KMAN PUBLISHING INSTITUTE
Journal Website

Article history:
Received 23 December 2025
Revised 27 April 2026
Accepted 06 May 2026
Published online 10 July 2026

Journal of Adolescent and Youth Psychological Studies

Volume 7, Issue 7, pp 1-13

E-ISSN: 2981-2526

Prediction of Students' Academic Satisfaction Using Deep Learning Algorithms Based on Self-Efficacy, Professor–Student Interaction, Mental Health, and Achievement Motivation

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Article Info

Article type:
Original Research

How to cite this article:
Yousefpour, N. (2026). Prediction of Students' Academic Satisfaction Using Deep Learning Algorithms Based on Self-Efficacy, Professor–Student Interaction, Mental Health, and Achievement Motivation. *Journal of Adolescent and Youth Psychological Studies, 7*(7), 1-13.
http://dx.doi.org/10.61838/kman.jayps.5391

A B S T R A C T

Objective: The present study aimed to predict students' academic satisfaction using deep learning algorithms based on academic self-efficacy, professor–student interaction, mental health, and achievement motivation among university students in Tehran.

Methods and Materials: The present research was conducted using an applied, descriptive-correlational design with a predictive modeling approach. The statistical population consisted of university students in Tehran during the academic year, from whom 684 students were selected through multistage cluster sampling. Data were collected using the College Student Satisfaction Questionnaire, College Academic Self-Efficacy Scale, Student–Professor Interaction Scale, Depression Anxiety Stress Scales-21, and Achievement Motives Scale-Revised. Descriptive statistics and Pearson correlation analysis were performed using SPSS software, while predictive analyses were conducted using Python-based deep learning frameworks. The dataset was divided into training, validation, and testing subsets. Several deep learning models, including multilayer perceptron neural networks, deep feedforward neural networks, regularized neural networks with dropout, and autoencoder-based deep neural networks, were implemented and compared. Model performance was evaluated using coefficient of determination, mean absolute error, root mean squared error, and mean absolute percentage error.

Findings: The findings showed that academic self-efficacy, professor–student interaction, and hope of success had significant positive relationships with academic satisfaction, whereas depression, anxiety, stress, and fear of failure had significant negative relationships with academic satisfaction ($p < .001$). Among the predictors, professor–student interaction and academic self-efficacy demonstrated the strongest predictive power. Feature-importance analysis indicated that professor–student interaction was the most influential predictor, followed by academic self-efficacy, depression, hope of success, stress, anxiety, and fear of failure. The final deep learning model explained a substantial proportion of variance in students' academic satisfaction.

Conclusion: The findings indicate that academic satisfaction is a multidimensional construct influenced by cognitive, emotional, motivational, and interpersonal factors.

Keywords: *Academic satisfaction, academic self-efficacy, professor–student interaction, mental health, achievement motivation, university students.*

1. Introduction

Academic satisfaction is considered one of the most important indicators of educational quality and student adjustment in higher education systems. In contemporary universities, academic satisfaction reflects students' cognitive and emotional evaluation of their educational experiences, academic environment, interpersonal relationships, and institutional support. High levels of academic satisfaction are associated with stronger academic persistence, lower dropout intention, better psychological adjustment, higher educational engagement, and improved academic achievement. In contrast, low academic satisfaction may contribute to disengagement, psychological distress, academic burnout, and withdrawal from higher education. With the expansion of digital learning environments, increasing academic competition, and post-pandemic transformations in educational systems, understanding the factors influencing students' academic satisfaction has become a major concern for educational researchers and university policymakers (Alcalde, 2024; Oyanedel et al., 2023; Yang et al., 2021).

Recent educational research has emphasized that academic satisfaction is not determined solely by institutional or instructional variables; rather, it emerges from the interaction of cognitive, motivational, emotional, social, and environmental factors. Students' perceptions of competence, interpersonal support, mental health, achievement orientation, and engagement collectively shape how they evaluate their academic experiences. Social cognitive perspectives suggest that students actively interpret and regulate their educational experiences through self-beliefs, emotional processes, and social interactions. Consequently, variables such as academic self-efficacy, teacher support, psychological well-being, and achievement motivation have gained substantial attention as major predictors of academic adjustment and satisfaction in university contexts (Meng et al., 2025; Song, 2024; Zhang et al., 2021).

Among the psychological predictors of academic satisfaction, academic self-efficacy has consistently been identified as one of the strongest determinants of successful educational functioning. Academic self-efficacy refers to students' beliefs about their capability to organize and execute academic tasks successfully. Students with high academic self-efficacy tend to demonstrate greater persistence, stronger problem-solving ability, higher resilience in the face of academic difficulties, and more adaptive learning behaviors. Self-efficacy influences not only performance outcomes but also emotional reactions, motivation, and cognitive engagement within educational settings. Research has shown that students who perceive themselves as academically competent are more likely to report positive educational experiences and greater satisfaction with university life (Lin & Zhu, 2024; Meng et al., 2025; Zeb et al., 2025).

