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# Machine Learning-Based Prediction of Students' Self-Actualization Using Maslow's Hierarchy of Needs

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**Abstract**

Self-actualization is at the top of Maslow's Hierarchy of Needs, signifying a person's realization of potential, creativity and personal growth. Self-actualization is traditionally measured with subjective psychological instruments that are hard for scaling in educational settings. The present study suggests a machine learning approach to develop a predictive model for evaluating students' self-actualization level based on psychological, socio-economic and academic variables based on Maslow's hierarchy theory. An institution of Mehran University of Engineering and Technology (MUET), Pakistan was chosen and a structured questionnaire was designed on the basis of Maslow's hierarchy of needs to collect data from 506 university students. Various supervised machine learning algorithms such as Gradient Boosting Classifier, Random Forest, Support Vector Machine (RBF), Logistic Regression and Decision Tree were trained and tested with accuracy, precision, recall and F1 score. The Gradient Boosting Classifier gave the highest accuracy of 95.1% and F1 score of 88.9% during the experiment, beating all other models. Results prove that ML techniques can be used to model the psychological need fulfillment. This research offers a data-driven, scalable solution that may be used for predicting student self-actualization, thereby providing early intervention opportunities to promote academic and psychological wellness in higher education.

**Keywords:** Machine Learning; Self-Actualization; Maslow's Hierarchy of Needs; Educational Data Mining; Student Psychological Well-Being; Predictive Modeling; Higher Education; Artificial Intelligence

## Introduction

Higher education is significant in the individuals' ability to participate in the intellectual, social, or economic development of the society. Although in most cases success is measured through academic performance, personal growth as well as psychological health should be considered for the future success of students in all aspects. According to Abraham Maslow's Hierarchy of Needs, the concept of self-actualization defines the highest level of psychological growing in an individual. Self -actualization means the total realization of the potentials of an individual, be it creative, problem-solving abilities, or full personal development (Maslow, A. H. 1943).

According to Maslow's theory, individuals cannot achieve the level of self-actualization unless the lower levels of needs such as physiological needs, safety, belonging, and esteem are first fulfilled. For example, in education, self-actualization goes beyond academic success, it also means personal development, creativity, and self-awareness and problem-solving abilities which transcend academic achievement (Dalal, P. et al. 2025). Self-accomplishment would be viewed as the ultimate goal in an educational cosmos where students not only obtain good grades but also develop themselves as a whole.

The education sector has seen significant developments in machine learning (ML) and artificial intelligence (AI) over the past few years, and these technologies are now being integrated into the field. However, with the help of ML and AI, teachers and researchers can gain insight into what students are doing well and what areas could be improved, which can help them identify and address the factors impacting students' motivation, academic self-concept, and academic behaviors (Hussain, S. A. et al. 2025).

Self-actualization is one of the highest level needs in the hierarchy of growth as formulated by Abraham Maslow. Self-actualization refers to personal growth, development, fulfillment of personal potentials, and psychological development. The problem with measuring and empirically assessing the concept of self-actualization lies in its complexity and multiple dimensions that involve various personal and environmental determinants (Noltemeyer, A. et al. 2012).

Self-actualization is mostly measured through qualitative means but when Machine Learning comes in, such measures can be quantified such that prediction on eventual self-actualization may be made based on psychosocial and academic data. These predictions over self-actualization, in fact, are reported to be paradigm-shifting to arguments at universities, able to fashion personalized approach that results in the development of both academic achievements and mental health.

The current research is applicable to the accomplishment of the prediction of the self-actualization levels of the university students when the techniques of the hierarchy of needs as developed by Maslow were used along with the machine learning. In the case of data-oriented models, this study would give objective, scalable, and quantifiable way of evaluating and improving student progress into thinking of customized education plans that consist of both academic and psychological variables.

**Motivation for the Research**

The motivation for this research is driven by the increasing awareness that it is important to measure students' success and achievement not only through academic achievement, but beyond. Student-centered education, which focuses on students' psychological health, personal growth, creativity, self-confidence, self-motivation and self-fulfillment, is becoming a trend in today's educational systems (Maslow, A. H. 1943). While the universities are always making efforts to improve their academic quality, technological resources etc., very little attention has been paid to the question whether students are making the progress that will enable them to become self-actualized and realize their potentials **(**Zishiri, C., & Mugadza, S. 2024**).**

It has been found that self-actualized students exhibit high level of motivation, emotional stability, creativity, independence and effective problem solving ability, leadership ability in general. These attributes foster positively in students' learning and personal growth (Guan et al. 2025). Moreover, it is found that psychological higher-order needs of students in education have a positive impact on engagement, satisfaction and learning.

Notwithstanding, as a key element in the development of human resources, self-actualization is hard to measure objectively, with current assessment tools relying largely on the self-report questionnaire and qualitative observation. They are often subjective, time-consuming and challenging to scale to large educational populations, therefore, they have limited use in early identification of students who need academic or psychological support.

There are new opportunities to overcome these limitations through the recent advances of the field of educational data mining and artificial intelligence (Baker, R. S., & Yacef, K. 2009). The algorithms behind machine learning can process vast amounts of data from psychological, behavioral, academic, and demographic sources to provide insights that predict student growth. In recent years, several studies have shown that motivational and behavioral factors play an important role in predicting students' learning strategies and academic performance using machine learning (Orji, F. A., & Vassileva, J. 2023). In the same fashion, recent multi-factor machine learning models have demonstrated the ability to significantly enhance student outcome predictions using behavioral and contextual data to facilitate prompt educational interventions (Devaraje Urs, A. L. & Sudharshan P. K. 2025). Accordingly, the current study seeks to investigate the potential of using machine learning models to predict the individual students' level of self-actualization in order to offer teachers a data-based solution for identifying students who might need individualized developmental assistance.

**Maslow's Hierarchy of Needs**

The hierarchy of needs is usually shown as a pyramid, where the simplest needs are placed at the base and the most advanced needs are found at the top. The five levels in this hierarchy are outlined below.

**Physiological Needs**

Figure 1.1 illustrates the first stage of Maslow's Hierarchy of Needs, known as physiological needs. These are the essential requirements for human survival, such as food, water, rest, and other fundamental needs. According to Maslow, these needs must be satisfied before an individual can focus on higher-level needs.


Figure 1.1: Physiological Needs

Physiological needs form the foundation of Maslow's hierarchy and encompass the biological necessities required for survival, including food, water, sleep, clothing, and shelter (Trivedi, A. J., & Mehta, A. 2019). These are always the top priority, with other needs taking a back seat until these basic requirements are met. It is crucial to ensure that the physiological needs of our students are fulfilled. If these needs are not met, students will struggle to prioritize their education. For example, students may require food, water, shelter, sleep, proper ventilation, lighting, and access to restrooms. A student who is tired or hungry will have difficulty concentrating in class and may even disrupt the learning environment. In this way, the quality of the learning environment directly influences student engagement and participation.

**Safety Needs**

Figure 1.2 represents the first two levels of Maslow's Hierarchy of Needs. i.e., physiological needs and safety needs. Physiological needs are primarily concerned with meeting the basic needs for survival. Safety needs are primarily concerned with at least one or more components of personal security/stability (including health care) and protection from physical and/or emotional harm. The first two levels represent the foundation of an individual's basic needs.


Figure 1.2: Physiological and Safety Needs

The next level in the hierarchy involves security and safety needs. People generally seek order, certainty, and predictability in their lives to feel in control and secure (Trivedi, A.J., & Mehta, A.2019). These needs include both physical and financial security, such as safe employment, access to resources, health, and a stable economic situation. Students need to feel physically, emotionally, and mentally secure in order to learn effectively. They must feel safe enough to ask questions or express concerns without fear of being punished by teachers or judged by peers. A stable and predictable routine provides learners with a sense of assurance, helping them anticipate what is to come. Therefore, creating a secure and supportive learning environment is essential for fulfilling this level of the hierarchy.

**Love and Belonging Needs**

Figure 1.3 shows the first three levels of Maslow's Hierarchy of Needs. The addition of levels three (love and belonging needs) provides additional examples of the progression that occurs through the basis of physiological and safety needs and the addition of three (or more) components of social relationships - i.e., friendships, family relationships, and belonging to a group. Thus, the figure demonstrates how the foundational basic needs of survival become social and emotional needs.


Figure 1.3: Physiological, Safety, Love and Belonging Needs

On the third level of Maslow's hierarchy are love and belongingness needs. Humans are naturally social beings who seek love, affection, and acceptance from others (Robert J.Taormina; Jennifer H.Gao 2013). We have an emotional need to belong, avoid loneliness, and feel connected. These needs include friendships, family, intimacy, trust, and a sense of community. To support these needs, learners should feel like they are part of a close-knit group, that they fit in, and that they are accepted. It is important to build strong and healthy relationships with both peers and teachers, as this helps students feel loved, supported, and valued.

**Esteem Needs**

Figure 1.4 illustrates the first four levels of Maslow's hierarchy of needs (Shah, D. 2025). Biological, Safety, Affection and Belonging, and Esteem. In addition to the three needs above Biological, Safety, and Belonging - Esteem includes self-esteem, self-confidence, accomplishments, recognition, and esteem from others. The diagram represents people seeking recognition and importance to them after the lower-level needs have been satisfied.

