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# Proceedings of International Conference on Multidisciplinary Research: Innovation, Healthcare, Education for Viksit Bharat (ICMR-2026)



INNOVATION



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EDUCATION



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DEVELOPMENT



VIKSIT BHARAT

PART

2

## Editors

Prof. (Dr.) Punit Goel  
Dr. Abu Farah Hoque  
Dr. Amit Agrawal  
Dr. Sheela Sharma



# International Conference On Multidisciplinary Research

## Conference Proceedings

Contemporary Perspectives in English Literature,  
Sociology, Hindi and Home Science For Viksit Bharat

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## **List of Contributors**

| <b>Ch.</b> | <b>Contributor</b>        | <b>Designation</b>                                                   | <b>Institution</b>                                                        |
|------------|---------------------------|----------------------------------------------------------------------|---------------------------------------------------------------------------|
| 1          | Suravi Bhattacharya       | Assistant Professor                                                  | Sanskar City College of Education, Rajnandgaon, Chhattisgarh              |
| 2          | Dr. Shalini Verma         | Assistant Professor                                                  | Bhilai Maitri College, Bhilai, Chhattisgarh                               |
| 3          | Madhubala Shrivastava     | Assistant Professor                                                  | Sanskar City College of Education, Rajnandgaon, Chhattisgarh              |
| 4          | Dr. Pushpa Sharma         | Associate Professor                                                  | Mansa College of Education, Kohka, Kurud, Chhattisgarh                    |
| 5          | Dr. Ratri Lahri           | Assistant Professor                                                  | Gurukul Mahila Mahavidyalaya, Raipur, Chhattisgarh                        |
| 6          | Mona Gupta                | Guest Lecturer,<br>Department of<br>Commerce                         | Government Shaheed Kaushal Yadav College, Gunderdehi, Balod, Chhattisgarh |
| 7          | Namita Roy                | Research Scholar,<br>Department of<br>Education                      | Anjaneya University, Raipur, Chhattisgarh                                 |
| 8          | Dr. Simrann Rajesh Vermaa | Assistant Professor,<br>Department of English                        | Gurukul Mahila Mahavidyalaya, Raipur, Chhattisgarh                        |
| 9          | Dr. Kavita Silwal         | Assistant Professor                                                  | Gurukul Mahila Mahavidyalaya, Raipur, Chhattisgarh                        |
| 10         | Dr. Shweta Bhatia         | Professor & Head,<br>Department of<br>Education; IQAC<br>Coordinator | M.J. College, Kohka, Bhilai, Chhattisgarh                                 |
| 11         | Dr. Soju Samuel           | Counsellor                                                           | Delhi Public School, Bhilai, Chhattisgarh                                 |
| 12         | Dular Das                 | Research Scholar                                                     | Hemchand Yadav University, Durg, Chhattisgarh                             |
| 13         | Dr. Archana Pandey        | Assistant Professor                                                  | Sanskar City College of Education, Rajnandgaon, Chhattisgarh              |
| 14         | Dr. Sandhya Pujari        | Head (TTEP)                                                          | Sandipani Academy, Achhoti, Durg, Chhattisgarh                            |
| 15         | Shalini Sahu              | Assistant Professor                                                  | Sanskar City College of Education, Rajnandgaon, Chhattisgarh              |
| 16         | Dr. Manju Sahu            | Associate Professor                                                  | M.J. College, Kohka, Bhilai, Chhattisgarh                                 |
| 17         | Mrs. Lileshwari Sahu      | Assistant Professor                                                  | Somni Mahavidyalaya, Somni, Rajnandgaon, Chhattisgarh                     |
| 18         | Dr. Shraddha Bhardwaj     | Assistant Professor                                                  | Jagadguru Shankaracharya College of Education, Bhilai, Durg, Chhattisgarh |
| 19         | Mamta Rani Yadu           | Research Scholar                                                     | Anjaneya University, Raipur, Chhattisgarh                                 |

