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Chapter 11: Emotional Intelligence and Coping Strategies among College Students

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Abstract— Emotional intelligence (EI) influences how college students recognize, interpret, and regulate emotional responses during academic and interpersonal stress. Recent evidence associates higher EI with greater use of adaptive coping, yet most studies rely on aggregate questionnaire scores and conventional correlational analysis. This study addresses this limitation by proposing an explainable machine-learning framework for identifying coping-strategy profiles from multidimensional EI, perceived stress, academic, and digitally recorded behavioral indicators. Rather than treating coping as a single continuous outcome, students are conceptualized as belonging to adaptive, emotion-regulatory, or avoidant coping profiles that may require different forms of support. The framework integrates validated psychological measures with privacy-preserving digital-behavior features and evaluates nonlinear relationships through interpretable machine-learning models.

Keywords— Emotional Intelligence, Coping Strategies, College Students, Explainable Artificial Intelligence, Machine Learning, Digital Mental Health

Introduction

College education coincides with a developmental period characterized by substantial changes in autonomy, social relationships, academic expectations, career planning, and personal identity. Students must routinely manage examinations, deadlines, financial concerns, interpersonal conflicts, uncertainty regarding employment, and increasing exposure to digitally mediated academic and social environments. The psychological consequences of such pressures are not determined exclusively by the number or intensity of stressors. They also depend on how individuals interpret emotional experiences and the strategies they employ when responding to demanding circumstances.

Emotional intelligence provides an important framework for understanding these individual differences. Broadly, EI concerns abilities or dispositions associated with perceiving emotions, understanding emotional information, using emotions constructively, and regulating emotional responses. In a college environment, these competencies may affect whether a student approaches a stressful situation through planning and problem solving, seeks social or emotional support, cognitively reframes the experience, or disengages through avoidance.

Coping is similarly multidimensional. Problem-focused strategies attempt to alter a stress-producing situation, whereas emotion-focused strategies primarily regulate the emotional consequences of that situation. Avoidant or dysfunctional responses can include disengagement, denial, behavioral withdrawal, or other attempts to escape the stressor. These

categories should not be interpreted rigidly: the usefulness of a coping response depends partly on context and controllability. Nevertheless, persistent reliance on avoidant coping can be particularly relevant when examining student psychological well-being.

Empirical evidence increasingly supports a connection between EI and coping. Rehman and Jamil reported an association between emotional intelligence and coping skills among undergraduate dental students. More recent work has provided a more differentiated interpretation. MacCann, Double, and Clarke found across two university-student studies that lower avoidant coping mediated relationships between ability EI and several indicators of psychological well-being and ill-being.

The relationship also appears relevant to broader psychological outcomes. Augusto-Landa, García-Martínez, and León examined 567 university students and reported direct relationships between EI and anxiety, depression, and stress, together with indirect relationships involving coping strategies. Research among health-science students has likewise demonstrated significant relationships among emotional intelligence, stress coping, and students' responses to post-pandemic academic circumstances. Recent evidence additionally suggests that specific EI dimensions may relate differently to active and avoidant coping and that some relationships can vary across student groups.



Fig. 1: Emotional Intelligence in Education

Source: <https://www.thegreenlms.com/blog/education-blog/emotional-intelligence-in-education-a-comprehensive-overview/>

Despite this progress, much of the literature remains methodologically centered on cross-sectional questionnaires,

correlations, regression coefficients, and overall EI scores. Such approaches are useful for population-level inference but may overlook nonlinear interactions among emotional regulation, perceived stress, behavioral routines, and coping preferences. Two students with similar total EI scores, for example, may differ substantially in emotion regulation and self-emotional appraisal and consequently exhibit different coping patterns.