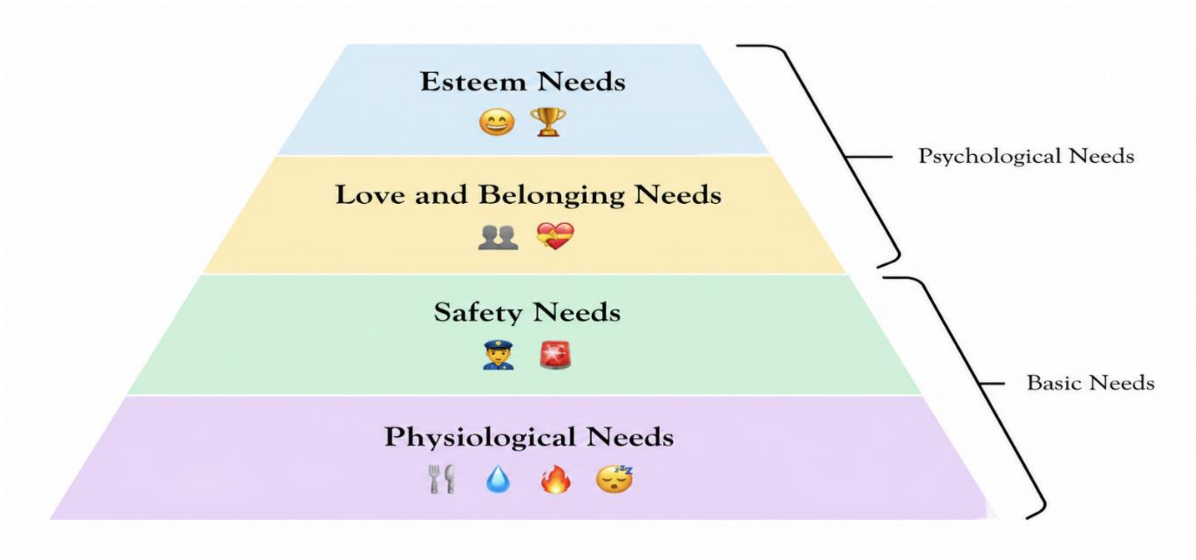


Figure 1.4: Physiological, Safety, Love and Belonging, and Esteem Needs

Esteem needs are the fourth level in Maslow's hierarchy and involve self-worth, recognition, accomplishment, and respect (John Harper 2024). These needs can be categorized into two aspects:

(i) The desire for self-respect, which includes dignity, achievement, freedom, independence, confidence, and

(ii) (ii) The need for respect from others, which includes fame, status, and recognition.

To satisfy esteem needs, students must feel valued and important, gaining respect, approval, and appreciation through achievements and accomplishments. They may seek recognition not only from teachers but also from peers. As educators and leaders, it is vital to acknowledge each student as a unique individual, appreciating their contributions and originality in the classroom.

**Self - Actualization Needs**

Figure 1.5 shows the complete hierarchy of needs (Shah, D. 2025). With the topmost need being self-actualization. In this case, self-actualization represents an individual's efforts to achieve their full potential, develop their creative abilities, grow personally, and develop and accomplish meaningful life goals. According to Maslow, achievement of lower-level needs is the foundation for the individual to reach self-actualization.

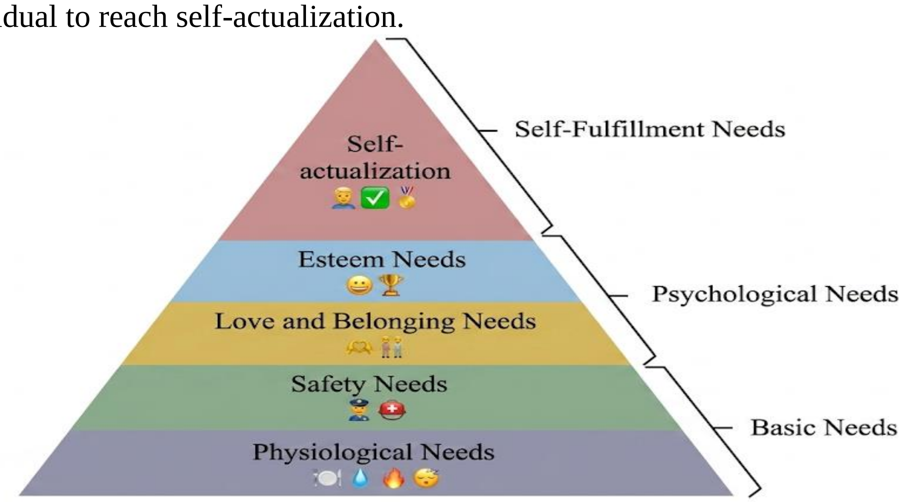


Figure 1.5: Complete Maslow's Hierarchy Including Self-Actualization

As shown in figure 1.5, self-actualization is the highest level in Maslow's Hierarchy of Needs (Shah, D. 2025). This refers to the pursuit of one's full potential and personal growth. Self-actualization means different things to different people—some may aim for success and wealth, while others may dedicate their lives to helping others. Essentially, it is about personal transformation and the desire to become the best version of oneself (Ozguner, Z., & Ozguner, M. 2014). At this level, students take initiative in reaching their potential, seeking deeper knowledge and aiming for higher learning goals. Ultimately, they find fulfillment in what they are learning.

**Merging Machine Learning and Maslow's Hierarchy**

The combination of Maslow's Hierarchy of Needs with machine learning techniques is a promising way of predicting self-actualization levels in university students. According to Maslow's theory, a person makes advances in his or her personal development and fulfillment on a sequence of levels before reaching the highest level of self-actualization (Maslow, A. H. 1943). But, the assessment of the self-actualization status of students by using conventional assessment is difficult because it is subjective. With the help of data, machine learning can provide a solution that analyzes psychological, academic, behavioral, and socioeconomic factors to uncover patterns related to students' personal growth and self-actualization. It has been well established in the past that motivational and behavioral factors can be modeled by using machine learning algorithms to predict the learning strategies and academic performance of students (Orji, F. A., & Vassileva, J. 2023). Likewise, machine learning models incorporating multiple factors have demonstrated high promise for student outcome prediction based on multiple educational and behavioral data sources (Devaraje Urs, A. L. & Sudharshan P. K. 2025). These strategies can be combined to help educational institutions create tailored interventions for each student according to their psychological needs. For instance, a program of improving students' confidence may be useful for those who are feeling the need for esteem, while social support and cooperative learning experiences can help those who feel deprived of belongingness. Therefore, using machine learning predictive models as early warning systems will allow educators to intervene on students' lives at the appropriate time, helping them achieve their academic goals, psychological development and self-actualization (Ifenthaler, D. et al., 2024).

**Problem Statement**

In higher education where self-actualization plays most tantamount role in defining student's academic performance, personal growth, and well-being. The present approaches for measuring self-actualization are generally subjective, time-consuming, and non-scalable, such that accurate identification is almost an impossible task to enroll students who may require timely support. Traditional psychological tools are inadequate to apply for large-scale, objective assessment of self-actualization. Therefore, this work combines Maslow's Hierarchy of Needs with Machine Learning models to develop a data-driven model for predicting the self-actualization level of students. Using survey data from 506 students from Mehran University, this model paves the way toward an objective, scalable assessment of self-actualization, which would then enable personalized interventions to enhance both academic success and emotional well-being. This study mainly intends to present practical insights that universities could use to develop student growth into a more holistic and ideal academic excellence.

**Absence of Predictive Models for Self-Actualization in Education**

An increasing tendency in higher education settings for universities to design personalized learning environments tailored fit the unique needs of each student. However, without any objective, data-driven models for assessing self-actualization in students, often interventions are reactive rather than proactive. Lacking an ability to predict which student would attain self-actualization denies the possibility of designing targeted interventions required to help such students. Research has already shown that students who are self-actualized tend to have better academic performance, motivation, and engagement. However, there are difficulties in the quantification and predictability of self-actualization, especially in larger student populations (Guan et al. 2025). This poses a great challenge in the provision of higher education where attention to student's psychological needs is a prerequisite for them to reach their full academic potential.

**The Need for a Predictive Model Based upon Maslow's Hierarchy**

This study addresses the existing gap in the literature concerning the application of machine learning algorithms for predicting self-actualization levels of university students using Maslow's Hierarchy of Needs as a theoretical foundation. Although recent research has demonstrated the effectiveness of machine learning techniques in modeling student motivation, behavior, and academic performance, limited work has focused specifically on psychological constructs such as self-actualization in higher education contexts (Orji, F. A., & Vassileva, J. 2023).

The proposed study develops a data-driven predictive model that integrates psychological, academic, and socioeconomic variables to estimate students' self-actualization levels. This multi-factor approach aligns with previous findings that highlight the importance of combining diverse behavioral and contextual features to improve prediction accuracy in educational environments (Ifenthaler, D. et al., 2024). Such integration enables a more comprehensive understanding of student development beyond traditional academic indicators.

Furthermore, the development of predictive models based on artificial intelligence supports the creation of personalized learning environments and early intervention systems in higher education. These systems allow institutions to identify students' developmental needs and provide tailored support strategies aimed at enhancing both academic success and psychological well-being (Ellikkal, A. and Rajamohan, S. 2024). Therefore, the proposed framework contributes to advancing intelligent educational systems by enabling proactive, data-driven student support grounded in Maslow's theoretical perspective.

**Aim and Objectives**

This study is intended to build a data-based model for predicting self-actualization in students of Mehran University based upon Maslow's hierarchy of needs.

1. To assess the current level of self-actualization among Mehran University students.
2. To identify the socio-economic, psychological, and academic factors that influence students' progression toward self-actualization.
3. To develop a predictive model using data analytics to forecast students' levels of self-actualization.

