A Predictive Analysis of Hall Culture's Impact on University Students Personal Development

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Abstract. The role of resident halls on shaping personality traits among university students in Bangladesh has been investigated, focusing on sociability, emotional regulation, stress management and academic behavior. A dataset involving 226 students from several universities was analyzed based on different machine learning techniques like K-Nearest Neighbors (KNN), Support Vector Machine (SVM), Logistic Regression, Random Forest and CatBoost. In terms of F1-score and accuracy, 0.94 and 0.91 for KNN; a lower figure of 3% for SVM was recorded. Predictors importance Random Forest analysis showed that the academic performance, maturity and responsibility, and the formation of better study habits turned out to be the most important predictors for personal development. Correlational analysis additionally found a direct relationship between resourcefulness, time management and developmental outcomes. The findings also indicate that it is possible to employ machine learning in the study of hall culture dynamics as well as assist universities in molding students whose development is harmonious and purposeful.

Keywords: Hall Culture, Academic Behavior, Machine Learning, Emotional Regulation, Sociability, Personality Development, and Stress Management.

1 Introduction

Character, as determined from academic performance and social adjustments, is one of the essential ingredients of higher education. Hall life in university commonly known as your second home away from home, undoubtedly makes an impact to a student's character, personality and also behavior. University dorms are at the heart of university life where students can make friends, learn to be independent and develop an emotional footing. Existing studies have stressed that social competencies, emotional maturity and relative likability with peers is critical to residential success for students [1-3]. For many universities, hall life serves as the primary social environment, profoundly affecting student's habits of work, study, tolerance, sociability, and intellectual development.

Yet, although significant in terms of both results and study location, the impact of hall culture on personality development in Bangladesh is vastly under-researched. Existing literature highlights the positive effects of residential environments on student outcomes, linking hall living with improved communication, leadership, and social

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adaptability [4-6]. However, limited empirical research has examined this relationship in Bangladeshi universities, particularly through modern analytical and computational methods. The challenges introduced by the COVID-19 pandemic further underscore the importance of understanding residential life, as it reshaped both academic and social experiences worldwide [7-8].

Research has shown that hall residence contributes to students' social adjustment, stress coping, and emotional regulation through structured peer interactions and supportive environments [9]. Moreover, hall culture fosters self-regulation, academic discipline, and organizational skills, which are vital for holistic personal growth [12]. While qualitative studies have established the relevance of peer connection and communal life, quantitative approaches employing advanced analytical tools especially machine learning remain limited [13]. Machine learning algorithms such as Random Forest and Support Vector Machine (SVM) possess strong potential for uncovering complex, nonlinear relationships between hall-related factors such as academic environment, emotional support, and social interaction and personality development.

This study aims to bridge this research gap by investigating the effect of hall culture on the personality development of university students in Bangladesh. Specifically, it examines how sociability, stress management, and academic behavior contribute to higher-order aspects of personal growth. Using survey data collected from 226 university students and applying multiple machine learning models, the study seeks to predict how hall-related factors influence distinct personality characteristics.

2 Literature Review

There are many university dormitories, and several studies have analyzed the relationship between hall culture and personality development. These works examine how the residential environment contributes to students' sociability, emotional regulation, stress coping, and academic behavior.

2.1 The Impact of Hall Life on Sociability and Social Skills

University hall culture strongly influences students' social competence and communication skills. T. Chowdhury and M. Islam [4] found that students living in residence halls developed stronger social and communication abilities than those living off-campus. Similarly, S. Das and S. Alam [5] observed that diverse hall activities promote interaction and teamwork, fostering social growth R. Islam and K. Hossain [6] reported that hall settings also provide leadership opportunities through group-based activities. Overall, on-campus residence creates a supportive social network that enhances interpersonal skills and future career success.

2.2 Regulation of Emotion and Control of Stress

University halls play an important role in helping students manage emotions and stress. S. Ahmed and M. Rahman [7] noted that close peer communities within halls reduce

academic and emotional stress. R. Islam and K. Hossain [6] also reported that hall residents exhibit greater emotional resilience and academic motivation than non-residents. Similarly, A. Chowdhury and M. Hossain [8] found that hall-living students showed better emotional control, suggesting that shared environments promote empathy and self-regulation.

