A Multilayered Predictive Framework for Student Attrition in Higher Education Using Psychosocial, Cognitive, and Technological Determinants

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ABSTRACT

The phenomenon of student attrition continues to pose a significant challenge for higher education institutions (HEIs), particularly in the wake of rapid technological transformation and the evolving psychological landscape of learners. This study introduces a novel conceptual model that integrates psychosocial, cognitive, and technological determinants—such as academic self-regulation, perceived fairness, AI-based learning, and peer academic support—to predict attrition intentions among undergraduate students. Drawing upon Self-Regulation Theory, Organizational Justice Theory, and Cognitive Load Theory, the model also incorporates academic burnout as a mediating factor. Drawing upon data from 604 undergraduate students in technical education, this research investigates the influence of factors such as academic self-regulation, cognitive engagement, mental health vulnerability, digital pedagogy alignment, and AI-based learning experience on academic burnout. Furthermore, it explores how elements like sense of belonging, peer academic support, and perceived institutional fairness directly shape attrition intentions. Structural Equation Modeling (SEM) was employed to validate the hypothesized relationships. The results highlight that academic burnout acts as a critical mediator in the attrition process, significantly influenced by both personal and technological stressors. The model underscores the need for early intervention through learning analytics and student-centric support systems that leverage explainable and ethical AI approaches. The findings provide strategic insights for policymakers and academic leaders to enhance student retention through targeted, data-driven reforms.

Keywords: Student Attrition, Academic Burnout, Cognitive Engagement, AI-Based Learning, Digital Pedagogy, Mental Health Vulnerability, Higher Education.

Introduction

Student attrition remains a persistent concern in global higher education systems, with dropout rates ranging from 30% to over 50% depending on national and institutional contexts. These figures represent more than academic disengagement, they embody systemic failures in delivering equitable, adaptable, and psycho-logically attuned educational experiences. As institutions increasingly shift toward digitized, learner-centred frameworks, there is a growing recognition that traditional predictors such as

GPA, academic integration, and demographic profiles are insufficient for capturing the complexity of student retention dynamics [3–5].

The modern higher education landscape is shaped by a convergence of challenges, including rising mental health concerns [6], the shift to blended learning modalities [7], and student perceptions of fairness, autonomy, and support [8]. Within this context, a deeper examination of cognitive, psychosocial, and technological influences on student engagement and persistence is warranted. Factors such as academic self-regulation, cognitive engagement, and perceived fairness have shown strong theoretical and empirical links to motivation, resilience, and long-term academic outcomes [9–11]. Simultaneously, emerging technologies such as AI-based learning environments and digital pedagogical platforms are reshaping how students interact with content and instructors. While these tools offer potential for personalization and efficiency, they may also increase cognitive load or alienate students who struggle with self-directed learning [12,13]. Moreover, academic burnout, a psychological construct linked to emotional exhaustion, depersonalization, and reduced accomplish-ment, is increasingly recognized as mediator between these environmental stressors and student withdrawal [14].

This research seeks to develop and validate a multi-layered model for predicting student attrition by synthesizing eight determinants into a cohesive framework. The study also explores academic burnout as a mediating variable that helps explain how cognitive and environmental pressures lead to dropout intention.

Research Questions

1. What is the predictive influence of psychosocial, cognitive, and digital factors on student attrition in higher education?
2. To what extent does academic burnout mediate the relationship between these factors and dropout intention?

Research Objectives

1. To explore the effect of academic self-regulation and cognitive engagement on academic burnout.

   These cognitive factors are analyzed to understand how internal student motivation and participation in learning activities impact emotional exhaustion and academic stress.

2. To evaluate the influence of mental health vulnerability and digital learning environments (digital pedagogy alignment and AI-based learning experience) on academic burnout.

   This objective aims to capture how psychological stress and the integration of technology affect student well-being.

3. To examine whether academic burnout mediates the relationship between cognitive, psychological, and technological factors and student attrition intention.

   This objective addresses the indirect pathway linking these variables to dropout behavior through emotional fatigue.

4. To determine the impact of social belongingness, peer academic support, and perceived institutional fairness on students' intentions to persist.

   These social-institutional variables are measured to determine how student experiences within the academic environment influence attrition tendencies.

5. To validate a structural model that integrates psychosocial, cognitive, and digital determinants of student attrition through SEM.

This final objective tests the theoretical model empirically using advanced statistical analysis to confirm causal relationships and mediating effects.

Theoretical Framework and Hypothesis Development

The process of student attrition is increasingly viewed as a multidimensional phenomenon, shaped by personal regulation, academic cognition, social integration, institutional treatment, and environmental alignment. This study proposes a new conceptual framework that builds upon three foundational theoretical domains: Self-Regulation Theory, Organizational Justice Theory, and Cognitive Load Theory. Together, these lenses offer a comprehensive explanation of how student experiences in the academic ecosystem can either promote persistence or accelerate disengagement.

