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Cultural Context, Stigma, and Teaching 4.0: Exploring Mediated Pathways to Academic Performance in Indian Higher Education

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ABSTRACT

Academic performance in higher education is shaped by individual aptitude and broader sociocultural and institutional factors. In collectivist societies such as India, the cultural imperative for academic excellence often leads to heightened psychological pressure, especially when students perceive themselves as falling short of expected standards. This study explores how cultural context influences academic performance through the mediating roles of perceived stigma, internalised stigma, and Teaching 4.0, an emerging paradigm that integrates technology, personalisation, and innovation in learning. While stigma has long been linked to academic disengagement and emotional distress, teaching 4.0 presents a new avenue for re-engagement and resilience. Drawing from a sample of students in India, the study uncovers how cultural expectations, psychological burdens, and technological empowerment influence student outcomes. The findings offer valuable insights for educators and policymakers seeking to improve academic performance through culturally informed and technologically adaptive strategies.

Keywords: Cultural Context, Perceived Stigma, Internalised Stigma, Teaching 4.0, Academic Performance, Higher Education, PLS-SEM

1. INTRODUCTION

In educational systems marked by rigid expectations and deep-rooted cultural norms, academic performance becomes a high-stakes pursuit, especially in collectivist societies such as India, where scholastic achievement is closely tied to social mobility, family honour, and personal worth (Chadda & Deb, 2013; Markus & Kitayama, 1991). For many students, academic underperformance is not just an individual setback but a deviation from culturally imposed standards of success. This societal pressure cultivates a fertile ground for perceived and internalised stigma, which can erode self-concept, academic motivation, and psychological well-being (Goffman, 1963; Corrigan & Watson, 2002). Despite India's expanding access to higher education, significant disparities in academic performance remain, often masked by institutional emphasis on outcomes rather than experiences.

In this context, stigma is a hidden yet pervasive barrier to academic engagement. Perceived stigma refers to the awareness of negative societal judgments, while internalised stigma captures how individuals internalise and accept those judgments as self-defining (Watson et al., 2007). Within the Indian education system, where high-stakes testing, parental expectations, and peer competition converge, stigma can deter students from seeking help, taking risks, or expressing learning difficulties, ultimately impeding their academic growth (Phelan et al., 1998; Major & O'Brien, 2005).

Nevertheless, the rapidly changing educational landscape presents a potential counter-narrative, especially with technology integration under Teaching 4.0. Teaching 4.0, rooted in the larger paradigm of Industry 4.0, brings together artificial intelligence, data analytics, personalised learning systems, and interactive digital tools to redefine how learning occurs (Romero et al., 2020). Unlike traditional one-size-fits-all instruction, teaching 4.0 offers adaptive, student-centric environments where learners can progress at their own pace, receive tailored feedback, and engage through multiple modalities. These innovations may enhance academic performance and buffer the psychological impact of cultural and stigmatising pressures, especially for students navigating identity-related stressors.

This study examines the complex interplay between cultural context, stigma, and academic performance in an Indian higher education setting. It investigates the mediating roles of perceived stigma, internalised stigma, and Teaching 4.0 in this relationship. Drawing on the Stress-Appraisal-Coping framework (Lazarus & Folkman, 1984), the study positions Teaching 4.0 as an adaptive coping mechanism that could mitigate the adverse effects of culturally rooted stigma. Using a sample of 400 students from diverse academic backgrounds, this research adds to a growing body of scholarship that interrogates how culture and technology intersect to shape learning outcomes in the global South.

2. LITERATURE REVIEW

2.1 Cultural Context and Academic Performance

Culture significantly influences how individuals interpret academic success and failure. In collectivist societies like India, where the self is often defined by others, particularly family and community, academic performance becomes a symbol of personal, familial, and social value (Nisbett, 2003; Chadda & Deb, 2013). These cultural scripts amplify pressure on students to conform to high academic standards, often with limited regard for individual interests or learning styles (Markus & Kitayama, 1991). Research suggests that students from such contexts may experience heightened anxiety, fear of failure, and stress due to societal expectations (Li & Wang, 2021), creating psychological barriers to optimal performance.

2.2 Perceived and Internalised Stigma in Educational Contexts

Stigma in education often arises when students perceive themselves or are perceived by others as failing to meet normative standards of academic competence. Perceived stigma involves believing others view one negatively due to their academic standing or background (Phelan et al., 1998). Internalised stigma takes this further, wherein students absorb these societal attitudes and apply them to themselves, leading to diminished self-worth, reduced effort, and academic disengagement (Corrigan & Rao, 2012; Watson et al., 2007). Empirical evidence has shown that stigma impairs academic functioning through mechanisms such as avoidance behaviours, test anxiety, and reluctance to seek help (Major & O'Brien, 2005; Eisenberg et al., 2009). In the Indian context, these effects may be even more pronounced due to heightened cultural expectations and limited mental health discourse in academic institutions.