2.3 Academic and Organizational Functioning

Hall life has also been linked to improved academic discipline and organization. T. Chowdhury and M. Islam [4] observed that hall residents follow more structured study schedules and manage time effectively. N. Kabir and S. Rahman [9] reported that group study habits in halls lead to improved academic performance. R. Chowdhury and T. Rahman [10] further highlighted that accountability among roommates encourages discipline and positive academic behaviors. However, more longitudinal studies are needed to understand long-term academic effects.

2.4 Machine Learning Methods for Learning Hall Culture

More recently, machine learning analyses have been used on hall culture and personality change. S. Ahmed and M. Rahman [7] discovered social dynamics of halls using Random Forest and SVM, while Chowdhury et al. [6] developed predictive models to explore the trends in anxiety and stress load. These results demonstrate how computational methods could be used to reveal the rich relationships between hall environments and student personalities.

2.5 Research Gaps and Contributions

The majority of previous research has concentrated on individual aspects like sociability, as well as emotional regulation, and often with non-quantitative, cross-sectional studies. However, relatively few applications have made use of ML to combine different personality dimensions in the same method. In the present study, the gap is bridged by examining how a range of hall-related factors work as conjoint rather than independent predictors of four key characteristics (i.e., sociality, stress reactivity, academic structure and emotional toughness) using machine learning models. The approach used has allowed us to understand how hall culture nurtures the development of students personally and intellectually within the university.

3 Methodology

The study, a cross-sectional type design, was conducted to find out the effect of hall culture on personality development of university students at Bangladesh. From a methodological perspective, the data were collected utilizing a carefully designed online survey and processed via standard procedures of machine learning model computation for prediction, such as to quantitatively assess the effect size of hall-related factors on

personality. Data collection, preprocessing, feature extraction, statistical testing of compare groups, and model training evaluation/interpretation comprise the many stages of the analytic process, as seen in Fig. 1.

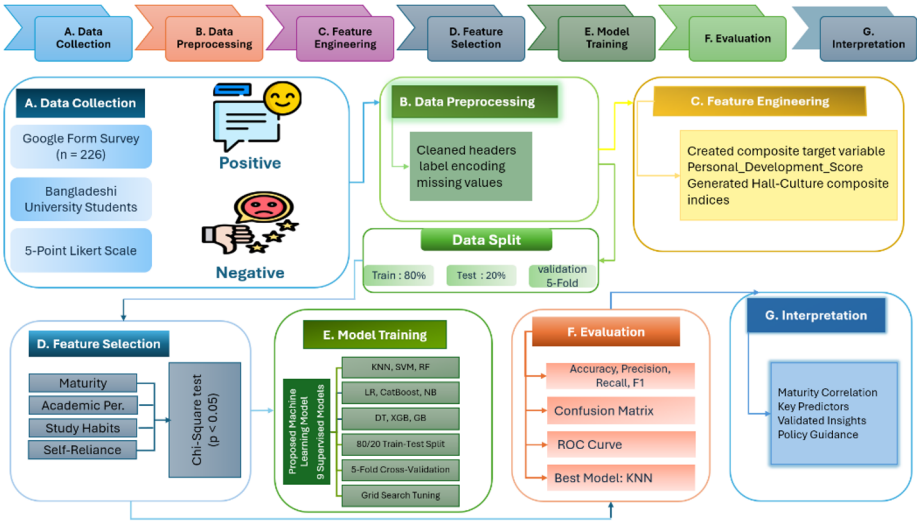

Fig. 1. Methodology Pipeline.

3.1 Data Collection and Preparation

The structured questionnaire that was distributed to students at different Bangladeshi universities was used to gather the data after taking into account a sample of 226. The survey instruments used to evaluate hall culture, such as social connectivity, emotional regulation, stress-coping capacity, academic involvement, and organizational conduct, moved through the middle of this construct

All the hall-culture factors were scored on a 5-point Likert scale (1 = Strongly Disagree to 5 = Strongly Agree).