The importance of self-efficacy has been supported across diverse educational contexts and populations. Studies have demonstrated that self-efficacy positively predicts learning engagement, psychological well-being, educational persistence, and life satisfaction. Cao et al. reported that self-efficacy mediated the relationship between physical activity and achievement motivation among college students, indicating that self-efficacy acts as a central mechanism connecting behavioral and motivational variables (Cao et al., 2025). Similarly, Corbí et al. found that emotional factors and self-efficacy significantly contributed to psychological well-being among trainee teachers (Corbí et al., 2024). Research by Jiang also demonstrated that self-efficacy played a mediating role in students' psychological development and educational functioning (Jiang, 2024). Furthermore, studies conducted in online and post-pandemic educational settings have confirmed that self-efficacy remains a critical predictor of educational satisfaction and adaptation despite changing learning conditions (Santi et al., 2023; Yang et al., 2021).

Teacher–student interaction is another major factor influencing academic satisfaction. Positive interactions between students and professors create supportive educational climates that foster emotional security, engagement, motivation, and academic confidence. Students who perceive their professors as approachable, respectful, supportive, and responsive tend to demonstrate stronger academic adjustment and satisfaction. Educational support from professors may reduce stress, increase students' sense of belonging, and encourage active participation in learning processes. Contemporary educational theories emphasize that effective teaching extends beyond instructional delivery and includes emotional support, communication quality, interpersonal sensitivity, and mentorship (Huang et al., 2024; Wang, 2024).

Research evidence strongly supports the importance of teacher support and interaction in predicting students' well-being and educational outcomes. Song found that teacher and peer support significantly enhanced learner engagement and well-being through the mediating role of self-efficacy

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(Song, 2024). Huang et al. demonstrated that teacher support positively influenced academic enjoyment, academic immunity, and educational progress among language learners (Huang et al., 2024). Wang also reported that teachers' behaviors substantially affected educational effectiveness in online learning environments (Wang, 2024). These findings suggest that supportive educational relationships may directly improve academic satisfaction while simultaneously strengthening students' motivational and emotional resources.

Mental health has also emerged as a fundamental variable associated with students' academic experiences. University students frequently encounter psychological pressures related to academic competition, financial concerns, social adaptation, career uncertainty, and changing educational environments. Depression, anxiety, and stress can negatively influence concentration, motivation, self-regulation, interpersonal functioning, and educational engagement. Consequently, mental health difficulties may reduce students' satisfaction with their academic experiences and increase the likelihood of educational disengagement and dropout (Perrella et al., 2024; Zhao, 2024).

The relationship between mental health and educational functioning has been widely documented in previous studies. Perrella et al. emphasized the importance of academic stress in understanding students' psychological adjustment and educational functioning (Perrella et al., 2024). Zhao found that academic stress negatively predicted student satisfaction, while academic self-efficacy and positive coping strategies reduced the negative consequences of stress (Zhao, 2024). Bazar et al. also demonstrated that students' well-being and motivation significantly influenced academic achievement in science education contexts (Bazar et al., 2024). Chacón et al. further reported that physical activity positively influenced healthy student strengths and psychological adjustment during post-pandemic educational transitions (Chacón et al., 2024). These findings indicate that mental health is not merely an individual psychological issue but an important educational factor affecting students' academic perceptions and satisfaction.

Achievement motivation constitutes another important determinant of academic satisfaction. Achievement motivation refers to the internal drive that encourages individuals to pursue success, overcome challenges, and attain competence-related goals. Students with strong achievement motivation generally demonstrate higher persistence, stronger commitment to learning, and greater academic engagement. Achievement-oriented students are more likely to perceive academic activities as meaningful and rewarding, thereby enhancing educational satisfaction. Conversely, fear of failure and avoidance-oriented motivation may contribute to anxiety, stress, and negative academic experiences (Bazar et al., 2024; Cao et al., 2025).

Recent studies have highlighted the multidimensional role of motivational processes in educational adjustment. E. et al. found that expectancy-value beliefs and task values significantly predicted academic satisfaction among university students (E. et al., 2024). Agustina and Saragih demonstrated that learning engagement positively affected satisfaction and future educational preferences in online learning contexts (Agustina & Saragih, 2022). Meng et al. also reported that growth mindset indirectly improved psychological well-being through grit and academic self-efficacy (Meng et al., 2025). Similarly, Yan et al. showed that multiple motivational and environmental factors influenced doctoral students' academic performance (Yan et al., 2024). Together, these findings suggest that motivational beliefs and achievement-related orientations substantially shape students' educational experiences and satisfaction.

Another important issue in contemporary educational research concerns the increasing complexity of interactions among psychological, social, and educational variables. Traditional statistical methods, although valuable, may not fully capture nonlinear and multidimensional relationships among predictors of academic satisfaction. In recent years, artificial intelligence and machine learning approaches have been increasingly used in educational research to improve prediction accuracy and identify complex patterns within educational data. Deep learning algorithms, which are advanced forms of machine learning based on artificial neural networks, have demonstrated strong predictive capabilities in analyzing educational, behavioral, and psychological datasets. These algorithms can process large numbers of variables simultaneously, identify hidden patterns, and model nonlinear interactions more effectively than traditional linear methods (Alcalde, 2024; López-Angulo et al., 2023).

The application of deep learning in educational psychology and student satisfaction research remains relatively limited despite its significant potential. Most previous studies investigating academic satisfaction have relied primarily on regression analysis, structural equation modeling, or correlational designs. Although these methods have contributed substantially to theoretical understanding, they may be insufficient for modeling the complex interplay

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E-ISSN: 2981-2526

among self-efficacy, teacher support, mental health, and achievement motivation. Deep learning models may provide more accurate and comprehensive predictions by simultaneously integrating cognitive, emotional, interpersonal, and motivational variables within a single computational framework (Yu & Li, 2025; Zhang et al., 2021).