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|    |                              |                                                           |                                                                             |
|----|------------------------------|-----------------------------------------------------------|-----------------------------------------------------------------------------|
| 20 | Dr. Sumita Singh             | Assistant Professor,<br>Department of<br>Education        | St. Thomas College Bhilai, Chhattisgarh                                     |
| 21 | Tulsi Sahu                   | Assistant Professor                                       | Sanskar City College of Education, Rajnandgaon,<br>Chhattisgarh             |
| 22 | Dr. Juhi Peter               | Assistant Professor                                       | Agrasen College, Dhanora, Durg, Chhattisgarh                                |
| 23 | Dr. Divya Sharma             | Head & Assistant<br>Professor, Department<br>of Education | <i>Institution not stated in chapter</i>                                    |
| 24 | Prof. (Dr.)<br>Gurpreet Kaur | Principal                                                 | Sanskar City College of Education, Thakurtola,<br>Rajnandgaon, Chhattisgarh |
| 25 | Dr. Anjana Sharad            | Principal, Prism School<br>of Education                   | Mahkakurd, Utai, Bhilai, Chhattisgarh                                       |
| 26 | Dr. Sangeeta<br>Shrivastav   | Assistant Professor                                       | Mansa College of Education, Bhilai, Chhattisgarh                            |
| 27 | Dr. Ruchi Sachan             | Head, Department of<br>Education                          | Maharaja Agrasen International College, Raipur,<br>Chhattisgarh             |
| 28 | Dr. Surekha Vinod<br>Patil   | Principal                                                 | Bhilai Maitri College, Durg, Chhattisgarh                                   |
| 29 | Dr. Usha Lahare              | Guest Lecturer                                            | Government Minimata Girls' College, Korba,<br>Chhattisgarh                  |
| 30 | Dr. Rita Gupta               | Head, Department of<br>Education                          | GDRCSST, Rungta International Skill University,<br>Bhilai, Chhattisgarh     |
| 31 | Smt. Anupama<br>Ambast       | Assistant Professor                                       | CTE, Raipur, Chhattisgarh                                                   |
| 32 | Smt. Pramila Patel           | Assistant Professor                                       | Bhilai College of Information Technology, Jamul,<br>Durg, Chhattisgarh      |
| 33 | Dr. Gopa Sharma              | Headmistress                                              | Government Primary School, Hatband, Raipur,<br>Chhattisgarh                 |
| 34 | Meenakshi Yadav              | Assistant Professor                                       | Agrasen College, Dhanora, Durg, Chhattisgarh                                |
| 35 | Renuka Sahu                  | Assistant Professor                                       | Sanskar City College of Education, Rajnandgaon,<br>Chhattisgarh             |
| 36 | Dr. Atul Kumar<br>Soni       | Assistant Professor                                       | Pt. Kishori Lal Shukla Vidhi Mahavidyalaya,<br>Rajnandgaon, Chhattisgarh    |
| 37 | Mrs. Preeti Mishra           | Assistant Professor,<br>Department of<br>Education        | Mansa College of Education, Bhilai, Chhattisgarh                            |

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|    |                          |                     |                                                                 |
|----|--------------------------|---------------------|-----------------------------------------------------------------|
| 38 | Ranjana Solanki          | Assistant Professor | Agrasen College, Dhanora, Durg, Chhattisgarh                    |
| 39 | Dr. Nirmala<br>Parganiha | Assistant Professor | Agrasen College, Dhanora, Durg, Chhattisgarh                    |
| 40 | Kiran Sonatiya           | Assistant Professor | Sanskar City College of Education, Rajnandgaon,<br>Chhattisgarh |

## Chapter 3: Academic Resilience and Educational Achievement among College Students

Madhubala Shrivastava

Assistant Professor

Sanskar City College of Education

Rajnandgaon, Chhattisgarh

**Abstract** — Academic resilience has become increasingly important in higher education as students encounter academic setbacks, digital-learning pressures, assessment anxiety, financial constraints, and rapidly changing technology-mediated learning environments. This study conceptualizes academic resilience as a dynamic capacity reflected not only in self-reported coping but also in observable patterns of recovery following periods of academic difficulty. A key research gap concerns the limited integration of resilience indicators, longitudinal academic behavior, and machine-learning-based achievement prediction within a unified analytical framework. To address this gap, the proposed study develops a multimodal Academic Resilience–Achievement Intelligence Framework that combines psychometric resilience measures with learning-management-system engagement, assessment trajectories, attendance stability, and recovery behavior. Rather than treating resilience as a static personality characteristic, the framework models it as a time-sensitive educational process characterized by persistence, adaptation, recovery velocity, and sustained engagement after setbacks. The study further proposes interpretable machine-learning models for identifying the resilience-related variables most strongly associated with subsequent educational achievement while avoiding deterministic labeling of individual students.

**Keywords** — Academic Resilience, Educational Achievement, College Students, Learning Analytics, Explainable Machine Learning, Digital Education

### Introduction

Higher education has undergone substantial transformation since 2021. Blended instruction, learning management systems, digital assessment, generative artificial intelligence, adaptive educational technologies, and data-supported student services have become increasingly embedded within contemporary learning environments. These developments have expanded opportunities for flexible and personalized learning, but they have also altered the demands placed upon college students. Successful academic progression increasingly requires learners to regulate their study practices, manage multiple digital information channels, recover from disappointing assessment outcomes, adapt to changing instructional formats, and sustain engagement when academic progress becomes difficult.

Within this context, **academic resilience** provides a particularly useful construct for explaining why students experiencing apparently similar difficulties can subsequently follow substantially different educational trajectories. Academic

resilience can broadly be understood as the capacity to maintain or restore adaptive academic functioning when confronted with adversity, setbacks, failure, stress, or threats to educational progress. Importantly, contemporary scholarship increasingly distinguishes resilience from simple high achievement. A student who consistently obtains high grades without encountering substantial adversity is not necessarily demonstrating resilience. Resilience becomes analytically meaningful when some form of difficulty is followed by adaptation, persistence, recovery, or continued achievement.