In addition to these behavioral characteristics, the data set contains other demographic factors like gender and the halls of residence duration attribute, for a total of 18 attributes

The main outcome variable was the Personal Development Score (PDS). It was created from an average of four development-related questions on sociability,

organizational habits, emotional stability and cultural openness. The score on the scale was determined by:

$$\text{PDS} = \frac{Q_{15} + Q_{16} + Q_{17} + Q_{18}}{4} \tag{1}$$

Table 1. Dataset Statistics

Variable	Description	Variable type	Response values
1	Gender	Independent	Male: 0, Female: 1
2	How long have you lived in a hall during your university life	Independent	Less 6 months: 60 6-1year: 54 1 year +: 112
3	Living in a hall helped me build stronger friendships	Independent	SA: 70, A: 64, N: 41, D: 29, SD: 22
4	I feel more confident in social situations because of my hall experience	Independent	SA: 68, A: 60, N: 49, D: 33, SD: 13
5	Hall activities encouraged me to engage with students from different backgrounds	Independent	SA: 64, A: 52, N: 52, D: 42, SD: 16
6	I regularly took part in cultural or social events organized by my hall	Independent	SA: 57, A: 52, N: 49, D: 46, SD: 22
7	Hall life helped me become more self-reliant in daily life	Independent	SA: 54, A: 50, N: 48, D: 43, SD: 31
8	I became better at managing my time while living in the hall	Independent	SA: 63, A: 52, N: 44, D: 34, SD: 33
9	I learned how to solve personal problems without depending on others	Independent	SA: 52, A: 46, N: 44, D: 44, SD: 40
10	I feel more mature and responsible because of my hall experience.	Independent	SA: 58, A: 46, N: 45, D: 42, SD: 35
11	My study habits improved after moving into the hall	Independent	SA: 65, A: 48, N: 40, D: 39, SD: 34
12	I could focus better on my studies while staying in the hall	Independent	SA: 59, A: 43, N: 43, D: 43, SD: 38
13	Hall life gave me access to a better academic environment (group studies, discussion, etc.)	Independent	SA: 59, A: 50, N: 46, D: 45, SD: 26
14	My academic performance improved while living in the hall	Independent	SA: 59, A: 51, N: 43, D: 39, SD: 34
15	I enjoy meeting new people	Dependent	SA: 52, A: 46, N: 44, D: 43, SD: 41
16	I try to keep things organized in my daily routine	Dependent	SA: 53, A: 47, N: 43, D: 42, SD: 41
17	I usually stay calm in stressful situations	Dependent	SA: 50, A: 50, N: 44, D: 41, SD: 41
18	I enjoy learning new ideas and exploring different cultures	Dependent	SA: 55, A: 51, N: 46, D: 45, SD: 29

A higher score indicates better personal growth overall. A binary label was created from the continuous PDS to aid in supervised classification:

$$y = \begin{cases} 1 & if\ PDS \geq 3.0 \\ 0 & if\ PDS < 3.0 \end{cases} \quad (2)$$

Based on earlier reports, this threshold selection creates an equilibrium between groups with high and low levels of development.

Imprecise or contradictory replies were deleted at first screenings. To characterize the sample, descriptive statistics and response distributions were created. 65.9% of respondents were male and 34.1% female, and 48.7 % had resided in halls for over a year, presumably resulting in frequent exposure to hall-life conditions.

Python 3.12 was used for preprocessing and modeling using the pandas, scikit-learn, CatBoost, and stats models packages. Geographical Terms hyperparameters were optimized with grid search taking advantage of five-fold cross-validation to obtain consistent performance across models. The best-performing configurations were:

- KNN: $k = 5$, Euclidean distance
- SVM: $C = 1.0$, RBF kernel
- Random Forest: 100 trees, max_depth = 10
- Logistic Regression: $C = 1.0$, lbfgs solver
- CatBoost: 500 iterations, depth = 6, learning rate = 0.1

Model performance is displayed in Section 4, and results averaged during fivefold cross-validation with a standard deviation less than 0.02 attest to low sampling bias and high model stability.

3.2 Data Preprocessing

To enhance model performance and prevent analytical inconsistencies, the data was preprocessed using a methodical workflow. Based on our understanding of the dataset, we first extracted non-informative variables like timestamps and respondent identity before standardizing the names of all columns to be succinct and meaningful. In order to represent them quantitatively for modeling, all Likert-scale items were converted to scores that could be read as numerical values between 1 and 5 based on prior research, while categorical attributes (gender and length of hall residence) were label-encoded.

