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Emotional development in postgraduate students through the application of machine learning

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Introduction: Emotional development is a central component in the academic formation and well-being of students, particularly at the postgraduate level, where academic, professional, and personal demands are considerable. This study aimed to analyze the emotional development of postgraduate students at the State University of Milagro through the application of machine learning.
Methodology: The approach was quantitative, with a non-experimental and cross-sectional design. The TMMS-24 scale was employed to measure perceived emotional intelligence across dimensions such as attention, clarity, and emotional regulation. The sample, composed of 1,412 participants, was analyzed using various machine learning models, including AdaBoost, Random Forest, SVM, logistic regression, and KNN, evaluated through metrics such as AUC, accuracy, and recall.
Results: AdaBoost and Random Forest were the most effective models, with AUC values of 0.996 and 0.972, respectively. AdaBoost achieved the highest F1-score (0.974), while Random Forest reached perfect recall (1.000) in students over 30. Both models showed strong predictive capacity across age groups. In contrast, logistic regression and SVM displayed limited performance, with AUCs below 0.56. These results confirm the superiority of ensemble methods in modeling emotional patterns.
Conclusion: It is concluded that ensemble algorithms such as AdaBoost and Random Forest are effective tools for analyzing emotions in educational contexts. However, the study's scope was restricted to an academic setting. As a practical implication, the findings support the integration of emotionally focused interventions in higher education programs to enhance students' emotional development according to their specific needs.

KEYWORDS

machine learning, emotional intelligence, higher education, ensemble algorithms, predictive analysis

1 Introduction

Emotional development has been widely recognized as an essential component of academic training, particularly in higher education (Cristóvão et al., 2023; Devis-Rozental, 2018; Moreira-Choez et al., 2023). Studies such as that of Pietarinen et al. (2014) on emotional intelligence have emphasized the relationship between emotional competencies and academic success, as well as their influence on students' mental health and overall wellbeing. In educational contexts, the ability for emotional self-regulation has proven crucial for managing academic stress, enhancing decision-making, and fostering positive social interaction critical aspects in the training of highly skilled professionals (Cevallos Zambrano et al., 2023; Moscoso Bernal and Castro López, 2022).

At the postgraduate level, emotional challenges take on a more complex dimension due to the inherent demands of this educational stage, such as the simultaneous management of academic, work-related, and personal responsibilities. Previous research has identified that postgraduate students experience higher levels of stress and anxiety compared to undergraduate students, which may adversely affect their academic performance and overall wellbeing (Mofatteh, 2021; Wyatt and Oswalt, 2013). Nevertheless, educational programs have shown limitations in incorporating effective strategies for strengthening emotional competencies, highlighting the need for more innovative and adaptive approaches.

Technological advancements have opened new possibilities to address these needs, especially through tools such as machine learning (ML) (Albreiki et al., 2021; Boutaba et al., 2018; Wang et al., 2018). In various studies, ML has proven effective in personalizing educational interventions and predicting student behaviors and needs (Albreiki et al., 2021; Al-Shabandar et al., 2019). However, its specific application to emotional development remains in early stages, with limited empirical evidence supporting its effectiveness in postgraduate contexts (Alzoubi, 2021; Ifenthaler and Widanapathirana, 2014).

Despite considerable advancements in the field of emotional intelligence, traditional approaches to its development in higher education continue to present significant limitations. Most notably, they often rely on static, one-size-fits-all methodologies that fail to address the diversity of emotional profiles and learning contexts encountered among postgraduate students (Chopra and Kanji, 2010). These conventional strategies typically lack the flexibility and responsiveness required to adapt interventions in real time, thereby limiting their long-term impact and effectiveness. In contrast, machine learning (ML) tools have shown notable success in various educational domains by facilitating adaptive systems, predictive modeling, and the personalization of learning processes (Almalawi et al., 2024). While these tools have been applied to predict academic performance, identify at-risk students, and personalize instruction, their specific application to emotional development particularly at the postgraduate level remains largely unexplored.

This gap is especially relevant given the complex emotional challenges that characterize postgraduate education, such as balancing academic pressure with professional and personal demands. The absence of scalable, data-driven strategies to support emotional growth in this population represents a critical shortfall in current educational practices. Addressing this issue is not only theoretically significant but also practically necessary to advance holistic educational models that integrate emotional well-being as a core component of academic and professional success. Furthermore, the application of ML offers an opportunity to generate novel methodological approaches capable of capturing nuanced emotional patterns and informing evidence-based interventions tailored to the evolving needs of postgraduate learners (Sestino and De Mauro, 2022; Thieme et al., 2020). Bridging this gap can contribute to the development of more equitable and emotionally responsive educational ecosystems in higher education.

In this context, the following research question is posed: How does the application of machine learning algorithms contribute to the emotional development of postgraduate students at the State University of Milagro? Based on this question, the following hypotheses are formulated, aimed at exploring the effectiveness of different machine learning models and the relevance of emotional intelligence dimensions according to the participants' age:

> *H1*: The Random Forest and AdaBoost algorithms exhibit higher predictive accuracy in postgraduate students both over and under 30 years of age.
>
> *H2*: Logistic regression and support vector machine (SVM) models show significantly lower performance in predicting emotional development.
>
> *H3*: The emotional repair dimension is the most important in the predictions generated by the applied models according to the precision metric.
>
> *H4*: The predictive impact of emotional variables varies by age. Emotional attention predominates in individuals under 30, while emotional repair shows a consistent influence across both groups.

To address the research question and test the proposed hypotheses, the general objective of the study was to analyze the emotional development of postgraduate students at the State University of Milagro through the application of machine learning algorithms, in order to identify predictive patterns within the dimensions of emotional intelligence and evaluate the effectiveness of various computational models in classifying and understanding affective variables associated with age and the emotional profile of students.

2 Materials and methods

This study adopted a quantitative approach, characterized by its ability to provide measurable and objective data that support the rigorous analysis of the investigated variables. A non-experimental, cross-sectional design was implemented, allowing for data collection

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at a single point in time. This design enabled the observation of existing relationships between the application of machine learning algorithms and emotional development in postgraduate students. Suitable for descriptive and correlational studies, this design provided a solid foundation for identifying relevant patterns without intervening in the natural conditions of the participants.

