Algorithmic Culture and AI-Augmented Learning: Examining Student Learning Quality through Cognitive Engagement and Perceived Learning Effectiveness

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HOW TO CITE:
Avradeep Ganguly, Diptayan Bhattacheryya, Moumita Bhattacharya, Mainak Chakraborty, Tanushree Dutta (2026). Algorithmic Culture and AI-Augmented Learning: Examining Student Learning Quality through Cognitive Engagement and Perceived Learning Effectiveness. International Journal of Special Education, 41(13s), 132-142

ABSTRACT:
In higher education, Artificial Intelligence has been widely adopted to improve learning environments and expand mediated academic practices. The present study examines the impact of algorithmic culture on learning quality with perceived learning efficiency and cognitive engagement as mediators. The study adopts a cross sectional quantitative approach using primary data collected from students of higher educational institutions across India. Exploratory factor analysis found a robust four-factor structure and demonstrated satisfactory sampling adequacy and variance explanation. Structural equation modeling using PLS-SEM revealed that algorithmic culture significantly affects cognitive engagement, perceived learning effectiveness, and learning quality. The findings highlighted the significant impact of both mediators on student learning quality. There is substantial variance explained in the quality of learning within the model. The mediation was found partial in the mediation analysis, with significant indirect impact through perceived learning effectiveness and cognitive engagement. AI-based learning improves academic outcomes with dual perceptual and cognitive pathways.

Keywords: Algorithmic Culture; AI-Augmented Learning; Cognitive Engagement; Perceived Learning Effectiveness; Learning Quality; PLS-SEM

1. Introduction

Digital technologies have widely transformed modern contexts of education and culture, which gives a rise of culture which is mediated by algorithm (Striphas, 2015; Couldry and Hepp, 2017). Algorithms shape access to information and how people engage in learning and build knowledge in those environments (Kitchin, 2017; Gillespie, 2014). This shift is especially relevant in context of higher education, where AI-based tools redefine traditional ways of learning and teaching, such as, smart tutoring and adaptive learning (Zawacki-Richter et al., 2019; Holmes et al, 2022).

The algorithmic culture widely transforms learning experience with data-based and automated systems (Striphas, 2015; Beer, 2017). These systems improve feedback in real-time and deliver personalized control to influence the process of data by students and cognitive engagement with study material (Luckin et al, 2016). While efficiency and accessibility are improved with technological advances, there are concerns over the effect on quality and depth of learning (Selwyn, 2019). Along with technical specifications, AI-based learning also relies on psychological systems for effectiveness (Fredricks et al, 2004). With sensible and effortful engagement in learning, cognitive engagement has been the major factor responsible for improving quality of learning (Chi and Wylie, 2014). Such engagement is more likely to be promoted by AI-based systems with adaptive and interactive functions, even though there is mixed empirical evidence on their efficiency (Holmes et al, 2022).

Additionally, perceptions of students are very important to shape overall experience of learning with effective AI-based training. Perceived effectiveness of learning reflects students' belief that their academic performance and knowledge is improved with digital environments (Sun et al, 2008). Responsiveness and usefulness of the system influence those perceptions which ultimately affect outcomes of AI-based learning (Venkatesh et al, 2012). Irrespective of growing integration of AI, current research investigates only the adoption of technology. There is also a lack of research on the association between psychological and cultural aspects (Zawacki-Richter et al., 2019; Selwyn, 2019). The present study investigates the impact of algorithmic culture on learning quality with perceived learning and cognitive engagement as mediators.

2. Literature Review and Hypotheses Development

2.1 Algorithmic Culture and Learning Quality

There is a rising impact of data-based system on access to information, social interaction, and decision-making in context of algorithmic culture (Kitchin, 2017). This transformation is observed in higher education by integrating AI technologies to provide automated feedback, tailored learning, and promote adaptive processes (Holmes et al, 2022; Zawacki-Richter et al., 2019). More recent studies have also focused on Gen AI playing vital role in improving experience of students and learning practices (Dwivedi et al, 2023; Kasneci et al, 2023). These advances improve access to information and efficiency in learning (Sun et al, 2008). Considering these arguments, here is the proposed hypothesis –

H1: There is a significant positive impact of algorithmic culture on learning quality.