2.3 The Transformative Potential of Teaching 4.0

The emergence of Teaching 4.0 presents new opportunities for inclusive and adaptive learning. This pedagogical model emphasises learner autonomy, artificial intelligence-driven feedback systems, immersive content, and data-informed personalisation (Chatti et al., 2017; Romero et al., 2020). Unlike traditional teaching methods, which often replicate hierarchical, lecture-based models, teaching 4.0 decentralises control and allows learners to navigate content in ways that align with their pace, preferences, and needs (Ifenthaler & Schumacher, 2016). Significantly, such systems may reduce stigma by normalising differentiated instruction and enabling private, self-directed learning, thereby removing the visibility of academic struggle. This is particularly relevant in collectivist cultures where public comparison and academic hierarchy intensify feelings of shame and inadequacy.

Recent studies have also linked Teaching 4.0 to increased academic motivation, engagement, and performance, particularly among marginalised students or at risk of academic failure (Hwang et al., 2020; Lee & Han, 2022). However, research on the intersection of Teaching 4.0 with psychological variables such as stigma remains limited, especially in non-Western contexts. This study aims to fill this gap by investigating whether Teaching 4.0 can mediate the adverse effects of cultural context and stigma on academic performance, thus offering a culturally responsive and technologically empowered framework for learning.

2.4 Theoretical Foundation and Model Justification

This study draws primarily from the Stress-Appraisal-Coping (SAC) framework proposed by Lazarus and Folkman (1984), which conceptualises stress not as a static stimulus but as a dynamic process involving the appraisal of external demands and the subsequent coping responses. In educational settings, particularly within collectivist societies like India, cultural expectations around academic success are potent environmental stressors. These expectations are not merely performance-related but deeply social and identity-driven, often shaping how students appraise themselves in academic contexts (Chadda & Deb, 2013; Markus & Kitayama, 1991).

According to SAC theory, when students interpret academic expectations as threatening or unattainable, they may experience negative emotional states such as shame, inadequacy, and fear. These emotional appraisals often lead to maladaptive coping responses, such as withdrawal, avoidance, or self-stigmatisation (Major & O'Brien, 2005). In this context, perceived stigma is a form of secondary appraisal in which students interpret others as viewing them negatively due to their academic shortcomings. On the other hand, internalised stigma reflects a deeper, internalised emotional response where students begin to view themselves through the lens of failure, leading to lowered academic engagement and performance (Watson et al., 2007).

While stigma functions as a psychological mediator that channels the effects of cultural context into academic behaviour, the SAC model also provides a framework for understanding how individuals can adopt adaptive coping strategies when supportive resources are available. Teaching 4.0 is conceptualised as a structural and pedagogical resource that can facilitate positive reappraisal. By offering personalised, student-driven, and non-comparative learning environments, teaching 4.0 allows students to reframe academic challenges as identity threats and growth opportunities (Ifenthaler & Schumacher, 2016; Romero et al., 2020). This aligns with the SAC model's emphasis on "reappraisal" as a constructive coping mechanism that can restore motivation and reduce stress.

Furthermore, from a sociocultural theoretical perspective (Vygotsky, 1978), the integration of technological tools in education is not a neutral process but one that reshapes how learners interact with knowledge, with others, and with themselves. Teaching 4.0 alters the zone of proximal development by offering scaffolding through intelligent tutoring systems,

adaptive content delivery, and AI-based feedback. These elements are compelling in collectivist cultures where students may avoid help-seeking due to shame or social comparison; private, self-paced technological learning bypasses these barriers and re-establishes student agency (Lee & Han, 2022).

Therefore, the conceptual model of this study posits that cultural context negatively influences academic performance, not directly, but through its impact on students' psychological appraisal systems. Perceived and internalised stigma serve as affective mediators that translate sociocultural expectations into cognitive and emotional barriers. Teaching 4.0, however, is a pedagogical mediator capable of interrupting this negative chain by providing emotionally safe, adaptive, and non-judgmental learning environments. In line with SAC and sociocultural theories, this study conceptualises academic performance as an outcome of personal capability and an emergent product of social meaning, psychological processing, and technological facilitation.

Thus, the model builds on and extends existing frameworks by integrating cultural psychology, stigma literature, and educational technology, offering a holistic lens to understand how cultural and emotional factors interact with instructional design to shape student success.

2.5 Hypotheses Development

In collectivist societies such as India, cultural values emphasise social conformity, academic success, and family honour (Markus & Kitayama, 1991; Nisbett, 2003). These sociocultural scripts often lead to elevated academic stress and shape students' performance appraisal. When students perceive themselves as falling short of these culturally embedded expectations, they may experience social disapproval or anticipate such judgment from others. This leads to perceived stigma, the sense of being evaluated or devalued by society or peers (Phelan et al., 1998). Over time, such perceptions may become internalised, as students adopt negative beliefs about their self-worth based on academic performance, leading to internalised stigma (Watson et al., 2007; Corrigan & Rao, 2012).