Academic Self-Regulation and Cognitive Engagement: Self-Regulation Theory asserts that learners who set goals, manage time effectively, and reflect on their learning are more likely to succeed academically. Lack of self-regulation often leads to academic overload and eventual burnout. Cognitive engagement, closely aligned with effortful learning and critical thinking, is essential for academic persistence. As per Cognitive Load Theory, when instructional materials overwhelm the learner's mental capacity, performance deteriorates, increasing dropout risk.

H1 : Academic self-regulation negatively influences student attrition.

H2 : Cognitive engagement negatively influences student attrition.

Sense of Belonging and Peer Academic Support: Belongingness reflects a student's perception of social integration and emotional acceptance in the academic environment, which is a known predictor of institutional commitment and academic satisfaction. Peer academic support enhances collaboration, academic efficacy, and emotional resilience.

H3 : Sense of belonging negatively influences student attrition.

H4 : Peer academic support negatively influences student attrition.

Perceived Institutional Fairness: Drawing from Organizational Justice Theory, perceived fairness involves judgments regarding transparency, consistency, and equity in institutional procedures. Negative perceptions of fairness can result in disengagement and attrition.

H5 : Perceived institutional fairness negatively influences student attrition.

Digital Pedagogy Alignment and AI-Based Learning Experience: As universities increasingly rely on remote and blended learning, students' alignment with digital pedagogy becomes critical for engagement. Mismatch in learning preferences and digital infrastructure may contribute to dissatisfaction and dropout. Moreover, AI-enhanced learning tools, though promising in personalization may introduce complexity, creating stress among less digitally fluent learners.

H6 : Digital pedagogy alignment negatively influences student attrition.

H7 : AI-based learning experience negatively influences student attrition.

Mental Health Vulnerability: Elevated stress, anxiety, and emotional imbalance are prominent drivers of academic burnout, which in turn elevates attrition risk. Mental health challenges have emerged as one of the leading indicators of poor academic outcomes in recent studies.

H8 : Mental health vulnerability positively

influences student attrition.

Academic Burnout as Mediator: Academic burnout mediates the relationship between psychological distress, technological stressors, and student withdrawal. It provides a psychological mechanism through which external and internal stress translates into dropout behaviour.

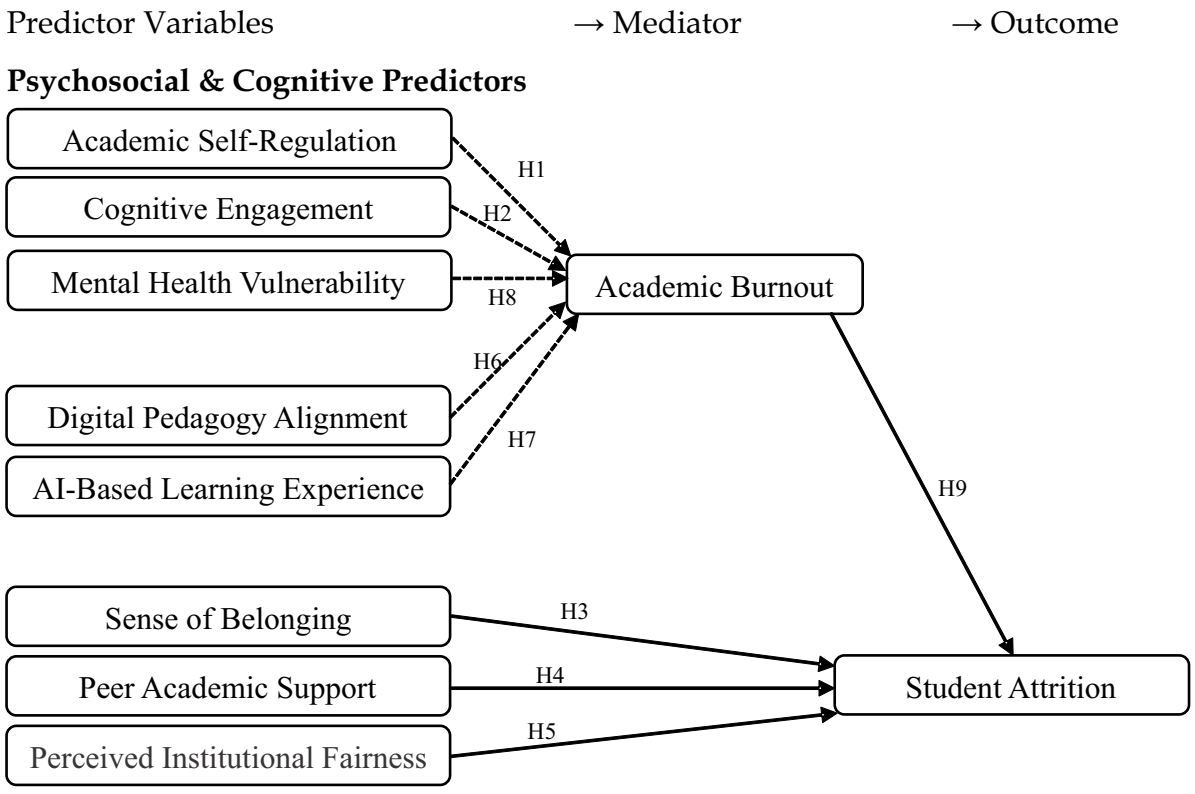
H9 : Academic burnout mediates the relationship between the independent determinants and student attrition.