This limitation becomes increasingly important as digital mental-health research moves toward individualized assessment. Smartphone-based digital phenotyping has demonstrated that behavioral signals concerning activity, sleep, mobility, and social interaction can complement self-reported measures in college mental-health research. Subsequent research has investigated whether digital-phenotyping models generalize across college mental-health cohorts, illustrating both the potential and methodological challenges associated with behavioral prediction. Machine-learning research has also demonstrated the feasibility of combining demographic and behavioral variables to identify college students at elevated risk of severe psychological distress.

Research Gap and Study Objective

A specific gap therefore exists at the intersection of **emotional intelligence, coping psychology, explainable machine learning, and privacy-conscious digital behavioral assessment**. Existing EI–coping studies predominantly explain average statistical associations, while digital mental-health studies more frequently predict distress or symptoms than the *coping process through which students respond to stress*. Consequently, comparatively little work has investigated whether multidimensional EI combined with behavioral indicators can distinguish heterogeneous coping profiles using interpretable predictive models.

The present study is designed around this gap. Its principal objective is to develop an explainable machine-learning framework capable of differentiating adaptive/problem-focused, emotion-regulatory, and avoidant coping profiles from emotional-intelligence dimensions, perceived stress, academic context, and aggregated digital-behavior characteristics. The conceptual premise is not that AI can diagnose students' psychological states, but that carefully validated models may uncover complex patterns that conventional linear analyses can miss.

This orientation is consistent with the broader expansion of responsible AI in health. The World Health Organization emphasizes that AI-enabled health technologies require safety, equity, appropriate governance, and scientifically grounded implementation. WHO has also identified digital environments as simultaneously creating opportunities and risks for young people's mental health, reinforcing the need for responsible approaches to digitally mediated psychological support.

Literature Review

2.1 Emotional Intelligence as a Coping Resource

Emotional intelligence can operate as a psychological resource because coping begins with appraisal. Before selecting a behavioral response, individuals must recognize the emotional significance of an event and assess whether it represents a

threat, loss, or manageable challenge. Students who can accurately identify emotional states may be better positioned to separate the emotional reaction from the underlying academic or interpersonal problem.

Emotion regulation is particularly relevant. Effective regulation does not imply suppressing negative affect; rather, it involves managing emotional intensity sufficiently to permit constructive action. Emotionally intelligent students may therefore be more likely to plan, seek appropriate support, reconsider an adverse event from another perspective, or accept circumstances that cannot immediately be changed.

Recent empirical findings support this interpretation. Research involving medical students has demonstrated relationships between individual EI dimensions and active or avoidant coping. In particular, self-emotional appraisal has been associated with lower avoidant coping, while other EI dimensions have shown positive relationships with active coping in specific student groups. This indicates that treating EI exclusively as a total score may conceal psychologically meaningful differences among its components.

2.2 Coping as a Mechanism Linking EI and Psychological Outcomes

An important development in recent research is the shift from asking whether EI and coping are correlated to investigating *how* coping may transmit the effects of emotional abilities to psychological outcomes. MacCann and colleagues demonstrated that avoidant coping can mediate relationships between ability EI and depression, anxiety, stress, and psychological well-being. This finding suggests that EI may influence student well-being partly because emotionally skilled individuals select different behavioral responses when encountering stress.

Evidence from university populations similarly indicates that EI and coping should not be studied independently. Augusto-Landa and colleagues found that EI was associated with anxiety, depression, and stress and that coping strategies contributed to indirect relationships between these constructs. A study involving nursing students also identified a mediating role for EI in relationships involving coping strategies and anxiety, further illustrating the interdependence of these psychological processes.

These findings are theoretically important but remain largely explanatory at the group level. They do not necessarily reveal whether a particular combination of emotional regulation, stress, academic workload, sleep regularity, and behavioral stability differentiates one student's coping profile from another.