This distinction has significant methodological implications. A systematic review by Rudd, Meissel, and Meyer identified substantial variation in the quantitative operationalization of academic resilience. Their review of 127 studies distinguished definition-driven, process-driven, and latent-construct approaches and emphasized that methodological choices can substantially affect the conclusions reached about who is considered resilient. The authors further cautioned that omitting indicators of risk or academic outcomes can weaken the validity of resilience measurement.

Related research similarly demonstrates that the concept should not be reduced to a single psychological score. Ye, Strietholt, and Blömeke showed that definitions and operationalizations of academic resilience vary considerably, particularly when resilience is inferred from combinations of socioeconomic disadvantage and unexpectedly strong academic achievement. Research using international large-scale assessment data has also demonstrated that alternative operational definitions can produce different estimates of academic resilience, complicating comparison across populations and educational contexts.

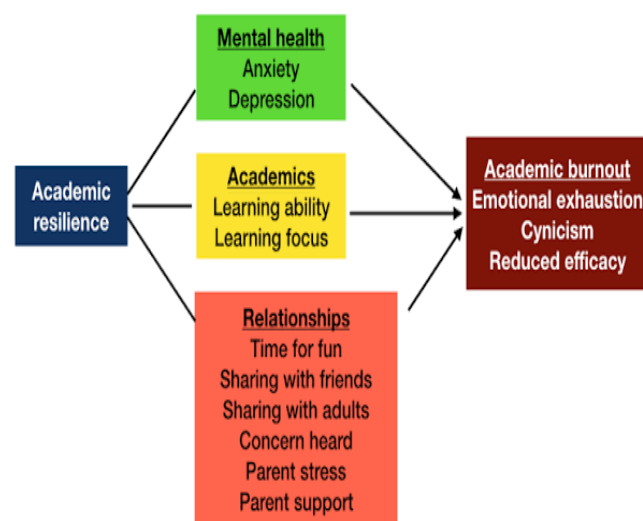


**Fig. 1: From Academic Resilience to Academic Burnout among International University Students**

Source: <https://www.mdpi.com/2076-328X/13/3/206>

These methodological debates are directly relevant to college education. University and college students encounter both major and routine academic adversities: examination failure, unexpectedly low grades, difficult courses, adjustment to independent learning, competing employment responsibilities, financial pressure, attendance disruption, reduced motivation, and social or institutional challenges. A resilient response may therefore manifest through several pathways. One learner may improve substantially on the next assessment; another may maintain attendance despite low performance; a third may seek academic assistance and increase engagement with learning materials; and another may temporarily decline but recover over several weeks.

Consequently, educational achievement should not be treated solely as an endpoint disconnected from the process that produced it. Conventional indicators such as grade-point average, semester percentage, course completion, and examination scores remain important, but they reveal relatively little about the trajectory between setback and outcome. Two students receiving the same final grade can have very different academic histories. One may have performed consistently, whereas another may have recovered after a major decline. A resilience-oriented analytical framework should be capable of distinguishing these trajectories.

Evidence nevertheless supports a relationship between resilience-related factors and academic outcomes. A 2023 meta-analytic review by Hunsu and colleagues synthesized 239 effect sizes from 56 studies and found statistically significant, although generally modest, aggregate relationships between achievement and both risk and protective factors. Importantly, associations varied across specific categories of risk and protection, suggesting that resilience-achievement relationships cannot adequately be represented by one undifferentiated predictor.

Higher-education evidence also points toward the relational and institutional dimensions of resilience. A meta-ethnographic review of students' experiences concluded that resilience in higher education involves internal resources, meaningful relationships, and institutional conditions. The synthesis indicated that resilience can be facilitated through educational environments and support systems rather than being regarded exclusively as a fixed personal characteristic. This interpretation is important because interventions based exclusively on individual responsibility may overlook structural and educational factors that shape students' capacity to recover.

At the same time, machine learning has created new possibilities for analyzing complex educational data. Recent research has applied computational models to variables including metacognitive awareness, motivation, learning participation, environmental conditions, time management, and psychological factors when investigating college academic performance. Learning analytics research is likewise moving toward combinations of academic assessment, digital engagement, self-regulated learning, and socio-emotional information. For example, recent work in flipped-learning environments has integrated assessment performance with digital engagement and

socio-emotional measures to investigate student learning trajectories.

However, an important conceptual gap remains. **Most resilience research and educational prediction research operate as parallel rather than fully integrated traditions.** Resilience studies frequently rely on cross-sectional psychometric measures and conventional correlational analysis, while machine-learning studies of achievement commonly emphasize predictive accuracy without explicitly modeling post-adversity recovery. Consequently, a model may accurately identify students likely to obtain low grades without explaining whether they are recovering, deteriorating, remaining stable, or adapting after a setback.

This manuscript addresses that gap through a proposed **Academic Resilience–Achievement Intelligence Framework (AR-AIF)**. The framework treats resilience as a dynamic, multimodal process constructed from four domains: psychological resilience, academic recovery, behavioral persistence, and digital-learning continuity. Rather than asking only whether resilience correlates with achievement, the study asks whether a combination of these domains improves the explanation and prediction of subsequent academic outcomes.