cross-sectional design was implemented to assess the perceptions of undergraduate students enrolled in higher education institutions (HEIs), particularly those studying technology-intensive programs.

Research Design and Approach

The research follows a positivist paradigm and applies a hypothesis-driven, deductive approach to examine causal relationships between latent constructs. A structured survey instrument was employed using pre-validated and adapted measurement items, supporting both measurement model validation and structural path testing. The SEM approach, well-established

Fig. 1: Conceptual Framework



Methodology

This study adopts a quantitative methodology to empirically test the proposed conceptual model using Structural Equation Modelling (SEM). A in behavioral and educational research, allows for simultaneous analysis of multiple dependent relationships.

Target Population and Sampling

The target population consisted of undergraduate students enrolled in engineering, computing, and applied science disciplines across public and private universities. A stratified random sampling strategy ensured proportional representation based on academic year, gender, and institution type. From 950 distributed surveys, 720 responses were collected, and after removing incomplete or inconsistent entries, 687 valid responses were retained for analysis, yielding a usable response rate of 72.3%. The final sample reflected geographic diversity from urban, semi-urban, and rural regions.

Survey Instrument and Measures

The instrument consisted of two sections: demographic data and construct measurements using a 5-point Likert scale (1 = Strongly Disagree to 5 = Strongly Agree). All multi-item constructs were adapted from validated scales used in prior research.

All items were piloted with 40 students to ensure clarity, and the survey achieved face and content validity through expert review.

Data Collection Procedure

Data collection occurred over six weeks using a hybrid distribution strategy, online via Google Forms and offline through printed questionnaires. Institutional ethics approval was secured prior to data collection. Informed consent was obtained, and participant confidentiality was maintained throughout. All responses were anonymized and stored securely. The study adhered to the European Commission's ethics guidelines for trustworthy AI in research and data protection.

Reliability and Validity Testing

Reliability was assessed through Cronbach's alpha and Composite Reliability (CR). A threshold of 0.70 was set for acceptability.

Table 1: Construct List and Items

Construct	Source/Adapted From	Items
Academic Self-Regulation	Pintrich & De Groot (1990) [20]; Zimmerman (2002) [21]	5
Cognitive Engagement	Fredricks et al. (2004) [22]; Appleton et al. (2006) [23]	4
Mental Health Vulnerability	WHO-5 Well-Being Index [24]; GAD-7 Scale [25]	4
Digital Pedagogy Alignment	Churchill (2009) [26]; Expert-reviewed items	4
AI-Based Learning Experience	Aljohani et al. (2021) [27]; Modified items [13]	3
Sense of Belonging	Goodenow (1993) [28]; Strayhorn (2012) [29]	4
Peer Academic Support	McKenzie & Schweitzer (2001) [30]	3
Perceived Institutional Fairness	Colquitt (2001) [31]; Greenberg (1990) [32]	4
Academic Burnout	MBI–SS [33]	5
Student Attrition Intention	Tinto (1975) [34]	3

Source: Literature based Compilation

- Convergent Validity was confirmed using Average Variance Extracted (AVE), where values above 0.50 were deemed adequate [37].
- Discriminant Validity further may be tested using Fornell-Larcker Criterion and HTMT ratio, ensuring that all constructs were conceptually and statistically distinct.

Data Analysis Strategy: Data analysis was conducted in two phases:

Preliminary Analysis using IBM SPSS 26 to check for missing values, normality, outliers, and multicollinearity. Structural Equation Modelling (SEM) was employed using AMOS 24 to:

- Test the measurement model via Confirmatory Factor Analysis (CFA).
- Examine path relationships through SEM.
- Assess the mediating effect of academic burnout using bootstrapping methods.