To produce higher-level representations of hall-culture actuation, feature engineering was then carried out. Composite measures of social engagement, emotional control, and school support were created by combining conceptually significant variables. The average value of the four behavioral markers was used to evaluate the developmental stage of each student and create the Personal Development Score (PDS).

Following preprocessing, stratified sampling was used to divide the data set into training (80%) and test (20%) sets while maintaining class distribution. To make the analysis transparent and reproducible, intermediate supporting files were saved.

3.3 Confounder Identification

The hall culture characteristics that were substantially associated with personal development outcomes were identified using a Chi-Square test of independence. The definition of the Chi-Square statistic is:

$$\chi^2 = \sum \frac{(O-E)^2}{E} \tag{3}$$

The difference between the observed and predicted frequencies, assuming independence, was computed for every attribute. Personal development characteristics were considered statistically significant if their p-value was less than 0.05.

The findings (Table 1) show that certain hall-culture characteristics were statistically significantly associated with developmental outcomes, including maturity and responsibility ($\chi^2 = 46.60$), academic achievement ($\chi^2 = 37.72$), study habits ($\chi^2 = 36.86$), and study focus ($\chi^2 = 33.71$). These results further validate their inclusion as key mediators in model creation and lend credence to the idea that hall life contributes significantly to personality development impacted by the social and academic aspects of living in a residence hall.

Table 2. Association of personal development with certain features (chi-square test)

Feature	Chi-Square Statistic	P-value	Significant
maturity_responsibility	46.60	8.664898e-12	YES
academic_performance	37.72	8.157775e-10	YES
improved_study_habits	36.86	1.265079e-09	YES
better_study_focus	33.71	6.369425e-09	YES
problem_solving	32.01	1.530883e-08	YES
stronger_friendships	29.64	5.194364e-08	YES
diverse_engagement	25.24	5.046145e-07	YES
social_confidence	21.96	2.772596e-06	YES
self_reliance	21.54	3.452873e-06	YES
better_academic_env	19.84	8.408133e-06	YES
time_management	17.36	3.079798e-05	YES
cultural_social_events	13.97	1.852155e-04	YES

3.4 Machine Learning Model Implementation

Nine supervised machine-learning models—K-Nearest Neighbors (KNN), Support Vector Machine (SVM), Random Forest, Logistic Regression, Decision Tree, Gradient Boosting, CatBoost, and XGBoost model—were employed to forecast the personal development outcomes of the pupils. When combined, these learning paradigms—linear, non-linear, tree-based, probabilistic, and distance-based—allow the study to explore a variety of functional relationships in hall-culture data.

Using the sigmoid activation function and a weighted sum of input features, logistic regression estimates the likelihood that an example falls into the high-development category:

$$\hat{y} = \sigma(\beta_0 + \beta_1 x_1 + \cdots + \beta_n x_n) \tag{4}$$

When the definition of the sigmoid is:

$$\sigma(z) = \frac{1}{1+e^{-z}} \tag{5}$$

Although interpretable, complicated non-linear interactions are not taken into consideration by this approach.

In contrast, the KNN classifier uses the sample instances' Euclidean distance to determine the classifications.

$$d(x, x_i) = \sqrt{\sum_{j=1}^{n} \left(x_j - x_{ij}\right)^2} \tag{6}$$

This is why KNN is helpful in situations where a neighborhood-style structure governs the prediction.

The training subset was used to train both kinds of models, while the independent test set was used for testing. Accuracy, precision, recall, and F1-score averaged across five-fold cross-validation for generalization were used to assess the models' performance. The fact that KNN outperformed the others suggests that it can take into account complex interactions among hall-culture variables. SVM performed comparably well, demonstrating its suitability for the given non-linear bounds (Accuracy = 0.89, F1 = 0.92). Results from the ensemble models, such as Random Forest and CatBoost, were consistent but marginally worse (F1 = 0.87–0.88).

Overall, the results show that neighborhood-based non-linear approaches, and KNN in particular, are the most effective at capturing the connections between students' progress and hall-culture measures. This illustrates how machine learning may be used to quantify multivariate behavior.