The descriptive-explanatory level of the study focused, on one hand, on describing the fundamental characteristics of the variables, such as the level of perceived emotional development and the performance of the applied machine learning models. On the other hand, it sought to explain the potential interactions between these variables, contributing to the understanding of how advanced technologies may influence key emotional competencies such as attention, clarity, and emotional regulation. This approach allowed for the generation of knowledge that goes beyond mere description, establishing significant relationships between the factors studied.

Table 1 presents the distribution of the surveyed population according to the sociodemographic variables of sex and age. This characterization allows for contextualizing the study sample and assessing the representativeness of the different age and gender groups.

As shown in Table 1, the study population consisted of postgraduate students from various higher education institutions in Ecuador, encompassing a broad disciplinary spectrum and diverse academic profiles. A total of 1,412 individuals participated, of whom 84.6% were women and 15.4% were men. Regarding age distribution, 10.9% were between 21 and 30 years old, 42.6% between 31 and 40, 32.7% between 41 and 50, and 13.8% were over 50. This demographic heterogeneity contributed to the analytical strength of the study by allowing the identification of differentiated patterns across stages of academic and professional development.

The marked predominance of women corresponds to an observable trend in access to postgraduate education, particularly in fields where female participation has traditionally been higher, such as social sciences, education, and health. This configuration does not represent a methodological bias but rather an accurate reflection of the institutional context in which the research was conducted. Therefore, the potential influence of gender on the perception and assessment of the evaluated content was acknowledged in the interpretation of the findings. This consideration ensures proper contextualization of the results and supports the internal validity of the study based on its actual sample composition.

TABLE 1 Population distribution.

Category	Frequency	Percentage
Sex		
Male	218	15,4%
Female	1,194	84,6%
Total sex	1,412	100,0%
Age		
21–30 years	154	10,9%
31–40 years	601	42,6%
41–50 years	462	32,7%
Over 50 years	195	13,8%
Total age	1,412	100,0%

To assess perceived emotional intelligence, the Trait Meta-Mood Scale (TMMS-24) was employed, using its Spanish-adapted version (Fernández-Berrocal et al., 2004). This instrument measures three key dimensions emotional attention, emotional clarity, and emotional repair and has demonstrated high internal consistency, with Cronbach's alpha coefficients exceeding 0.85 in all subscales. The survey was deployed digitally via Google Forms and distributed through institutional and academic WhatsApp channels. Before responding to the instrument, participants were required to review and accept a digitally embedded informed consent form, presented at the beginning of the questionnaire. This form outlined the study's purpose, ensured data confidentiality, and emphasized the voluntary nature of participation, thereby adhering to essential ethical principles.

For analytical modeling, the age variable was recoded into a binary format (0 = under 30 years; 1 = over 30 years). This transformation was grounded in psychological literature indicating significant cognitive and emotional developmental differences around the age of 30. The binary classification facilitated the implementation of supervised machine learning algorithms designed to predict class membership and to explore how emotional competencies vary across age thresholds with statistical clarity and interpretability.

The selection of machine learning models was based on their proven performance in the analysis of high-dimensional, non-linear, and heterogeneous educational and psychological data. Ensemble models such as AdaBoost and Random Forest were prioritized due to their ability to combine multiple decision trees, reduce bias and variance, and improve classification performance—particularly in contexts involving complex interactions between predictors. These algorithms have consistently demonstrated superior predictive accuracy and robustness against overfitting in comparative studies.

In parallel, baseline classifiers such as logistic regression, support vector machines (SVM), and k-nearest neighbors (KNN) were included to provide a performance benchmark and assess the added value of ensemble methods. Logistic regression was selected for its interpretability in linear contexts, while SVM and KNN allowed exploration of boundary-based and distance-based classification behaviors. Model performance was evaluated using established metrics, including Area Under the ROC Curve (AUC), classification accuracy, recall, F1-score, and the Matthews Correlation Coefficient (MCC), offering a comprehensive assessment of predictive validity.

Additionally, SHAP (SHapley Additive Explanations) values were calculated to quantify the relative contribution of each emotional intelligence dimension to the predictive outputs. This explainability component enhanced the transparency of the modeling process and facilitated an evidence-based interpretation of the emotional variables most associated with age group classification. The integration of these analytical strategies supported a robust exploration of emotional development using machine learning in postgraduate academic settings.

Figure 1 illustrates the workflow used to analyze emotional development in postgraduate students through five machine learning algorithms: kNN, Random Forest, AdaBoost, Logistic Regression, and SVM. The models were trained using a sample of 1,300 observations, representing 85.25% of the total population (1,412 students), which allowed for a portion of the dataset to be reserved for testing. This approach aligns with best practices in supervised machine learning, ensuring cross-validation and model generalization while reducing the risk of overfitting and enhancing the robustness of the results.