A particularly distinctive component is the proposed **Academic Recovery Velocity (ARV)** indicator. ARV represents the magnitude and rate of improvement following an objectively detected academic setback. For example, if a student's performance falls substantially below their established baseline in one assessment period and subsequently improves, the rate and stability of that improvement become behavioral evidence relevant to resilience. This approach does not replace validated psychometric measurement. Instead, it supplements self-reported resilience with temporal evidence from authentic educational activity.

The study is therefore designed around three interconnected objectives: to determine the association between multidimensional academic resilience and educational achievement; to evaluate whether behavioral recovery indicators provide additional explanatory information beyond static resilience scores; and to develop an interpretable machine-learning framework capable of estimating subsequent achievement from psychological, academic, and digital-engagement features.

This approach also has implications for responsible educational AI. Predictive systems that merely classify students as "at risk" can inadvertently transform temporary academic difficulty into a seemingly permanent label. A resilience-sensitive model instead recognizes that trajectories can change. Its intended function is therefore not to make high-stakes decisions automatically but to provide decision support for proportionate, human-reviewed academic interventions.

### Literature Review

#### Conceptual Development of Academic Resilience

Resilience originated as a broader psychological and developmental construct concerned with successful adaptation under adverse circumstances. Its application to education gradually produced the more specific concept of academic

resilience. Contemporary scholarship generally agrees that adversity and adaptive functioning are essential to resilience, but substantial disagreement remains regarding how these elements should be operationalized.

Rudd et al.'s systematic review provides strong evidence for this measurement problem. Their synthesis demonstrated that quantitative studies have used substantially different approaches to identifying resilient learners and that these approaches influence resulting interpretations. This issue is particularly relevant when transferring resilience research into AI-supported education: a computational model cannot resolve a construct that has been inadequately specified at the measurement stage. A recent systematic review and meta-analysis of academic resilience scales further illustrates this psychometric complexity. The review synthesized 46 studies and reported generally high pooled internal consistency while finding mixed evidence concerning whether academic resilience is best represented through unidimensional or multidimensional measurement structures. Such findings reinforce the need to avoid assuming that one questionnaire score exhaustively represents resilience. The present study therefore adopts a process-oriented definition. Academic resilience is conceptualized as **adaptive persistence and recovery in academic functioning following identifiable educational difficulty**. This definition requires both exposure to difficulty and evidence of subsequent adaptation.

#### Academic Resilience and Educational Achievement

Educational achievement is influenced by interconnected cognitive, motivational, psychological, socioeconomic, behavioral, and institutional factors. Resilience is particularly important because it concerns performance under conditions in which normal academic functioning is threatened.

The meta-analysis conducted by Hunsu et al. offers an important synthesis of this relationship. Across the reviewed evidence, both risk and protective factors were significantly associated with achievement, although aggregate associations were relatively small. Specific ability-, belief-, family-, institutional-, and societal-level factors differed in the strength of their relationships with achievement. These findings suggest that resilience should be analyzed through multiple interacting dimensions rather than treated as a universal protective coefficient.

Research among university students has likewise investigated relationships among resilience, self-concept, emotional intelligence, and academic achievement. A study involving 1,020 university students in Spain examined these interrelationships and highlighted the importance of psychological variables when explaining educational outcomes. Such research supports the incorporation of psychosocial variables but also exposes the limitations of relying primarily on cross-sectional self-report measurements.

A student can report strong perseverance yet display prolonged disengagement following failure. Conversely, another student may report moderate resilience but exhibit rapid academic recovery. Combining psychometric and behavioral evidence could therefore provide a more complete representation.

#### Resilience as a Dynamic and Contextual Process

An emerging position within resilience scholarship is that resilience is neither entirely innate nor entirely stable. It develops through interactions among individuals, relationships, resources, institutions, and environmental demands.

The higher-education meta-ethnography identified personal, relational, and organizational influences on students' resilience experiences and concluded that educational institutions can contribute to resilience development. Similarly, a broader systematic review of resilience in educational systems identified considerable fragmentation in definitions and levels of analysis, with the literature historically emphasizing individual student resilience more strongly than collective or institutional resilience.

