UE ($r = .32$, $p < .001$).

Table 4: Correlation Matrix among Constructs with Square Root of AVE

Construct	Mean	SD	BI	Dt	IN	DE	UE	LI	TD	LO
Behavioural Intention	4.11	1.11	(.872)							
Digital Technology	3.45	1.01	.41***	(.854)						
Innovation	3.61	0.98	.41***	.33***	(.883)					
Development of e-content	4.28	1.12	.33***	.49***	.30***	(.854)				
Use of e-content	3.46	1.06	.24***	.25***	.14**	.15**	(.894)			
Learning Interventions	2.97	0.97	.14**	.07	.07	.14**	.16**	(.860)		
Teacher Deployment	3.92	1.05	.42***	.29***	.28***	.42***	.32***	.26***	(.860)	
Learning Outcomes	3.72	1.16	.34***	.28***	.37***	.26***	.14**	.06	.35***	(.872)

Note. *$p < 0.05$; **$p < 0.01$; ***$p < .001$. Values on the diagonal in parentheses represent the square root of the AVE; BI: behavioural intention.

Structural Model Analysis

Bootstrapping with 5,000 subsamples was used to assess path significance (Table 5). Empirical testing validated ten of the 15 hypothesised structural pathways, while the remaining five did not reach statistical significance (Figure 2). The empirical results indicate that the path from IN to UE had the strongest link in the model ($\beta = .342$, $t = 28.500$, $p < .001$), followed closely by the path from DE to UE ($\beta = .325$, $t = 23.214$, $p < .001$). These exceptionally high *t*-values indicate very low variance and high stability across the bootstrap samples. In predicting BI, all four hypothesised relationships were highly significant. The path from DT to BI emerged as the strongest direct relationship ($\beta = .372$, $t = 6.414$, $p < .001$), followed by the path from UE to BI ($\beta = .362$, $t = 6.582$, $p < .001$), from LI to BI ($\beta = .321$, $t = 4.521$, $p < .001$), and from TD to BI ($\beta = .273$, $t = 4.200$, $p < .001$). Additionally, the path from DE to BI was significant ($\beta = .246$, $t = 3.370$, $p < .001$). The direct path from UE to LO ($\beta = .346$, $t = 4.806$, $p < .001$) and from BI to LO were found to be significant ($\beta = .306$, $t = 4.026$, $p < .001$). Finally, the structural path from LI to DE was statistically significant ($\beta = .265$, $t = 8.548$, $p < .001$).

Conversely, five pathways could not reach the critical threshold ($t > 1.96$). Notably, TD, LI, DT, and IN showed no direct statistical relationships with LO, as evidenced by the path from TD to LO ($t = 1.375$, $p > .169$), from LI to LO ($t = 1.574$, $p > .116$), from DT to LO ($t = 1.170$, $p > .242$), and from IN to LO ($t = 1.134$, $p > .257$). This suggests that these variables might relate to LO through an indirect pathway rather than a direct path. The model explained 76% of the variance in BI (adjusted $R^2 = .76$) and 58% of the variance in LO (adjusted $R^2 = .58$).