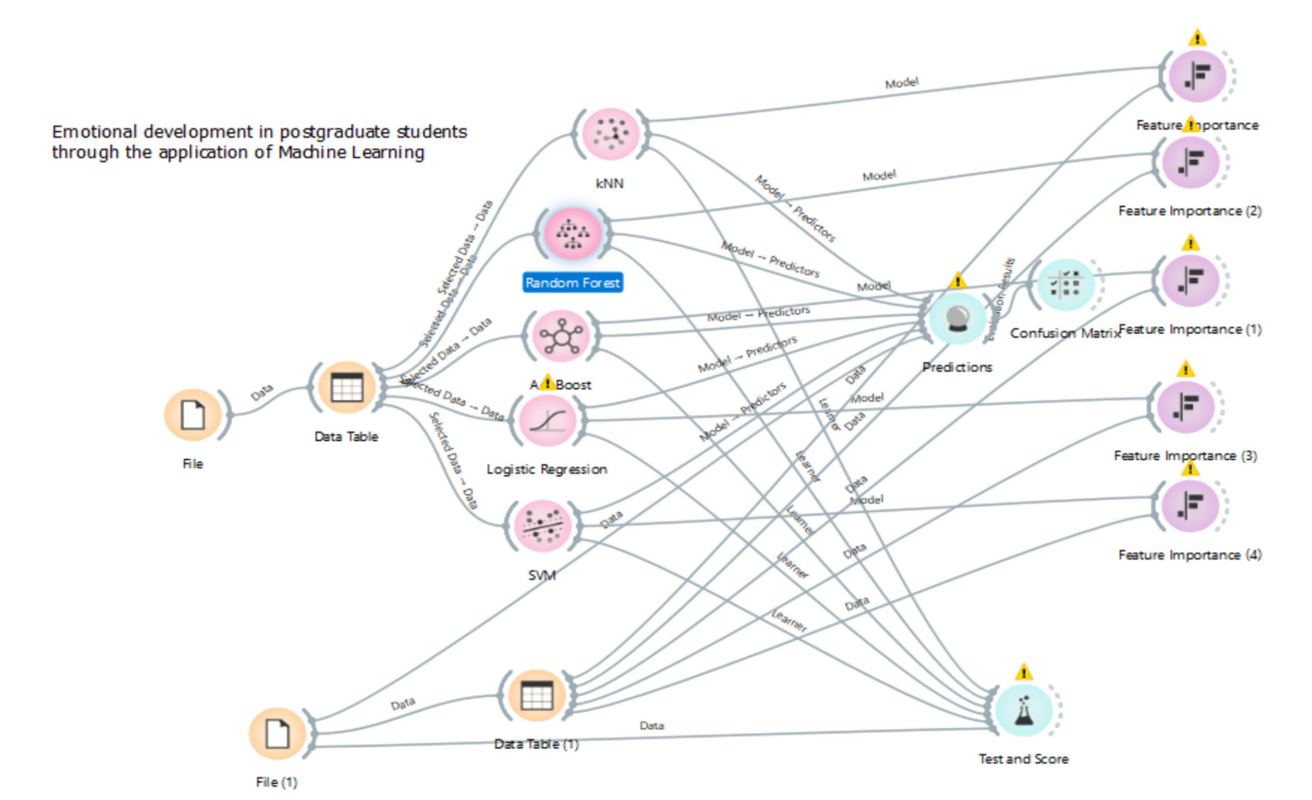

FIGURE 1
Workflow for emotion prediction in postgraduate students using machine learning models.

The analytical flow included interpretation modules such as the confusion matrix and feature importance indicators, which made it possible to identify the most influential predictors of emotional development. The inclusion of the "Test and Score" node enabled model performance evaluation using key classification metrics, supporting a rigorous comparison across techniques. Altogether, this multi-algorithmic approach provides a solid empirical foundation for understanding and addressing emotional factors in university settings. The collected information was processed using machine learning tools such as Random Forest, AdaBoost, SVM, and logistic regression, in order to evaluate model effectiveness through metrics like the confusion matrix and ROC analysis. For the mathematical and statistical simulation based on Artificial Intelligence, the Orange Data Mining software (Orange version 3.38.1) was used. This is an advanced visualization tool that enables the modeling and prediction of exogenous variables as a function of the endogenous variable (Forero-Corba and Negre Bennasar, 2024).

2.1 Ethical considerations

The present investigation involves human participants and therefore complies with all the fundamental ethical standards applicable to studies in human subjects (national standards and institutional policy). All participants gave informed consent to participate in the study, and they were informed about the purpose of the study, the procedures involved, the risks and benefits, if any, and their rights of voluntary participation and for withdrawal at any time without penalties or negative consequences. To protect privacy and freedom, strong anonymization of all personal information was made.

This study was authorized by the Graduate School ethical committee, which supervises moral considerations in academic research. In order to ensure scientific integrity and transparency in the reporting of the results, formal methodological specifications were followed to allow other scholars to replicate the research. This model increases the internal and external validity of results by permitting similar setting comparisons. Throughout the process of data gathering, summarization, and analysis, standard procedures were followed to minimize bias and ensure an impartial and non-subjective interpretation of results.

3 Results and discussion

This section analyzes the results derived from the application of five machine learning models to evaluate their predictive capacity in the emotional development of postgraduate students at the State University of Milagro. Key metrics were assessed, including Area Under the Curve (AUC), Accuracy (CA), F1-Score, Recall (Sensitivity), and the Matthews Correlation Coefficient (MCC). Within this context, differences between age groups (under and over 30 years old) and the general population were highlighted.

Table 2 presents the performance metrics of the applied machine learning models and reveals that AdaBoost and Random Forest stand out as the most effective in classifying emotional patterns in postgraduate students, regardless of age group. The analysis confirms

TABLE 2 Estimated coefficients of models for the development of emotions in postgraduate students, considering age.

Group/age of postgraduate students	Model	AUC	CA	F1	PREC	Recall	MCC
Global	KNN	0.848	0.893	0.851	0.873	0.893	0.189
	Random forest	0.972	0.916	0.893	0.923	0.916	0.474
	AdaBoost	0.996	0.975	0.974	0.974	0.975	0.867
	Logistic regression	0.560	0.499	0.807	0.807	0.499	0.015
	SVM	0.493	0.852	0.804	0.804	0.852	0.008
Under 30 years	KNN	0.848	0.893	0.117	0.700	0.064	0.189
	Random forest	0.979	0.916	0.394	1.000	0.245	0.474
	AdaBoost	0.996	0.975	0.878	0.947	0.818	0.867
	Logistic regression	0.560	0.499	0.190	0.116	0.527	0.015
	SVM	0.493	0.852	0.075	0.122	0.055	0.008
Over 30 years	KNN	0.848	0.893	0.943	0.895	0.997	0.189
	Random forest	0.972	0.916	0.955	0.914	1.000	0.474
	AdaBoost	0.996	0.975	0.986	0.978	0.994	0.867
	Logistic regression	0.560	0.499	0.638	0.894	0.496	0.015
	SVM	0.493	0.852	0.919	0.890	0.951	0.008

AUC, area under the curve; CA, classification accuracy; F1, F1-score; PREC, precision; recall, sensitivity; MCC, Matthews Correlation Coefficient; KNN, k-nearest neighbors; SVM, support vector machine.

that both models consistently achieve superior values in terms of precision, recall, and area under the curve (AUC), highlighting their predictive robustness. These results are consistent with previous studies that emphasize the adaptability and effectiveness of ensemble algorithms, particularly in educational and psychological contexts, where relationships among variables tend to be complex and non-linear (Madroñal et al., 2025; Tang et al., 2024).