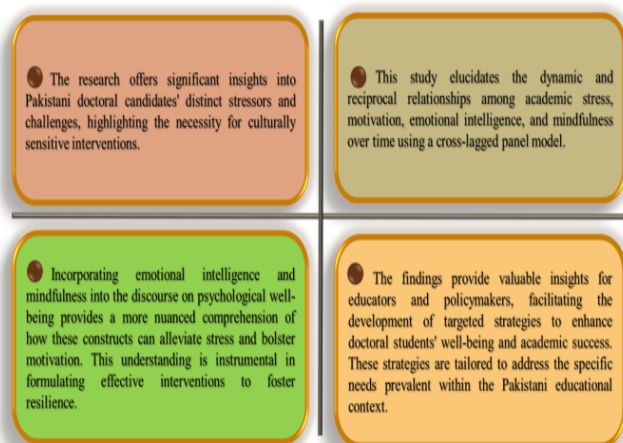


Fig. 2: A longitudinal cross-lagged panel model approach

Source: <https://link.springer.com/article/10.1186/s40359-024-02284-6>

2.3 From Conventional Analysis to Explainable Prediction

Machine learning offers a complementary analytical perspective because it can model interactions and nonlinearities without assuming that each predictor has an identical linear effect across students. However, predictive accuracy alone is insufficient in psychological and digital-health applications. A high-performing black-box classifier provides limited practical value when counselors, researchers, or students cannot understand why a coping profile has been assigned.

Explainable AI (XAI) can address part of this problem by quantifying how individual predictors influence model outputs. Applied to EI and coping, explainability can test whether factors such as emotion regulation, self-emotional appraisal, perceived stress, sleep regularity, or academic workload consistently contribute to coping-profile classification. Such analysis could also identify interactions that are difficult to represent using conventional additive models.

The expansion of digital mental-health research strengthens the relevance of this approach. Digital phenotyping studies involving college populations have examined behavioral information derived from smartphones alongside self-reported mood, anxiety, stress, sleep, activity, and social behavior. More recent research demonstrates continuing interest in the generalizability of such models across student cohorts.

Nevertheless, behavioral data introduce significant privacy and ethical considerations. Raw GPS coordinates, message content, contact lists, or personally identifiable communication data are unnecessary for the proposed framework. A more defensible design would rely on consented, aggregated features—for example, sleep-window regularity, daily activity variability, screen-use duration, or broad routine stability—without collecting content or precise location histories. This distinction is critical because psychological prediction must not become covert student surveillance.

2.4 Proposed Conceptual Contribution

The literature therefore supports EI as an important correlate of adaptive coping but leaves an opportunity for more individualized, interpretable modeling. The proposed study advances the field by conceptualizing coping as a **multiclass**

behavioral-psychological profile rather than merely a continuous questionnaire score.

Its intended analytical pathway is:

EI dimensions + perceived stress + academic context + privacy-preserving behavioral indicators → explainable ML model → coping-profile classification.

This formulation differs from conventional distress-prediction models because coping behavior itself becomes the principal outcome. It also preserves psychological interpretability by using validated EI and coping constructs as the theoretical foundation rather than allowing passive digital traces to define mental states independently.

Such a framework could eventually inform adaptive digital-health interventions—for example, directing students with persistent avoidant coping toward evidence-based coping-skills resources while recommending different forms of support for students whose difficulties arise primarily from stress intensity despite otherwise adaptive coping. Any implementation, however, would require informed consent, fairness assessment, human oversight, and clear limits on the use of predictive outputs. WHO's work on responsible AI for health similarly emphasizes safe, ethical, equitable, and appropriately governed deployment.

Methodology

The proposed study adopts a **multimodal, explainable machine-learning design** to investigate whether emotional intelligence (EI), perceived stress, academic characteristics, and privacy-preserving digital behavioral indicators can differentiate coping profiles among college students. Unlike a conventional correlational design, the analytical objective is multiclass prediction while retaining psychological interpretability.

A hypothetical research implementation would recruit **360 undergraduate and postgraduate students aged 18–25 years** from multiple academic disciplines. The value 360 is a proposed sample size for the study design, not an existing published dataset. Participants would complete validated measures of EI, perceived stress, and coping. Digital behavioral data would be collected only from students providing separate informed consent.