Hence, the following hypotheses are proposed:

- **H1**: Cultural context is positively related to perceived stigma.
- **H2**: Cultural context is negatively associated with internalised stigma.

Once internalised, stigma disrupts learning by lowering self-efficacy, reducing motivation, and increasing disengagement. Students experiencing internalised stigma may avoid participation, conceal difficulties, and avoid seeking academic support (Major & O'Brien, 2005; Eisenberg et al., 2009). Similarly, even the anticipation of social judgment, i.e., perceived stigma, can contribute to anxiety, fear of failure, and emotional distress, all of which negatively influence academic performance.

- **H3**: Perceived stigma is negatively related to academic performance.
- **H4**: Internalised stigma is negatively related to academic performance.

Without mediating factors, cultural context can directly influence academic performance. Cultural beliefs and expectations may foster academic commitment or burden students with fear and psychological strain. Prior studies in Indian and East Asian contexts have found that rigid cultural scripts often intensify performance pressure and emotional exhaustion, undermining academic outcomes (Li & Wang, 2021; Chadda & Deb, 2013). Therefore:

- **H5**: Cultural context is negatively related to academic performance.

Teaching 4.0 introduces adaptive, learner-centric pedagogies that can reduce the psychological burden associated with stigma. By promoting personalised and autonomous learning environments, these technologies create spaces where students can engage without the fear of social comparison or failure (Ifenthaler & Schumacher, 2016; Romero et al., 2020). In collectivist cultures where public academic performance is often scrutinised, the private and flexible nature of Teaching 4.0 becomes particularly relevant. Moreover, its interactive feedback mechanisms and real-time adaptability enhance students' sense of competence and control, key ingredients for academic success.

As such, this study positions Teaching 4.0 not merely as a pedagogical tool but as an affective and motivational mediator that can attenuate the adverse effects of stigma and cultural pressure on academic performance.

- **H6**: Cultural context is positively related to Teaching 4.0 adoption.
- **H7**: Perceived stigma is negatively related to Teaching 4.0 adoption.
- **H8**: Teaching 4.0 is positively related to academic performance.

Mediating Effects

Based on the proposed direct relationships, the model further assumes that:

- **H9**: Perceived stigma mediates the relationship between cultural context and academic performance.
- **H10**: Internalised stigma mediates the relationship between cultural context and academic performance.
- **H11**: Teaching 4.0 mediates the relationship between cultural context and academic performance.
- **H12**: Teaching 4.0 mediates the relationship between perceived stigma and academic performance.

3. METHODOLOGY

3.1 Research Design

The present study employed a quantitative research design using Partial Least Squares Structural Equation Modelling (PLS-SEM) to examine the relationships between cultural context, perceived stigma, internalised stigma, Teaching 4.0, and academic performance. PLS-SEM was selected due to its robustness in handling complex models with multiple mediators and its suitability for exploratory research with non-normal data distributions (Hair et al., 2019). The model also includes indirect effects and non-recursive relationships, making variance-based SEM an appropriate analytical technique. In addition to bootstrapping, Cross-Validated Predictive Ability Testing (CVPAT) was used to assess the model's predictive relevance.

3.2 Sample and Participants

Data were collected from a purposive sample of 400 students. The inclusion criteria required that participants be full-time students currently enrolled in at least their second semester of study to ensure sufficient exposure to academic evaluation and teaching modalities. The sample was diverse in gender, socioeconomic background, and academic standing. Students were informed about the voluntary nature of participation and assured anonymity and confidentiality.

3.3 Data Collection Procedure

Participants were given an online questionnaire administered via a secure Google Form link. Prior to beginning the survey, participants provided informed consent. The study was conducted by the ethical standards of the American Psychological Association (APA, 2017).

3.4 Measures

The constructs in this study were measured using standardised, previously validated scales. **Cultural Context**

Cultural context was assessed using the Cultural Intelligence Scale (CQS) developed by Ang et al. (2007). The scale comprises 20 items distributed across four dimensions: meta-cognitive, cognitive, motivational, and behavioural cultural intelligence. Participants responded on a 7-point Likert scale ranging from 1 ("Very Strongly Disagree") to 7 ("Very Strongly Agree"). Higher scores reflect greater awareness and navigation of culturally rooted academic expectations.

Perceived Stigma

Perceived stigma was measured using the Stigma Scale developed by King et al. (2007), originally designed to assess stigma associated with psychological distress. The 28-item scale includes both positively and negatively phrased items, with responses recorded on a 5-point Likert scale (0 = "Strongly Disagree" to 4 = "Strongly Agree"). Scores were calculated toward higher stigma, following the original scoring rubric.