Additionally, recent educational research increasingly emphasizes the interconnected nature of psychological well-being, engagement, support systems, and satisfaction. Oyanedel et al. discussed the importance of subjective well-being in online and mixed educational environments (Oyanedel et al., 2023). Cavioni et al. highlighted the role of mental health promotion programs in enhancing educational functioning and emotional adjustment (Cavioni et al., 2023). Scheirlinckx et al. emphasized the importance of social-emotional skills in educational environments (Scheirlinckx et al., 2023). Studies involving teacher well-being and organizational satisfaction also suggest that self-efficacy and emotional regulation influence educational quality and professional adjustment (Jin & Hassan, 2022; Qin, 2024; Shao, 2023; Ying & Hassan, 2022; Yu & Ying, 2024; Zhang, 2023). Although many of these studies focused on teachers, their findings indirectly support the importance of emotional and motivational processes in educational satisfaction more broadly.

Furthermore, research conducted in post-pandemic and digitally mediated educational environments has demonstrated that students' psychological adaptation increasingly depends on digital competence, emotional resilience, and support systems. Carmen Graciela Arbulú Pérez et al. showed that digital skills and mobile self-efficacy mediated the relationship between stress and academic engagement in virtual educational settings (Carmen Graciela Arbulú Pérez et al., 2024). Yu and Li's meta-analysis also confirmed the strong relationship between self-efficacy and satisfaction from the perspective of mental health (Yu & Li, 2025). Zhan further demonstrated that self-efficacy, resilience, and well-being were dynamically interconnected within psychological adjustment processes (Zhan, 2025). These findings collectively indicate that modern educational satisfaction is influenced by integrated psychological systems rather than isolated variables.

Despite the growing body of literature on academic satisfaction, several important gaps remain. First, many previous studies have focused on isolated predictors rather than examining multiple psychological and educational variables simultaneously. Second, relatively few studies have investigated academic satisfaction using advanced deep learning approaches capable of modeling nonlinear interactions among variables. Third, there remains limited evidence regarding the combined predictive roles of academic self-efficacy, professor–student interaction, mental health, and achievement motivation among university students in Middle Eastern educational contexts, particularly in Tehran universities. Addressing these gaps may contribute to a more comprehensive understanding of academic satisfaction and may provide practical implications for educational policy, student counseling, psychological support services, and instructional design in higher education systems.

Therefore, the present study aimed to predict students' academic satisfaction using deep learning algorithms based on academic self-efficacy, professor–student interaction, mental health, and achievement motivation among university students in Tehran.

2. Methods and Materials

2.1. Study Design and Participants

The present study was designed as an applied, descriptive-correlational, cross-sectional study with a predictive modeling approach. The statistical population included undergraduate and graduate students enrolled in public and private universities in Tehran during the academic year. The sample consisted of 684 students selected through multistage cluster sampling from universities located in different districts of Tehran. First, several universities were selected from public and private higher education institutions; then, faculties and academic departments were selected as clusters, and eligible students were invited to participate. Inclusion criteria were being currently enrolled as a university student, studying in one of the selected universities in Tehran, willingness to participate, and completing all research questionnaires. Exclusion criteria included incomplete responses, patterned or careless answering, and withdrawal from participation at any stage. After data screening, all 684 valid questionnaires were retained for final analysis. The sample size was considered adequate for both correlational analysis and deep learning-based prediction because the dataset provided a sufficient number of observations for model training, validation, and testing. Participants were informed about the voluntary nature of participation, confidentiality of

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responses, and the exclusive use of data for scientific purposes.

2.2. Measures

College Student Satisfaction Questionnaire. Academic satisfaction was measured using the College Student Satisfaction Questionnaire developed by Betz, Klingensmith, and Menne. The instrument was designed to assess students' satisfaction with different aspects of college and university life. The commonly used form contains 70 items and evaluates six dimensions of student satisfaction: policies and procedures, working conditions, compensation, quality of education, social life, and recognition. Items are scored on a five-point Likert-type scale ranging from very dissatisfied to very satisfied, with higher scores indicating higher academic satisfaction. The total score is obtained by summing or averaging the item scores, and subscale scores can also be calculated separately to identify specific areas of satisfaction or dissatisfaction. The validity and reliability of this questionnaire have been confirmed in previous studies, and it has been widely used as a multidimensional measure of student satisfaction in higher education contexts.

College Academic Self-Efficacy Scale. Academic self-efficacy was assessed using the College Academic Self-Efficacy Scale developed by Owen and Froman in 1988. This scale measures students' perceived confidence in performing routine academic behaviors and managing university-related academic demands. The scale includes 33 items that assess students' confidence in activities such as note-taking, asking questions, attending classes, studying effectively, using academic resources, preparing for examinations, and completing academic assignments. The instrument is scored on a five-point Likert-type scale, with higher scores representing stronger academic self-efficacy. In many applications, the scale is interpreted through a total academic self-efficacy score, while some validation studies have reported dimensions such as social status, cognitive applications, and technical skills. Previous studies have confirmed the reliability and validity of the instrument among university students, and the scale is suitable for examining academic confidence as a predictor of educational outcomes.