2.2 Algorithmic Culture and Cognitive Engagement

Cognitive engagement refers to active investment of efforts by learners and use of higher thinking capabilities in the process of learning (Greene, 2015; Fredricks et al, 2004). With adaptability and interactivity, AI-based learning promotes in-depth engagement when study material meets the needs of learners and offering feedback on timely basis (Luckin et al, 2016; Chi and Wylie, 2014). In context of education, AI improves interactive learning and cognitive engagement (Holmes et al, 2022).

H2: There is a significant positive impact of algorithmic culture on cognitive engagement.

2.3 Cognitive Engagement and Learning Quality

Cognitive engagement has widely been recognized as major factor affecting the outcomes of learning as it promotes long-term attention and processing (Bond et al, 2020). With active engagement, learners engage well with content and improve their academic performance and knowledge. Engagement is very important in digital environments as students are assigned to work with digital content (Greene, 2015).

H3: There is a significant positive impact of cognitive engagement on learning quality.

2.4 Algorithmic Culture and Perceived Learning Effectiveness

Perceived learning effectiveness represents learners' evaluation of how well a system enhances their knowledge and performance (Davis, 1989; Sun et al., 2008). In AI-driven learning environments, factors such as personalization, responsiveness, and perceived usefulness play a key role in shaping these perceptions (Venkatesh et al., 2012). Emerging evidence suggests that AI-enabled systems, particularly those using advanced analytics and generative capabilities positively influence learners' perceptions of effectiveness (Kasneci et al., 2023; Ifenthaler & Yau, 2020).

H4: Algorithmic Culture positively influences Perceived Learning Effectiveness.

2.5 Perceived Learning Effectiveness and Learning Quality

Learners' perceptions of effectiveness are closely linked to their academic outcomes, as they influence motivation, satisfaction, and continued engagement (Sun et al., 2008; Venkatesh et al., 2012). When students perceive that learning systems contribute meaningfully to their understanding and performance, they are more likely to achieve higher learning quality.

H5: Perceived Learning Effectiveness positively influences Student Learning Quality.

2.6 Parallel Mediation Effects

There are several psychological mechanisms playing a vital role in improving learning quality. Regarding learning quality, there is a significant impact of algorithmic culture because of several psychological mediums. Cognitive engagement is based on process, while evaluative aspect is covered with effective learning. Previous studies suggest, such systems act in technological learning by working simultaneously (Ifenthaler & Yau, 2020; Bond et al, 2020). Here are the proposed hypotheses for these arguments –

H6: Cognitive Engagement acts as a mediator between Algorithmic culture and Learning Quality.

H7: Perceived Learning Effectiveness acts as a mediator between Algorithmic culture and Learning Quality.

3. Research Methodology

This study is based on cross-sectional, quantitative research design for hypotheses testing in context of Indian higher education system and exposure to AI-based learning for students (Zawacki-Richter et al., 2019; Creswell & Creswell, 2018). A structured questionnaire was used with various items for four relative variables - Cognitive Engagement (CE), Algorithmic Culture (AC), Learning quality (LQ) and Perceived Learning Effectiveness (PLE). These variables will be measured with 5-point Likert scale, which is used largely in academic and behavioral research (Hair et al, 2019; Likert, 1932).

The measurement items on learner engagement, technological acceptance, and perceived effectiveness were based on previous studies to ensure consistency of the concept and validity of content (Fredricks et al, 2004; Davis, 1989; Venkatesh et al, 2012). In SPSS, Exploratory Factor Analysis (EFA) was conducted to discover the factor structure with "Principal Axis Factoring" as per suggested processes to handle the constructs (Costello & Osborne, 2005). In the same way, SmartPLS was used to conduct "Partial Least Squares Structural Equation Modeling (PLS-SEM)" test to determine both structural and measurement models as it is ideal for mediation analysis and predictive frameworks (Sarstedt et al., 2020; Hair et al, 2022). This sequential method enables proper testing of relationships and validation of model in a coherent model (Sarstedt et al, 2020).