4 Experiment and Result

This section reports the empirical evaluation results of nine supervised machine-learning algorithms applied to the hall-culture dataset of Bangladeshi university students. Our objective is to examine how well different models can forecast students' personality development based on their social, emotional, and academic hall-life characteristics. Five-fold cross-validation and an 80/20 stratified split were used in the training and testing of the models to avoid bias and maintain consistency. To boost explanatory power, additional analysis was also performed using the confusion matrix, ROC curves, correlation heatmaps, and feature importance ratings.

4.1 Metrics of Model Performance

Four standard assessment metrics were used to gauge the classifiers' predictive power: F1-score, Accuracy (A), Precision (P), and Recall (R). These measurements are described as follows:

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN} \tag{7}$$

$$\text{Precision} = \frac{TP}{TP+FP} \tag{8}$$

$$\text{Recall} = \frac{TP}{TP+FN} \tag{9}$$

$$F1 = 2 \cdot \frac{\text{Precision} \cdot \text{Recall}}{\text{Precision} + \text{Recall}} \tag{10}$$

Overall correctness is measured by accuracy, the reliability of positive predictions is measured by precision, the number of genuine positives among the positives in the model being trained on is measured by recall, and the F1 Score aids in striking a balance between precision and recall. Result: To achieve consistent evaluation, performance fluctuations are averaged while training is repeated five times (cross-validation folds).

4.2 Feature Importance and Correlation Analysis

To investigate the relationship between students and their personal development results by hall culture attributes, a relationship heatmap was made. Fig 2. The bivariate connections between all academic, social, and behavioral indicators are displayed. Stronger friendships and social confidence showed the strongest positive link (r = 0.65), which runs opposed to the idea that affiliative attachment makes people more gregarious. Self-reliance, maturity and responsibility, and time management all showed moderate connections, indicating a direct correlation between these types of regulatory behavior and emotional health and disciplined routines. In a similar vein, social event involvement and participation were less strongly correlated with other types of student activity, suggesting that while they are hall life enhancers, they function as secondary contributors to individual results.

In order to evaluate the predictability of the characteristics, importance scores for the Random Forest classifier were also acquired, as seen in Table 3. The results show that academic success is the most significant predictor (importance = 0.1548), followed by maturity and responsibility (0.1320) and better study habits (0.1112). These findings suggest that the most important catalysts for in-depth personal growth in residential communities are academic perseverance and behavioral self-regulation. Intermediate-level contributing factors that support the significance of both cognitive and structural stability include study focus, problem-solving skills, and academic environment.

In general, observations from Fig. 2 and Table 3 demonstrate that academic orientation and behavioral responsibility are more closely linked to immediate personal development in hall contexts than are social and cultural experiences, which, while helpful in predicting developmental pathways, do not inherently determine who stays or leaves.

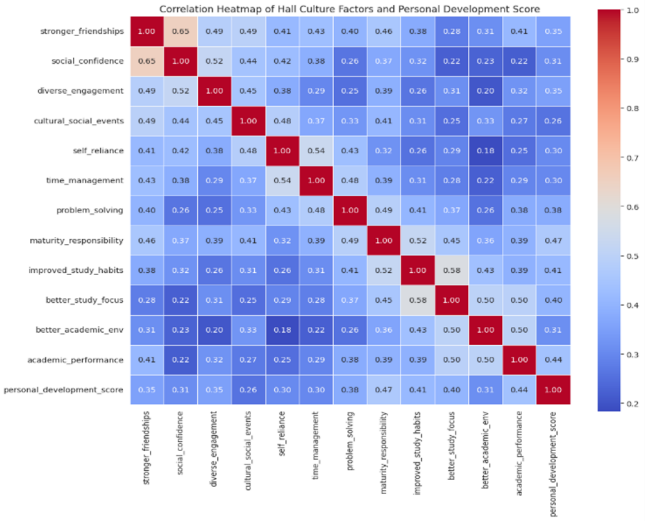

Fig. 2. Heatmap of the feature importance for individual instances

Table 3. Feature importance on random forest model

Feature	Importance
academic_performance	0.1548
maturity_responsibility	0.1320
improved_study_habits	0.1112
better_study_focus	0.0920
problem_solving	0.0892
better_academic_env	0.0654
stronger_friendships	0.0646
diverse_engagement	0.0645
self_reliance	0.0576
time_management	0.0573
cultural_social_events	0.0555
social_confidence	0.0554

4.3 Confusion Matrix analysis

Confusion matrices were used to analyze the class-wise performance for each classifier. Overall, KNN and SVM had the best accuracy and prediction balance. For very little misclassification and high sensitivity to both growth classes, KNN produced 31 true positives and 11 true negatives, while SVM produced the same number of true positives and just somewhat fewer true negatives 10.