Model fit was evaluated using indices including: Chi-square/df (≤3); CFI, GFI, and TLI (≥0.90); RMSEA (≤0.08)

Data Analysis and Results

Descriptive Statistics: Descriptive statistics provided initial insights into the demographic

Table 2: Demographic Profile of Respondents (N = 687)

Variable	Categories	Frequency (N)	(%)
Age Group	18–20 years	208	30.3
	21–23 years	352	51.2
	24+ years	127	18.5
Gender	Male	389	56.6
	Female	298	43.4
Type of Programme	Undergraduate (B.Tech/B.Sc./BCA etc.)	621	90.4
	Diploma/Certificate	66	9.6
Course / Discipline	Computer Science & IT	256	37.3
	Engineering (ECE, ME, EE, etc.)	208	30.3
	Applied Sciences	115	16.7
	Other Technical Programs	108	15.7
Mode of Study	Full-Time	641	93.3
	Part-Time	46	6.7
Type of Institution	Public University	406	59.1
	Private University	281	40.9
Location of Institution	Urban	371	54.0
	Semi-Urban	193	28.1
	Rural	123	17.9

Source: Test Output

and academic characteristics of the respondents. Most students were enrolled in full-time undergraduate programs in technical fields such as engineering, computer science, and applied sciences.

Table 2 presents the demographic characteristics of the 687 respondents who participated in this study. The age distribution reveals that a majority of students (51.2%) fall within the 21–23 years range, followed by 30.3% between 18–20 years, and 18.5% aged 24 or older. This suggests that the sample predominantly consists of students in the typical undergraduate age bracket. In terms of gender, male students constituted 56.6% of the sample, while females made up 43.4%. Although the distribution reflects a modest gender imbalance, the sample maintains a reasonable representation of both groups.

The type of academic program showed that overwhelming majority (90.4%) were enrolled in full-time undergraduate degree programs such as B.Tech., B.Sc., or BCA. Only a small portion (9.6%) pursued diploma or certification-based programs, indicating that the study primarily reflects the perspectives of traditional degree-seeking students. With respect to disciplinary affiliation, the highest representation came from students enrolled in Computer Science and IT programs (37.3%), followed by engineering disciplines (30.3%), applied sciences (16.7%), and other technical courses (15.7%). This distribution reflects the focus of the research on students in technology-intensive education pathways.

A vast majority of participants (93.3%) were enrolled in full-time study, while 6.7% were pursuing their education through part-time or flexible modes. This trend is consistent with the structure of most technical and engineering programs, which typically require full-time commitment. Regarding the type of institution, 59.1% of the respondents were from public universities, while 40.9% were studying at private institutions. The sample captures a balanced institutional diversity, offering insights into the student experience across different governance models. Finally, the geographical location of institutions was also noted: 54% of

Table 3: Descriptive Statistics – Academic Characteristics

Variable	Mean	Standard Deviation	Variance	Skewness
Academic Self-Regulation	3.68	0.71	0.50	0.12
Cognitive Engagement	3.51	0.66	0.44	0.05
Mental Health Vulnerability	2.97	0.81	0.66	0.31
Digital Pedagogy Alignment	3.43	0.73	0.53	−0.04
AI-Based Learning Experience	3.12	0.78	0.61	0.10
Sense of Belonging	3.84	0.70	0.49	−0.22
Peer Academic Support	3.59	0.74	0.55	0.03
Perceived Institutional Fairness	3.46	0.68	0.46	0.07
Academic Burnout	2.82	0.85	0.72	0.39
Student Attrition Intention	2.21	0.91	0.83	0.65

Source: Test Output

students studied in urban campuses, 28.1% in semi-urban areas, and 17.9% in rural locations. This spread ensures that the results are not limited to a single demographic region and enhances the external validity of the findings.

Overall, the demographic composition of the sample ensures a broad representation of students across age groups, program types, institutional classifications, and regional settings, thereby supporting the generalizability of the study outcomes.

The descriptive statistics offer key insights into the central tendencies and variability of the measured constructs. Most variables demonstrated mean values ranging between 3.1 and 3.8, suggesting generally favourable perceptions among students toward academic support structures and peer engagement. The highest mean score was observed for Sense of Belonging (M = 3.84), indicating a strong emotional and social connection among students to their institutions. In contrast, Student Attrition Intention scored the lowest (M = 2.21), implying a generally low inclination toward dropping out, though variation exists. Standard deviations across constructs ranged from 0.66 to 0.91, with Student Attrition Intention and Academic Burnout reflecting higher dispersion, indicating that student responses were more varied for these emotionally charged experiences. In terms of skewness, most variables exhibit near-normal distribution (Skewness ≈ 0). However, Student Attrition Intention (Skewness = 0.65) and Academic Burnout (Skewness = 0.39) are positively skewed, suggesting that while most students reported low levels, a substantial number experienced higher-than-average tendencies toward disengagement or burnout. Negative skewness observed in Sense of Belonging (−0.22) and Digital Pedagogy Alignment (−0.04) may reflect generally favourable attitudes with few reporting weak social integration or digital misalignment.