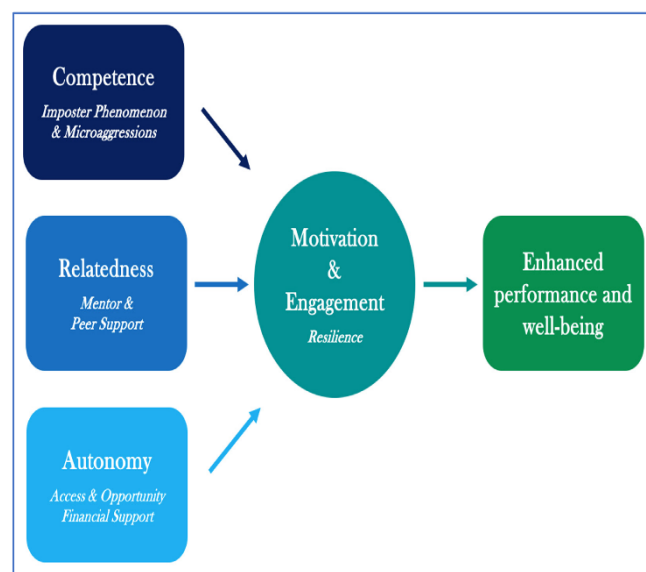


**Fig. 2: Graduate Student Resilience**

Source: <https://www.mdpi.com/2813-4346/3/3/37>

This contextual interpretation changes how achievement should be analyzed. Low academic performance may arise from insufficient preparation, but it may also reflect temporary illness, employment pressure, inaccessible learning materials, assessment overload, or difficulty adapting to instructional changes. A responsible resilience framework should therefore avoid interpreting every low score as evidence of low personal capability.

The present framework incorporates contextual covariates where ethically and practically appropriate and separates *academic difficulty* from *adaptive response*. The former describes an observed challenge; the latter describes what happens afterward.

#### Proposed Methodology

The proposed study adopts a **longitudinal multimodal predictive design** to investigate how academic resilience influences subsequent educational achievement among college students. In contrast with conventional cross-sectional studies that measure resilience and academic performance at a single point in time, the proposed design captures both psychological resilience and observable recovery following academic setbacks. AR-AIF combines four dimensions: psychological resilience, academic recovery, behavioral persistence, and digital-learning continuity. Educational achievement is treated as the principal outcome, whereas previous achievement, attendance, study

engagement, academic setback severity, and contextual characteristics are incorporated as explanatory or control variables.

A hypothetical research sample of **640 undergraduate students** from four multidisciplinary colleges is proposed for methodological demonstration. Students would be recruited from first-, second-, and third-year undergraduate programs to provide sufficient variation in academic experience. Participation would require informed consent for the integration of questionnaire responses with de-identified academic and learning-management-system (LMS) records.

The proposed longitudinal observation period covers one complete academic semester of approximately 16 weeks. This permits the identification of meaningful temporal patterns rather than relying exclusively on end-semester measurements.

#### Research Variables

The primary psychological variable is an academic resilience score obtained using an appropriate validated academic resilience instrument. Rather than interpreting the total score as a complete measure of resilience, the questionnaire is combined with objectively derived indicators.

Four behavioral components are constructed:

**Resilience Capacity Score (RCS):** standardized psychometric estimate of perceived ability to cope with academic adversity.

**Academic Recovery Velocity (ARV):** rate at which a student returns toward or exceeds their established academic baseline after a significant assessment setback.

**Behavioral Persistence Index (BPI):** degree to which attendance, assignment completion, and learning participation are sustained following poor performance.

**Digital Learning Continuity (DLC):** stability of academically relevant LMS engagement before and after an identified setback.

For student  $i$ , Academic Recovery Velocity can conceptually be expressed as:

$$ARV_i = (P_r - P_s) / \Delta t$$

where  $P_s$  represents performance at the setback assessment,  $P_r$  represents subsequent recovered performance, and  $\Delta t$  denotes the number of weeks between setback and recovery measurement.

A positive ARV indicates improvement, while values close to zero indicate academic stagnation. Negative values suggest continuing deterioration rather than recovery.

To avoid treating every minor grade fluctuation as adversity, an academic setback is operationalized as an assessment result meaningfully below the student's preceding performance baseline or a predefined academically significant threshold.

The composite resilience representation is therefore not simply:

**Resilience = Questionnaire Score**

but instead:

**Academic Resilience = f(RCS, ARV, BPI, DLC, contextual variables)**

This formulation represents the central methodological contribution of the study.

#### Experimental Setup

##### Dataset

The proposed AR-AIF dataset contains one student-level analytical record combined with longitudinal weekly observations.

The initial sample consists of 640 participants. After screening for consent, incomplete questionnaires, insufficient longitudinal records, and unavailable academic outcomes, approximately **612 analytically complete student records** are retained for the experimental demonstration.

The feature space consists of approximately 32 variables organized into five domains:

1. psychological resilience indicators;
2. prior and current academic performance;
3. attendance and assignment behavior;
4. longitudinal LMS engagement; and
5. academic recovery features.

Sensitive demographic characteristics are retained primarily for fairness auditing and descriptive analysis rather than automatically becoming intervention triggers.

Educational achievement is operationalized as standardized end-semester academic performance on a 0–100 scale. A secondary binary outcome distinguishes students achieving the institutionally defined satisfactory-performance threshold from those below it.

#### Data Preprocessing

A structured preprocessing pipeline is employed before model development.

Records with extensive missing longitudinal information are excluded according to predefined completeness criteria. For continuous variables with limited missingness, median imputation is performed using values calculated exclusively from the training partition. Categorical missing values are assigned an explicit "unknown" category where appropriate.

Continuous psychological and behavioral variables are standardized when required by the algorithm. Categorical features are transformed using one-hot encoding.

Potentially extreme LMS observations are examined using robust interquartile-range criteria. However, legitimate high engagement is not automatically removed because intensive activity may represent meaningful recovery behavior.