4. Results

4.1 Exploratory Factor Analysis (EFA)

EFA was conducted to determine the dimensions of items before structural modeling. The data is found highly suitable for conducting factor analysis with significant levels of Bartlett's Test numbers (df = 190; $\chi^2 = 5429.065$; p<0.001), which indicates adequacy of samples and sensible correlations across items (Bartlett, 1954; Kaiser, 1974; Field, 2018; Hair et al, 2019). With expected interrelationships, this study has also applied "Principal Axis Factoring with Promax rotation" (Costello and Osborne, 2005). There is a 4-factor structure, which is well-defined in the analysis – LQ, PLE, CE, and AC, which explained 72.431% of overall variance, exceeding the suggested threshold for behavioral studies (Tabachnick & Fidell, 2019; Hair et al., 2019). From 0.549 to 0.734, the communalities were extracted and significant part of variance of item was measured with the given factors (MacCallum et al, 1999). All indicators had stronger loadings on their constructs, without any major cross-loadings and factor loadings from 0.699 to 0.879 (Worthington and Whittaker, 2006). The inter-factor relationships were moderate with correlation matrix, which justified using oblique rotation (Fabrigar et al, 1999). Overall, robust findings are available about validity of constructs and measurement structure is confirmed to be ideal for following analysis.

4.2 Measurement Model Assessment

The measurement model was assessed in SmartPLS to examine the reliability, convergent validity, and discriminant validity (Henseler et al, 2009; Hair et al, 2022).

4.2.1 Reliability and Convergent Validity

The constructs have shown robust internal consistency, with composite reliability and Cronbach's Alpha values are well above the suggested threshold of 0.70 (Hair et al, 2022). Since "Average Variance Extracted (AVE)" were exceeding 0.50 to confirm convergent validity, which means adequacy of constructs has properly covered the variance of signs (Fornell and Larcker, 1981).

Table 1. Construct Reliability and Convergent Validity

	Cronbach's alpha	**Composite reliability (rho_a)**	**Composite reliability (rho_c)**	**Average variance extracted (AVE)**
AC	0.902	0.904	0.928	0.719
CE	0.899	0.901	0.925	0.713
LQ	0.910	0.911	0.933	0.736
PLE	0.902	0.905	0.927	0.719

Source: Author's computation using SmartPLS

4.2.2 Indicator Reliability

Connecting outer loadings, they exceeded 0.70 threshold, which means that each indicator plays a significant role to its construct (Hair et al, 2022). This avoids the need for removal of item and strong reliability of indicator.

Table 2. Outer Loadings

	AC	**CE**	**LQ**	**PLE**
AC1	0.839			
AC2	0.859			

AC3	0.848			
AC4	0.871			
AC5	0.823			
CE1		0.849		
CE2		0.849		
CE3		0.880		
CE4		0.808		
CE5		0.834		
LQ1			0.860	
LQ2			0.883	
LQ3			0.848	
LQ4			0.854	
LQ5			0.844	
PLE1				0.863
PLE2				0.853
PLE3				0.824
PLE4				0.832
PLE5				0.867

Source: Author's computation using SmartPLS

4.2.3 Collinearity Assessment

With collinearity diagnostics, all the values were under the needed threshold in "Variance Inflation Factor (VIF)", which shows that there is a lack of multicollinearity issues (Hair et al, 2019).

Table 3. VIF Values (Outer Model)

	VIF
AC1	2.301
AC2	2.501
AC3	2.269
AC4	2.714
AC5	2.096
CE1	2.442
CE2	2.329
CE3	2.765
CE4	1.970
CE5	2.242
LQ1	2.559
LQ2	2.866
LQ3	2.362
LQ4	2.418
LQ5	2.330
PLE1	2.499
PLE2	2.373
PLE3	2.117
PLE4	2.258
PLE5	2.506

Source: Author's computation using SmartPLS

4.2.4 Discriminant Validity

Both Fornell & Larcker's (1981) criterion and "Heterotrait–Monotrait (HTMT) ratio" were established with discriminant validity. All values were under the suggested threshold, which refers to empirically different construct (Henseler et al, 2015). For each construct, the AVE's square root were above its correlations, which further confirmed the validity.