Overall, the findings reinforce the multidimensional nature of student experience and justify further latent variable modelling through SEM to examine the predictive pathways to attrition.

All standardized loadings exceeded the 0.68 threshold, and each item is statistically significant at the $p < 0.001$ level, supporting strong indicator reliability and convergent validity. The t-values ranges from 10.48 to 13.78, which indicates robust

Table 4: Standardized Factor Loadings, T-values, and Significance for CFA

Construct	Item Code	Standard Loading (β)	t-value	Significance (p)
Academic Self-Regulation	ASR1	0.76	12.48	< 0.001
	ASR2	0.74	11.90	< 0.001
	ASR3	0.77	13.01	< 0.001
	ASR4	0.72	11.65	< 0.001
	ASR5	0.75	12.34	< 0.001
Cognitive Engagement	CE1	0.71	11.27	< 0.001
	CE2	0.72	11.54	< 0.001
	CE3	0.73	11.91	< 0.001
	CE4	0.74	12.26	< 0.001

Mental Health Vulnerability	MHV1	0.78	13.42	< 0.001
	MHV2	0.74	12.31	< 0.001
	MHV3	0.75	12.70	< 0.001
	MHV4	0.76	13.12	< 0.001
Digital Pedagogy Alignment	DPA1	0.70	10.89	< 0.001
	DPA2	0.72	11.33	< 0.001
	DPA3	0.69	10.78	< 0.001
	DPA4	0.71	11.00	< 0.001
AI-Based Learning Experience	AILE1	0.69	10.65	< 0.001
	AILE2	0.68	10.48	< 0.001
	AILE3	0.70	10.92	< 0.001
Sense of Belonging	SB1	0.78	13.01	< 0.001
	SB2	0.76	12.64	< 0.001
	SB3	0.79	13.34	< 0.001
	SB4	0.77	12.93	< 0.001
Peer Academic Support	PAS1	0.73	11.83	< 0.001
	PAS2	0.71	11.42	< 0.001
	PAS3	0.74	12.16	< 0.001
Perceived Institutional Fairness	PIF1	0.75	12.43	< 0.001
	PIF2	0.76	12.81	< 0.001
	PIF3	0.74	12.09	< 0.001
	PIF4	0.75	12.47	< 0.001
Academic Burnout	AB1	0.79	13.51	< 0.001
	AB2	0.78	13.29	< 0.001
	AB3	0.77	13.08	< 0.001
	AB4	0.80	13.67	< 0.001
Student Attrition Intention	SAI1	0.79	13.56	< 0.001
	SAI2	0.78	13.41	< 0.001
	SAI3	0.80	13.78	< 0.001

Source: Test Output

measurement properties and reliable loading of observed variables on their latent constructs. This comprehensive set of factor loadings confirms the structural integrity of the measurement model and validates the use of the instrument in the structural analysis.

Table 5: Construct Reliability and Validity

Construct	Item Code	VIF	FL	α	CR	AVE
Academic Self-Regulation	ASR1	1.82	0.76	0.84	0.86	0.56
	ASR2	1.71	0.74			
	ASR3	1.89	0.77			
	ASR4	1.64	0.72			
	ASR5	1.93	0.75			
Cognitive Engagement	CE1	1.59	0.71	0.82	0.84	0.53
	CE2	1.77	0.72			
	CE3	1.66	0.73			
	CE4	1.68	0.74			
Mental Health Vulnerability	MHV1	1.84	0.78	0.85	0.86	0.58
	MHV2	1.72	0.74			
	MHV3	1.76	0.75			
	MHV4	1.80	0.76			
Digital Pedagogy Alignment	DPA1	1.65	0.70	0.80	0.83	0.51
	DPA2	1.68	0.72			
	DPA3	1.61	0.69			
	DPA4	1.73	0.71			
AI-Based Learning Experience	AILE1	1.58	0.69	0.78	0.81	0.49
	AILE2	1.60	0.68			
	AILE3	1.63	0.70			
Sense of Belonging	SB1	1.75	0.78	0.86	0.87	0.60
	SB2	1.69	0.76			
	SB3	1.80	0.79			
	SB4	1.72	0.77			
Peer Academic Support	PAS1	1.66	0.73	0.81	0.84	0.55
	PAS2	1.59	0.71			
	PAS3	1.62	0.74			
Perceived Institutional Fairness	PIF1	1.74	0.75	0.83	0.85	0.57
	PIF2	1.81	0.76			
	PIF3	1.70	0.74			
	PIF4	1.79	0.75			