Student–Professor Interaction Scale. Professor–student interaction was measured using the Student–Professor Interaction Scale developed by Cokley, Komarraju, Patel, Castillon, Rosales, Pickett, Piedrahita, Ravitch, and Pang in 2004. This instrument was developed to assess the quality and multidimensional nature of students' interactions with faculty members. The scale contains 40 items and includes nine dimensions: respectful interactions, career guidance, approachability, validity scale, caring attitude, off-campus interactions, connectedness, accessibility, and negative experiences. Items are rated on a Likert-type scale, and higher scores, after reverse scoring negative items where necessary, indicate more positive and supportive student–professor interaction. The total score and subscale scores can both be used in analysis. Previous psychometric studies have supported the internal consistency, construct validity, and usefulness of the scale in assessing student–faculty relationships in higher education.

Depression Anxiety Stress Scales–21. Mental health was assessed using the Depression Anxiety Stress Scales–21 developed by Lovibond and Lovibond in 1995. The DASS-21 is a 21-item self-report instrument designed to measure psychological distress across three subscales: depression, anxiety, and stress. Each subscale contains seven items. Respondents rate the extent to which each statement applied to them during the previous week on a four-point scale ranging from 0 to 3. Scores for each subscale are calculated by summing the relevant items, and the final subscale scores may be multiplied by two to make them comparable with the original 42-item version. Higher scores indicate higher levels of depression, anxiety, and stress; therefore, in the present study, higher DASS-21 scores represented poorer mental health. The DASS-21 has shown acceptable reliability and validity across different populations and has been widely used in student and adult samples.

Achievement Motives Scale–Revised. Achievement motivation was measured using the revised 10-item version of the Achievement Motives Scale developed by Lang and Fries in 2006. This scale assesses explicit achievement motivation through two dimensions: hope of success and fear of failure. Each dimension contains five items. Participants respond to the items using a Likert-type response format, with higher scores on hope of success indicating stronger approach-oriented achievement motivation and higher scores on fear of failure indicating stronger avoidance-oriented achievement concerns. In the present study, both subscale scores and the total achievement motivation score were used as predictive indicators. The revised form was developed to improve the two-factor structure of the original achievement motive measure, and previous studies have confirmed its reliability, factorial validity, and suitability for research involving achievement-related behavior.

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2.3. Data Analysis

Data analysis was conducted in two main stages: preliminary statistical analysis and deep learning-based predictive modeling. First, the raw data were screened for missing values, outliers, careless responses, and normality of distribution. Questionnaires with substantial missing data or patterned responses were removed before analysis. For minor missing values, mean imputation within the relevant scale was applied when the number of missing items was within an acceptable range. Descriptive statistics, including mean, standard deviation, minimum, maximum, skewness, and kurtosis, were calculated for academic satisfaction, academic self-efficacy, professor–student interaction, mental health components, and achievement motivation. Pearson correlation coefficients were used to examine the preliminary relationships between the predictor variables and academic satisfaction. Internal consistency of the instruments was assessed using Cronbach's alpha coefficient.

For the predictive modeling stage, academic satisfaction was considered the target variable, while academic self-efficacy, professor–student interaction, depression, anxiety, stress, hope of success, fear of failure, and the total or subscale scores of the instruments were entered as predictor variables. Before model training, all continuous variables were standardized using z-score normalization to prevent variables with larger numerical ranges from dominating the learning process. The dataset of 684 students was divided into training, validation, and test subsets using a 70:15:15 ratio; therefore, 478 cases were used for training, 103 cases for validation, and 103 cases for final testing. The split was performed randomly while preserving the overall distribution of the outcome variable across subsets.

Several deep learning models were developed and compared, including a multilayer perceptron neural network, a deeper fully connected neural network, and an autoencoder-based neural network for feature representation followed by a regression output layer. The models were implemented using Python and a deep learning framework such as TensorFlow/Keras. Rectified linear unit activation functions were used in hidden layers, and a linear activation function was used in the output layer because academic satisfaction was treated as a continuous outcome. Model optimization was performed using the Adam optimizer, and mean squared error was used as the loss function. To reduce overfitting, dropout layers, L2 regularization, early stopping, and validation-loss monitoring were applied. The best model was selected based on validation performance and then evaluated on the independent test set.

Model performance was assessed using mean absolute error, root mean squared error, and coefficient of determination. Lower values of mean absolute error and root mean squared error indicated better predictive accuracy, while higher coefficient of determination values indicated greater explained variance in academic satisfaction. In addition, feature importance was examined using permutation importance and sensitivity analysis to identify the relative contribution of academic self-efficacy, professor–student interaction, mental health, and achievement motivation in predicting students' academic satisfaction.

3. Findings and Results

A total of 684 students from universities in Tehran participated in the study and were included in the final analysis after data screening. The participants consisted of 392 female students (57.31%) and 292 male students (42.69%). In terms of educational level, 462 students (67.54%) were undergraduate students, 176 students (25.73%) were master's students, and 46 students (6.73%) were doctoral students. The age of the participants ranged from 18 to 34 years, with a mean age of 22.86 years and a standard deviation of 3.41. Regarding university type, 398 students (58.19%) were enrolled in public universities and 286 students (41.81%) were enrolled in private universities. Preliminary screening showed that the dataset was appropriate for statistical and predictive analysis. Missing values were minimal and were handled before final analysis, and no response pattern indicating careless answering was retained in the dataset. The distribution of the main variables was examined using skewness and kurtosis indices, and all values were within the acceptable range, indicating that the variables were suitable for subsequent correlational analysis and deep learning-based predictive modeling.