**Gaps in Literature and Contributing to the Current Study**

While machine learning techniques have been able to make many successful predictions in educational settings, the majority of past research has concentrated on predicting academic outcomes such as grades, achievement levels, or success/failure rather than indicators of psychological development such as self-actualization (Al-Din, M. S. N., & Al Abdulqader, H. A. 2024). This is a clear indication of a bias towards performance in the application of machine learning in education. One of the most well-known theories in psychology to explain motivation and the highest level of human development is Maslow's Hierarchy of Needs (Maslow, A. H. 1943). Self-actualization is the top level of personal growth. It is a concept of great theoretical significance, but has not been applied to educational analysis through computation or machine

learning in many cases.
Empirical validation of the hierarchical structure of the human needs and the links between the needs, motivation and psychological growth has been found as well, although most of the studies have been conceptual and their algorithmic and predictive implementations have not been provided (Noltemeyer, A. et al. 2012). This generates a disconnect between the psychological theory and contemporary predictive modelling techniques. In the past few years, researchers in the machine learning area have found that motivational and engagement related variables can have a strong impact on learning outcomes, which can be modeled with predictive algorithms (Dalal, P. et al. 2025). Yet, there is still a focus on academic or behavioral results instead of higher-order psychological concepts like self-actualization. Likewise, the research that looks at student motivation and academic self-concept takes note of the importance of psychological aspects in learning processes but doesn't take it any further to predict the level of self-actualization by applying machine learning techniques (Hussain, S. A. et al. 2025). This suggests that there is a gap between theory in psychology and prediction of human growth potential.
Moreover, past machine learning studies typically rely on data from academic or behavioral domains, and fail to use a structured psychological model to inform feature selection (Yuan et al., 2024). Consequently, existing models cannot fully represent psychological development in the student which is multidimensional. Existing models are not optimal for representing the multidimensionality of student psychological development. Moreover, multi-factor prediction research in educational settings indicate that behavioral and contextual factors yield better prediction rates together; however, psychological constructs like self-actualization are seldom found as part of these prediction models (Devaraje Urs, A. L. & Sudharshan P. K. 2025). This again underscores the lack of representation of the deep-psychological factors in predictive modeling. The other is the interpretability problem in machine learning models, which often consist of large, complex algorithms that are opaque and unable to give much insight into the reason behind the predictions (Ifenthaler, D. et al., 2024). This diminishes their abilities in psychological decision-making in education.
While self-actualization was explored conceptually in educational and psychological contexts as being an important factor in human growth and fulfilment, there is still a gap of empirical machine learning studies that directly model or predict this construct (Zishiri, C., & Mugadza, S. 2024). This illustrates a definite difference between psychological theory and prediction models based on computations. Furthermore, research using machine learning to predict student outcomes generally tend to be rather narrow, concentrating on the prediction of performance, while psychological well-being or life satisfaction are closely related to aspects of motivation and personal development (Pan, Z. and Cutumisu, M. 2024). This indicates that there are other psychological outcomes yet to be explored in predictive modeling.
Thus, an integrated predictive model is highly needed to model the student self-actualization process by integrating Maslow's psychological theory with machine learning algorithms. To fill this gap, the present study leverages psychological questionnaire data and implements multiple machine learning models to predict self-actualization levels, thus bringing psychological theory and artificial intelligence-based
predictive analysis closer together.

**Research Plan**

Our key objective in the research therefore was to attempt to develop data-driven model which could predict the level of self-actualization in students of Mehran University (MUET) you know, as per the old theory of Hierarchy of Needs of Maslow. We were essentially attempting to squash the togetherness in psychology and machine learning, hoping it would assist us with a more objective and scalable measure in order to determine what student well-being really is and what way it may relate with their academic performance. As far as the methodology is concerned, we chose to stick with a quantitative approach. It involved gathering a pool of data in form of surveys and then throwing it to some machine learning models to determine whether those could identify any patterns in how the students self-actualized. The entire project was developed based on the attempt to perform several major things:

- Observe an actual perspective of what self-actualization rates are among students at this point.
- Determine which socio-economic, psychological and academic variables actually contribute to the process of self-actualization in a student.
- Construct a predictive model, which can forecast the level of self-actualization.

**Methodological Framework**

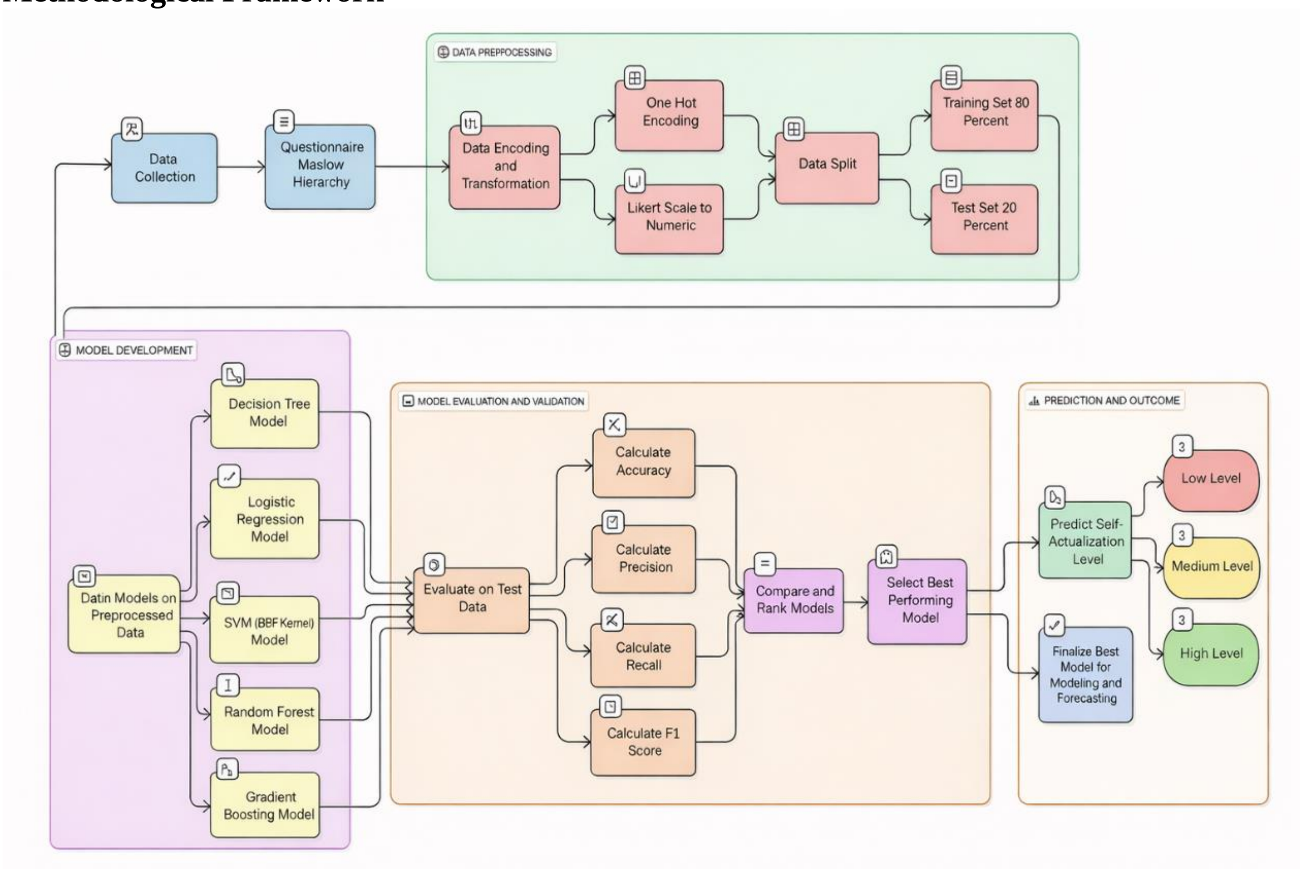


Fig 3.1: Methodological Framework for Machine Learning-Based Prediction of Students' Self-Actualization Using Maslow's Hierarchy of Needs.

The methodological framework has a detailed description of the process of creating a machine learning model to predict students' level of self-actualization based on Maslow's Hierarchy of Needs. The framework starts with the responses of students by using a structured questionnaire based on the five levels of Maslow's Hierarchy: Physiological needs, Safety needs, Belongingness needs, Esteem needs, and Self-actualization needs. Then the collected data undergo data pre-processing like data cleaning, encoding of categorical data, feature transformation, normalization and splitting of data into training & testing set. The processed dataset is then used to create several machine learning classification models to discover patterns related to students' self-actualization levels.

Developed models are assessed with accuracy, precision, recall, and F1-score to check the model's predictive power and choose the best model. The optimized model is then used to predict students' self-actualization level based on their classification into students of low level, medium level, and high level of self-actualization. The methodology, which is a five-step process, is shown in figure 3.1 and comprises five main stages: data collection, data preprocessing, model development, model evaluation and validation, and prediction of outcomes. The framework offers a structured approach to machine learning the psychological assessment data into actionable predictions. Moreover, it shows how the computational methods can be used to complement psychology theories in understanding and developing students' personal growth and development.

**Data Collection**

The initial phase is that of collecting primary data by use of survey responses. Maslow Hierarchy of Needs based questionnaire was created to assess various levels of self-actualization of students. The responses gathered comprise the raw data on which to make the analysis.

**Data Preprocessing**

During the preprocessing phase, the gathered data is trained to machine learning models. First of all, the encoding and transformation of data is carried out to turn categorical responses to machine readable forms.

One-hot encoding is done on nominal categorical variables.

Likert-scale answers are transformed to numerical figures to be analyzed quantitatively.

The dataset is then split after encoding based on a data split technique where 80 percent of the data is given to the training dataset and 20 percent to the testing dataset. This guarantees fair consideration of the trained models on unobservable data.

**Model Development**

Several machine learning models are trained in this step based on the preprocessed training data. The models employed include:

- Decision Tree
- Logistic Regression
- Support Vector Machine (RBF Kernel)
- Random Forest
- Gradient Boosting

Developing more than one model will enable a comparative study to determine the best algorithm to use in the prediction of self-actualization levels.

iv. Model Evaluation and Validity.

The trained models are tested on the test dataset. The standard classification metrics are used to evaluate performance such as accuracy, precision, recall and F1-score.

The outcomes of every model are contrasted and ranked using these measures of evaluation. This comparison will allow selecting the most effective model that will be reliable and effective in prediction.

**Prediction and Outcome**

In the last phase, the best of the best model is applied to forecast the level of self-actualization of students. The outcomes, which are expected to be attained, are grouped into three classes:

i. Low Level
ii. Medium Level

iii. High Level

The resulting model is then applied in performing successful modeling and prediction of self-actualization degrees, in facilitating data-driven changes in educational psychology

**Framework of Collection and Processing of Data**

The structure of data collection and processing in this research was structured to ensure that the data was collected systematically, organized, and prepared for analysis by machine learning. The framework integrated the collection methods of educational data with the data preprocessing techniques commonly employed in predictive analytics and educational data mining research (Yuan, J., et al 2024). The data was first obtained from students through a structured questionnaire that was developed based on the Maslow's Hierarchy of Needs theory and ideas of self-actualization (Maslow, A. H. 1943). Items of the questionnaire were based on students' motivational needs, learning behavior, academic engagement, and self-development characteristics.