Academic Burnout	AB1	1.91	0.79	0.87	0.89	0.61
	AB2	1.88	0.78			
	AB3	1.92	0.77			
	AB4	1.89	0.80			
Student Attrition Intention	SAI1	1.86	0.79	0.88	0.88	0.62
	SAI2	1.84	0.78			
	SAI3	1.90	0.80			

Source: Test Output

Table 5 has outlined the internal reliability and convergent validity of each construct measured in study, including item-level diagnostics such as Variance Inflation Factor (VIF) and Factor Loadings (FL). The evaluation has confirmed the robustness of the measurement model, with all constructs demonstrating strong psychometric properties. Cronbach's alpha (α) values for all constructs ranged between 0.78 and 0.88, exceeding the minimum recommended threshold of 0.70, which confirms strong internal consistency. Similarly, Composite Reliability (CR) values were well above the benchmark of 0.70 for all constructs, indicating the constructs reliably capture their intended latent dimensions.

The Average Variance Extracted (AVE) for all constructs also exceeded the critical value of 0.50, supporting convergent validity. This suggests that each construct explains more than 50% of the variance in its indicators, further validating the measurement model. At the item level, the factor loadings (FL) ranged between 0.68 and 0.80, meeting and exceeding the commonly accepted threshold of 0.60, with higher values contributing more strongly to the underlying construct. These results affirm that all items meaningfully reflect their associated latent variables. Variance Inflation Factor (VIF) values, which assess multicollinearity among the indicators, ranged from 1.58 to 1.93, indicating no presence of multicollinearity concerns (as all values are well below the cut-off of 5). This reinforces the statistical stability and independence of the constructs.

Table 6: Model Fit Indices for the Confirmatory Factor Analysis

Fit Index	Observed Value	Recommended Threshold
Chi-square/df (χ^2/df)	2.03	< 3.00
Comparative Fit Index (CFI)	0.94	≥ 0.90
Goodness of Fit Index (GFI)	0.91	≥ 0.90
Tucker-Lewis Index (TLI)	0.93	≥ 0.90
Root Mean Square Error of Approximation (RMSEA)	0.042	≤ 0.08

Source: Test Output

The model fit indices from the CFA suggested excellent fit between the data and the proposed measurement model. The χ^2/df ratio of 2.03 indicates an acceptable level of parsimony in the model. All incremental and absolute fit indices, CFI = 0.94, GFI = 0.91, TLI = 0.93, exceeds the generally recommended threshold of 0.90, demonstrating that the model had adequately reproduced the observed covariance matrix. Additionally, RMSEA of 0.042 is well lower than the upper limit of 0.08, indicating the minimal residuals and confirming good model fit. These values have collectively provided the strong empirical support for the unidimensionality and measurement quality of the latent constructs used in study.