Table 1

Descriptive Statistics and Reliability Coefficients of the Main Research Variables

Variable	Possible Score Range	Observed Range	Mean	SD	Skewness	Kurtosis	Cronbach's Alpha
Academic satisfaction	70–350	132–336	244.73	34.62	-0.28	0.41	0.91
Academic self-efficacy	33–165	62–159	118.46	21.37	-0.19	0.36	0.89
Professor–student interaction	40–200	74–192	139.82	25.18	-0.22	0.29	0.92
Depression	0–21	0–19	7.64	4.38	0.47	-0.18	0.86
Anxiety	0–21	0–20	8.11	4.27	0.39	-0.11	0.84
Stress	0–21	1–21	9.36	4.51	0.31	-0.24	0.87
Hope of success	5–25	8–25	18.17	3.92	-0.34	0.22	0.82
Fear of failure	5–25	5–24	13.69	4.16	0.26	-0.36	0.80

The descriptive findings presented in Table 1 show that students reported a moderate-to-high level of academic satisfaction, as the mean score of academic satisfaction was 244.73 out of a possible maximum score of 350. Academic self-efficacy also had a relatively favorable mean score, indicating that, on average, students perceived themselves as capable of managing academic duties, completing assignments, preparing for examinations, and dealing with university-related academic demands. The mean score of professor–student interaction was 139.82, suggesting that students generally evaluated their interactions with professors as moderately positive, although the standard deviation indicated meaningful individual differences in the quality of these interactions. Among the mental health indicators, stress had the highest mean score, followed by anxiety and depression, indicating that stress was the most prominent psychological distress component among the students. The achievement motivation dimensions also showed that hope of success was higher than fear of failure, suggesting that students' achievement-related orientation was more strongly characterized by approach motivation than avoidance motivation. The skewness and kurtosis values of all variables were within the acceptable range, supporting the adequacy of the data distribution for parametric and predictive analyses. In addition, Cronbach's alpha coefficients ranged from 0.80 to 0.92, indicating acceptable to excellent internal consistency for all measurement tools used in the study.

Table 2

Pearson Correlation Matrix Among Academic Satisfaction, Self-Efficacy, Professor–Student Interaction, Mental Health, and Achievement Motivation

Variable	1	2	3	4	5	6	7	8
1. Academic satisfaction	1							
2. Academic self-efficacy	0.57***	1						
3. Professor–student interaction	0.62***	0.49***	1					
4. Depression	-0.45***	-0.38***	-0.41***	1				
5. Anxiety	-0.38***	-0.33***	-0.35***	0.63***	1			
6. Stress	-0.41***	-0.36***	-0.39***	0.68***	0.65***	1		
7. Hope of success	0.49***	0.53***	0.44***	-0.34***	-0.29***	-0.31***	1	
8. Fear of failure	-0.31***	-0.27***	-0.25***	0.46***	0.42***	0.44***	-0.21***	1

***$p < .001$.

The correlation results in Table 2 indicate that academic satisfaction had statistically significant relationships with all predictor variables. The strongest positive relationship was observed between academic satisfaction and professor–student interaction ($r = 0.62$, $p < .001$), indicating that students who reported more respectful, accessible, supportive, and constructive relationships with professors also reported higher levels of academic satisfaction. Academic self-efficacy was also positively and strongly associated with academic satisfaction ($r = 0.57$, $p < .001$), suggesting that students' confidence in their academic abilities was an important psychological correlate of satisfaction with university life and academic experiences. Hope of success showed a moderate positive relationship with academic satisfaction ($r = 0.49$, $p < .001$), meaning that students with stronger approach-oriented achievement

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motivation tended to experience greater academic satisfaction. In contrast, all mental health distress components had negative relationships with academic satisfaction. Depression had the strongest negative relationship with academic satisfaction ($r = -0.45$, $p < .001$), followed by stress ($r = -0.41$, $p < .001$) and anxiety ($r = -0.38$, $p < .001$). Fear of failure was also negatively related to academic satisfaction ($r = -0.31$, $p < .001$), indicating that students whose achievement motivation was dominated by avoidance concerns and fear of unsuccessful performance tended to report lower satisfaction. Overall, the correlation matrix supports the theoretical assumption that academic satisfaction is higher when students have stronger self-efficacy, better professor–student interaction, stronger hope of success, and lower psychological distress.