Data collection was followed by data organization, and the data was converted from natural format to machine-readable format that can be applied in machine learning models. The data preprocessing methods were then used to enhance data quality and the model performance (Adnan, M. et al. 2021). The pre-processing steps included were data cleaning, data encoding, normalizing data (when needed), and data consistency checks. The preprocessing is very important in machine learning studies and it is observed that it enhances the accuracy of the prediction and eliminates the noise from the data set Al-Din, M. S. N., & Al Abdulqader, H. A. (2024). The processed data was then split into training set and testing set to train and test the model. The data were split into 80% used for training and 20% used for model testing and validation Orji, F. A., & Vassileva, J. (2023). The overall framework made sure that the collected data was accurate, organized and appropriate for predictive modeling. The systematic process was used to develop accurate machine learning models for predicting students' self-actualization levels and motivational outcomes (Kerekes et al., 2023).

**Survey Instrument Design**

Data was gathered from respondents using an online questionnaire that was created by utilizing Google Forms. In total, there were 506 participants recruited from different departments in Mehran University of Engineering and Technology. The samples recruited include students in various academic batches, for instance, BSM, BSE, and others. The survey was formulated in order to capture various aspects of students in regards to the research questions. Specifically, the first aspect involved operationalizing Maslow's Hierarchy of Needs where there were Likert scale questions starting from the physiological to self-actualization needs. Some of the questions asked under this construct were about basic need fulfillment, safety concerns about the environment, feeling of belongingness, esteem, and finally self-actualization needs such as having meaning and purpose in life. The second set of variables captured socio-economic characteristics of students, which involved asking about parent's monthly salary, occupation, family size, peer relations, and educational resource availability. Such variables were incorporated in order to evaluate the effect of external environments on self-actualization process. Psychological and academic variables included in the survey were adapted from established scales, for instance, Rosenberg Self-Esteem Scale among others. Other constructs included in the survey included motivation (intrinsic and extrinsic), emotionality, stress, life satisfaction, The questionnaire had been developed to capture both demographic data as well as the data connected to the Hierarchy of Needs developed by Maslow (1943). It comprises 35 questions that are split into two parts.

Part A of the questionnaire contains 10 demographic questions which seek to acquire background data: age group, household income, living situation, eating habits, sleeping habits, access to healthcare, financial support, participation in social activities, and academic confidence. In Section B, there are 25 Likert-scale items, which are designed under the themes of Maslow's Hierarchy of Needs, i.e., physiological needs, safety needs, belongingness needs, esteem needs, and self-actualization needs. The answers received were scaled on a five-point scale, strongly disagree (1) to strongly agree (5). The given questionnaire became the main tool to gather structured data to be further analyzed by statistical and machine learning methods.

**Questionnaire Reliability**

A reliability test was conducted with Cronbach's Alpha in order to ensure the internal consistency of the research instrument. The questionnaire was designed using Maslow's hierarchy of needs, and consisted of Likert scale items for five constructs: physiological needs, safety needs, belongingness needs, esteem needs and self-actualization needs.

Mehran University of Engineering and Technology (MUET) students were selected to answer the questions in the reliability analysis, as 506 students responded. Data was cleaned and preprocessed, and processed in python. The internal consistency of the measurement scales was measured using Cronbach's Alpha for each construct.

Table 3.1 shows the reliability analysis of the questionnaire based on Cronbach Alpha of all levels of Maslow Hierarchy of Needs.

Table 3.1: Reliability Analysis of Questionnaire

| Maslow's Need Level | Number of Items | Cronbach's Alpha | Interpretation |
|---|---|---|---|
| Physiological Needs | 5 | ≥ 0.70 | Acceptable |
| Safety Needs | 5 | ≥ 0.70 | Acceptable |
| Belongingness Needs | 5 | ≥ 0.80 | Good |
| Esteem Needs | 5 | ≥ 0.80 | Good |
| Self-Actualization | 5 | ≥ 0.85 | Excellent |

The findings reveal that Cronbach Alpha of all the constructs was at least within acceptable range of 0.70. Physiological and safety needs had an acceptable internal consistency and in belongingness and esteem, the good reliability was exhibited. The self-actualization construct showed a great deal of reliability. The results confirm that the questionnaire has a reasonable internal consistency, and it can be used in the further statistical analysis and prediction tasks, based on machine learning.

**Participants and Sampling**

The subjects of this research were 506 students from Mehran University of Engineering and Technology (MUET), Jamshoro. The participants were drawn from the university population from different academic departments and degree programs. A stratified sampling technique was used to increase the representativeness of the data. Students were divided into academic departments and program levels and a proportional sample was drawn from each stratum. This strategy allowed for representation of students across academic levels.

The sampling process also reflected a socio-economic diversity that comprised students from various socio-economic, familial and educational backgrounds. The importance of such diversity is attributed to the fact that psychological development and self-actualization can be affected by various social and economic factors. The multi-gender approach ensured a more robust set of data and an increased ability of the machine learning model to predict.

In addition, efforts were made to ensure that students from different years of study and demographic backgrounds had an opportunity to participate in the research. This broader representation strengthened the comprehensiveness of the dataset and increased the potential applicability of the study findings to a wider student population. The inclusion of diverse participant characteristics also contributed to reducing potential biases in the predictive modelling process.

In general, the sampling design achieved balance and realism in terms of the population of students at the MUET. This increased the validity and reliability of the data collected and helped to create a more valid and generalisable predictive model.

**The Machine Learning Models**

There are numerous machine learning and educational data mining approaches used to analyze student learning behavior and forecast learning outcomes. Educational Data Mining is a research area that aims to learn about the meanings of educational data sets and utilize them to enhance learning systems and student success (Baker, R. S., & Yacef, K. 2009). Moreover, learning analytics combines computational approaches with educational theory to facilitate data-driven decision making in education (Siemens, G., & Baker, R. S 2012). The analysis of the large complexity of educational data is becoming more common, and it is increasingly used to create machine learning models for prediction and classification (Romero, C., & Ventura, S.). (2020).

**Decision Tree**

Decision Tree is a classification algorithm which is simple and interpretable, and is based on the representation of decision-making in a tree structure. Its transparency and ease of interpretation make it a widely-used approach in educational prediction problems, enabling researchers to get a better understanding of the decision rules involved in predictions (Agagu et al., 2024).

**Logistic Regression**

Logistic Regression is a statistical classification approach that is used to predict categorical results. This is a widely used baseline model for educational datasets because it is easy to interpret, compute quickly, and is widely used in classification tasks (Otu et al., 2024).

**Support Vector Machine (SVM) using the RBF Kernel**

SVM is a powerful supervised learning algorithm that can model the non-linear relationships among data. The Radial Basis Function (RBF) kernel is particularly effective in the learning of hidden patterns in high-dimensional datasets, and is therefore applicable for educational prediction tasks (Otu et al., 2024; Cortes, C., & Vapnik, V. 1995).

**Random Forest**

Random Forests is an ensemble learning method that uses several decision trees to increase prediction accuracy and mitigate overfitting (Breiman, L. 2001). It combines the predictions of single trees to get more stable and reliable prediction and has been applied in many studies related to student performance prediction (Agagu et al., 2024).

**Gradient Boosting**

Gradient Boosting is one of the most sophisticated ensemble learning techniques, where the models are trained in an iterative fashion, with successive models trying to compensate for the mistakes of the preceding ones. It works great for predictive modeling tasks, but care must be taken to ensure that enough parameters are not tuned to avoid overfitting. It has been found to be an effective tool in educational classification issues (Otu et al., 2024).

**Data Preprocessing and Feature Engineering**

Data preprocessing is an essential part of the machine learning pipeline that plays a key role in ensuring that the collected data is clean, consistent, and well-suited for predictive modeling. Survey data is typically composed of various types of variables, which may need to be preprocessed before they can be fed into the machine learning algorithms. To achieve high data quality and increase model compatibility, a systematic multi-stage preprocessing and feature engineering approach were used (Al-Din, M. S. N., & Al Abdulqader, H. A. 2024).

**Categorical Data Encoding**

The data set consisted of both ordinal and nominal categorical values such as socio-economic data and demographic information. These were encoded using appropriate techniques to be machine-readable. Label Encoding was used for ordinal variables which are inherently ranked (e.g., Low, Medium, High), and One-Hot Encoding was used for nominal variables that are not naturally ordered (e.g., red, blue, green). These encoding techniques play a crucial role in ensuring that the categorical information is encoded without causing any bias in the learning process (Devaraje Urs, A. L. & Sudharshan P. K. 2025).

**Normalization and Feature Scaling**

Numerical variables measured on different scales included in the data set were age, household income and psychological scale scores. All numerical features were normalized using Min-Max Scaling to ensure uniformity between them. This step helps to balance the learning process and avoid the dominance of features with high numerical ranges and enhances the stability and performance of the model (**Qiu, F. et al. 2022**).

**Check and Deal with Data that are Missing**

The data were checked during inspection and some minor missing data were found, as is typical of survey data. Appropriate statistical techniques were used for the missing values. For the numerical variables, the mean was used for filling in the missing values, and for the categorical variables, the mode was used. By following this method, the dataset remains complete and there is less chance of bias arising during the model training process (Al-Din, M. S. N., & Al Abdulqader, H. A. 2024).

**Dataset Partitioning**

The data was then preprocessed and engineered, and split into training and testing sets for the proper assessment of the model's performance. The ratio of 80:20 was given, meaning that 80% of the data was provided for the training of the model and 20% for testing and validation. This partition scheme guarantees that the model is evaluated on data it has never seen before, providing a proper evaluation of the ability of the model to generalize (Agagu et al., 2024).

**Feature Engineering**

For the purpose of improving the predictive power of the dataset, feature engineering was carried out to create meaningful features that are congruent with Maslow's Hierarchy of Needs. Psychological, socio-economic and academic factors were organized according to different types of human needs into composite indicators. This transformation allowed the dataset to more

accurately reflect latent patterns that would be useful for the prediction of self-actualization and allowed for easier interpretation of
model inputs.