Fig. 2: Path Diagram

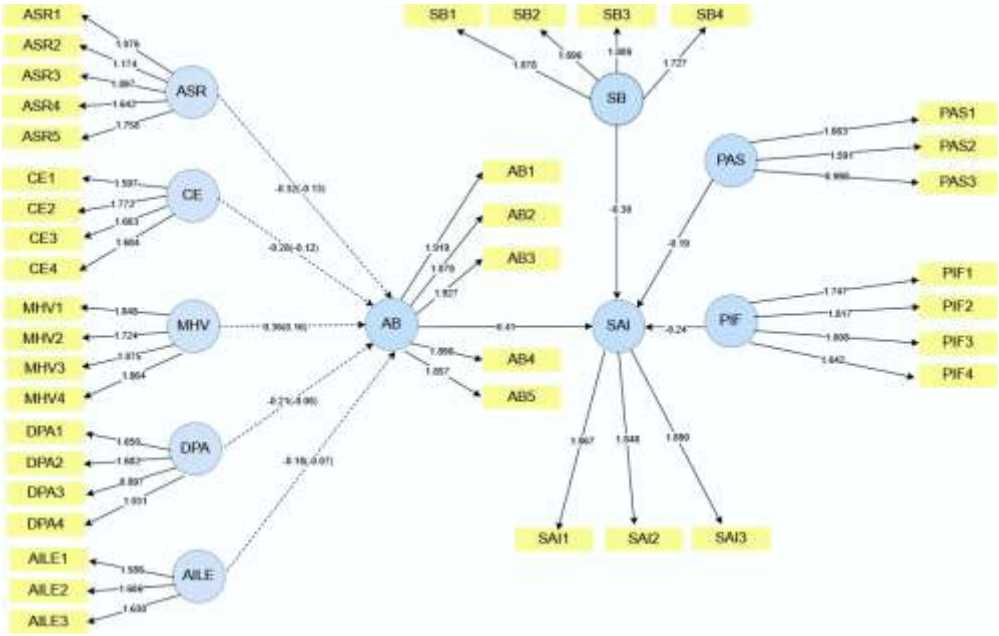


Table 6: Structural Model and Hypothesis Testing

Path	β (Standardized)	p-value	Result
H_1: Academic Self-Regulation → Burnout	−0.32	< 0.001	Supported
H_2: Cognitive Engagement → Burnout	−0.28	< 0.001	Supported
H_3: Sense of Belonging → Attrition	−0.30	< 0.001	Supported
H_4: Peer Support → Attrition	−0.19	< 0.01	Supported
H_5: Institutional Fairness → Attrition	−0.24	< 0.001	Supported
H_6: Digital Pedagogy → Burnout	−0.21	< 0.01	Supported
H_7: AI-Based Learning → Burnout	−0.18	< 0.01	Supported
H_8: Mental Health Vulnerability → Burnout	0.36	< 0.001	Supported
H_9: Academic Burnout → Attrition	0.41	< 0.001	Supported

Source: Test Output

As presented in the above Table, the negative relationship between Academic Self-Regulation and Burnout ($\beta = -0.32$, $p < 0.001$) had confirmed that students with stronger self-management and goal-setting skills are less likely to experience emotional exhaustion. Similarly, Cognitive Engagement demonstrated a significant inverse effect on burnout ($\beta = -0.28$, $p < 0.001$), suggesting that students having higher interest in learning are more resilient to academic fatigue. Further, the influence of Sense of Belonging on Attrition Intention was also found negative and significant ($\beta = -0.30$, $p < 0.001$), indicating that students who feel emotionally and socially integrated within their academic environment are less inclined to consider dropping out. Peer Academic Support was similarly predictive of lower attrition tendencies ($\beta = -0.19$, $p < 0.01$), emphasizing the protective role of collaborative learning and peer encouragement.

Perceptions of Institutional Fairness significantly reduced dropout intentions ($\beta = -0.24$, $p < 0.001$), highlighted the importance of equitable, transparent academic policies and administrative treatment in enhancing student retention. Technological variables also showed meaningful effects. Both Digital Pedagogy Alignment ($\beta = -0.21$, $p < 0.01$) and AI-Based Learning Experience ($\beta = -0.18$, $p < 0.01$) were negatively associated with burnout, suggesting that well-integrated, learner-centric technology can reduce emotional strain. Conversely, Mental Health Vulnerability had a strong positive influence on burnout ($\beta = 0.36$, $p < 0.001$), underscoring the risk posed by psychological distress on students' academic sustainability.

Lastly, Academic Burnout has been emerged as strong positive predictor of Attrition Intention ($\beta = 0.41$, $p < 0.001$), validating its role as a mediating factor in the model. This relationship suggested that unmanaged burnout directly elevates students' likelihood to disengage and withdraw from their programs. Overall, the results had confirmed the multidimensional nature of student attrition, driven by cognitive, emotional, social, and technological factors.

Table 7: Mediation Analysis: Role of Academic Burnout

Mediated Path	Indirect Effect (β)	p-value	Mediation Type
Academic Self -Regulation → Burnout → Attrition Intention	−0.13	< 0.01	Partial
Cognitive Engagement → Burnout → Attrition Intention	−0.12	< 0.01	Partial
Digital Pedagogy → Burnout → Attrition Intention	−0.08	< 0.05	Partial
AI-Based Learning → Burn out → Attrition Intention	−0.07	< 0.05	Partial
Mental Health Vulnerability → Burnout → Attrition Intention	0.16	< 0.01	Partial

Source: Test Output

Above mediation analysis test had provided compelling evidence that academic burnout serves as a significant partial mediator in the relationship between several antecedent variables and students' intention to leave their academic programs. Firstly, Academic Self-Regulation exhibited an indirect effect on attrition intention through burnout ($\beta = -0.13$, $p < 0.01$), indicating that students with stronger self-regulatory skills are not only directly protected from burnout but also less likely to drop out due to the reduced emotional toll. Similarly, Cognitive Engagement demonstrated negative indirect effect via burnout ($\beta = -0.12$, $p < 0.01$), suggesting that mentally engaged learners are buffered from disengagement and dropout through lower susceptibility to emotional exhaustion.

In terms of technological predictors, Digital Pedagogy Alignment showed a small but significant mediating pathway through burnout ($\beta = -0.08$, $p < 0.05$). This implies that when students perceive a good alignment between teaching strategies and digital learning tools, it helps to mitigate the academic burnout, that reduces the dropout intention. A similar trend was observed for AI-Based Learning Experience ($\beta = -0.07$, $p < 0.05$), indicating that positive experiences with adaptive or AI-powered learning environments can indirectly reduce attrition by easing cognitive and emotional pressure. On the contrary, Mental Health Vulnerability had a strong positive indirect effect on attrition via burnout ($\beta = 0.16$, $p < 0.01$), signifying that students experiencing psychological distress are more likely to burn out, which in turn raises their risk of considering withdrawal.