Moreover, AdaBoost emerged as the most robust model, distinguished by its capacity to handle complex and noisy data. Studies such as those by Hussain and Zaidi (2024) have emphasized that this algorithm efficiently combines weak learners, substantially enhancing its predictive performance. Its high sensitivity in both the overall group and the over-30 group underscores its ability to minimize omissions, a critical aspect in research related to human emotions. Random Forest, in turn, demonstrated competitive performance, particularly within the over-30 age group, where it achieved perfect sensitivity. This result underscores its ability to handle large volumes of data and variables with complex interactions. These characteristics make it a robust tool, as noted by Pudlo et al. (2016), who highlighted its stability against overfitting.

In contrast, Logistic Regression and SVM exhibited significant limitations, revealing that their capacity to capture nonlinear relationships is insufficient in this context. Logistic regression, more appropriate for simple and linear associations, proved less effective with emotional data, a finding consistent with the studies by Kumar and Chong (2018). Similarly, SVM's performance was limited, aligning with research indicating its inefficiency in classifying high-dimensional data with complex features (Erfani et al., 2016; Zhang et al., 2019).

Figure 2 displays the contribution of three emotional variables emotional attention, emotional clarity, and emotional reparation to the precision of five distinct machine learning models. The decrease in precision (Decrease in Prec) observed when each variable is permuted serves as an indicator of its predictive relevance. The analysis was performed using 11 permutations per model. The highlighted bars identify the most influential emotional dimension within each algorithm, offering a comparative view of how different emotional traits contribute to predictive accuracy in the context of postgraduate students' emotional development.

The results presented in Figure 2 reveal notable differences in the relative importance of emotional variables Attention, Clarity, and Reparation across five predictive models. Emotional Attention emerges as the most influential variable in the majority of algorithms, including Logistic Regression, SVM, and Random Forest, while Emotional Clarity dominates in the kNN model, and Emotional Reparation stands out in AdaBoost. This variability underscores the multidimensional nature of emotional development in postgraduate students and the need to consider algorithmic differences when interpreting feature relevance. The prominence of Emotional Attention aligns with literature emphasizing its role in enhancing self-awareness and promoting adaptive emotional responses (Salovey and Mayer, 1990). Notably, Emotional Reparation displays a higher impact in AdaBoost, particularly among older participants, reinforcing findings from prior research that associate this construct with mature emotional regulation strategies (Peña-Sarrionandia et al., 2015; Quoidbach et al., 2015).

Furthermore, ensemble models such as AdaBoost and Random Forest demonstrate superior performance in capturing emotional complexity, as evidenced by their more refined distribution of feature importance. These models leverage decision tree architectures capable of managing non-linear interactions and multidimensional data structures. The robustness of AdaBoost, in particular, has been previously validated in contexts involving emotional data, showing high precision and discriminative power through elevated AUC values

FIGURE 2
Relative importance of emotional dimensions in prediction models across algorithms.

(Ballings et al., 2015; Jahanbani et al., 2024). In contrast, traditional algorithms such as Logistic Regression and SVM exhibit more constrained feature importance profiles, which correlates with their limited ability to capture non-linear patterns, as also reported by Shanmugasundar et al. (2021). These findings reinforce the strategic advantage of ensemble learning approaches in educational and psychological research, where emotional phenomena often manifest through intricate and dynamic relationships. Supporting evidence confirms that tree-based models are particularly suitable for managing the variability inherent in human behavior and emotions, offering more accurate and context-sensitive predictions (Benzaamia et al., 2024; Biró et al., 2023; Hu et al., 2012; Rane et al., 2024).

The following section presents the results of the SHAP (SHapley Additive exPlanations) value analysis, which enabled the evaluation of the contribution of emotional variables to the model's predictions. Figure 3 displays the individual impact of emotional intelligence dimensions (emotional clarity, emotional attention, and emotional repair) on the model's performance for the group of participants over 30 years old.

In Figure 3, it can be observed that the variables with the greatest impact on the predictions correspond to emotional repair and emotional attention, followed by emotional clarity, whose effect appears more limited. Higher SHAP values indicate that these dimensions play a significant role in the model's output, reinforcing their relevance in emotional assessment. This finding aligns with previous research highlighting emotional repair as a key skill in self-regulation and psychological well-being (Cevallos Zambrano et al., 2023; Inwood and Ferrari, 2018).

The predominance of emotional repair may be explained by its direct relationship with individuals' ability to manage their emotions and reduce the negative impact of adverse experiences. Studies by Moreira-Choez et al. (2023) have pointed out that this skill is essential for promoting emotional balance in both educational and occupational settings. On the other hand, emotional attention also shows a considerable impact, suggesting that awareness of one's own and others' emotions is crucial for understanding the overall emotional context and, consequently, for predicting behaviors.

However, emotional clarity shows a relatively lower impact, which could be attributed to the fact that this dimension may act more as a mediator than a direct predictor. Research such as that by Parke et al. (2015) argues that emotional clarity facilitates the interpretation and management of emotions, but its influence may depend on how it interacts with other emotional dimensions.

The following section presents results that include a SHAP analysis to evaluate the impact of emotional variables on the model's predictions for students under 30 years of age. Figure 4 shows the individual contributions of the emotional intelligence dimensions (emotional repair, emotional attention, and emotional clarity) to the model's performance, highlighting the relative impact of each variable.

Figure 4 shows that, for the group of students under 30 years old, emotional repair remains the variable with the greatest positive impact on predictions, reinforcing its relevance as a key indicator of emotional development. This result is consistent with previous studies that emphasize the importance of this dimension in emotional self-regulation and in managing stressful situations among young populations (de la Fuente et al., 2020; Midkiff et al., 2018; Wang and Saudino, 2011). The predominance of this variable may be explained by the need for effective skills to manage negative emotions during the academic and personal transitions that characterize this stage of life.