Internalised Stigma

Internalised stigma was assessed using the 9-item version of the Internalised Stigma of Mental Illness Scale (ISMI-9) developed by Hammer and Toland (2017). Respondents rated their agreement on a 4-point Likert scale from 1 ("Strongly Disagree") to 4 ("Strongly Agree"). Two items (2 and 9) were reverse-coded before computing the overall mean score. Higher scores indicate greater internalised academic stigma.

Teaching 4.0

Experience with Teaching 4.0 was measured using a custom-compiled scale adapted from the frameworks proposed by Ifenthaler and Schumacher (2016) and Romero et al. (2020). The scale captures students' experiences with AI-enabled feedback, personalised content delivery, digital scaffolding, and student-centred pedagogical design. The items were rated on a 7-point Likert scale ranging from 1 ("Strongly Disagree") to 7 ("Strongly Agree"). The final scale reflects how students perceive their learning environment to embody the principles of Teaching 4.0.

Academic Performance

Academic performance was measured using the Academic Performance Scale (APS) developed by Birchmeier et al. This self-report scale includes 8 items assessing behaviours such as attention during class, assignment management, effort, and academic motivation. Responses were recorded on a 5-point Likert scale (1 = "Strongly Disagree" to 5 = "Strongly Agree"), with total scores ranging from 8 to 40. Higher scores reflect stronger academic engagement and performance-related behaviours. The APS has demonstrated strong reliability, with Cronbach's alpha reported at .89 and test–retest reliability at .85.

3.5 Data Analysis

After preliminary screening for missing values, outliers, and normality, the measurement model was assessed for reliability, convergent validity, and discriminant validity using criteria such as Cronbach's alpha, composite reliability (CR), average variance extracted (AVE), and Fornell-Larcker criterion. Once the measurement model was validated, the structural model was evaluated to test the proposed hypotheses using bootstrapping with 10,000 resamples to generate robust standard errors and confidence intervals.

Model fit indicators, including R^2, f^2, and Q^2 values, were examined to assess the explanatory and predictive power of the model. Finally, CVPAT (Cross-Validated Predictive Ability Test) was applied to compare the out-of-sample predictive performance of the model to benchmark linear regression models, establishing the model's real-world applicability.

4. RESULTS

4.1 Common Method Bias

To check for Common Method Bias (CMB), this study followed the complete collinearity approach recommended by Kock (2015). A random standard method variance (CMV) variable was introduced into

the PLS-SEM model, and the variance inflation factor (VIF) values were examined for all constructs. The analysis showed that all VIF values were below the acceptable threshold of 3.3, indicating that common method bias is insignificant or a concern. These results suggest that the relationships in the model are unlikely to be distorted by response biases**,** ensuring the credibility and reliability of the findings.

4.2 Measurement Model Evaluation

The measurement model was rigorously assessed to ensure the reliability and validity of the constructs used in the study. For indicator reliability, most items showed standardised factor loadings above the acceptable threshold of 0.60, with several exceeding 0.70, indicating satisfactory individual item contributions to their respective constructs. Internal consistency was supported across all constructs. Cronbach's Alpha, rho_a, and composite reliability (CR) values were consistently above the recommended minimum of 0.70 and below the upper limit of 0.95, reflecting stable and consistent measurement (Hair et al., 2022). Convergent validity was confirmed through Average Variance Extracted (AVE) values, surpassing the 0.50 criterion. Although a few items had slightly lower loadings, the overall construct validity remained acceptable due to strong cumulative metrics.

Discriminant validity was evaluated using the Heterotrait-Monotrait (HTMT) ratio, which has emerged as a robust technique for identifying conceptual overlap between constructs. All HTMT values in this analysis were well below the threshold of 0.85, as Henseler et al. (2015) suggested, indicating that the constructs were sufficiently distinct. The highest correlation was observed between academic performance and teaching 4.O (HTMT = 0.711), which, while relatively high, still demonstrated adequate separation. Other construct pairs exhibited low to moderate HTMT values, further supporting the uniqueness of each latent variable in the model. Together, these results affirm the sound psychometric properties of the measurement model.

Table 1 presents the reliability, convergent, and discriminant validity assessment using the HTMT criterion. The findings confirm that all constructs meet the necessary reliability and validity standards.