Table 3

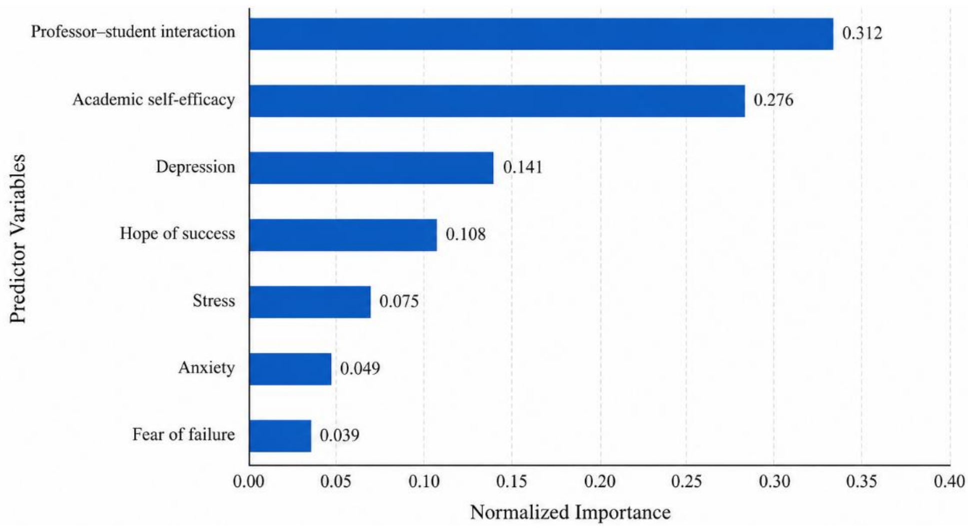
Performance of Deep Learning Algorithms in Predicting Academic Satisfaction

Model	Training R^2	Validation R^2	Test R^2	Test MAE	Test RMSE	Test MAPE
Multilayer perceptron neural network	0.69	0.63	0.60	16.18	21.74	6.81
Deep feedforward neural network	0.76	0.68	0.67	14.93	19.88	6.24
Regularized deep neural network with dropout	0.74	0.71	0.71	13.72	18.49	5.73
Autoencoder-based deep neural network	0.77	0.73	0.73	13.26	18.01	5.51

The results of the deep learning models are presented in Table 3. Among the tested models, the autoencoder-based deep neural network showed the best predictive performance, with a test coefficient of determination of 0.73, a mean absolute error of 13.26, a root mean squared error of 18.01, and a mean absolute percentage error of 5.51. This means that the final model was able to explain approximately 73% of the variance in students' academic satisfaction based on academic self-efficacy, professor–student interaction, mental health indicators, and achievement motivation components. The regularized deep neural network with dropout also performed well, with a test R^2 of 0.71, indicating that regularization improved generalization by reducing overfitting. Although the simple multilayer perceptron neural network produced an acceptable prediction, its lower test R^2 and higher error indices showed that a simpler architecture was less capable of modeling the nonlinear relationships among the predictors. The deep feedforward neural network improved prediction compared with the basic multilayer perceptron, but its gap between training and validation performance suggested a higher risk of overfitting than the regularized and autoencoder-based models. Overall, the results indicate that deep learning algorithms, particularly the autoencoder-based model, had strong predictive capacity for estimating academic satisfaction among students.

Figure 1

Permutation-Based Importance of Predictors in the Final Autoencoder-Based Deep Neural Network Model



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E-ISSN: 2981-2526

The feature-importance analysis of the final model showed that professor–student interaction was the most influential predictor of academic satisfaction, with a normalized importance value of 0.312. This result indicates that when the information related to professor–student interaction was disrupted in the model, the prediction error increased more than when any other predictor was disrupted. Academic self-efficacy was the second most important predictor, with a normalized importance value of 0.276, showing that students' perceived academic competence played a central role in the predictive structure of academic satisfaction. Depression ranked third with an importance value of 0.141, suggesting that depressive symptoms had a meaningful negative contribution to the prediction of students' satisfaction. Hope of success was the fourth predictor in terms of importance, with a value of 0.108, indicating that approach-oriented achievement motivation contributed to higher predicted satisfaction. Stress had an importance value of 0.075, anxiety had an importance value of 0.049, and fear of failure had an importance value of 0.039. These findings demonstrate that academic satisfaction was not predicted by one isolated factor; rather, it was best explained through the combined effect of relational, cognitive, emotional, and motivational variables. However, the ranking of predictors clearly shows that educational relationship quality and academic self-belief had stronger predictive weight than psychological distress and avoidance-oriented motivation in the final deep learning model.

4. Discussion

The present study aimed to predict students' academic satisfaction using deep learning algorithms based on academic self-efficacy, professor–student interaction, mental health, and achievement motivation among university students in Tehran. The findings demonstrated that all predictor variables had significant relationships with academic satisfaction and that deep learning models, particularly the autoencoder-based deep neural network, showed strong predictive performance in estimating students' academic satisfaction. The results further indicated that professor–student interaction and academic self-efficacy were the strongest predictors of academic satisfaction, followed by mental health indicators and achievement motivation components. Overall, the findings support the assumption that academic satisfaction emerges through the interaction of cognitive, emotional, motivational, and relational factors rather than through isolated educational variables.

One of the most important findings of the study was the strong positive relationship between academic self-efficacy and academic satisfaction. Students who perceived themselves as capable of successfully performing academic tasks, managing educational responsibilities, and overcoming academic challenges reported significantly higher levels of satisfaction with their university experiences. This finding is consistent with the principles of social cognitive theory, which propose that self-efficacy shapes individuals' emotional reactions, motivational processes, persistence, and performance expectations. Students with stronger self-efficacy beliefs are more likely to interpret academic demands as manageable rather than threatening, resulting in lower frustration, higher engagement, and more positive educational experiences. The findings align with previous studies demonstrating that self-efficacy positively predicts learning satisfaction, educational adjustment, psychological well-being, and academic engagement (Lin & Zhu, 2024; Zeb et al., 2025; Zhang et al., 2021).