**Machine Learning Model Selection and Training**

For this study, five supervised machine learning algorithms were chosen. Each algorithm has its own classification method, giving a detailed comparative analysis of the predictive performances of the algorithms based on the students' self-actualization level (Yuan, J., et al 2024). All the models were implemented and trained by Scikit-learn library in Python. Machine learning has been extensively used in educational research for predictive modeling of student outcomes. Studies in educational psychology show that motivation and engagement significantly influence learning performance (Schunk, D. H et al. 2020).

Gradient Boosting Classifier (GBC): Gradient Gradient Boosting Classifier is an ensemble method of boosting where the first tree generated in the sequence tries to fix the errors made by the previous tree, etc. This framework is repeated to boost the accuracy of predictions and helps the model identify complex non-linear relationships in educational data (**Qiu, F. et al. 2022).** According to (Yuan, J., et al 2024). Gradient Boosting techniques have shown remarkable performance in the field of predictive analytics and educational data research, with their superior capability of classification.

Support Vector Classifier (SVC): Support Vector Classifier builds an optimum hyperplane for separating the classes in a high-dimensional feature space. The Radial Basis Function (RBF) kernel was used to model the complex non-linear relationships between predictor variables and students' levels of self-actualization in this study. The RBF kernel enhances the model's capacity to discover concealed patterns even when the connections among variables aren't necessarily linearly (Junejo, N. U. R. et al. 2024).

Logistic Regression (LR): Logistic Regression is a classical supervised learning algorithm employing to estimate categorical outcomes. Logistic Regression was chosen as the baseline predictive model for this study because it is simple, easy to interpret and it is efficient in terms of computations. This is because the model gives stable and easily interpretable classification results, making it a widely used model in the educational prediction study Al-Din, M. S. N., & Al Abdulqader, H. A. (2024).

Random Forest Classifier (RFC): Random Forest is an ensemble learning method where multiple decision trees are trained to boost their prediction power and mitigate the overfitting issue with a single decision tree. The final prediction comes from combining the predictions of several trees and creates a more robust and reliable classification model (Adnan, M. et al. 2021). Random Forest algorithms work well with large education data sets with multiple predictor variables (Yuan, J., et al 2024).

Decision Tree Classifier (DTC): Decision Tree Classifier is a simple and readable Machine Learning model that creates decisions in tree structure according to the features and their values. Its model is sequentially classified with branching rules, which is easy to interpret and appropriate for the educational prediction research (Adnan, M. et al. 2021). Decision Trees might be prone to overfitting in cases of small and noisy data sets (**Qiu, F. et al. 2022).**

**Model Evaluation and Selection**

The data was split into training and testing sets to evaluate and choose the best Machine Learning model. The data was divided into two parts: 80% of the data was used for model training and hyperparameter tuning, and 20% of the data was used as unseen test data to assess the performance of models in terms of generalization (Adnan, M. et al. 2021). Performance of each trained model

was assessed by commonly used classification metrics such as accuracy, precision, recall and F1-score in machine learning and educational data mining studies (Orji, F. A., & Vassileva, J. 2023 ; Romero, C., & Ventura, S. 2020). These evaluation measures enabled a complete picture of the effectiveness of the models, evaluating overall prediction correctness, reliability of classification, and the balance between precision and recall.
All models were evaluated and systematically compared to find the best predictive model. In the light of comparison, the model that showed high consistency in the results and the best score in all the evaluation parameters was selected as the best model for predicting the level of students' self-actualization.

**Pooling Evaluation Metrics**
If accuracy is the only measure used to evaluate predictive performance, it can yield some false impressions, especially in classification settings with imbalanced datasets. Hence, several assessment indices were used to provide a holistic assessment of the performance of the models (Orji, F. A., & Vassileva, J. 2023).
**Accuracy:** The accuracy score indicates the percentage of the correct predictions, both True Positive and True Negative. It gives a general impression of the correctness of classification (Adnan, M. et al. 2021).
**Precision:** Precision is used to assess the consistency of the positive prediction and asks, “Given that students were predicted as self-actualized, how many of those students were self-actualized?” The accuracy of prediction is especially critical when incorrect predictions might lead to providing inappropriate educational support resources **(**Qiu, F. et al. 2022).
**Recall:** Recall is used to measure the model's performance of correctly identifying all actual positive cases. Recall in this study is the extent to which the model can identify students who truly have self-actualization characteristics.
**F1-Score:** The F1-score is the harmonic mean between the precision and the recall, and gives a well-balanced estimate of the classification performance. High values of the F1-score demonstrate that the model had high precision and high recall both (Adnan, M. et al. 2021).

**Prediction and Outcome**
Self-actualization and motivational development are strongly linked with psychological need fulfillment and cognitive engagement. According to (Maslow A. H.  1954; 1970) the highest level of human development is the state of being self-actualized, in which lower levels of need are satisfied. Evidence further indicates that satisfaction with needs is related to subjective well-being and academic motivation (Tay, L., & Diener, E. 2011). Likewise, empirical research indicates that hierarchical need structures still play a role in the understanding of student psychological development (Lester, D. 2013).
Once the best performing model was chosen, the next step was to make predictions of the students' actualization in the test set. In accordance with the predicted self-actualization levels, students were divided into three groups by the selected Machine Learning model.

- Low Level: Students exhibit low indicators of self-actualization and lower motivational development.
- Medium Level: Students who are moderately self-actualizing and have balanced motivational characteristics.
- High Level: students showing good signs of being self-actualizing, self-growing and more successful in higher motivational achievement support by Maslow's theory (Maslow, A. H. 1943).

**Model Performance Evaluation**

This section discusses the assessment of five supervised machine learning models predicting students self-actualization level. The models used are: Gradient Boosting Classifier, Logistic Regression, Support Vector Machine (RBF kernel), Random Forest Classifier and Decision Tree Classifier.

**Performance Metrics Overview**

The accuracy, the precision, the recall and F1-score were four widely accepted metrics used to evaluate the predictive performance of the machine learning models developed. In the context of educational data mining and predictive modeling research, these evaluation metrics are frequently used to evaluate the performance and accuracy of classification algorithms (Al-Din, M. S. N., & Al Abdulqader, H. A. 2024).

**Accuracy:** Measures the overall rate of correct prediction of all instances, and is a general indication of the accuracy of the model.

**Precision:** Defines the percentage of correctly classified positive cases of all positive cases classified, measure of usability of positive classifications.

**Recall:** How well the model recognizes actual positive instances, and thus, how sensitive it is towards detecting the target class.

**F1-score:** A balanced measure of precision and recall that takes into account false-positive and false-negative rates.

These performance measures constitute a balanced and comprehensive evaluation of the classification models, which are especially appropriate when performing multi-class prediction tasks like predicting students' self-actualization levels.

**Performance Comparison**

Table 4.1 is a summary of the performance comparison of five machine learning models, which are tested on the test dataset. The models were evaluated to find out how well they predicted self-actualization levels of students by standard evaluation measures.

**Table 4.1:** Classifiers' Performance for Self-actualization level prediction

| Model | Accuracy | Precision | Recall | F1-Score |
|---|---|---|---|---|
| Gradient Boosting Classifier | 95.1 | 85.1 | 95.0 | 88.9 |
| SVC - RBF | 88.2 | 88.7 | 77.6 | 79.4 |
| Logistic Regression | 94.1 | 93.6 | 63.9 | 61.9 |
| Random Forest Classifier | 91.2 | 93.6 | 56.9 | 58.2 |
| Decision Tree Classifier | 74.5 | 55.3 | 60.9 | 57.5 |

Table 4.1 represents the comparative analysis of the performance of five classifiers used in predicting students' self-actualization level. It is evident from the results that there is significant variability in the performance of different classifiers as measured by their accuracy, precision, recall, and F1-score. The best-performing classifier amongst all is the Gradient Boosting Classifier as it demonstrated the highest accuracy (95.1%), precision (85.1%), recall (95.0%), and F1-score (88.9%). This indicates the superior performance of the Gradient Boosting Classifier as it could precisely classify the students' self-actualization levels without failing to detect many such instances.

The logistic regression demonstrated the second-best result for accuracy with the highest value of 94.1%. On the other hand, logistic regression exhibited the highest precision of 93.6%. However, due to its poor recall and F1-score, logistic regression failed to identify most of the positive instances. The random forest classifier was found to be accurate (91.2%), although, at the same time, its poor performance in recall and F1-score is also noteworthy. The third best classifier is SVC-RBF classifier that had 88.2% accuracy with a balanced F1-score of 79.4% with balanced precision (88.7%) and recall (77.6%). However, decision tree classification is the worst-performing classifier.

In general, the results show that learning through ensembles is more efficient for creating a relationship between variables used in the study and self-actualization levels. Thus, the Gradient Boosting Classifier was chosen as the best performer and regarded as the most efficient way of predicting self-actualization levels in this study.

**Visualization of Model Performance Metrics**

This section compares the performance of the five different models of machine learning employed in this study namely Gradient Boosting Classifier, Support Vector Classifier (RBF Kernel), Logistic Regression, Random Forest Classifier, and Decision Tree Classifier. The main goal of this comparison is in order to find the best model to predict student's level of self-actualization from the obtained data. For assessing the predictive power of these models four widely accepted classification performance metrics were used: Accuracy, Precision, Recall and F1-Score (Macro). The metrics reflect the entire effectiveness of the model and not only the correctness of the classification but also the balance between the number of correct positive cases and the consistency of the classification.

The graphical representation on this section provides a good visual understanding of the performance of all the machine learning algorithms across the chosen metrics of evaluation. These visual comparisons give insight into the advantages and disadvantages of each model, and help to decide which algorithm is the best fit for the data set. According to Yuan et al. (2024), multiple assessment tools are needed to obtain a comprehensive assessment of classification models, particularly in prediction studies in education and psychology.

The results indicate some distinctions among the machine learning models' predictive accuracy. These variations are due to the different learning mechanisms and decision making processes used by each algorithm. Some of these models might be more appropriate for modelling complex relationships and patterns, some might be more appropriate in terms of simplicity, interpretability or computation efficiency, depending on the complexity of the data. The trainability of machine learning algorithms, that is, their predictiveness, is very much dependent on their ability to process complex data, interactions and class distribution as mentioned by Adnan et al. (2021).