Table 1: Measurement Model Evaluation (Reliability & Validity)

Construct	Item	Factor Loading	Cronbach's Alpha	CR (rho_a)	CR (rho_c)	AVE
CC	CC 1	0.729	0.887	0.902	0.908	0.524
	CC 2	0.747				
	CC 3	0.789				
	CC 4	0.752				
	CC 5	0.679				
	CC 6	0.704				
	CC7	0.703				
	CC 8	0.629				
	CC 12	0.768				
ISS	ISS 1	0.707	0.866	0.896	0.894	0.527
	ISS 3	0.712				
	ISS 4	0.792				
	ISS 5	0.797				
	ISS 6	0.771				
	ISS 7	0.811				
	ISS 8	0.787				
	ISS 9	0.277				
PSS	PSS 1	0.681	0.954	0.978	0.957	0.507
	PSS 2	0.758				
	PSS 3	0.633				
	PSS 4	0.733				
	PSS 5	0.722				
	PSS 6	0.663				
	PSS 7	0.564				
	PSS 8	0.599				
	PSS 9	0.763				
	PSS 10	0.724				
	PSS 11	0.744				
	PSS 12	0.758				
	PSS 13	0.737				
	PSS 14	0.788				
	PSS 15	0.773				
	PSS 16	0.577				
	PSS 18	0.753				

	PSS 20	0.699				
	PSS 21	0.712				
	PSS 22	0.764				
	PSS 23	0.738				
	PSS 24	0.737				
	PSS 28	0.735				
T	T 1	0.765	0.897	0.904	0.918	0.584
	T 2	0.816				
	T 3	0.795				
	T 4	0.815				
	T 5	0.818				
	T 6	0.621				
	T 7	0.781				
	T 8	0.679				
AP	AP 1	0.696	0.875	0.890	0.900	0.532
	AP 2	0.793				
	AP 3	0.724				
	AP 4	0.745				
	AP 5	0.647				
	AP 6	0.628				
	AP 7	0.802				
	AP 8	0.777				

Discriminant Validity (HTMT Criterion)

Construct	AP	CC	ISS	PSS	T
AP					
CC	0.127				
ISS	0.305	0.163			
PSS	0.162	0.174	0.141		
T	0.711	0.123	0.400	0.201	

4.3 Structural Model Evaluation

The explanatory strength of the model was assessed using R^2 values, which indicate the proportion of variance in each outcome variable accounted for by its predictors. The highest explanatory value was observed for academic performance (AP), with an R^2 of 0.436 (adjusted R^2 = 0.430), suggesting that the predictors in the model explained nearly 44% of the variation in AP. By contrast, both internalised stigma (IS) and perceived stigma (PS) had low explanatory values (R^2 = 0.030 and 0.033, respectively), indicating limited predictive power. Teaching 4.0 (T) showed slightly higher explanatory potential with an R^2 of 0.053.

Effect size (f^2) analysis was conducted to understand the impact of individual predictor variables better. The most substantial effect was found between Teaching 4.0 and academic performance, with a large effect size of 0.584. This suggests that Teaching 4.0 is a significant contributor to predicting academic success. In contrast, critical consciousness (CC) had minimal effects on internalised stigma (f^2 = 0.014), perceived stigma (f^2 = 0.034), and Teaching 4.0 (f^2 = 0.004), indicating weak predictive relationships. Perceived stigma also showed minor effects on internalised stigma (f^2 = 0.011) and Teaching 4.0 (f^2 = 0.045). The remaining predictors had negligible effects.

Model fit was evaluated using the standardised root mean square residual (SRMR), which was found to be 0.075. As this value falls below the widely accepted cut-off of 0.08 (Hu & Bentler, 1998), the model can be considered to have a satisfactory overall fit with the observed data.

Table 2: Explanatory Power & Model Fit

Explanatory Power: R Square		
Construct	R Square	R Square Adjusted
AP	0.436	0.430
ISS	0.030	0.025
PSS	0.033	0.031
T	0.053	0.048

Effect Size: f Square

	AP	CC	ISS	PSS	T
AP					
CC	0.002		0.014	0.034	0.004
ISS	0.003				

PSS	0.002	0.011	0.045
T	0.584		

Model Fit	
SRMR	Value
SRMR	0.075

4.4 Structural Model Evaluation

Table 3 presents the outcomes of the structural model, examining both direct and indirect relationships among cultural context (CC), perceived stigma (PSS), internalised stigma (ISS), Teaching 4.0 (T4.O), and academic performance (AP). Among the direct effects, CC significantly predicted PSS (β = 0.182, p = 0.000) and negatively predicted ISS (β = -0.118, p = 0.021), supporting both H1 and H2. Additionally, PSS had a significant adverse effect on T4.O (β = -0.209, p = 0.000), while T4.O strongly and positively predicted AP (β = 0.630, p = 0.000), lending support to H7 and H8. In contrast, the direct effects of PSS (β = -0.031, p = 0.241), ISS (β = 0.044, p = 0.145), and CC (β = -0.035, p = 0.228) on AP were not statistically significant, resulting in the rejection of H3, H4, and H5. Furthermore, the relationship between CC and T4.O (β = -0.064, p = 0.155) was non-significant, indicating no support for H6.

Regarding indirect effects, only the mediating pathway from PSS to AP through T4.O was significant (β = -0.132, p = 0.000), confirming H12. All other indirect paths, including CC through PSS, ISS, or T4.O, were not statistically significant (p > 0.05), leading to rejection of H9, H10, and H11. These results underscore the critical role of Teaching 4.0 as a mediating mechanism in the link between perceived stigma and academic performance, while indicating that other proposed mediators do not significantly transmit the effects of cultural or stigma-related factors on academic outcomes.