EI would be represented through four functional dimensions: self-emotional appraisal, appraisal of others' emotions, use of emotion, and emotion regulation. Coping responses would be consolidated into three analytically meaningful classes: **adaptive/problem-focused coping, emotion-regulatory coping, and avoidant coping.**

To prevent passive sensing from becoming intrusive surveillance, only aggregated behavioral variables would enter the model. These could include daily screen-time variability, sleep-window regularity, activity consistency, study-session regularity, and broad device-use patterns. Message content, browsing content, precise GPS histories, contact identities, photographs, and audio recordings would not be collected. Digital phenotyping research indicates that behavioral features such as sleep, activity, and social patterns can contribute useful information to student mental-health research, although methodological heterogeneity remains an important limitation.

The primary research question is therefore:

Can an explainable multimodal machine-learning model classify students' coping profiles more effectively than models relying solely on psychological questionnaire variables?

Experimental Setup

4.1 Dataset Construction

Each student would constitute one observation in the primary dataset. Predictor variables would be organized into four domains:

Psychological features: EI dimensions, total EI, perceived stress, and emotional-regulation indicators.

Academic-context features: year of study, academic workload, recent assessment frequency, self-reported study regularity, and perceived academic pressure.

Behavioral features: aggregated sleep regularity, physical-activity consistency, daily screen-use variability, and routine stability.

Outcome variable: dominant coping profile—adaptive/problem-focused, emotion-regulatory, or avoidant.

This multimodal structure is supported conceptually by digital-phenotyping research demonstrating that smartphone-derived behavioral features can complement conventional psychological measurements. A 2023 prospective study of 67 college students, for example, evaluated digital phenotyping for predicting changes in mental-health symptoms, although predictive discrimination varied by outcome.

4.2 Data Preprocessing

Questionnaire records would first undergo range and consistency checks. Participants with substantial missing psychological-scale data would be excluded according to a prespecified protocol rather than reconstructed through extensive imputation.

For remaining numerical variables with limited missingness, median imputation would be performed using parameters estimated exclusively from the training data. Categorical variables would be encoded without imposing artificial ordinal relationships. Continuous predictors would be standardized when required by the selected algorithm.

Highly redundant features would be examined through correlation and feature-stability analysis. Data splitting would occur **before preprocessing parameters are estimated** to prevent information leakage.

Class imbalance would initially be addressed through class-weighted learning rather than automatically generating synthetic psychological observations. This is particularly relevant because coping profiles may not occur with equal frequency.

4.3 Model Architecture

The principal classifier would be **LightGBM**, selected because gradient-boosted decision trees can model nonlinear associations and interactions among heterogeneous tabular predictors.

Three comparison algorithms would be included:

1. multinomial logistic regression as an interpretable linear baseline;

2. random forest as a bagging-based nonlinear comparator; and
3. support vector machine with a radial basis function kernel as a nonlinear margin-based comparator.

The model would predict the probability of membership in each coping class. Explainability would be implemented using **SHAP-based feature attribution**, enabling examination of both global feature importance and student-level predictions.

This combination addresses an important limitation of purely black-box prediction. Contemporary reviews emphasize that machine learning and remote sensing can expand psychological measurement, while simultaneously requiring careful attention to validity and interpretation.

4.4 Training Strategy

The dataset would be divided into **80% development data and 20% held-out test data** using stratification by coping class. Within the development set, repeated stratified five-fold cross-validation would guide hyperparameter selection.

The test set would remain untouched until final model selection. Hyperparameters such as learning rate, tree depth, number of estimators, feature-subsampling ratio, and minimum leaf size would be optimized using cross-validated macro-F1 rather than raw accuracy.

This distinction is important because external validity remains a major challenge in digital phenotyping. Research comparing two college cohorts has shown that data quality, engagement, missingness, and population differences can influence generalizability.