Table 4. HTMT Matrix

	AC	CE	LQ	PLE
AC				
CE	0.583			
LQ	0.582	0.516		
PLE	0.427	0.172	0.449	

Source: Author's computation using SmartPLS

Table 5. Fornell–Larcker Criterion

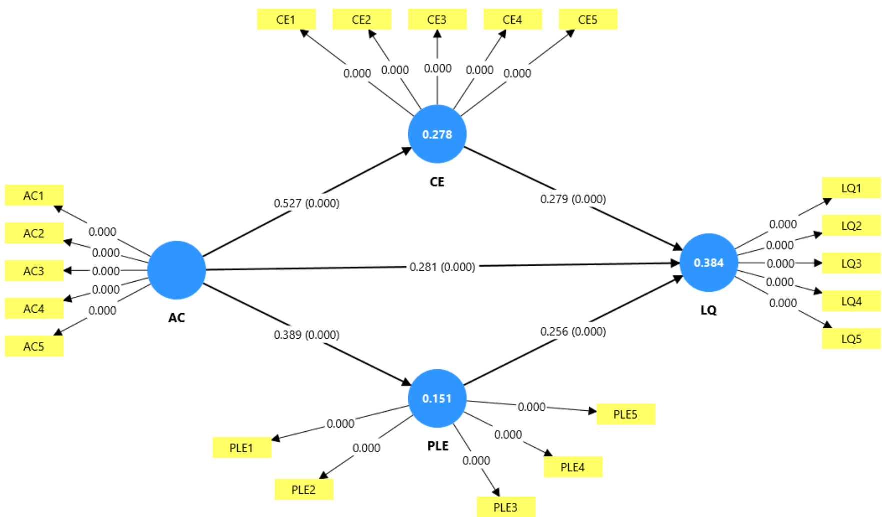
	AC	CE	LQ	PLE
AC	0.848			
CE	0.527	0.844		
LQ	0.528	0.467	0.858	
PLE	0.389	0.157	0.409	0.848

Source: Author's computation using SmartPLS

4.3 Structural Model Assessment

Bootstrapping analysis was performed to determine the structural model to determine explanatory power, coefficients, and sizes of effect (Hair et al, 2022).

Figure 1. Structural Model with Standardized Path Coefficients



Source: An output from SmartPLS software

4.3.1 Path coefficients

As per the findings of the study, all proposed relationships are statistically significant and positive. There is a strong impact of AC on CE and moderate impact on PLE and LQ. Both PLE and CE were found with significant contribution to LQ (Table 9).

Table 6. Path Coefficients

	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	p values
AC -> CE	0.527	0.528	0.036	14.464	0.000
AC -> LQ	0.281	0.281	0.048	5.882	0.000
AC -> PLE	0.389	0.390	0.040	9.647	0.000
CE -> LQ	0.279	0.280	0.044	6.330	0.000
PLE -> LQ	0.256	0.257	0.038	6.767	0.000

Source: Author's computation using SmartPLS

4.3.2 Coefficient of Determination (R^2)

When it comes to Learning Quality (LQ), there is 34% of variance, which means consistent explanatory strength as per standards suggested in behavioural studies (Hair et al, 2022).

Table 7. Coefficient of Determination (R^2) and Adjusted R^2

Construct	R^2 (Original Sample)	R^2 (Sample Mean)	Adjusted R^2 (Original Sample)	Adjusted R^2 (Sample Mean)
CE	0.278	0.28	0.276	0.278
LQ	0.384	0.389	0.379	0.384
PLE	0.151	0.153	0.149	0.151

Source: Author's computation using SmartPLS

4.3.3 Mediation Analysis

As per mediation analysis, there is a significant mediation of both PLE and CE on the relation between LQ and AC. With significant effects of both indirect and direct effects, a partial model was supported on parallel mediation (Hair et al, 2022).

Table 8. Specific Indirect Effects

	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	p values
AC -> CE -> LQ	0.147	0.148	0.026	5.556	0.000
AC -> PLE -> LQ	0.100	0.100	0.019	5.325	0.000

Source: Author's computation using SmartPLS

4.3.4 Total Effects

As per total effects, there is a significant overall impact of AC on LQ when considering both indirect and direct paths.

Table 9. Total Effects

	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	p values
AC -> CE	0.527	0.528	0.036	14.464	0.000
AC -> LQ	0.528	0.529	0.035	14.970	0.000
AC -> PLE	0.389	0.390	0.040	9.647	0.000
CE -> LQ	0.279	0.280	0.044	6.330	0.000
PLE -> LQ	0.256	0.257	0.038	6.767	0.000

Source: Author's computation using SmartPLS

4.3.5 Effect Size (f^2)

As per the analysis of effect size, there is a significant impact of AC on CE and moderate impact on PLE, while its direct impact is comparatively smaller on LQ. There are sensible effects of CE and PLE on LQ, which suggests their significance when it comes to explain outcomes of learning (Cohen, 1988).