Table 3: Structural Model Results

Path	Coefficient (β)	T-statistic	P-value	Confidence Interval (Bias Corrected)	Inference
Direct Effects					
CC → PSS	0.182	3.396	0.000	0.073 – 0.255	H1 Supported
CC → ISS	-0.118	2.037	0.021	-0.199 - -0.001	H2 Supported
PSS → AP	-0.031	0.702	0.241	-0.102 - 0.043	H3 Not Supported
ISS → AP	0.044	1.059	0.145	-0.027 - 0.110	H4 Not Supported
CC → AP	-0.035	0.745	0.228	-0.107 - 0.045	H5 Not Supported
CC → T4.O	-0.064	1.017	0.155	-0.156 – 0.052	H6 Not Supported
PSS → T4.O	-0.209	3.571	0.000	-0.295 - -0.102	H7 Supported
T4.O → AP	0.630	14.876	0.000	0.554 – 0.693	H8 Supported
Specific Indirect Effects					
CC → PSS → AP	-0.006	0.635	0.263	-0.006 - -0.006	H9 Not Supported
CC → ISS → AP	-0.005	0.840	0.200	-0.005 - -0.006	H10 Not Supported
CC → T4.O → AP	-0.040	1.016	0.155	-0.040 - -0.043	H11 Not Supported
PSS → T4.O → AP	-0.132	3.573	0.000	-0.132 - -0.135	H12 Supported

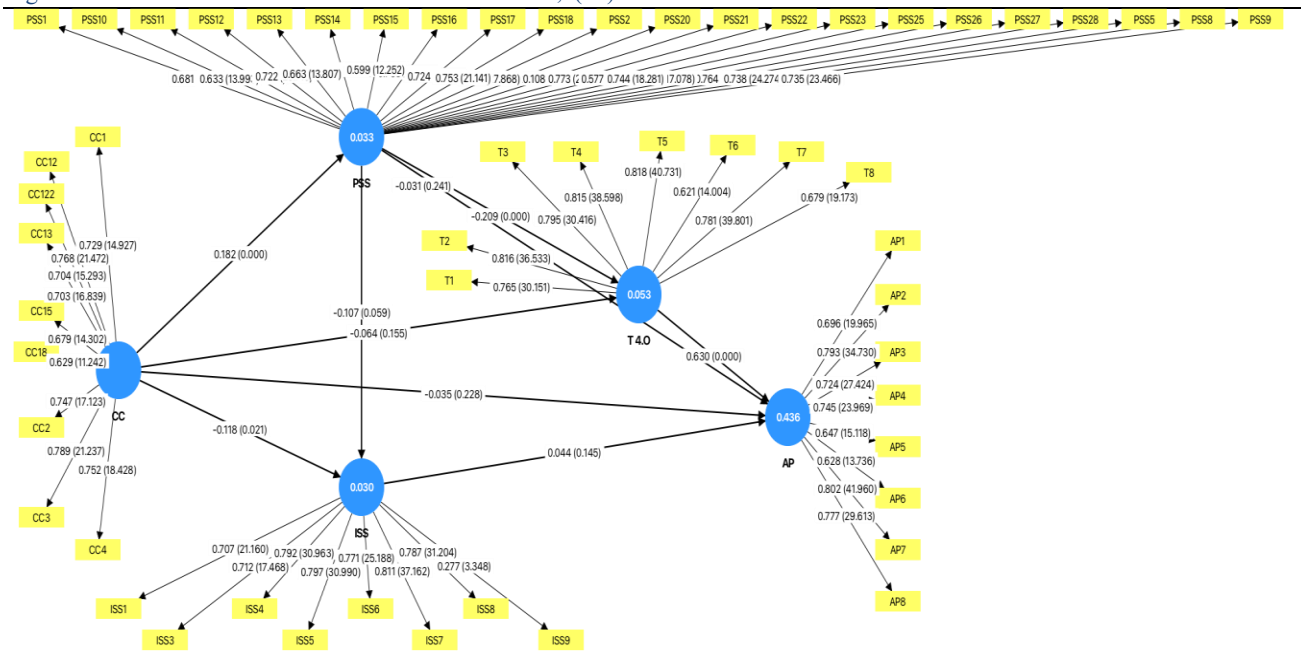

Figure 2: Model Estimation Results

4.5 PLS Predict

The out-of-sample predictive performance of the structural model was evaluated using the PLS Predict algorithm and Cross-Validated Predictive Ability Testing (CVPAT) in SmartPLS 4. This assessment method determines how accurately the model can predict new, unseen data. The Q^2 predicted values for all endogenous constructs, Internalised Stigma (ISS), Perceived Stigma (PSS), Teaching 4.0 (T4.0), and Academic Performance (AP), were mostly positive, indicating that the model has meaningful predictive relevance. Specifically, Q^2 values ranged from –0.007 to 0.012 for ISS, –0.013 to 0.041 for PSS, –0.011 to 0.013 for T4.0, and –0.015 to 0.012 for AP. These values suggest that the model predicts better than a naive benchmark, particularly for PSS and AP, which showed comparatively stronger prediction accuracy.