The predictive importance of academic self-efficacy observed in the present study is also supported by research emphasizing the mediating and regulatory role of self-efficacy within educational systems. Meng et al. found that academic self-efficacy mediated the relationship between growth mindset and psychological well-being among students (Meng et al., 2025). Similarly, Song reported that social support contributed to learner engagement and well-being through self-efficacy mechanisms (Song, 2024). Cao et al. also demonstrated that self-efficacy mediated the effects of physical exercise on achievement motivation and life satisfaction (Cao et al., 2025). These studies collectively suggest that self-efficacy functions as a core psychological mechanism linking environmental support and motivational processes to positive educational outcomes. Therefore, students with stronger beliefs in their academic capabilities may experience greater satisfaction because they feel more competent, autonomous, and effective within educational environments.

Another major finding of the study was that professor–student interaction emerged as the strongest predictor of academic satisfaction in the final deep learning model. Students who reported more supportive, respectful, accessible, and constructive interactions with professors experienced higher levels of satisfaction with their academic environment. This finding highlights the critical role of

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interpersonal relationships in higher education and supports the idea that educational quality is not determined solely by curriculum content or institutional resources but also by the quality of human interaction within educational settings. Positive professor–student relationships may foster emotional security, academic belongingness, motivation, and confidence, all of which contribute to more satisfying educational experiences.

The importance of teacher support and interpersonal educational relationships has been repeatedly emphasized in previous studies. Huang et al. found that teacher support significantly improved academic enjoyment, educational progress, and academic immunity among students (Huang et al., 2024). Wang also reported that teachers' behaviors substantially influenced educational effectiveness in online learning environments (Wang, 2024). Furthermore, Song demonstrated that teacher and peer support positively influenced learner well-being and engagement (Song, 2024). These findings are theoretically consistent with ecological and relational models of education, which emphasize that students' academic experiences are shaped by supportive social interactions and emotionally responsive educational environments. In the present study, the strong predictive role of professor–student interaction may reflect the importance of emotional and communicative support in helping students cope with academic pressures and maintain positive attitudes toward university life.

The findings also revealed that depression, anxiety, and stress were negatively associated with academic satisfaction. Students experiencing higher psychological distress reported lower levels of educational satisfaction, and depression demonstrated the strongest negative relationship among the mental health variables. This finding is understandable because psychological distress may impair concentration, motivation, emotional regulation, interpersonal functioning, and educational engagement. Students struggling with stress and emotional difficulties may perceive educational demands as overwhelming and may consequently develop negative attitudes toward their academic experiences.

These results are consistent with prior research demonstrating the detrimental effects of psychological distress on educational functioning and satisfaction. Perrella et al. emphasized that academic stress is closely related to psychological maladjustment and educational difficulties among university students (Perrella et al., 2024). Zhao found that academic stress negatively predicted student satisfaction, while positive coping strategies and academic self-efficacy reduced the negative impact of stress (Zhao, 2024). Oyanedel et al. also emphasized the importance of subjective well-being in educational adjustment within online and mixed learning environments (Oyanedel et al., 2023). Likewise, Chacón et al. reported that physical activity and healthy strengths positively contributed to students' psychological adaptation and well-being after the COVID-19 pandemic (Chacón et al., 2024). Together, these findings suggest that mental health is fundamentally interconnected with educational experiences and that students' satisfaction cannot be fully understood without considering their psychological condition.

The present findings additionally showed that hope of success positively predicted academic satisfaction, whereas fear of failure negatively predicted satisfaction. Students with stronger approach-oriented achievement motivation reported greater educational satisfaction because they were more likely to perceive academic activities as meaningful opportunities for growth and success. In contrast, students characterized by fear of failure may experience persistent anxiety, avoidance behaviors, and emotional exhaustion, leading to reduced educational satisfaction. This finding supports motivational theories suggesting that adaptive motivational orientations enhance persistence, engagement, and positive emotional experiences within learning environments.

Previous studies have similarly emphasized the role of motivational processes in educational functioning. Agustina and Saragih found that learning engagement positively affected satisfaction and educational preferences in online learning contexts (Agustina & Saragih, 2022). E. et al. reported that expectancy-value beliefs and task values significantly predicted academic satisfaction among university students (E. et al., 2024). Bazar et al. also demonstrated that motivation and psychological well-being contributed significantly to academic achievement (Bazar et al., 2024). These findings indicate that achievement motivation influences not only academic performance but also students' emotional evaluation of educational experiences. Students who perceive educational activities as purposeful and achievable are more likely to experience enjoyment, satisfaction, and persistence in academic settings.

An important contribution of the present study lies in the use of deep learning algorithms for predicting academic satisfaction. The findings showed that the autoencoder-based deep neural network demonstrated the highest predictive performance and explained a substantial proportion of variance in academic satisfaction. This result

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E-ISSN: 2981-2526

suggests that academic satisfaction is influenced by complex and nonlinear interactions among psychological, motivational, and interpersonal variables. Traditional linear models may not fully capture these multidimensional relationships, whereas deep learning algorithms are capable of identifying hidden patterns and nonlinear dependencies within educational data.