Emotional attention also shows a significant impact, although slightly lower than that observed in the over-30 group. This suggests that younger students prioritize the identification of their emotions as

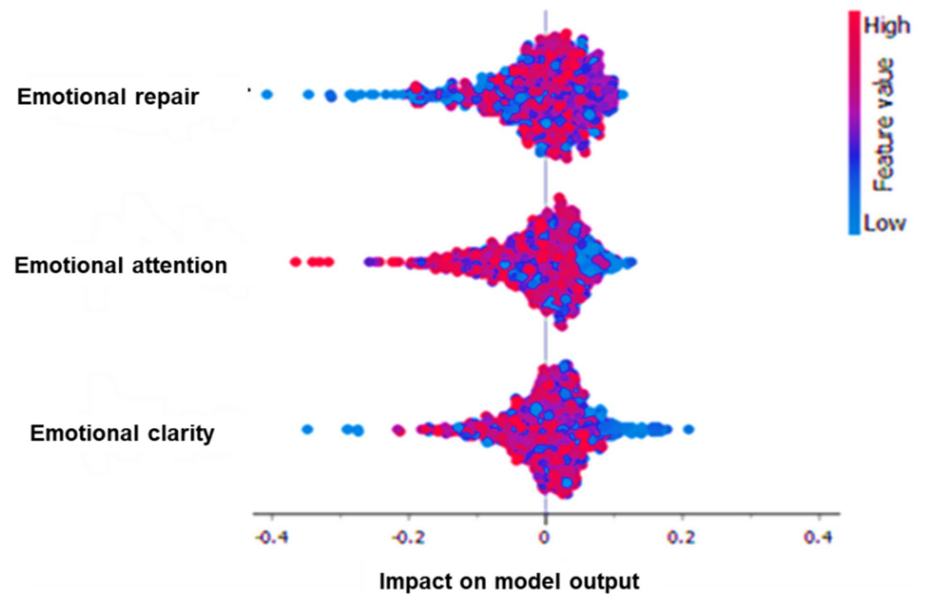

FIGURE 3
SHAP Analysis of the impact of emotional variables on prediction (over 30 years old).

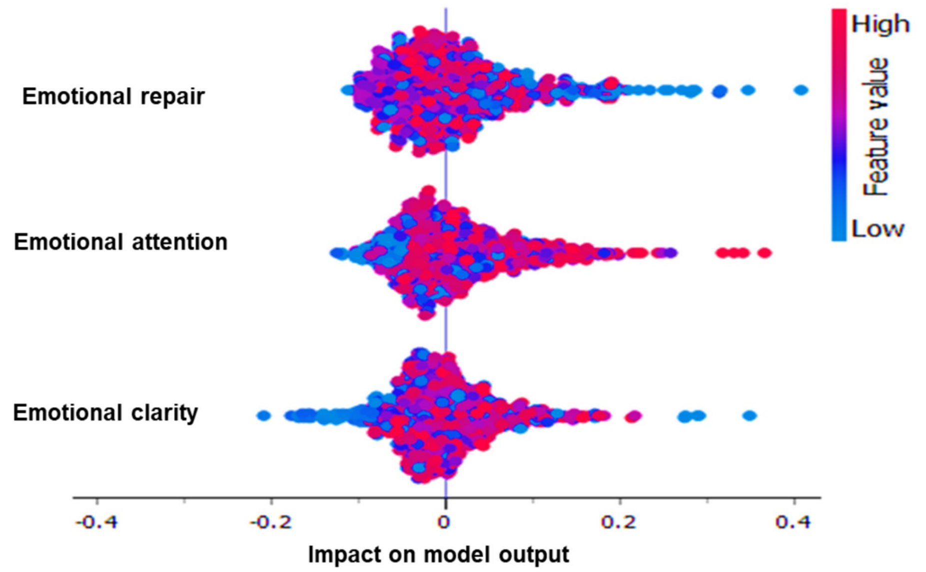

FIGURE 4
SHAP Analysis of the impact of emotional variables on prediction (under 30 years old).

a strategy to understand their emotional states, which aligns with studies that associate this skill with greater emotional awareness during early adulthood (Campbell et al., 2022; Mankus et al., 2016). However, as in the analysis of the older group, emotional clarity presents a lower impact, possibly because this dimension indirectly facilitates emotional processing and functions as a mediator in the use of other emotional competencies.

These findings underscore the importance of designing educational strategies that strengthen emotional repair and attention among young students. Recent studies have emphasized that interventions aimed at enhancing these skills can improve both academic performance and overall well-being (Sverdlik et al., 2018; Upsher et al., 2022). Therefore, integrating these dimensions into educational programs represents a valuable opportunity to address the specific emotional needs of this age group.

The following section, presented in Figure 5, shows a comparison of the impact of emotional intelligence dimensions on model predictions, distinguishing between students under and over 30 years old. This analysis details how emotional repair, emotional attention, and emotional clarity influence the model's outcomes for both groups, highlighting similarities and differences in the relevance of these variables.