To further validate the model's predictive strength, CVPAT was conducted by comparing prediction errors between the PLS-SEM model and a traditional linear regression benchmark. The results showed that the PLS-SEM model significantly outperformed the linear model across all constructs. The LM average loss difference was –0.023 (p = 0.014) for ISS, –0.035 (p = 0.008) for PSS, –0.038 (p = 0.004) for T4.0, and –0.041 (p = 0.000) for AP. These negative values indicate that the PLS-SEM model had lower prediction error, and the associated p-values confirm that the differences were statistically significant. Notably, the most substantial predictive improvement was observed for academic performance, highlighting the model's effectiveness in forecasting academic outcomes. Overall, these results confirm that the PLS-SEM model has robust predictive capabilities, outperforming traditional regression approaches across key constructs in the model.

Table 4: Predictive Model Assessment

Construct	Item	PLS Predict Q^2 Predict	RMSE PLS- SEM	LM RMSE	CVPAT IA average loss difference (p value)	LM average loss difference (p value)
ISS	ISS 1	0.007	0.978	0.997	-0.000 (0.995)	-0.023 (0.014)
	ISS 3	-0.004	0.959	0.966		
	ISS 4	0.009	1.032	1.050		
	ISS 5	0.008	1.011	1.014		
	ISS 6	0.003	1.007	1.015		
	ISS 7	0.007	0.989	1.007		
	ISS 8	0.012	0.994	1.009		
	ISS 9	-0.007	1.062	1.064		
PSS	PSS 1	0.041	1.324	1.327	-0.014 (0.426)	-0.035 (0.008)
	PSS 2	0.014	1.237	1.261		
	PSS 3	0.018	1.265	1.275		
	PSS 4	0.018	1.263	1.276		
	PSS 5	-0.001	1.274	1.277		
	PSS 6	0.026	1.237	1.265		
	PSS 7	0.016	1.215	1.226		

	PSS 8	0.005	1.240	1.252		
	PSS 9	-0.009	1.253	1.257		
	PSS 10	0.002	1.234	1.242		
	PSS 11	0.027	1.283	1.301		
	PSS 12	0.004	1.271	1.289		
	PSS 13	0.000	1.246	1.266		
	PSS 14	0.005	1.274	1.289		
	PSS 15	-0.010	1.254	1.267		
	PSS 16	0.003	1.218	1.241		
	PSS 18	0.005	1.272	1.302		
	PSS 20	-0.001	1.289	1.285		
	PSS 21	-0.013	1.228	1.224		
	PSS 22	0.005	1.282	1.289		
	PSS 23	0.012	1.317	1.346		
	PSS 24	0.010	1.336	1.355		
	PSS 28	0.027	1.283	1.301		
T4.O	T 1	-0.005	1.182	1.191	-0.000 (0.998)	-0.038 (0.004)
	T 2	0.001	1.140	1.159		
	T 3	0.007	1.140	1.150		
	T 4	0.002	1.203	1.226		
	T 5	0.013	1.166	1.179		
	T 6	-0.011	1.165	1.180		
	T 7	0.002	1.304	1.329		
	T 8	-0.009	1.169	1.181		
AP	AP 1	-0.006	1.139	1.164	-0.000 (0.995)	-0.041 (0.000)
	AP 2	-0.001	1.082	1.102		
	AP 3	0.004	1.382	1.405		
	AP 4	0.005	1.145	1.151		
	AP 5	-0.015	1.146	1.168		
	AP 6	0.001	1.099	1.116		
	AP 7	0.012	1.181	1.199		
	AP 8	-0.003	1.167	1.175		
Overall					-0.007 (0.427)	-0.034 (0.000)

5. DISCUSSION

The findings of this study illuminate the nuanced interplay between cultural context, stigma, and academic performance in the Indian higher education landscape. Grounded in the Stress-Appraisal-Coping (SAC) framework, the results partially support the hypothesised model while revealing unexpected complexities.

5.1 Cultural Context and Stigma

As expected, cultural context significantly predicted perceived stigma (H1 supported), aligning with previous research that suggests collectivist values, such as academic conformity and family honour, increase vulnerability to social judgment (Markus & Kitayama, 1991; Li & Wang, 2021). The inverse relationship between cultural context and internalised stigma (H2 supported) was unexpected. However, it may reflect a cultural resilience mechanism, where students externalise failure due to the societal emphasis on systemic pressures rather than personal inadequacy. This finding resonates with recent Indian-based research highlighting that students often attribute underperformance to institutional or systemic inefficiencies rather than self-failure (Singh & Kaur, 2023). Such interpretations are consistent with cross-cultural psychological studies demonstrating that East Asian and South Asian students may attribute setbacks to external rather than internal causes, a form of cultural resilience (Heine, 2016). Similarly, Rao et al. (2019) observed that stigma in Indian higher education often reflects broader institutional shortcomings rather than personal flaws.