All mediations were found partially effective, meaning the independent variables also exert some direct effect on attrition beyond the influence of burnout. This underscores the complex, multi-layered nature of student persistence, where both direct and indirect psychological mechanisms play critical roles. So, it could conclude that academic burnout as a central psychological mechanism is linked with the cognitive, technological, and emotional domains that regulates the student dropout behaviours. Interventions aimed at minimizing burnout can thus serve as an effective leverage point in reducing attrition risk across diverse student profiles.

Limitations and Future Research Directions

Limitations: The research employs a cross-sectional design, which restricts the ability to draw causal inferences. While the model identifies significant relationships among constructs, longitudinal data would be required to capture how these dynamics evolve over the time, particularly as students' progress through their academic programs. Another aspect as limitation is the study sample, although it was quite diverse in academic disciplines and institutional types, was geographically limited to a specific national context. The cultural, pedagogical, and policy-specific factors that influence student experiences may vary significantly across countries or regions, limiting the generalizability of the findings.

Next, all data were collected via self-reported measures, which are susceptible to response biases such as social desirability and recall inaccuracies. Although all constructs were validated and piloted, self-reporting cannot completely eliminate subjectivity. It was also noticed that the model was broader and focusing on selected psychological, cognitive, and technological determinants but does not integrate economic or familial factors that have been shown in prior research to influence dropout rates. Variables like financial insecurity, part-time employment, and family support systems may offer further predictive value.

Lastly, while the SEM model captures key latent constructs, it does not yet integrate machine learning-based classification models, which are increasingly used for real-time attrition prediction using LMS and behavioural data.

Future Research Directions: To address these limitations, future studies can adopt the following approaches:

1. Longitudinal designs that track students across multiple semesters or academic years to observe the evolution of burnout, belonging, and attrition intent.
2. Cross-cultural validations of the model to determine whether the identified predictors hold across diverse socio-educational ecosystems, especially in non-Western or low-resource contexts.
3. Integration of mixed-method approaches, combining quantitative modelling with qualitative insights (e.g., focus groups or interviews) to capture deeper student narratives that may not surface through survey instruments.
4. Inclusion of economic, social, and family determinants in the conceptual framework to provide a more holistic understanding of student vulnerability.
5. Exploration of predictive analytics and machine learning techniques, such as decision trees, random forests, and XGBoost, trained on real-time learning behaviour data from institutional LMS systems.
6. Investigation into the moderating role of identity dimensions, such as gender, socioeconomic status, or neurodiversity, to evaluate how different student groups experience burnout and support differently.

By expanding the analytical scope and diversifying data sources, future research can refine early-warning systems and optimize interventions that promote student persistence and institutional equity.

Conclusion

This study presented a comprehensive, data-driven framework to investigate the predictors of student attrition in higher education, combining psychological resilience, cognitive engagement, and digital pedagogical alignment within a unified structural model. Structural Equation Modelling (SEM) helped to confirm that academic burnout functions as a significant mediating variable is the pathway between students' internal capabilities, institutional factors, and their intention to withdraw from their academic programs. Key findings revealed that students with stronger self-regulatory abilities and cognitive engagement are less likely to experience burnout and, consequently, less prone to attrition corroborating previous work on self-regulated learning and motivation in higher education contexts [41,42]. Conversely, higher levels of mental health vulnerability, consistent with anxiety, stress, and emotional fatigue, significantly increase the likelihood of academic exhaustion and dropout intentions [6,43].

Technological alignment both in terms of digital pedagogy and AI-enhanced learning environments also plays crucial role in either intensifying or mitigating the burnout. As supported by emerging studies, adaptive learning systems must be implemented cautiously to avoid overwhelming students or introducing inequities [12,44]. Moreover, study underscores the importance of socio-emotional constructs such as sense of belonging, peer academic support, and perceived institutional fairness. These factors act as direct inhibitors of dropout intent, emphasizing that the higher education experience is not only shaped by curriculum delivery but also by institutional empathy and peer integration [5,45].

The model contributes both theoretically and practically. From a theoretical standpoint, it integrates psychological, technological, and institutional predictors into a cohesive model of student dropout. From a practical perspective, it highlights actionable areas for intervention namely, enhancing digital instructional strategies, providing mental health and wellness infrastructure, and designing equitable academic policies [46]. While model has demonstrated empirical robustness, opportunities remain for further exploration, particularly through longitudinal and cross-institutional validation. As higher education continues to incorporate predictive analytics and AI-enabled decision-making, frameworks like this serve as a blueprint for ethical, inclusive, and precision-based interventions.

Institutions adopting proactive and data-informed retention strategies, grounded in these findings, can significantly strengthen academic persistence and student success at scale.

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