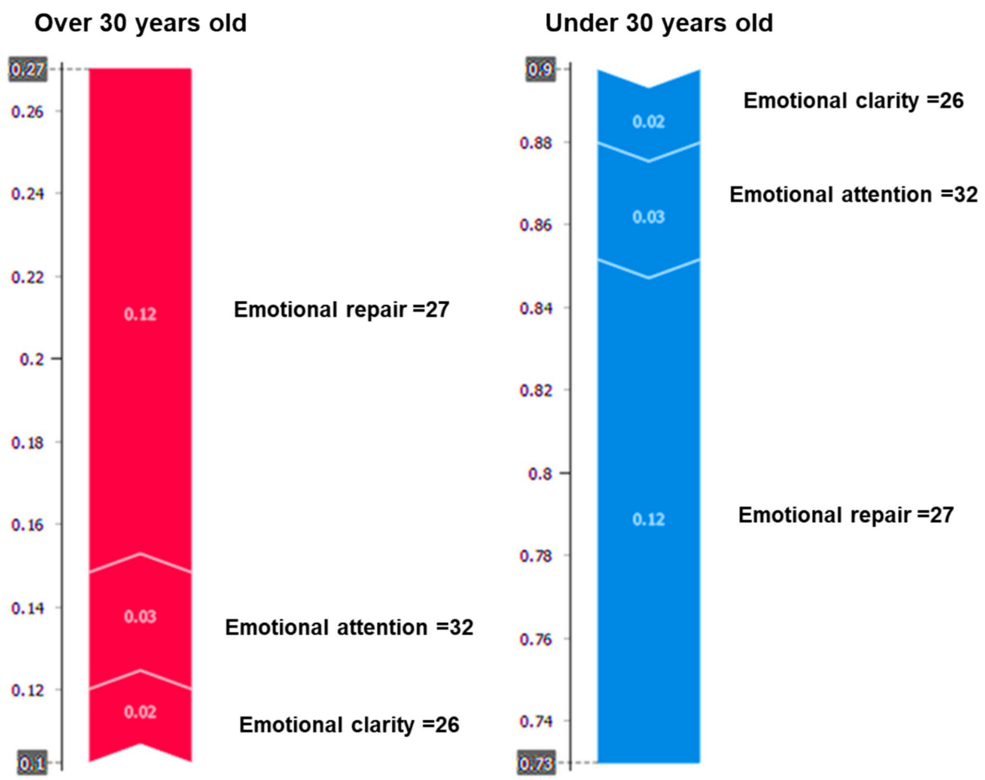

FIGURE 5
Comparison of SHAP prediction analysis between students under and over 30 years old.

Figure 5 presents the results of the feature importance analysis across different machine learning models used to predict emotional development in postgraduate students. The results indicate that, in both age groups, emotional repair is the most influential variable in the prediction models, with a slightly stronger effect observed among students over 30 years old. This underscores the central role of emotional repair in self-regulation processes and aligns with previous studies linking this dimension to the effective management of negative emotions and the preservation of emotional stability (Peña-Sarrionandia et al., 2015; Quoidbach et al., 2015). Its predominance in the older group may reflect the cumulative impact of life experience and the development of more mature emotional strategies over time.

In contrast, emotional attention emerged as the second most impactful variable, with greater relevance among students under 30, suggesting that younger individuals tend to focus more on emotional perception as a means of self-awareness and social understanding an observation consistent with early emotional development literature (Ecclestone, 2011; Hargreaves, 2000; Miller et al., 2006). Although emotional clarity had a lower direct predictive weight, it contributed indirectly by supporting the comprehension and regulation of emotional states. These findings have practical implications for educational interventions: while strategies for older students should prioritize the strengthening of emotional repair capacities, programs targeting younger students may benefit from fostering emotional awareness and reflective practices that enhance their ability to identify and process emotional experiences. Integrating these differentiated approaches into university curricula could promote more adaptive emotional development aligned with the specific needs of each age group.

4 Conclusion

Emotional development represents a fundamental dimension in postgraduate education, as it directly influences academic performance, professional adaptation, and overall wellbeing. This study aimed to examine the applicability of machine learning algorithms in analyzing emotional intelligence dimensions among postgraduate students at the State University of Milagro. The findings confirm the achievement of this objective, offering empirical evidence that supports the integration of computational approaches in educational psychology research.

Among the machine learning models evaluated, ensemble algorithms particularly AdaBoost and Random Forest demonstrated superior predictive performance in identifying emotional patterns. These models outperformed traditional classifiers such as logistic regression and support vector machines, especially in contexts where emotional variables interact in complex and non-linear ways. The high classification accuracy, recall, and interpretability of the ensemble models confirm their suitability for emotion-related data analysis in higher education.

Although the study yielded relevant insights, certain methodological constraints must be acknowledged. The research was conducted within an academic context and relied on a single validated instrument, which may not capture the full spectrum of emotional intelligence. Additionally, the representativeness of the sample, while demographically diverse, may still limit the extrapolation of results to broader populations. These factors suggest the need for cautious interpretation and point toward future avenues for more comprehensive inquiry.

The practical implications of this study are significant. The identification of emotional repair as a key predictor among students over 30, and emotional attention among younger participants, provides a foundation for designing age-sensitive educational interventions. Universities and postgraduate programs can leverage these insights to implement training strategies that strengthen specific emotional competencies according to the developmental and contextual needs of their students.

Future research should consider expanding the emotional variables analyzed, incorporating mixed-method designs that integrate qualitative insights with algorithmic prediction, and exploring longitudinal trajectories of emotional growth. Furthermore, the application of these models in non-academic or intercultural contexts could offer additional perspectives on the generalizability and impact of artificial intelligence in the development of emotional competencies in adult learners.

Data availability statement

The original contributions presented in the study are included in the article/supplementary material, further inquiries can be directed to the corresponding author.

Ethics statement

The studies involving humans were approved by Institutional Review Board (IRB) of Milagro State University. The studies were conducted in accordance with the local legislation and institutional requirements. The participants provided their written informed consent to participate in this study. Written informed consent was obtained from the individual(s) for the publication of any potentially identifiable images or data included in this article.

Author contributions

JM-C: Conceptualization, Formal analysis, Investigation, Methodology, Supervision, Visualization, Writing – original draft, Writing – review & editing. WV-O: Conceptualization, Data curation, Formal analysis, Validation, Writing – original draft, Writing – review & editing. DM-A: Data curation, Formal analysis, Methodology, Software, Writing – original draft, Writing – review & editing. RV-C: Conceptualization, Formal analysis, Investigation, Writing – original draft, Writing – review & editing. ML-R: Conceptualization, Formal analysis, Investigation, Methodology, Writing – original draft, Writing – review & editing. VM-F: Conceptualization, Formal analysis, Investigation, Writing – original draft, Writing – review & editing. ML-P: Data curation, Formal analysis, Methodology, Validation, Writing – original draft, Writing – review & editing. ÁS-G: Data curation, Formal analysis, Methodology, Software, Validation, Visualization, Writing – original draft, Writing – review & editing.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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References

Albreiki, B., Zaki, N., and Alashwal, H. (2021). A systematic literature review of student' performance prediction using machine learning techniques. *Educ. Sci.* 11:552. doi: 10.3390/educsci11090552

Almalawi, A., Soh, B., Li, A., and Samra, H. (2024). Predictive models for educational purposes: a systematic review. *Big Data Cogn. Comput.* 8:187. doi: 10.3390/bdcc8120187