5.2 Stigma and Academic Performance

Contrary to prior findings in Western literature (Corrigan & Rao, 2012; Eisenberg et al., 2009), neither perceived nor internalised stigma directly predicted academic performance (H3 and H4 not supported). This may be due to collectivist coping tendencies where academic struggles are shared or compensated for by familial and peer networks (Tripathi & Cervone, 2020). Additionally, stigma may influence other psychological or behavioural outcomes such as help-seeking attitudes or emotional regulation, rather than academic metrics directly. Prior studies also suggest that stigma often exerts its impact indirectly by shaping avoidance behaviours and reduced help-seeking, rather than directly impairing academic performance (Link et al., 2001; Chen et al., 2019). This indicates that stigma's role in academic contexts may be more subtle and mediated than previously assumed, particularly in collectivist societies.

5.3 The Role of Teaching 4.0

One of the most striking findings was the robust positive effect of Teaching 4.0 on academic performance (H8 supported), indicating its transformative potential. Teaching 4.0, characterised by AI-based feedback, personalised learning, and digital scaffolding, emerged as the strongest predictor in the model, with a large effect size ($f^2 = 0.584$). This supports global trends in education technology, suggesting that personalised, adaptive instruction increases student engagement and academic outcomes (Hwang et al., 2020; Lee & Han, 2022). Notably, perceived stigma negatively influenced adopting Teaching 4.0 (H7 supported), implying that students who feel socially judged may hesitate to utilise anonymous or private technological platforms. This aligns with the idea that stigma limits interpersonal engagement and intrapersonal openness to growth tools (Schomerus et al., 2019). These results reinforce broader evidence that digital and AI-enabled teaching models enhance motivation and reduce barriers to participation in higher education (Zawacki-Richter et al., 2019; Bond et al., 2021). Moreover, by allowing students to engage privately and autonomously, Teaching 4.0 may mitigate the visibility of academic struggles, thus indirectly reducing stigma-related barriers.

Interestingly, cultural context did not predict the adoption of Teaching 4.0 (H6 not supported), suggesting that students may perceive technology as neutral or universally beneficial regardless of cultural values. Moreover, the direct and indirect paths from cultural context to academic performance via stigma types and Teaching 4.0 were insignificant (H5, H9–H11 not supported). This further underscores the unique role of Teaching 4.0 in mediating stigma–performance dynamics, primarily through the significant indirect effect of perceived stigma on academic performance via Teaching 4.0 (H12 supported).

6. CONCLUSION

This study contributes to an emerging body of research examining the convergence of culture, stigma, and digital pedagogy in higher education. While traditional sociocultural factors like stigma retain influence in shaping educational experiences, it is clear that technologically advanced learning environments can serve as powerful buffers against these pressures. Teaching 4.0 enhances academic performance and offers psychological safety, flexibility, and learner autonomy qualities crucial in stigma-laden academic settings. The findings call for a reorientation in pedagogical priorities, where student well-being and adaptive technologies are central to educational planning, especially in high-pressure collectivist contexts.

6.1 Theoretical and Practical Implications

Theoretically, this study extends the SAC framework by empirically demonstrating how a technology-enabled learning environment can function as an adaptive coping resource. It also contributes to cross-cultural educational psychology by contextualising stigma dynamics within a non-Western framework.

Practically, the results urge educators and policymakers to prioritise implementing Teaching 4.0 practices, especially for students grappling with performance-related stigma. Customisable learning platforms, AI-driven feedback, and gamified modules may enhance learning and confidence in socially anxious students. Furthermore, stigma-reduction campaigns in higher education institutions should address mental health and academic self-concept.

6.2 Limitations

This study is not without limitations. First, self-report measures raise concerns of social desirability and response bias, despite statistical checks for standard method variance. Second, while the sample was diverse, it was geographically restricted to Indian institutions and may not generalise across cultural or national contexts. Third, the cross-sectional design limits causal inference. Finally, the measurement of Teaching 4.0 was based on perception and not actual system usage analytics, which could affect the reliability of interpretations.

6.3 Future Directions

Future research should explore longitudinal models to assess the causal relationships between stigma, technology adoption, and performance. Integrating behavioural usage data (e.g., log files from LMS platforms) with self-report measures could offer more nuanced insights. Moreover, qualitative studies could deepen our understanding of how students internalise or resist stigma in the presence of adaptive technology. Future work could also expand the model to include moderating factors such as gender, socioeconomic background, or institutional support systems.

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