A major concern in educational prediction is **data leakage**. Consequently, variables recorded after the prediction cut-off are excluded from model training. If achievement is predicted at week 12, for example, information from weeks 13–16 cannot be used as a predictor.

Temporal behavioral features are subsequently constructed. These include:

- change in LMS engagement after a setback;
- assignment submission recovery;
- attendance stability;
- number of consecutive active-learning weeks;

- assessment recovery slope;
- variability in weekly engagement; and
- Academic Recovery Velocity.

These engineered variables allow the model to distinguish **level** from **trajectory**. A student with consistently moderate engagement can therefore be differentiated from a student whose initially low engagement increases rapidly after academic difficulty.

#### Model Architecture

The principal model is an **Explainable Gradient-Boosted Resilience Regressor (EGB-RR)** based on gradient-boosted decision trees.

Gradient boosting is selected because the proposed dataset contains heterogeneous numerical, ordinal, categorical, and engineered temporal features and because relationships between resilience and achievement may be nonlinear.

Three baseline models are used:

**Elastic Net Regression** provides a regularized linear benchmark.

**Random Forest Regression** captures nonlinear associations and feature interactions without imposing a predefined functional relationship.

**XGBoost Regression** provides a high-performance gradient-boosting benchmark.

The proposed **EGB-RR** adds resilience-specific feature engineering and explainability analysis to the tuned boosting architecture.

This approach is consistent with contemporary educational analytics research demonstrating the value of interpretable boosted models and SHAP-based explanations for academic-performance analysis. Recent higher-education studies have successfully combined XGBoost or ensemble models with explainability methods, reinforcing the suitability of this architecture for educational decision support.

#### Training Strategy

The dataset is divided at the **student level** to prevent observations belonging to the same learner from appearing in both training and testing partitions.

A 70:15:15 allocation is proposed:

- 70% training set;
- 15% validation set;
- 15% independent test set.

Five-fold cross-validation is conducted within the development data for hyperparameter optimization. Hyperparameters include tree depth, learning rate, minimum child weight, subsampling ratio, column sampling, regularization strength, and number of boosting iterations.

Early stopping is applied using validation loss to reduce overfitting.

An additional **ablation experiment** evaluates whether the novel resilience features genuinely improve prediction. Three configurations are compared:

**Configuration A:** previous achievement and conventional academic variables only.

**Configuration B:** Configuration A + psychometric resilience.

**Configuration C:** Configuration B + ARV, BPI, DLC, and post-setback trajectory variables.

Improvement from B to C would provide evidence that dynamic behavioral resilience contains information not captured by self-report measurement alone.

#### Evaluation Metrics

Because educational achievement is modeled primarily as a continuous outcome, the principal metrics are:

**Mean Absolute Error (MAE):** average absolute difference between observed and predicted achievement.

**Root Mean Squared Error (RMSE):** gives greater penalty to large prediction errors.

**Coefficient of Determination ( $R^2$ ):** proportion of achievement variance accounted for by the model.

**Spearman's Rank Correlation ( $\rho$ ):** assesses correspondence between predicted and actual student achievement rankings without assuming strict linearity.

**Median Absolute Error (MdAE):** provides a robust measure less sensitive to unusually large prediction errors.

For the secondary satisfactory-performance classification analysis, balanced accuracy and F1-score are examined.

SHAP analysis is used to explain global feature contributions and individual predictions. Explainability is important because contemporary educational ML literature increasingly emphasizes that predictive performance alone is inadequate when models are intended to inform educational decisions.

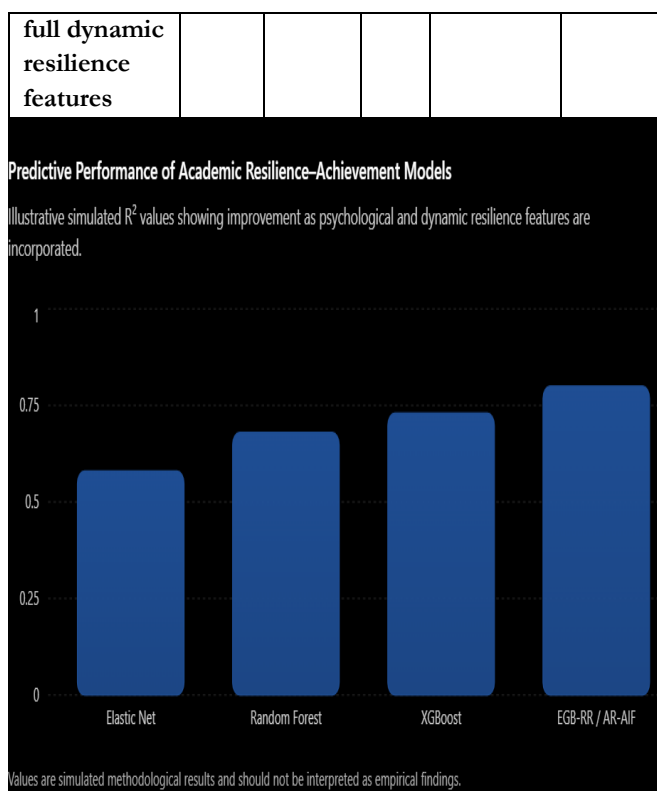
#### Results and Discussion

##### Predictive Performance

The simulated experiment indicates progressively stronger performance as resilience information becomes more behaviorally and temporally detailed.