Al-Shabandar, R., Hussain, A. J., Liatsis, P., and Keight, R. (2019). Detecting at-risk students with early interventions using machine learning techniques. *IEEE Access* 7, 149464–149478. doi: 10.1109/ACCESS.2019.2943351

Alzoubi, H. (2021). Predicting the intention to use google glass: A comparative approach using machine learning models and PLS-SEM. *Int. J. Data Netw. Sci.* 5, 311–320. doi: 10.5267/j.ijdns.2021.6.002

Ballings, M., Van den Poel, D., Hespeels, N., and Gryp, R. (2015). Evaluating multiple classifiers for stock price direction prediction. *Expert Syst. Appl.* 42, 7046–7056. doi: 10.1016/j.eswa.2015.05.013

Benzaamia, A., Ghrici, M., and Rebouh, R. (2024). Machine Learning Approaches for Predicting Compressive and Shear Strength of EB FRP-Reinforced Concrete Elements: A Comprehensive Review. In: Bekdaş, G., Nigdeli, S.M. (eds) New Advances in Soft Computing in Civil Engineering. *Studies in Systems, Decision and Control*, vol 547. Cham: Springer. doi: 10.1007/978-3-031-65976-8_12

Biró, A., Cuesta-Vargas, A. I., and Szilágyi, L. (2023). AI-assisted fatigue and stamina control for performance sports on IMU-generated multivariate times series datasets. *Sensors* 24:132. doi: 10.3390/s24010132

Boutaba, R., Salahuddin, M. A., Limam, N., Ayoubi, S., Shahriar, N., Estrada-Solano, F., et al. (2018). A comprehensive survey on machine learning for networking: evolution, applications and research opportunities. *J. Internet Serv. Appl.* 9:16. doi: 10.1186/s13174-018-0087-2

Campbell, F., Blank, L., Cantrell, A., Baxter, S., Blackmore, C., Dixon, J., et al. (2022). Factors that influence mental health of university and college students in the UK: a systematic review. *BMC Public Health* 22:1778. doi: 10.1186/s12889-022-13943-x

Cevallos Zambrano, D. P., Moreira-Choez, J. S., Lamus de Rodríguez, T. M., and Sánchez-Urdaneta, A. B. (2023). Psychosocial effects of COVID-19 in Ecuadorian university professors. *Revista de Ciencias Sociales* 29, 15–31. doi: 10.31876/rcs.v29i2.39960

Chopra, P. K., and Kanji, G. K. (2010). Emotional intelligence: a catalyst for inspirational leadership and management excellence. *Total Qual. Manag. Bus. Excell.* 21, 971–1004. doi: 10.1080/14783363.2010.487704

Cristóvão, A. M., Valente, S., Rebelo, H., and Ruivo, A. F. (2023). Emotional education for sustainable development: a curriculum analysis of teacher training in Portugal and Spain. *Front. Educ.* 8:1165319. doi: 10.3389/feduc.2023.1165319

de la Fuente, J., Paoloni, P., Kauffman, D., Yilmaz Soylu, M., Sander, P., and Zapata, L. (2020). Big five, self-regulation, and coping strategies as predictors of achievement emotions in undergraduate students. *Int. J. Environ. Res. Public Health* 17:3602. doi: 10.3390/ijerph17103602

Devis-Rozental, C. (2018). Developing socio-emotional intelligence in higher education scholars. *1st* Edn. Reino Unido: Springer International Publishing. doi: 10.1007/978-3-319-94036-6

Ecclestone, K. (2011). Emotionally-vulnerable subjects and new inequalities: the educational implications of an 'epistemology of the emotions. *Int. Stud. Sociol. Educ.* 21, 91–113. doi: 10.1080/09620214.2011.575100

Erfani, S. M., Rajasegarar, S., Karunasekera, S., and Leckie, C. (2016). High-dimensional and large-scale anomaly detection using a linear one-class SVM with deep learning. *Pattern Recogn.* 58, 121–134. doi: 10.1016/j.patcog.2016.03.028

Fernández-Berrocal, P., Extremera, N., and Ramos, N. (2004). Validity and Reliability of the Spanish Modified Version of the Trait Meta-Mood Scale. *Psychological Reports* 94, 751–755. doi: 10.2466/pr0.94.3.751-755

Forero-Corba, W., and Negre Bennasar, F. (2024). Diseño y simulación de un modelo de predicción para la evaluación de la competencia digital docente usando técnicas de Machine Learning. *Edutec. Rev. Electrón. Tecnol. Educ.* 89, 18–43. doi: 10.21556/edutec.2024.89.3201

Hargreaves, A. (2000). Mixed emotions: teachers' perceptions of their interactions with students. *Teach. Teach. Educ.* 16, 811–826. doi: 10.1016/S0742-051X(00)00028-7

Hu, C., Youn, B. D., Wang, P., and Taek Yoon, J. (2012). Ensemble of data-driven prognostic algorithms for robust prediction of remaining useful life. *Reliab. Eng. Syst. Safety* 103, 120–135. doi: 10.1016/j.ress.2012.03.008

Hussain, S. S., and Zaidi, S. S. H. (2024). Adaboost ensemble approach with weak classifiers for gear fault diagnosis and prognosis in DC motors. *Appl. Sci.* 14:3105. doi: 10.3390/app14073105

Ifenthaler, D., and Widanapathirana, C. (2014). Development and validation of a learning analytics framework: two case studies using support vector machines. *Technol. Knowl. Learn.* 19, 221–240. doi: 10.1007/s10758-014-9226-4

Inwood, E., and Ferrari, M. (2018). Mechanisms of change in the relationship between self-compassion, emotion regulation, and mental health: a systematic review. *Appl. Psychol. Health Well Being* 10, 215–235. doi: 10.1111/aphw.12127

Jahanbani, M., Vahidnia, M. H., Aghamohammadi, H., and Azizi, Z. (2024). Flood susceptibility mapping through geoinformatics and ensemble learning methods, with an emphasis on the AdaBoost-decision tree algorithm, in Mazandaran, Iran. *Earth Sci. Inform.* 17, 1433–1457. doi: 10.1007/s12145-023-01213-2