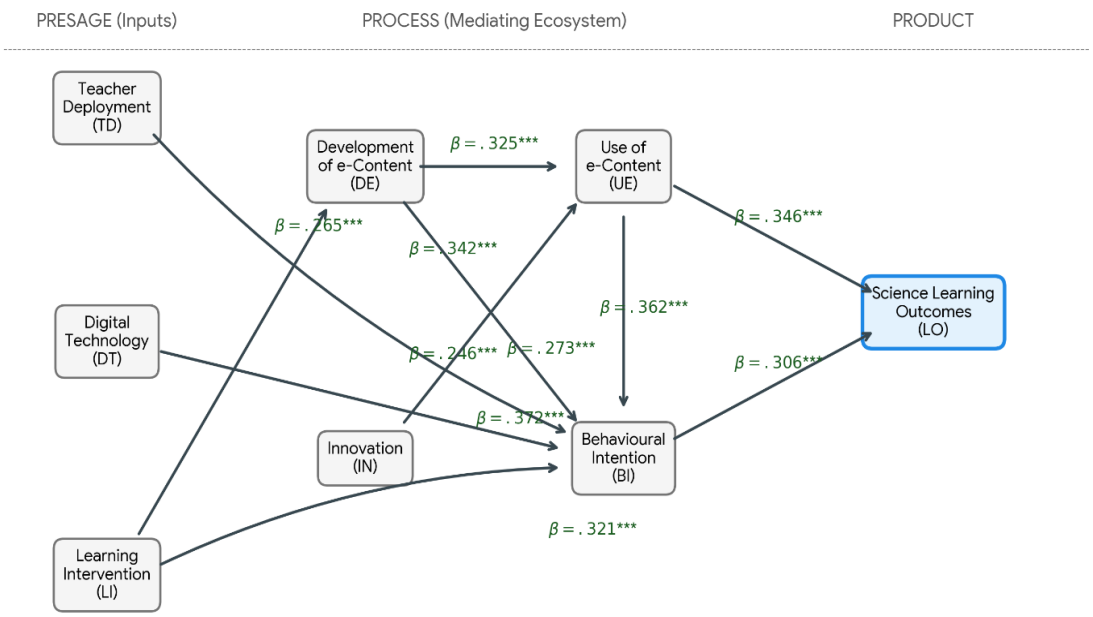

Figure 2: Structural model after bootstrapping

Indirect Pathways and Mediation Analysis

The inferential significance of all specific and total indirect effects was assessed using a nonparametric bootstrapping procedure with 5,000 resampling iterations. Path significance was determined using 95% Bias-Corrected and Accelerated (BCa) confidence intervals (Table 6). The structural indirect pathways show a distinct pattern (Figure 3). The total effect matrix provides a deeper understanding of the system by accounting for both direct structural paths and indirect layered relationships. The UE emerged as the most powerful path to LO (Total Effect = .457). This was achieved because the UE had both a strong direct (β = .346) and an indirect association with BI (Indirect Effect = .111). BI served as the second most vital predictor of LO (β = .306). LI had an indirect path to LO (β= .158). It linked to four variables in explaining the LO (Total Effect = .265). Similarly, DE had three structural paths to LO. However, an indirect-path analysis showed that the DE played a substantial role (Total Effect = .224). IN (Indirect Effect = .156) had two structural paths to LO (Total Effect = .266).

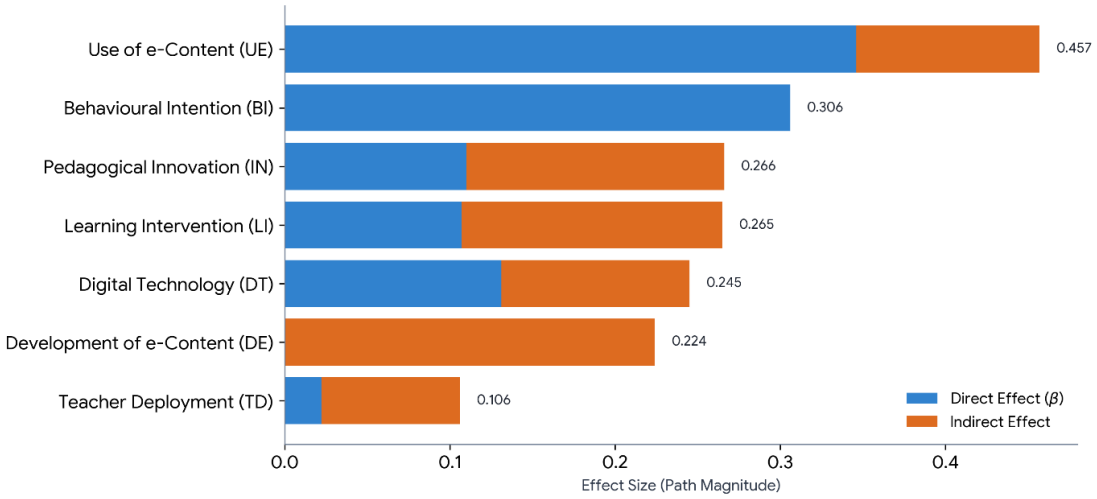

Figure 3: Total structural influence on Science Learning Outcomes (LO)