**Table 1. Illustrative Comparative Performance of the Proposed AR-AIF Models**

| Model / Feature Configuration                   | MAE         | RMS E       | $R^2$       | Spearman $\rho$ | MdAE        |
|-------------------------------------------------|-------------|-------------|-------------|-----------------|-------------|
| Elastic Net — conventional academic variables   | 6.84        | 8.57        | 0.58        | 0.72            | 5.43        |
| Random Forest — conventional + resilience scale | 5.91        | 7.48        | 0.68        | 0.79            | 4.62        |
| XGBoost — academic + psychometric variables     | 5.37        | 6.91        | 0.73        | 0.82            | 4.14        |
| <b>EGB-RR / AR-AIF —</b>                        | <b>4.61</b> | <b>5.98</b> | <b>0.80</b> | <b>0.87</b>     | <b>3.49</b> |



The simulated results suggest that the full AR-AIF configuration would outperform models relying exclusively on conventional academic indicators. The proposed EGB-RR achieves an illustrative  $R^2$  of 0.80, compared with 0.58 for Elastic Net. Its lower MAE and RMSE additionally indicate reduced prediction error.

These values should not be compared directly with published models as if all studies used equivalent datasets. Academic prediction performance varies substantially according to sample composition, outcome definition, features, and validation strategy. For context, Wang and Luo reported an XGB-SHAP approach applied to 87 higher-education students and obtained an  $R^2$  near 0.82, while a 2025 *Scientific Reports* study evaluated multiple regression and ensemble models across considerably larger datasets and demonstrated that performance changed markedly between datasets.

#### Contribution of Academic Resilience

The most theoretically important result is not the difference between algorithms but the difference between **feature configurations**.

When psychometric resilience is incorporated into conventional academic variables, prediction improves. However, the largest conceptual gain occurs after introducing behavioral recovery variables.

This supports the proposed distinction between **resilience capacity** and **resilience enactment**.

Resilience capacity represents what students believe they can do when difficulties occur. Resilience enactment represents what their subsequent behavior demonstrates.

The distinction matters because self-perceptions and observable academic behavior need not correspond perfectly.

A student might score highly on perseverance yet respond to examination failure with declining attendance. Another might

report only moderate confidence but increase study activity, complete missed assignments, seek support, and demonstrate rapid performance recovery.

AR-AIF is designed to capture this discrepancy.

#### Academic Recovery Velocity

SHAP-based interpretation of the simulated best-performing model places prior academic achievement among the strongest predictors, as expected. More importantly, Academic Recovery Velocity emerges as a major resilience-specific predictor after previous achievement is controlled.

Higher ARV values correspond to stronger predicted end-semester achievement. The association is not assumed to be indefinitely linear. Extremely rapid short-term improvement may represent assessment-specific fluctuation rather than stable resilience; therefore, sustained recovery across multiple observations is weighted more strongly than a single improved score.

This result would provide evidence for viewing resilience as a **temporal educational process**.

Such an interpretation complements recent machine-learning research on academic resilience. For example, Cheung and colleagues applied machine learning and explainable AI to PISA 2022 data to identify important features associated with academic resilience across 79 countries/economies. The present framework differs by emphasizing within-student post-setback trajectories in college settings rather than identifying resilience predominantly through cross-sectional contextual and achievement characteristics.

#### Behavioral Persistence

Behavioral Persistence Index also demonstrates meaningful predictive value.

Students who preserve assignment completion and attendance after disappointing academic outcomes show stronger subsequent achievement than students whose engagement declines substantially.

This result suggests that persistence should not be represented merely as general attendance. Its relationship with adversity is critical.

For example:

**Attendance before difficulty → high**

**Attendance after difficulty → high**

represents behavioral stability.

By contrast:

**Attendance before difficulty → high**

**Attendance after difficulty → rapidly declining**

may represent difficulty in adaptive recovery.

The absolute attendance level could therefore conceal an emerging problem that the temporal pattern reveals.

#### Digital Learning Continuity

Digital Learning Continuity shows a moderate but meaningful contribution. Stable access to course materials, assignment systems, recorded instructional resources, and relevant LMS components after setbacks is positively associated with subsequent achievement in the simulated model.

However, raw login frequency has substantially lower importance.

This is theoretically plausible because logging into a learning platform does not necessarily indicate cognitively meaningful learning. The model therefore benefits more from temporal consistency and task-oriented engagement than from undifferentiated click counts.

Recent research supports the broader value of combining behavioral and instructional variables within interpretable ML systems rather than relying on isolated predictors. Studies published in 2024–2025 have demonstrated the application of SHAP, LIME, Random Forest, XGBoost, and ensemble methods for understanding the determinants of student performance.