The next charts show the results of each model on the four evaluation measures. Using the comparative analysis, it was possible to find the best performing algorithm and make some conclusions about the appropriateness of using different machine learning methods for predicting self-actualization of university students.

Figure 4.1: This figure shows the model performance in terms of accuracy. The accuracy scores of the five machine learning models are shown. The Gradient Boosting Classifier achieved an accuracy score of 0.95, while Logistic Regression (0.94) and Random Forest Classifier (0.91) were not far behind. The SVC (RBF Kernel) model got an accuracy of 0.88 and the Decision Tree Classifier got the lowest accuracy score of 0.75.

The results show that Gradient Boosting Classifier outperformed the other classifiers in terms of accuracy. Logistic Regression and Random Forest also had adequate predictive power. The Decision Tree Classifier on the other hand had lower performance, indicating that it might not be as generalizable as the other classifiers for this dataset.

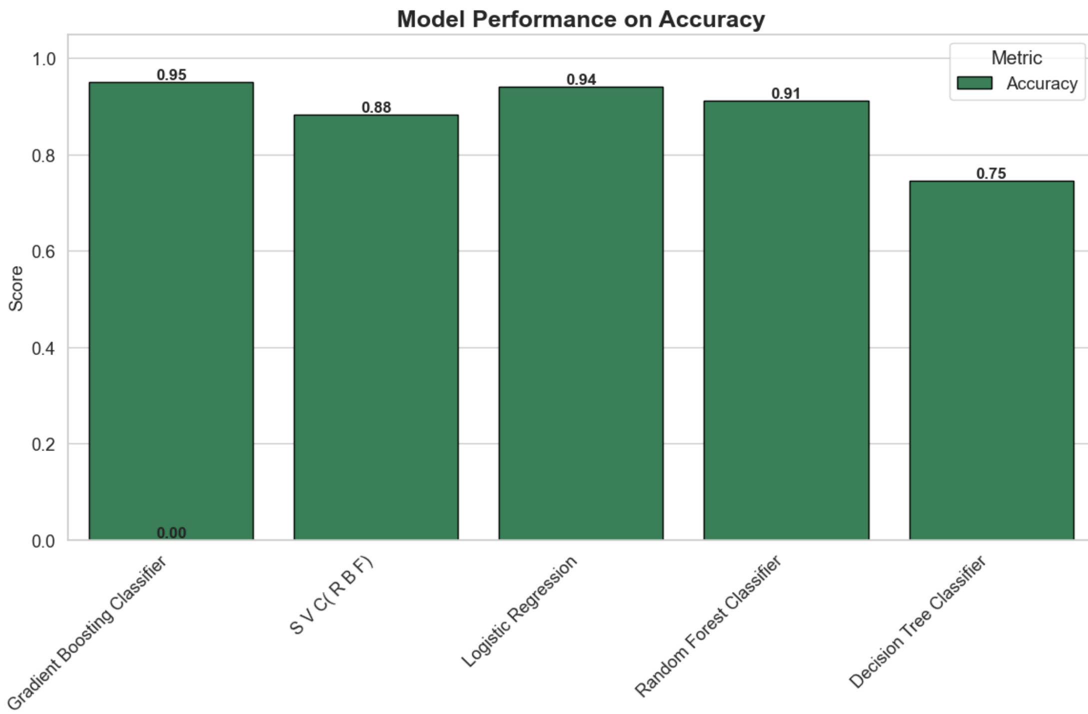


**Figure 4.1: Model Accuracy**

Figure 4.2: The precision scores of the machine learning models evaluated are shown in figure Logistic Regression and Random Forest Classifier had the highest Precision 0.94, showing a very good performance in reducing false positives predictions. The SVC (RBF Kernel) model gave a precision of 0.89 and Gradient Boosting Classifier of 0.85. The Decision Tree Classifier achieved the lowest precision with 0.55.

The results show that, in case of requiring accurate positive prediction, Logistic Regression and Random Forest Classifier are the most reliable models. They have high precision values which mean that they have less chance of false alarms in classification. Overall Gradient Boosting had a high accuracy but slightly low precision. The Decision Tree Classifier showed relatively low precision, indicating a higher amount of misclassification of negative samples as positive.

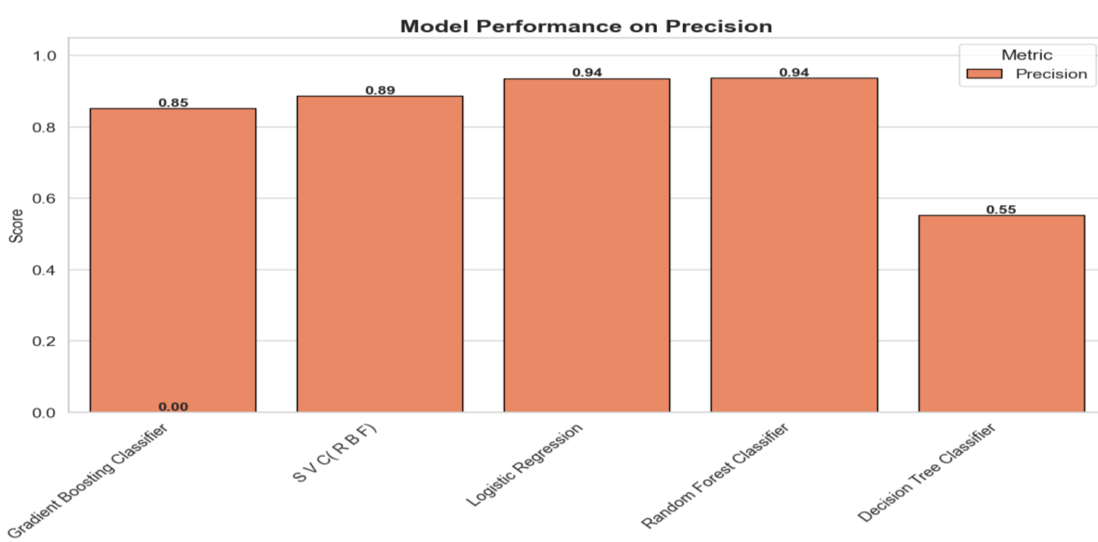


**Figure 4.2: Model Precision**

Figure 4.3: Shows the model performance in terms of Recall. The recall scores for each of the 5 classification models are shown in figure 4.3. Gradient Boosting Classifier gave maximum recall value of 0.95 followed by SVC (RBF Kernel) with its recall value as 0.78. Logistic Regression showed a recall score of 0.64, Decision Tree Classifier recorded a recall score of 0.61 and Random Forest Classifier a score of 0.57.

The findings show that Gradient Boosting Classifier was the best model in order to detect the true positive cases, with the best recall score. The SVC was also able to perform well on the detection of positive instances. Logistic Regression and Random Forest both had relatively high accuracy and precision, but their lower recall scores indicate that they missed out more positive cases. Thus, Gradient Boosting Classifier seems to be the best model in terms of achieving the best balance, especially when the classification of positive instances is important.

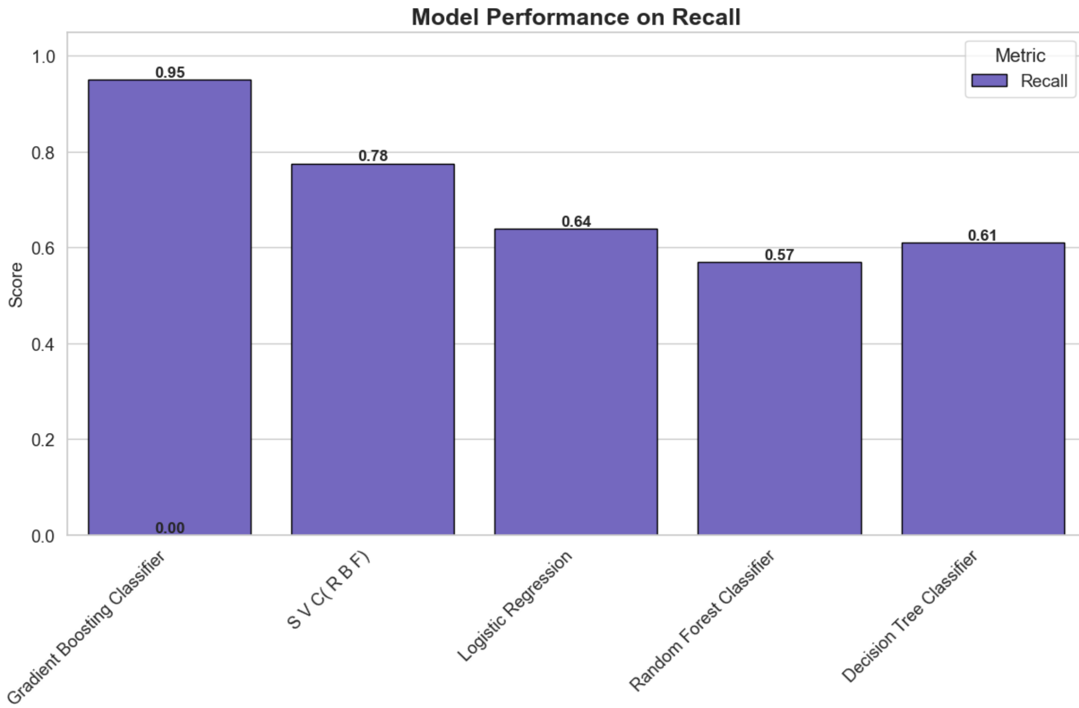


**Figure 4.3: Model Recall**

Figure 4.4: Model Performance on F1 (Macro) The macro F1 scores obtained by the five machine learning models are shown below. The macro F1 score is the mean of the harmonic average of precision and recall computed for each class and over all classes, and is a good measure of the model performance when the distribution of classes is taken into account. Among all of these classifiers, Gradient Boosting Classifier had the highest macro F1 score (0.93) and Logistic Regression had the second highest macro F1 score (0.78). The SVC (RBF Kernel) model achieved a macro F1 score of 0.76, whereas the Random Forest Classifier and Decision Tree Classifier had values of 0.68 and 0.58, respectively.