Non-Substantive Paths

TD emerged as an insignificant predictor of LO (Total Effect = .106). Because the direct relationship was statistically non-significant (β = .022), this small total contribution depended almost entirely on a pathway to BI (Indirect Effect = .084). These results indicate that structural administrative inputs, such as TD, were associated with LO through an indirect relationship with BI.

Hypothesis 1: Teacher Deployment (TD) Indirectly Predicts Science Learning Outcomes (LO) through Behavioural Intention (BI)

Table 6 shows a significant indirect path (β = .084) from TD to BI to LO. The direct path from TD to LO (TD→LO) was not statistically significant (β = .022, t = 1.375, p > .169). However, the paths from TD to BI (t = 4.200, p < .001) and from BI to LO (t = 4.026, p < .001) were both highly significant. Hence, the result supports H1.

Hypothesis 2: Innovation (IN) in Teaching Practices Mediates the Relationship between the Development of e-content (DE) and the Use of e-content (UE)

Table 5 shows that DE was directly related to UE (DE→UE: β = .325, t = 23.214, p < .001) and IN directly to UE (IN→UE: β = .342, t = 28.500, p < .001). However, the path from DE to IN is not significant (β=.014, t = 1.667, p > .171). Consequently, an indirect path spanning from DE to IN to UE was not supported by the structural model. Hence, the result does not substantiate H2.

Hypothesis 3: Learning Interventions (LI) link to LO Indirectly by Shaping Teachers' Behavioural Intention (BI)

Table 6 shows a strong total indirect path (β = .158), linking LI to LO, which includes the primary paths from LI to BI to LO. In Table 5, the direct path from LI to LO (LI→LO) is not significant (β = .107, t = 1.574, p > .116). However, the direct path from LI to BI is highly significant (β = .321, t = 4.521, p < .001). Thus, the indirect path supports H3.

Hypothesis 4: The Use of e-content (UE) Shapes the Relationship between Pedagogical Innovation (IN) and LO

The UE's indirect link (β = .156) to IN shows an indirect path from IN to UE to LO. Table 5 shows that the direct path from IN to LO was not significant (β= 0.110, t = 1.134, p > .257). But the direct path from IN to UE was exceptionally strong (β =.342, t = 28.500, p < .001). This

demonstrates that IN alone does not predict variance in LO unless it is channelled through the actual usage of e-content. The result confirms H4.

Table 5: Path Coefficients after Bootstrapping

Construct	Original Sample (O)	Sample Mean (M)	SD	*t*-Values	*p*-Values	Result
BI -> LO	.306	.289	.076	4.026	< .001	Supported***
TD -> BI	.273	.267	.065	4.200	< .001	Supported***
LI -> LO	.107	.107	.068	1.574	.116	Not Supported
DE -> BI	.246	.238	.073	3.370	<.001	Supported***
DT -> LO	.131	.192	.112	1.170	.242	Not Supported
UE -> BI	.362	.277	.055	6.582	< .001	Supported***
TD -> LO	.022	.011	.016	1.375	.169	Not Supported
UE -> LO	.346	.345	.072	4.806	< .001	Supported***
DT ->BI	.372	.374	.058	6.414	< .001	Supported***
IN -> LO	.110	.112	.097	1.134	.257	Not Supported
LI -> BI	.321	.291	.071	4.521	< .001	Supported***
LI -> DE	.265	.262	.031	8.548	< .001	Supported***
IN -> UE	.342	.321	.012	28.500	< .001	Supported***
DE -> UE	.325	.331	.014	23.214	< .001	Supported***
DE -> IN	.014	.113	.012	1.667	.171	Not Supported

Note. BI; behavioural intention; LO: science learning outcomes; DE; development of e-content; UE: use of e-content; IN: innovation; TD: teacher deployment; LI: learning interventions; DT: digital technology.