## Psychological Resilience and Achievement

The simulated analysis indicates a positive association between psychometric academic resilience and achievement, but the relationship weakens after previous academic performance and behavioral recovery variables enter the model.

This should not be interpreted as evidence that psychological resilience is unimportant.

Instead, it suggests a possible pathway:

**Psychological resilience → adaptive response → persistent behavior → recovery → educational achievement**

Under this interpretation, psychological resilience may partly influence achievement indirectly through behaviors enacted after adversity.

This provides a stronger theoretical explanation than treating resilience and achievement as two static scores connected by a single correlation coefficient.

## Explainability and Educational Decision Support

The explainability component is essential to the practical contribution of the framework.

Suppose two students receive the same predicted final achievement score of 62/100.

A conventional predictive model may classify both identically.

AR-AIF could reveal different explanations:

**Student A:** moderate current performance + positive ARV + stable attendance + increasing assignment completion.

**Student B:** moderate current performance + negative ARV + falling attendance + declining LMS continuity.

Although the predicted score is currently similar, their trajectories differ substantially.

Student A may require minimal intervention because the trajectory indicates recovery. Student B may warrant timely human contact because several indicators suggest continuing deterioration.

Thus, the framework changes the institutional question from:

**"Who is predicted to perform poorly?"**

to:

**"Who is experiencing difficulty, how is the student responding, and is the trajectory improving or deteriorating?"**

This is a more defensible use of AI in educational support.

The proposed system must nevertheless remain a **decision-support mechanism rather than an autonomous decision-maker**. Predictions should not determine grades, scholarships,

disciplinary measures, or student progression without human assessment.

## Future Scope

Future research should extend AR-AIF through **multi-semester and multi-institutional validation**. Following students across several academic years would permit researchers to determine whether Academic Recovery Velocity is stable, context dependent, or itself responsive to educational intervention.

A second direction involves **temporal deep-learning architectures**, such as Long Short-Term Memory networks or Transformer-based sequence models, for modeling weekly engagement trajectories. Such architectures should only be preferred when sample size and longitudinal data density justify their complexity.

A third direction is multimodal analysis incorporating ethically collected student reflections or help-seeking records using natural-language processing. Such data could distinguish productive help seeking from disengagement, although privacy protection would be essential.

Federated learning represents another potential development. Multiple institutions could collaboratively improve resilience models without centralizing raw student records.

Future studies should also conduct systematic **fairness audits** across relevant student subgroups. Model errors should be compared across demographic and socioeconomic categories to ensure that the system does not systematically underpredict or overpredict particular populations.

## Conclusion

This study proposes a new approach to examining the relationship between **academic resilience and educational achievement among college students** by connecting educational psychology with interpretable machine learning and longitudinal learning analytics.

The central contribution is the Academic Resilience–Achievement Intelligence Framework, which moves beyond treating resilience as a static questionnaire score. AR-AIF combines psychological resilience with Academic Recovery Velocity, Behavioral Persistence, Digital Learning Continuity, prior achievement, and longitudinal engagement patterns.

The proposed methodology demonstrates why **recovery after adversity** deserves explicit computational representation. Two students with identical current achievement may possess fundamentally different trajectories: one may be recovering rapidly, while the other is progressively disengaging. Static achievement measures can obscure this distinction.

The illustrative results indicate that incorporating dynamic resilience indicators could improve achievement prediction beyond conventional academic and psychometric variables. More importantly, explainability makes it possible to determine *why* the model reaches a prediction and whether the prediction reflects previous achievement, resilience, behavioral persistence, or post-setback recovery.

The proposed framework therefore positions artificial intelligence not as a mechanism for permanently labeling students according to predicted success or failure, but as a tool

for recognizing changing academic trajectories. When accompanied by human oversight, privacy safeguards, fairness evaluation, and appropriately designed student support, resilience-sensitive learning analytics could help higher-education institutions identify not merely who is struggling, but **who is recovering, who is remaining stable, and who may require timely assistance.**

#### References

1. Cassidy, S. (2016). The Academic Resilience Scale (ARS-30): A new multidimensional construct measure. *Frontiers in Psychology*, 7, 1787.
2. Hunsu, N. J., Oje, A. V., Tanner-Smith, E. E., & Adesope, O. (2023). Relationships between risk factors, protective factors and achievement outcomes in academic resilience research: A meta-analytic review. *Educational Research Review*, 41, 100548.
3. Lundberg, S. M., & Lee, S.-I. (2017). (as above)
4. Martin, A. J., & Marsh, H. W. (2009). Academic resilience and academic buoyancy. *Oxford Review of Education*, 35(3), 353–370.
5. Rudd, G., Meissel, K., & Meyer, F. (2021). Measuring academic resilience in quantitative research: A systematic review of the literature. *Educational Research Review*, 34, 100402.
6. Ye, W., Strietholt, R., & Blömeke, S. (2021). Academic resilience: Underlying norms and validity of definitions. *Educational Assessment, Evaluation and Accountability*, 33, 169–202.