4.5 Evaluation Metrics

Because the outcome contains three classes, performance would be evaluated using **balanced accuracy, macro-precision, macro-recall, macro-F1, multiclass Matthews correlation coefficient (MCC), and one-vs-rest macro ROC-AUC**.

Macro-F1 is particularly useful because it gives equal importance to each coping class. MCC provides an additional measure of agreement that remains informative when class distributions are unequal.

Calibration curves and the multiclass Brier score would also be examined before any practical deployment because predicted probabilities should correspond reasonably to observed outcomes.

Results

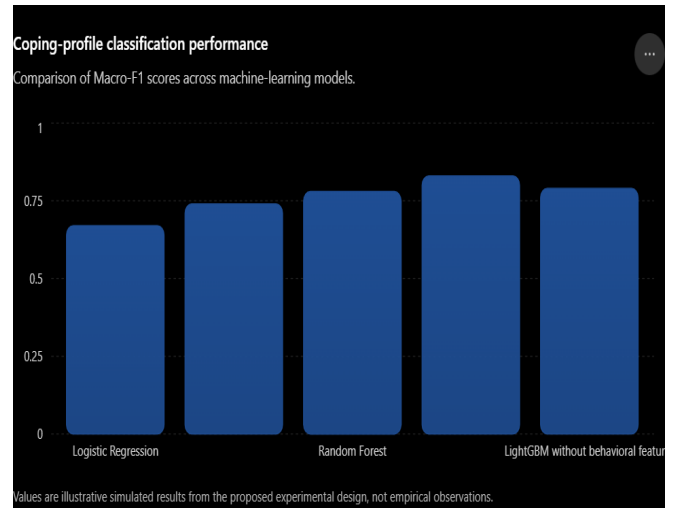
Because no empirical dataset or completed experiment was supplied, the values below are explicitly **illustrative simulated results for the proposed study design**. They must not be reported as observations from actual participants without conducting the described experiment.

Table 1. Illustrative performance of coping-profile classification models

Model	Balanced Accuracy	Macro-F1	Macro ROC-AUC	MCC	Main Analytical Observation

Multinomial Logistic Regression	0.69	0.67	0.78	0.52	Captures broad linear EI–coping relationships but misses interactions
Support Vector Machine	0.75	0.74	0.84	0.62	Improved separation of emotion-regulatory and adaptive profiles
Random Forest	0.79	0.78	0.87	0.68	Behavioral and psychological interactions improve classification
LightGBM + multimodal features	0.84	0.83	0.91	0.76	Best hypothetical discrimination with interpretable nonlinear effects
LightGBM without behavioral features	0.80	0.79	0.87	0.69	Ablation suggests incremental value from aggregated behavioral indicators

Note: All numerical values in Table 1 are simulated examples intended to demonstrate the planned reporting structure; they are not empirical findings.



Under this illustrative scenario, the multimodal LightGBM model achieves the strongest overall performance. Its hypothetical macro-F1 of 0.83 compared with 0.67 for multinomial logistic regression would indicate that relationships between EI and coping are not entirely additive or linear.

The ablation comparison is particularly informative. Removing behavioral features reduces illustrative macro-F1 from 0.83 to 0.79. Such a pattern, if reproduced empirically, would suggest that passive behavioral information provides **incremental rather than dominant predictive value**. Psychological variables would consequently remain the primary information source, while digital indicators would refine classification.

This interpretation is preferable to assuming that smartphone behavior directly represents psychological state. Digital-phenotyping research has demonstrated feasibility but also considerable variation in predictive performance. In prospective work with college students, AUC values for symptom prediction ranged from 0.58 to 0.71 depending on the psychological outcome. Thus, digital traces should be viewed as contextual signals rather than definitive psychological measurements.