Table 10. Effect Size (f^2)

	Original sample (O)	**Sample mean (M)**	**Standard deviation (STDEV)**	**T statistics (|O/STDEV|)**	**p values**
AC -> CE	0.385	0.392	0.075	5.139	0.000
AC -> LQ	0.080	0.083	0.030	2.656	0.008
AC -> PLE	0.178	0.183	0.044	3.999	0.000
CE -> LQ	0.091	0.094	0.031	2.942	0.003
PLE -> LQ	0.090	0.094	0.029	3.105	0.002

Source: Author's computation using SmartPLS

4.3.6 Predictive Relevance (Q^2)

PLSpredict was used to determine the relevance of the model. All the constructs have shown positive values of Q-square, which suggests that model has ideal predictive capability (Shmueli et al, 2019).

Table 11. PLSpredict Results

	Q^2predict	**RMSE**	**MAE**
CE	0.272	0.857	0.696
PLE	0.147	0.927	0.770
LQ	0.274	0.856	0.706

Source: Author's computation using SmartPLS

4.3.7 Hypothesis Testing Summary

Bootstrapping was used for hypothesis testing in PLS-SEM, with value of significance determined with p-values and t-values aligned with set processes (Sarstedt et al, 2020; Hair et al, 2022). The results demonstrate there are significant and positive direct paths, which supported all hypotheses from H1 to H5. There is a significant impact AC on PLE, CE, and LQ, while significant effects were illustrated by both mediators on LQ. Similarly, indirect effects are significant to confirm mediating roles of PLE and CE. With significant indirect and direct effects, partial parallel mediation was observed in the findings, which means that there is a significant impact of AC on LQ with both indirect and direct paths (Hair et al, 2022; Nitzl et al, 2016).

5. Discussion and Implications

The findings confirm that there is a significant impact of algorithmic culture on learning outcomes in AI-based academic environments, which strengthened its key roles in environments mediated with digital learning (Kitchin, 2017). As per significant indirect and direct effects, it is observed that AI-based systems improve quality of learning with both experiential and structural systems, which are relevant with previous studies on tailored and adaptive learning (Zawacki-Richter et al., 2019). Cognitive engagement acts as a major pathway as AC deeply promotes meaningful learning experience with sustained attention (Chi and Wylie, 2014; Fredricks et al, 2004).

There is a significant role played by effectiveness of perceived learning on quality of learning, focusing on the significance of responsiveness and usefulness of the system by learners (Ifenthaler & Yau, 2020). When analyzing parallel mediation, it is confirmed that AC operates with perceptual and cognitive systems at the same time, extending previous studies on AI-based learning (Bond et al, 2020; Selwyn, 2019).

5.1 Theoretical Implications

The study contributes to existing studies with integration of AC in context of acceptance of technology and theory of engagement, offering a universal model of association between perceptual and conceptual learning and technology (Dwivedi et al., 2023). Identifying the pathways for parallel mediation provides complete explanation of the impact of AI-based environments on learning quality along with specific behaviors or technologies (Holmes et al, 2022).

5.2 Practical Implications

Along with AI adoption, schools and colleges should also focus on effectively designing AI to improve perceived usefulness and engagement (Ifenthaler & Yau, 2020). Adaptive and interactive learning promote critical thinking and active participation to boost student outcomes (Holmes et al, 2022). In addition, usability and transparency are improved with AI tools to boost perceived effectiveness and trust of learners to improve overall quality of learning (Venkatesh et al, 2012).

6. Conclusion

As per the study, AC is very important to improve quality of learning with influence of both PLE and CE in AI-based settings (Holmes et al, 2022). Findings of the study have suggested institutions to consider both theoretical and cognitive aspects of digital learning to provide deeper knowledge with AI-based learning.

7. Limitations and Future Research

Regarding limitations, this study is based on cross-sectional research design which affects causal relation. Hence, longitudinal research design is needed to determine dynamic processes of learning (Creswell and Creswell, 2018). Generalizability of findings is also affected by focusing only on a country. Future studies are more likely to focus on various cultures. Other mediating variables should also be focused on future studies like trust, motivation, and digital literacy to improve knowledge of learning mediated by AI (Kasneci et al., 2023). With the evolution of generative AI, new opportunities have been presented to determine the long-run effect on equity and quality of education.

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