Table 6: Mediation Effects on Science Learning Outcomes

Pathways	Specific Indirect Path	Point Estimate (*β*)	Bootstrapped SD (SE)	*t*-Value	*p*-Value
Total Indirect Effect	TD→LO	.084	.021	4.000	< .001
Specific Indirect Path	TD→BI→LO	.084	.021	4.000	< .001
Total Indirect Effect	LI→LO	.158	.038	4.158	< .001
Specific Indirect Path 1	LI→BI→LO	.098	.027	3.630	< .001
Specific Indirect Path 2	LI→DE→BI→LO	.020	.007	2.857	= .004
Specific Indirect Path 3	LI→DE→UE→LO	.030	.009	3.333	< .001
Specific Indirect Path 4	LI→DE→UE→BI→LO	.010	.004	2.500	= .012
Total Indirect Effect	DT→LO	.114	.024	4.750	< .001
Specific Indirect Path	DT→BI→LO	.114	.024	4.750	< .001
Total Indirect Effect	DE→LO	.224	.043	5.209	< .001
Specific Indirect Path 1	DE→BI→LO	.075	.023	3.261	= .001
Specific Indirect Path 2	DE→UE→LO	.112	.025	4.480	< .001
Specific Indirect Path 3	DE→UE→BI→LO	.037	.011	3.364	< .001
Total Indirect Effect	IN→LO	.156	.031	5.032	< .001
Specific Indirect Path 1	IN→UE→LO	.118	.026	4.538	< .001
Specific Indirect Path 2	IN→UE→BI→LO	.038	.011	3.455	< .001
Total Indirect Effect	UE→LO	.111	.023	4.826	< .001
Specific Indirect Path	UE -> BI > LO	.111	.023	4.826	< .001

Note. BI; behavioural intention; LO: science learning outcomes; DE; development of e-content; UE: use of e-content; IN: innovation; TD: teacher deployment; LI: learning interventions; DT: digital technology.

Cohen's f^2 of Independent Variables

This study calculated Cohen's (f^2) effect size for each variable (Table 7), benchmarking thresholds at .02 (small), .15 (medium), and .35 (large). While multiple predictors demonstrated medium-to-large effects, BI (f^2 = .36) emerged as the strongest predictor with a large effect size. Conversely, LI and IN had negligible small effects (f^2 = .07 and .06). Within resource utilisation, the actual UE showed a medium effect (f^2 = .16), outperforming the small effect recorded for its DE (f^2 = .09). Finally, DT (f^2 = .26) and TD demonstrated medium effects (f^2 = .21).

Table 7: Cohen's Effect Size on Science Learning Outcomes

Variables	Effect Size (f^2)	Result
Behavioural Intention (BI)	.36	Large
Digital Technology (DT)	.26	Medium
Teacher Deployment (TD)	.21	Medium
Use of e-Content (UE)	.16	Medium
Development of e-content (DE)	.09	Small
Learning Intervention (LI)	.07	Small
Innovation (IN)	.06	Small

Predictive Power of the Proposed Model

To evaluate the out-of-sample predictive validity of the Model, the CVPAT was executed across all latent constructs. The PLS path model's loss values were systematically compared against two reference baselines: the naïve Indicator Average (IA) benchmark and the highly competitive Linear Model (LM) benchmark. As shown in Table 8, the overall average loss difference against the IA benchmark is statistically significant (-.460, $p < .001$), indicating a substantial error reduction. Crucially, the overall average loss difference against the LM baseline was also negative and significant (-.075, $p < .05$). Because the PLS path model consistently outperformed both the IA and LM frameworks across all target constructs, the Model shows high predictive power, confirming that the hypothesised structural pathways deliver meaningful predictive value over simple linear combinations.