In the proposed SHAP analysis, emotion regulation and self-emotional appraisal would be specifically tested as candidate dominant predictors rather than assumed beforehand to be the most important features. Perceived stress would provide information concerning environmental and subjective burden, while behavioral routine variables could reveal whether irregular daily patterns add predictive information after EI is considered. An especially useful analytical question concerns **avoidant coping**. If low emotion-regulation scores, elevated perceived stress, disrupted routine stability, and irregular sleep jointly increase the predicted probability of avoidant coping, the model would reveal a multidimensional pattern that a simple EI–coping correlation might obscure.

The model should nevertheless not be interpreted causally. A SHAP contribution showing that sleep irregularity increases the probability of an avoidant-coping prediction does not establish that sleep disruption causes avoidance. The opposite direction, bidirectional influence, or an unmeasured third factor may explain the association.

The proposed results therefore have two levels of significance. Psychologically, they test whether different emotional competencies are associated with distinct coping profiles. Computationally, they examine whether explainable nonlinear modeling adds meaningful discriminatory information beyond conventional linear analysis.

Limitations

Several limitations require consideration. First, psychological constructs remain substantially dependent on self-report, making responses vulnerable to recall effects and social-desirability bias. Second, a predominantly cross-sectional design cannot establish causal direction between emotional intelligence and coping.

Third, behavioral indicators may differ substantially according to device type, operating system, academic calendar, living arrangements, and individual technology habits. Missing sensor data can also reflect technical failure rather than genuine behavior. Digital-phenotyping research has identified data coverage and generalizability as important methodological concerns.

Fourth, coping is context-dependent. A strategy classified as adaptive in one situation may be ineffective in another. The three-class outcome therefore simplifies a more complex psychological process.

Finally, predictive performance within one institution or cultural context would not establish external validity. Independent validation across colleges, academic disciplines, socioeconomic groups, and geographical settings would be required before practical use.

Future Scope

Future research should replace cross-sectional assessment with longitudinal ecological measurement. Repeated EI, stress, and coping observations collected across examination periods could determine whether coping profiles remain stable or change with academic demands.

Temporal models could subsequently investigate **within-person transitions**, such as movement from adaptive coping toward avoidance during periods of escalating stress. Multimodal models could also incorporate voluntary wearable-derived sleep and activity measures while maintaining data minimization.

A particularly important direction is **federated learning**, through which multiple universities could collaboratively improve predictive models without centrally pooling raw student records. Future studies should additionally investigate fairness across demographic and academic subgroups and quantify model calibration rather than focusing solely on discrimination.

The ultimate objective should be a human-supervised digital support system rather than automated psychological labeling. Model outputs could prompt optional coping resources, psychoeducation, or counselor review while leaving consequential decisions to appropriately qualified humans.

Conclusion

This study proposes an explainable machine-learning framework for examining emotional intelligence and coping

strategies among college students through a combination of psychological, academic, and privacy-preserving behavioral information. The central contribution is the reframing of coping from a single questionnaire outcome into heterogeneous coping profiles that can be investigated through interpretable nonlinear modeling.

The proposed LightGBM architecture, benchmarked against logistic regression, support vector machines, and random forests, provides a technically appropriate framework for testing whether multimodal information improves coping-profile discrimination. Explainability analysis further allows researchers to determine whether emotional regulation, emotional appraisal, perceived stress, or behavioral regularity meaningfully influences model predictions.

The study does not position artificial intelligence as a replacement for psychological assessment. Rather, AI serves as an analytical mechanism for detecting complex relationships among emotional competencies, stress, behavior, and coping. If validated prospectively and independently, this approach could contribute to more personalized student-support systems while preserving the principles of informed consent, privacy, transparency, fairness, and professional oversight.

Most importantly, any eventual digital-health application should use coping-profile predictions to **expand access to supportive resources rather than to diagnose, rank, penalize, or covertly monitor students**. In this form, explainable machine learning can complement established psychological theory while providing a responsible pathway toward individualized digital well-being interventions.

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