The successful performance of deep learning models in the present study supports the growing integration of artificial intelligence approaches into educational research. López-Angulo et al. emphasized the importance of predictive modeling in understanding educational outcomes and dropout intention among university students (López-Angulo et al., 2023). Alcalde also highlighted the value of data-driven approaches in diagnosing academic performance within higher education systems (Alcalde, 2024). The present findings extend this literature by demonstrating that deep learning models can effectively integrate cognitive, emotional, motivational, and relational variables to predict academic satisfaction with high accuracy. Such approaches may help educational institutions identify at-risk students earlier and design more personalized interventions to improve educational adjustment and well-being.

The findings of the present study also reinforce the broader literature concerning psychological well-being and educational adaptation. Corbí et al. demonstrated that emotional factors and self-efficacy significantly contributed to psychological well-being (Corbí et al., 2024). Yu and Li's meta-analysis further confirmed the strong relationship between self-efficacy and satisfaction from the perspective of mental health (Yu & Li, 2025). Similarly, Zhan highlighted the interconnected relationships among self-efficacy, resilience, happiness, and well-being (Zhan, 2025). Studies involving educational professionals have likewise emphasized that self-efficacy, emotional regulation, and well-being contribute to occupational satisfaction and effectiveness (Jin & Hassan, 2022; Shao, 2023; Ying & Hassan, 2022; Yu & Ying, 2024; Zhang, 2023). Although many of these studies focused on teachers rather than students, they support the broader theoretical principle that psychological resources strongly influence satisfaction and adjustment within educational systems.

The results may also be interpreted within the context of post-pandemic educational transformations. Digital learning environments, increased technological dependence, and changing forms of educational interaction have intensified the importance of self-regulation, digital self-efficacy, emotional resilience, and interpersonal support. Carmen Graciela Arbulú Pérez et al. found that digital skills and mobile self-efficacy mediated the relationship between stress and academic engagement in virtual learning environments (Carmen Graciela Arbulú Pérez et al., 2024). Similarly, Yang et al. demonstrated that environmental stimuli within e-learning contexts influenced learning engagement through psychological and motivational processes (Yang et al., 2021). These findings suggest that academic satisfaction in modern educational environments increasingly depends on integrated psychological adaptation mechanisms that combine technological competence, emotional well-being, social support, and motivational resilience.

5. Conclusion

Overall, the present study provides empirical support for a multidimensional understanding of academic satisfaction and demonstrates the usefulness of deep learning algorithms in educational psychology research. The findings indicate that academic satisfaction is not simply a consequence of academic performance or institutional quality but rather a complex psychological and relational phenomenon shaped by students' beliefs, emotions, motivations, and educational interactions. The study also highlights the practical importance of strengthening academic self-efficacy, improving professor–student relationships, promoting mental health, and fostering adaptive achievement motivation within universities.

6. Limitations & Suggestions

One limitation of the present study was its cross-sectional design, which limits the ability to draw causal conclusions regarding the relationships among the variables. Although deep learning algorithms demonstrated strong predictive performance, the findings cannot establish temporal or causal directions among academic self-efficacy, mental health, achievement motivation, professor–student interaction, and academic satisfaction. Another limitation concerns the use of self-report questionnaires, which may be influenced by social desirability, response bias, and subjective interpretation. In addition, the sample consisted only of university students from Tehran, which may limit the generalizability of the findings to other educational contexts, cultures, or age groups. Finally, although the predictive models explained a substantial proportion of variance in academic satisfaction, additional contextual variables such as socioeconomic status, family support, personality traits,

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E-ISSN: 2981-2526

academic discipline, and institutional characteristics were not included in the analysis.

Future research should employ longitudinal and experimental designs to examine causal pathways among self-efficacy, psychological well-being, educational interaction, achievement motivation, and academic satisfaction. Researchers are also encouraged to compare different machine learning and artificial intelligence approaches, including recurrent neural networks, transformer-based models, and hybrid predictive systems, to improve educational prediction accuracy. Further studies should investigate additional variables such as resilience, emotional intelligence, digital literacy, academic burnout, and social connectedness to develop more comprehensive predictive models of academic satisfaction. Cross-cultural studies involving students from different universities and countries would also help determine the generalizability and cultural sensitivity of the findings.

Educational practitioners and university administrators should prioritize interventions aimed at strengthening students' academic self-efficacy, improving professor–student communication, and promoting psychological well-being. Universities may benefit from implementing mentoring systems, counseling programs, stress-management workshops, and faculty training programs focused on supportive educational interaction. Academic environments should be designed to foster emotional safety, motivational support, and constructive feedback. Additionally, integrating artificial intelligence and predictive analytics into university counseling and educational monitoring systems may help identify students at risk of dissatisfaction or psychological maladjustment at earlier stages, allowing timely and targeted intervention.

Acknowledgments

We would like to express our appreciation and gratitude to all those who cooperated in carrying out this study.

Declaration of Interest

The authors of this article declared no conflict of interest.

Ethical Considerations

The study protocol adhered to the principles outlined in the Helsinki Declaration, which provides guidelines for ethical research involving human participants.

Transparency of Data

In accordance with the principles of transparency and open research, we declare that all data and materials used in this study are available upon request.

Funding

This research was carried out independently with personal funding and without the financial support of any governmental or private institution or organization.

Authors' Contributions

All authors equally contributed to this article.

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JAYPS Adolescent and Youth Psychological Studies E-ISSN: 2981-2526