Kumar, S., and Chong, I. (2018). Correlation analysis to identify the effective data in machine learning: prediction of depressive disorder and emotion states. *Int. J. Environ. Res. Public Health* 15:2907. doi: 10.3390/ijerph15122907

Madroñal, M. R., Ramírez, E. S., Ruiz, L. G. B., Serrano-Fernández, M. J., Pérez-Moreiras, E., and Pegalajar Jiménez, M. d. C. (2025). Exploring emotional stability: from conventional approaches to machine learning insights. *Appl. Intell.* 55:213. doi: 10.1007/s10489-024-06130-5

Mankus, A. M., Boden, M. T., and Thompson, R. J. (2016). Sources of variation in emotional awareness: age, gender, and socioeconomic status. *Personal. Individ. Differ.* 89, 28–33. doi: 10.1016/j.paid.2015.09.043

Midkiff, M. F., Lindsey, C. R., and Meadows, E. A. (2018). The role of coping self-efficacy in emotion regulation and frequency of NSSI in young adult college students. *Cogent Psychol.* 5:1520437. doi: 10.1080/23311908.2018.1520437

Miller, A. L., Fine, S. E., Kiely Gouley, K., Seifer, R., Dickstein, S., and Shields, A. (2006). Showing and telling about emotions: interrelations between facets of emotional competence and associations with classroom adjustment in head start preschoolers. *Cogn. Emot.* 20, 1170–1192. doi: 10.1080/02699930500405691

Mofatteh, M. (2021). Risk factors associated with stress, anxiety, and depression among university undergraduate students. *AIMS Public Health* 8, 36–65. doi: 10.3934/publichealth.2021004

Moreira-Choez, J. S., Lamus de Rodríguez, T. M., Espinoza-Solís, E. J., and Castro-Castillo, G. J. (2023). Comparative analysis of psychological well-being and emotional education in graduate students. *F1000Res* 12:1403. doi: 10.12688/f1000research.141849.1

Moscoso Bernal, S., and Castro López, D. P. (2022). Características y propósitos de los sistemas de aseguramiento de la calidad de Ecuador y Argentina: un estudio de Educación Comparada. *Debate Univer* 12, 59–92. doi: 10.59471/debate20224

Parke, M. R., Seo, M.-G., and Sherf, E. N. (2015). Regulating and facilitating: the role of emotional intelligence in maintaining and using positive affect for creativity. *J. Appl. Psychol.* 100, 917–934. doi: 10.1037/a0038452

Peña-Sarrionandia, A., Mikolajczak, M., and Gross, J. J. (2015). Integrating emotion regulation and emotional intelligence traditions: a meta-analysis. *Front. Psychol.* 6:160. doi: 10.3389/fpsyg.2015.00160

Pietarinen, J., Soini, T., and Pyhältö, K. (2014). Students' emotional and cognitive engagement as the determinants of well-being and achievement in school. *Int. J. Educ. Res.* 67, 40–51. doi: 10.1016/j.ijer.2014.05.001

Pudlo, P., Marin, J.-M., Estoup, A., Cornuet, J.-M., Gautier, M., and Robert, C. P. (2016). Reliable ABC model choice via random forests. *Bioinformatics* 32, 859–866. doi: 10.1093/bioinformatics/btv684

Quoidbach, J., Mikolajczak, M., and Gross, J. J. (2015). Positive interventions: an emotion regulation perspective. *Psychol. Bull.* 141, 655–693. doi: 10.1037/a0038648

Rane, N., Choudhary, S. P., and Rane, J. (2024). Ensemble deep learning and machine learning: applications, opportunities, challenges, and future directions. *Stud. Med. Health Sci.* 1, 18–41. doi: 10.48185/smhs.v1i2.1225

Salovey, P., and Mayer, J. D. (1990). Emotional Intelligence. *Imagination, Cognition and Personality* 9, 185–211. doi: 10.2190/DUGG-P24E-52WK-6CDG

Sestino, A., and De Mauro, A. (2022). Leveraging artificial intelligence in business: implications, applications and methods. *Technol. Anal. Strateg. Manag.* 34, 16–29. doi: 10.1080/09537325.2021.1883583

Shanmugasundar, G., Vanitha, M., Čep, R., Kumar, V., Kalita, K., and Ramachandran, M. (2021). A comparative study of linear, random forest and AdaBoost regressions for modeling non-traditional machining. *PRO* 9:2015. doi: 10.3390/pr9112015

Sverdlik, A., Hall, N. C., McAlpine, L., and Hubbard, K. (2018). The PhD experience: a review of the factors influencing doctoral students' completion, achievement, and well-being. *Int. J. Dr. Stud.* 13, 361–388. doi: 10.28945/4113

Tang, B., Li, S., and Zhao, C. (2024). Predicting the performance of students using deep ensemble learning. *J. Intelligence* 12:124. doi: 10.3390/jintelligence12120124

Thieme, A., Belgrave, D., and Doherty, G. (2020). Machine learning in mental health. *ACM Trans. Comput. Hum. Interact.* 27, 1–53. doi: 10.1145/3398069

Upsher, R., Nobili, A., Hughes, G., and Byrom, N. (2022). A systematic review of interventions embedded in curriculum to improve university student wellbeing. *Educ. Res. Rev.* 37:100464. doi: 10.1016/j.edurev.2022.100464

Wang, M., Cui, Y., Wang, X., Xiao, S., and Jiang, J. (2018). Machine learning for networking: workflow, advances and opportunities. *IEEE Netw.* 32, 92–99. doi: 10.1109/MNET.2017.1700200

Wang, M., and Saudino, K. J. (2011). Emotion regulation and stress. *J. Adult Dev.* 18, 95–103. doi: 10.1007/s10804-010-9114-7

Wyatt, T., and Oswalt, S. B. (2013). Comparing mental health issues among undergraduate and graduate students. *Am. J. Health Educ.* 44, 96–107. doi: 10.1080/19325037.2013.764248

Zhang, C., Zhou, Y., Guo, J., Wang, G., and Wang, X. (2019). Research on classification method of high-dimensional class-imbalanced datasets based on SVM. *Int. J. Mach. Learn. Cybern.* 10, 1765–1778. doi: 10.1007/s13042-018-0853-2