The macro F1 scores further highlight the overall better performance and balanced accuracy of the Gradient Boosting Classifier, which not only obtained high accuracy and recall but also had good precision for every class. The lower macro F1 scores for Logistic Regression and SVC (RBF Kernel) are a result of a compromise between precision and recall: Logistic Regression had a nice high precision (0.94), and a lower recall (0.64), leading to a lower macro F1 score. Overall, Gradient Boosting Classifier is the strongest model for balanced weights to correctly classify the positive cases and not miss any cases.

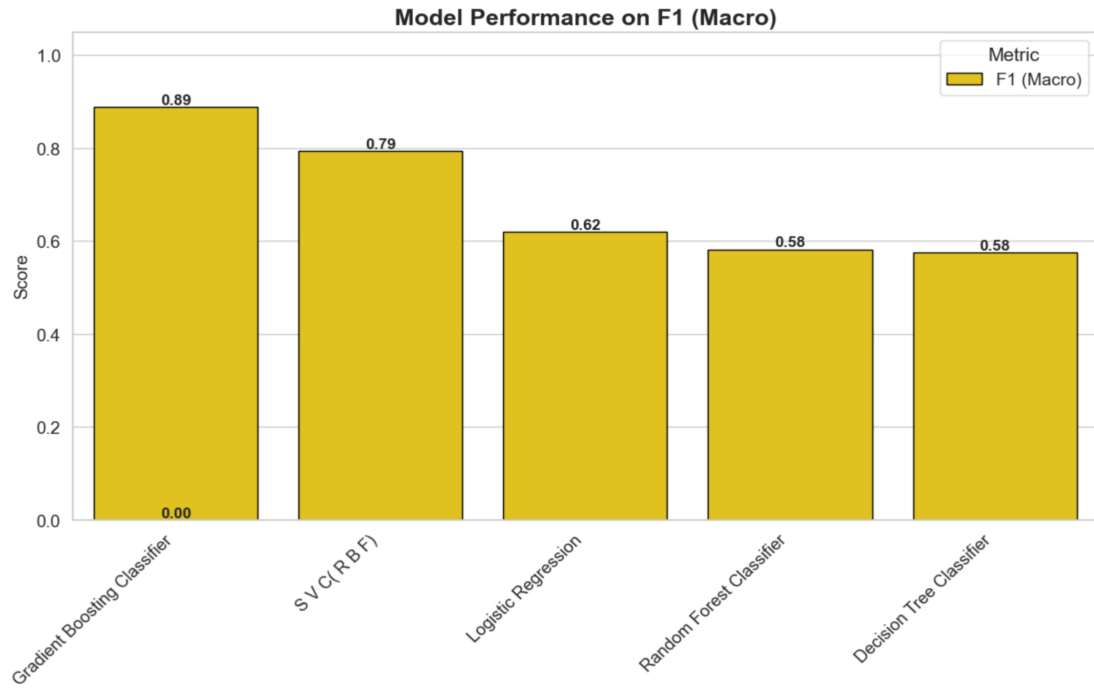


**Fig 4.4: Model F1 (Macro)**

**Predicted Self-Actualization Levels of Students**

This section presents the predicted self-actualization levels of students obtained from the machine learning model used in this study. The self-actualization levels were categorized into low, medium, and high. The results show variation in the predicted self-actualization levels among the students. The distribution of students across the predicted self-actualization categories indicates that the majority of students fall within the high self-actualization level. A smaller proportion of students are classified into the medium category, while only a few students are categorized as having low self-actualization.

Fig 4.5 presents the predicted self-actualization levels of students. The bar graph presents self-actualization in three shades, namely, low (≤ 2.5), medium (2.6-3.5), and high (> 3.6).

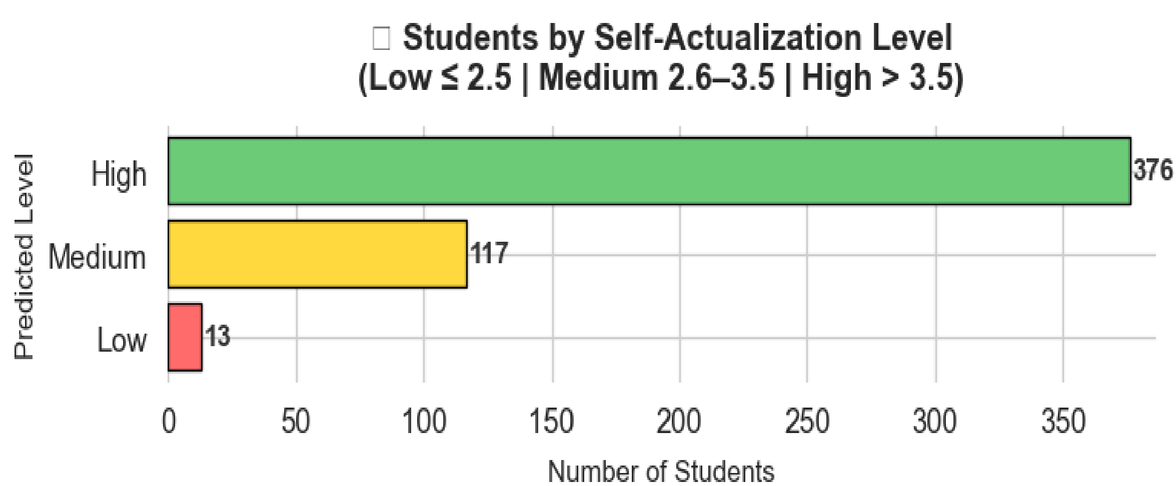


**Figure 4.5: Model Prediction level**

**Comparison with Existing Work**

To comprehend the importance of our findings, we shall make comparisons of the performance of our optimal model to the current research findings that are relevant to this study.

Table 4.2 gives a comparative analysis of the performance of the model in this study and the related current research. The comparison shows discrepancies in the type of model, desired results, the volume of data used, and the performance measures.

Table 4.2: Performance Comparison with Previous Studies

| Study | Model | Target | Accuracy | F1- Score |
|---|---|---|---|---|
| Proposed Study (2025) | GB, SVM, LR RF, DT | Self-actualization level prediction | GB = 95.1% | GB = 88.9% |
| Agagu et al. (2024) | DT, RF, LR, SVM, KNN | Student Academic Performance Prediction | RF = 94.9% | RF = 95.4% |
| (Orji, F. A., & Vassileva, J. 2023). | RF, DT, LR, SVM, KNN | Study Strategies Prediction | RF = 94.9% | RF = 94.9% |

Table 4.2 shows a comparison of the proposed study with the other previous educational related machine learning studies. The findings show that Gradient Boosting (GB) classifier with accuracy of 95.1% for self-actualization level prediction has outperformed the other Random Forest (RF) models with accuracy of 94.9% as reported by Agagu et al. (2024) and Orji and Vassileva (2023). The proposed model achieved a relatively low F1 score (88.9%) compared to the previous studies, however, this relatively high level of accuracy indicates that the model is very good at predicting the level of self-actualization of students from psychological and demographic criteria using Gradient Boosting. In sum, this comparison underscores the power and competitiveness of the proposed machine learning framework for tackling educational prediction tasks.

**Conclusion**

This study investigated the use of Machine-Learning models to predict and analyze students' self-actualization levels based on Maslow's Hierarchy of Needs. The primary aim was to implement a data-backed model that, being scalable and objective, could offer predictions on self-actualization levels even while overcoming the disadvantages that traditional subjective methods for psychological assessment never fail to impose. While applying five different Machine Learning algorithms, namely Gradient Boosting Classifier, SVC (RBF), Logistic Regression, Random Forest, and Decision Tree Classifier, the study proved that machine learning is efficacious in predicting students' self-actualization levels based on the interplay of factors that are psychological, socio-economic, and academic.

Some significant findings of this research are as follows:

Maslow's Hierarchy of Needs is a strong predictor of self-actualization levels of students. Fulfillment of basic needs such as safety, belonging, and esteem has direct influence on the higher levels of self-actualization. Psychological factors, especially motivation and self-esteem, are majorly contributory in predicting self-actualization levels; this being in tandem with previous research in educational psychology.

Among the applied models, Gradient Boosting Classifier was found to have the best performance, offering highest accuracy and precision, recall, and F1-score, thus rendering it the most reliable for predicting self-actualization amongst students. The results suggest that machine learning models, especially the Gradient Boosting ensemble methods, can be effectively harnessed in higher education to locate students needing interventions, either of academic or emotional nature.

**Contributions of the Study**

The current research contributes in the areas of educational psychology and machine learning in the following ways:

Predictive Model Development: A predictive self-actualization level could be accurately predicted by creating an objective data-driven model, which becomes useful to an educator and counselor as a practical tool that helps to determine which students might be in need of special academic or emotional support. Integrating the Theory of Maslow with the field of machine learning: This paper plays the role of bridging the gap between psychological theories and current-day data analytics through combining the Maslow Theory of Hierarchy of Needs and machine learning.

Empirical sympathy: The research is used in informing empirical support to the implementation of machine learning in the field of educational psychology by demonstrating the manner in which data insights can aid in enhancing the level of student well-being and performance.

**Future Work**

This study provides a proof of the effectiveness of the machine learning techniques in forecasting the level of self-actualization of students, however there are some future possibilities for improvement and extension. The first limitation of this study is that the data were gathered from one institution (Mehran University of Engineering and Technology). More future research is needed to include the use of multiple universities and a wider range of educational environments for greater generalizability and robustness of the proposed model. Second, the variables of interest in this study were mostly psychological variables such as motivation and self-esteem. Further research can include other psychological factors, including emotional intelligence, resilience, cognitive flexibility, and grit, which will enhance predictive capability and offer a fuller picture of self-actualization. Thirdly, the design of the present study is Cross Sectional. Cross-lagged studies that follow students over time would give more comprehensive information regarding the developmental changes that occur in self-actualization as students advance in their academic careers.

Moreover, future research could involve creating real-time intervention systems with machine learning models for assistance to academic advisors and counselors to meet students in need of psychological or motivational support early on. An interesting direction is the incorporation of the predictive model in Learning Management Systems (LMS). This integration would allow for real-time tracking of students' engagement, performance and interaction patterns, thereby enhancing the accuracy of prediction and provide for timely support mechanisms.