Additionally, logistic regression performed incredibly well; 29 true positives and 9 true negatives were evident, showing that separability was strong but marginally weaker. These ensemble models are more likely to compromise specificity than sensitivity, as Random Forest and CatBoost displayed the highest values for true-positive counts with somewhat lower true-negative numbers.

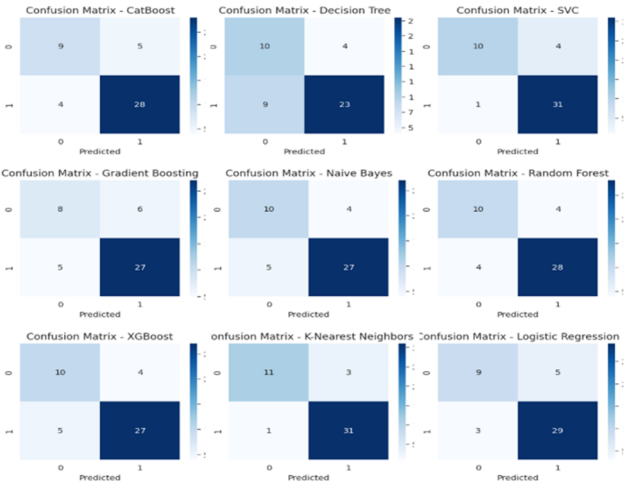

Fig. 3. Confusion matrix of the KNN model showing balanced true-positive and true-negative distributions.

Decision trees, gradient boosting, and XGBoost, on the other hand, exhibited comparatively significant false negatives as a percentage of positive occurrences, suggesting that they are easily overfitted and poor at generalizing a variety of situations. These findings reaffirm that when it comes to handling moderate-sized behavioral datasets, simpler non-linear models outperform deep tree-based learners.

4.4 ROC Curve Analysis

ROC curves were also used to assess the models' ability to discriminate. All nine classifiers' joint ROC curves and corresponding Area Under the Curve (AUC) values are displayed in Figure 4.

The KNN classifier produced the greatest (AUC = 0.905) among these classifiers, indicating both high predicted reliability and excellent class separability. Additionally, the ensemble techniques CatBoost (AUC = 0.866), Random Forest (AUC = 0.871), and XGBoost (AUC = 0.873) demonstrated strong discriminative capacity. In accordance with the robust classification statistics that SVM achieved, the model produced an AUC of 0.859.