Table 8: Cross-Validated Predictive Ability Test Summary

Latent Variables	PLS Loss	IA Loss	Loss Diff.	*t*-Value	LM Loss	PLS-LM Loss Diff.	*t*-Value	Predictive Power (PP)
BI	.994	1.148	-.154	2.318*	1.052	-.058	2.045*	High PP
DE	1.025	1.483	-.458	3.921**	1.110	-.085	2.112*	High PP
IN	.682	1.550	-.868	6.863**	0.744	-.062	2.224*	High PP
LI	.982	1.594	-.612	4.064**	1.036	-.054	2.016*	High PP
LO	1.044	1.215	-.171	2.296*	1.098	-.054	2.011*	High PP
TD	1.304	1.467	-.163	2.294*	1.345	-.041	1.988*	High PP
UE	.754	1.359	-.605	4.484**	0.821	-.067	2.305*	High PP
Overall	.936	1.396	-.460	4.819**	1.011	-.075	2. 111*	High PP

Note. $*p < 0.05$; $**p < 0.01$. Negative loss differences indicate a reduction in predictive error by the PLS path model compared to the benchmark.

Discussion and Implications

The findings of this study offer crucial insights into the structural and systemic dynamics of LO. Analysing only direct structural paths misleads conclusions to LO. This was evident in the case of DE. It was not directly associated with LO but served as an indirect path to it (Niyibizi, 2026). This result shows how teachers use e-content and develop BI accordingly. Similarly, LI emerged as a weak but direct path to LO. However, the total effect was more substantial through structural indirect relationships. TD does not necessarily improve student academic performance; it remains static without psychological and pedagogical activation (Kumar, 2026). Consequently, these findings do not support conventional, resource-centric educational paradigms. They demonstrate that infrastructural investments do not necessarily deliver tangible returns unless institutional systems optimise the process-oriented mechanisms within the learning ecosystem. High use of e-content often yields marginal academic success, as evidenced in Germany (Haleem et al., 2022). Therefore, the state has yet to reach a digital saturation plateau; rather, it is suffering from a utilisation bottleneck caused by institutional hurdles and digital friction. When the UE is seamless, it directly links to LO. It also fosters the BI to keep teachers academically engaged. This is further supported by the direct path from BI to LO. This path reinforces the idea that teacher motivation and commitment remain key pillars of learning outcomes. Teacher professional development bridges the gap between digital readiness and motivational leadership (Das & Madhusudan, 2026).

Research on schools in America and Africa found that teachers spent less time on digital activities due to other school commitments (McShane, 2022). In Germany, only 23% of schoolteachers incorporated digital technologies into their teaching (Fraillon et al., 2019; Sailer et al., 2021). The educational environment in India differs from that of African countries. The disconnect between Indian teachers' BI and their actual use of available digital tools supports the idea that high-intensity users eventually reach a plateau of diminishing returns (Haleem et al., 2022). Indeed, teachers' willingness and preparedness reinforce the integration of technology into traditional teaching methods (Global Education Monitoring Report Team, 2023). Many developing countries witnessed significant improvements in student performance following substantial investment in digital technology for education (Mo, 2017). A meta-analysis by Lewin et al. (2019) confirms that appropriate technology integration predicts substantial gains in science and mathematics.

Implications

Policymakers should shift from a resource-provision mindset to a usage-centric framework. This framework should prioritise the innovation and development of e-content exercises. National education strategies should prioritise the quality of digital engagement over the quantity of hardware distributed. There is a critical need to incentivise pedagogical innovation within the digital curriculum.

Limitations and Future Research Directions

This study acknowledges several limitations. First, because this cross-sectional study captured data at a single point in time, it could not establish temporal precedence or prove causal relationships. Future studies should utilise longitudinal designs to trace how these variables evolve. Second, reliance on self-reported survey scales introduces potential common method and social desirability biases. Teachers may have overestimated their digital proficiency, pedagogical

innovation, or behavioural intention to align with institutional expectations or training guidelines. Future research should combine self-reports with objective classroom observations or digital log data to triangulate behaviours and minimise response bias. Finally, because the sample was restricted to state-run rural secondary schools within a single institutional framework in Bihar, the generalisability of these findings remains limited.

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