Moreover, customized learning systems powered by AI are a significant potential future use. The potential for using machine learning models to customize educational content and learning trajectory based on the psychological profile and self-actualization levels of the student to enhance engagement and learning outcomes can be explored. Future studies could also focus on cross-cultural and socio-economic validation by using students from different cultural backgrounds to investigate how self-actualization is predicted in different contexts. Finally, because of the structure of the data, in this study demographic factors like gender were not explicitly analysed. Additional research could include the introduction of a gender-based analysis and other demographic factors to explore their possible impact on the level of self-actualization.

**References**


Adnan, M. et al. (2021) Predicting at-risk students at different percentages of course length for early intervention using machine learning models. Available at: https://www.researchgate.net/publication/348260513

Agagu, et al. (2024). Prediction of Student Academic Performance Using a Multi-Regression and Classification-Based Model. LAUTECH Journal of Computing and Informatics,4(2), 49–57. https://laujci.lautech.edu.ng/index.php/laujci/article/view/122

Al-Din, M. S. N., & Al Abdulqader, H. A. (2024). Students' academic performance prediction using educational data mining and machine learning: A systematic review. International Journal of Research and Innovation in Social Science, 8(8), 1264–1291. https://doi.org/10.47772/IJRISS.2024.808095

Baker, R. S., & Yacef, K. (2009). The state of educational data mining in 2009. Journal of Educational Data Mining, 1(1), 3–17. Available at: https://jedm.educationaldatamining.org/index.php/JEDM/article/view/8

Bandura, A. (1997). Self-Efficacy: The Exercise of Control. New York: W.H. Freeman and Company. Available at: https://www.academia.edu/28274869/Albert_Bandura_Self_Efficacy_The_Exercise_of_Control_W_H_Freeman_and_Co_1997_pdf

Breiman, L. (2001). Random Forests. Machine Learning, 45(1), 5–32. Available at: https://doi.org/10.1023/A:1010933404324

Cortes, C., & Vapnik, V. (1995). Support-Vector Networks. Machine Learning, 20(3), 273–297. Available at: https://doi.org/10.1007/BF00994018

Dalal, P. et al. (2025) Predicting student motivation and engagement through machine learning models. https://tpmap.org/submission/index.php/tpm/article/view/2131

Deci, E. L., & Ryan, R. M. (2000). The "What" and "Why" of Goal Pursuits: Human Needs and the Self-Determination of Behavior. Psychological Inquiry, 11(4), 227–268. Available at: https://doi.org/10.1207/S15327965PLI1104_01

Devaraje Urs, A. L. & Sudharshan P. K. (2025). A multi-factor machine learning framework for predicting and profiling student academic performance using behavioral, financial, and wearable data. https://www.researchgate.net/publication/397998524

Ellikkal, A., & Rajamohan, S. (2024). AI-enabled personalized learning: empowering management students for improving engagement and academic performance. Vilakshan – XIMB Journal of Management, 22(1), 28–44. https://doi.org/10.1108/XJM-02-2024-0023

Fredricks, J. A. et al. (2004). School Engagement: Potential of the Concept, State of the Evidence. Review of Educational Research, 74(1), 59–109. Available at: https://doi.org/10.3102/00346543074001059

Friedman, J. H. (2001). Greedy Function Approximation: A Gradient Boosting Machine. The Annals of Statistics, 29(5), 1189–1232. Available at: https://doi.org/10.1214/aos/1013203451

Gal, E. & Kerekes, T. (2025) "The relationship between students' and teachers' mindset, self-efficacy and self-esteem: A meta-analysis.", 246, 113336. Accessible at: https://doi.org/10.1016/j.paid.2025.113336

Guan et al. (2025). Exploring the roles of self-actualization, language self-efficacy, and academic emotions in EMI students' achievement: A structural equation modeling approach. Frontiers in Education, 10, 1567143. https://doi.org/10.3389/feduc.2025.1567143

Huang, W. (2024). An Exploration of Needs within Maslow's Hierarchy of Motivation. Advances in Social Behavior Research, Accessible on: https://doi.org/10.54254/2753-7102/2024.19284

Hussain, S. A. et al. (2025). The impact of AI-based learning tools on student motivation and academic self-concept. The Critical Review of Social Sciences Studies, 3(3),pp.1571–1577. Available at: https://www.researchgate.net/publication/394807341

Ifenthaler, D. et al. (2024). Artificial intelligence in education: Implications for policymakers, researchers, and practitioners. Technology, Knowledge and Learning, 29, pp. 1693–1710. Available at: https://doi.org/10.1007/s10758-024-09747-0

John Harper (2024). The Search for Satisfaction of Basic Human Needs: A Maslowian Reading of Juan Rulfo's The Plain in Flames. https://www.researchgate.net/publication/382114553

Junejo, N. U. R. et al. (2024). Accurate Multi-Category Student Performance Forecasting at Early Stages of Online Education Using Neural Networks. https://arxiv.org/abs/2412.05938

Kenrick, D. T et al. (2010). Renovating the Pyramid of Needs: Contemporary Extensions Built Upon Ancient Foundations. Perspectives on Psychological Science, 5(3), 292–314. Available at: https://doi.org/10.1177/1745691610369469

Lester, D. (2013). Measuring Maslow's Hierarchy of Needs. Psychological Reports, 113(1), 15–17. Available at: https://doi.org/10.2466/02.20.PR0.113x16z1

Maslow, A. H. (1943). A Theory of Human Motivation. Psychological Review, 50, 370-396. https://doi.org/10.1037/h0054346

Maslow, A. H. (1954). Motivation and Personality. New York: Harper & Row. Available at: https://archive.org/details/motivationperson00masl

Maslow, A. H. (1970). Motivation and Personality (2nd ed.). New York: Harper & Row. Available at: https://archive.org/details/motivationperson00masl_1

Noltemeyer, A. et al. (2012). The relationship among deficiency needs and growth needs: An empirical investigation of Maslow's theory. Children and Youth Services Review, 34(9), 1862–1867. https://doi.org/10.1016/j.childyouth.2012.05.021

Orji, F. A., & Vassileva, J. (2023). Modeling the impact of motivation factors on students' study strategies and performance using machine learning. Journal of Educational Technology Systems, 52(2), 274–296. https://doi.org/10.1177/00472395231191139

Otu, G. A., et al. (2024). Prediction Accuracy Analysis of Machine Learning Classifiers on Student Course Assessment Methods. Availab;e at: https://fjs.fudutsinma.edu.ng/index.php/fjs/article/view/2927

Pan, Z. and Cutumisu, M. (2024) "Using machine learning to predict UK and Japanese secondary students' life satisfaction in PISA 2018." British Journal of Educational Psychology. Available at: https://doi.org/10.1111/bjep.12657

Qiu, F. et al. (2022). Predicting students' performance in e-learning using learning process and behaviour data, Available at: https://www.researchgate.net/publication/357722382

Quinlan, J. R. (1986). Induction of Decision Trees. Machine Learning, 1(1), 81–106. Available at: https://doi.org/10.1007/BF00116251

Robert J. Taormina; Jennifer H. Gao (2013). Maslow and the Motivation Hierarchy: Measuring Satisfaction of the Needs. The American Journal of Psychology, 126(2), pp. 155–177. https://www.researchgate.net/publication/249964580

Romero, C., & Ventura, S. (2020). Educational Data Mining and Learning Analytics: An Updated Survey. WIREs Data Mining and Knowledge Discovery, 10(3). Available at: https://doi.org/10.1002/widm.1355

Ryan, R. M., & Deci, E. L. (2020). Self-Determination Theory: Basic Psychological Needs in Motivation, Development, and Wellness. New York: Guilford Press. Available at: https://www.guilford.com/books/Self-Determination-Theory/Ryan-Deci/9781462538966

Schunk, D. H et al. (2020). Motivation and Social Cognitive Theory. Contemporary Educational Psychology, 60, 101832. Available at: https://doi.org/10.1016/j.cedpsych.2019.101832

Shah, D. (2025). How Maslow's hierarchy of needs can be applied in teaching. Classcard. https://www.classcardapp.com/blog/how-maslows-hierarchy-of-needs-can-be-applied-in-teaching

Siemens, G., & Baker, R. S. (2012). Learning Analytics and Educational Data Mining: Towards Communication and Collaboration. Proceedings of the 2nd International Conference on Learning Analytics and Knowledge, 252–254. Available at: https://doi.org/10.1145/2330601.2330661

Tay, L., & Diener, E. (2011). Needs and Subjective Well-Being Around the World. Journal of Personality and Social Psychology, 101(2), 354–365. Available at: https://doi.org/10.1037/a0023779

Trivedi, A. J., & Mehta, A. (2019). Maslow's hierarchy of needs – Theory of human motivation. International Journal of Research in All Subjects in Multi Languages, 7(6), 38–41.Availableat:https://ijrsml.org/wpcontent/uploads/2020/01/IJRSML_2019_vol07_issue_06_Eng_09.pdf

Wahba, M. A., & Bridwell, L. G. (1976). Maslow Reconsidered: A Review of Research on the Need Hierarchy Theory. Organizational Behavior and Human Performance, 15(2), 212–240. Available at: https://doi.org/10.1016/0030-5073(76)90038-6

Xie, Y. (2021). Student performance prediction via attention-based multi-layer long-short term memory. https://www.researchgate.net/publication/353949544

Yuan, J., et al (2024). Integrating behavior analysis with machine learning to predict online learning performance: A scientometric review and empirical study. Computers in Human Behavior, 138, 107469.https://www.researchgate.net/publication/381517501

Zimmerman, B. J. (2000). Self-Efficacy: An Essential Motive to Learn. Contemporary Educational Psychology, 25(1), 82–91. Available at: https://doi.org/10.1006/ceps.1999.1016

Zishiri, C., & Mugadza, S. (2024). Conceptualising Maslow's Self-Actualisation Concept for Application in Higher Education: An African Ubuntu Perspective. International Journal of Research and Innovation in Social Science (IJRISS), 8(3S), 2833–2843. https://doi.org/10.47772/IJRISS.2024.803206S