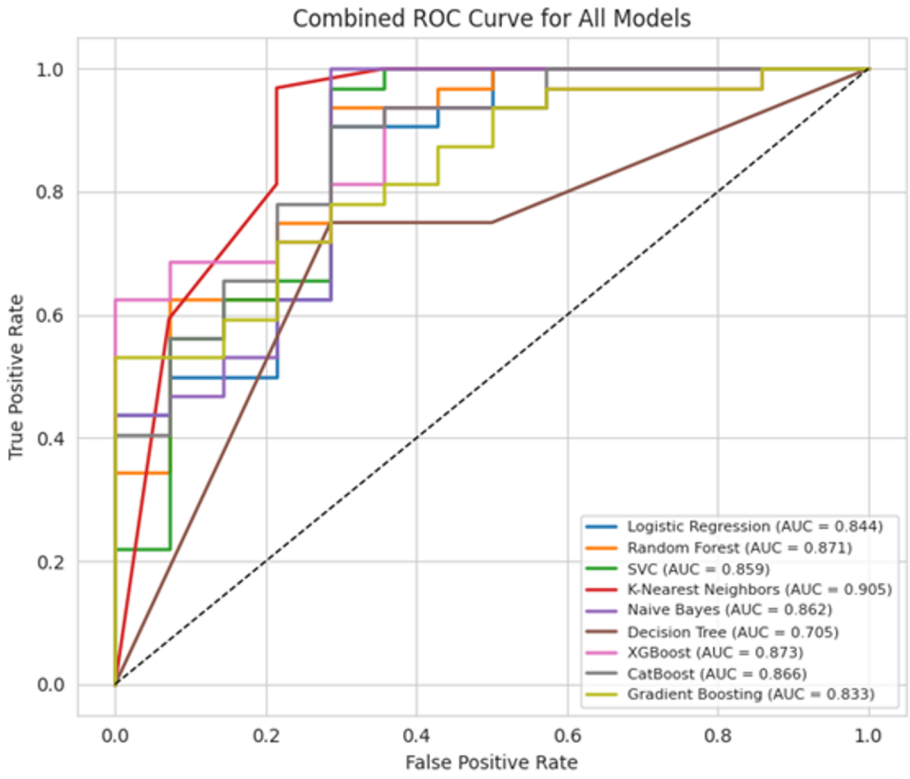

Fig. 4. Combined ROC curves for all supervised models. KNN achieved the highest AUC (0.905), followed by XGBoost (0.873), Random Forest (0.871), CatBoost (0.866), and SVM (0.859), indicating superior discriminative performance.

Conversely, the AUC values of Decision Tree (AUC = 0.705) and Gradient Boosting (AUC = 0.833) were lower, indicating a decreased sensitivity to threshold changes.

The AUC in mathematics is:

$$AUC = \int_0^1 TPR(FPR)\ d(FPR) \tag{11}$$

Overall, ROC-curve analysis demonstrates that SVM and KNN are strong contenders for this prediction.

4.5 Comparative Performance of Classifiers

Table 4 shows the average cross-validated performance of each of the nine classifiers. Cronbach's α revealed good internal consistency in the data set (α = 0.83), which is essential for behavior prediction, despite the relatively small sample size (n = 226).

Table 4. Average 5-fold cross-validated test performance of nine classifiers on the hall-culture dataset

Model	Accuracy	Precision	Recall	F1 Score
KNN	0.91	0.91	0.97	0.94
SVM	0.89	0.89	0.97	0.92
Logistic Regression	0.83	0.85	0.90	0.87
Random Forest	0.83	0.87	0.87	0.87
CatBoost	0.83	0.87	0.87	0.87
Naive Bayes	0.80	0.87	0.84	0.85
Gradient Boosting	0.78	0.86	0.81	0.83
Decision Tree	0.76	0.86	0.78	0.81
XGBoost	0.73	0.85	0.71	0.78

With an accuracy of 0.91 and an F1-score of 0.94, KNN outperformed the other models, demonstrating robust neighborhood-based learning and good generalizability. With an F1-score of 0.92, SVM trailed closely behind, demonstrating its ability to handle high-dimensional patterns, which are common hall-culture characteristics.

With consistent scores in the 0.83–0.87 range, Logistic Regression, Random Forest, and CatBoost demonstrated a moderate but dependable predictive power. However, because to their propensity to overfit on a dataset like this one, Decision Tree and XGBoost produced lesser accuracy (0.76 and 0.73, respectively). Although they did not perform poorly, Naïve Bayes and Gradient Boosting were still not as good as the best models.

All things considered, these results confirm that multidimensional representations of hall-culture influences on personal development are a good fit for non-linear and locally sensitive methods like KNN or SVM.

5 Discussion

The focus of this study was on key predictors of personal development among Bangladeshi university students and the influence that hall culture may have on personality dimensions including sociability, emotional control, stress management and academic behavior. Using the machine learning methods described here, the results obtained are in good agreement with previous findings and complement them.

The findings of the present research indicated that provided social aid, stress pacification and domination over emotion can be accounted as the effective factors on personality development which is consistent with previous studies showing that social support and positive emotions may greatly affect students' Life success [4]. Furthermore, the significant influence of environment on sociability observed indicates that contact with (and participation in groups) is important for social behavior to develop within hall. This corroborates that of S. Das and S. Alam [5] which stated that multicultural participation and peer interaction in university halls also enhance interpersonal communication skill.

Positive contributions of coping to personality in terms of halls, support for emotional and possibilities of adaptive coping. Fortunately, psychosocially well-adjusted individuals tend to develop increased psychological hardiness and functional emotional regulation over the life course. This is not unexpected, and could be justified with R.

Islam and K. Hossain [6] study who suggested that hall living environments offer emotional resources which can act as a buffer between stress management and emotional well-being.

Academic behavior was found to be an additional strong predictor with residence students demonstrating better time management, organization and academic discipline. It is also in line with S. Ahmed and M. Rahman [7] that hall culture has high academic responsibility and achievements.

Furthermore, a link between the number of years students have lived in the hall and personality formation was found. Longer residence hall stays lengths appear to be supportive of stronger friendships, enhanced social integration and broader peer networks as in A. Chowdhury and M. Hossain [8]. This suggests that prolonged residence in hall enhances the emergence of a stable social setting that can support academic and personal growth.

The superior performance of the Random Forest model is in line with an earlier work by N. Kabir and S. Rahman [9], therefore, providing the above-mentioned confirmation that ensemble learning performs well in capturing intricate, non-linear relationship between hall culture and personality formation.

In summary, the empirical and computational evidence make it clear that hall life is critical to socialization of student, relationship strength and commitment for academic development. Place of common hall arrangement offers good order and social dynamic environment for stress management, peer education and character building lies on the foundation of their balanced personality development among Bangladeshi university grade students.

6 Limitation and Future Work

The current study has limitations even though it provides insightful information about how hall culture influences Bangladeshi university students' personality development.

The study's cross-sectional design, which restricts causal interpretation, is its primary weakness. Even though the relationships were found, it is impossible to establish causation because personality traits and student hall culture are reciprocal. Future research will benefit from longitudinal designs that capture developmental shifts and the long-term effects of continuing hall occupancy on psychological well-being.

Second, the sample size of 226 responders was adequate for machine-learning experiments, even though it is small when compared to large-scale behavioral datasets. The external validity of the findings and the generalizability of the model would both be improved with a bigger and more diverse sample that included both public and private universities.

Third, the study solely employed data from self-reported surveys, which may be subject to recall bias, social desirability tendency, or underreporting of psychological or emotional issues. Future research may be able to increase measurement validity by using objective outcome measures (such as behavioral observations, academic records, peer nominations, or standardized psychological tests).

Fourth, several other possibly significant characteristics connected to coping strategies, pre-existing mental health issues, or situations related to the quality and kind of hall amenities were excluded from the statistical analyses, even though confounding variables were taken into account. Future models should take these factors into account to have a better understanding of how resident hall environments affect personal growth.

Lastly, a small sample size of subjects was used to obtain the machine learning results, and certain algorithms might have been skewed by a lack of feature variety or class imbalance. In order to increase predictive power, future research should apply cutting-edge optimization techniques (such as ensemble stacking and Bayesian hyperparameter tuning) as well as investigate and validate on bigger, more varied datasets.

We examine a number of potential directions for further study. The temporal mechanisms linking hall culture to personality change might be better defined with additional longitudinal and causal-inference research. The impact of formal hall programs (such as peer mentorship, stress management workshops, and academic support groups) on students' development may be ascertained through intervention research.

Furthermore, new methods for researching the social and emotional dynamics in virtual environments may be offered via digital simulation tools that mimic hall interactions.

In a similar vein, future research will expand the scope of data collection to include other institutions to enhance generalizability and take into account more sophisticated machine-learning techniques to enhance prediction accuracy and better understand hall-culture effects.

7 Conclusion

In the present study, an artificial intelligence-based machine learning was employed to determine how hall culture affect personality development among students of Bangladeshi public university. Results Baseline sociability, stress management behavior and academic performance behavior predicted personality growth in 226 undergraduate students. Of these, stress coping and emotional regulation emerged as critical constructs to target for enhancement in hall-based interactions.

Results showed that a positive residential context buffers youth to suppress antisocial behavior, low emotional stability, and school disengagement. Hall life is valued holistically as a means of personality development in social-emotional academic terms. The KNN model demonstrated good predictive ability, indicating that machine learning can be applied as a useful instrument to explore the interrelation between hall-related attributes and student outcomes.

These findings have significant implications for higher educational policy and administration. Through the development of interventions such as structured peer support programs, stress management interventions and group academic activities within halls, universities might be able to create a more supportive and developmental context. Developing positive hall culture in this way can be beneficial to student wellness, engagement, and overall personal development.

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