Academic Performance of Engineering Students

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The Impact of Systems Thinking Skills and Proactive Personality on Academic Performance of Engineering Students

Abstract

Academic performance of college students, particularly those who are in an engineering program, continues to receive attention in the literature. However, there is a lack of studies that examine the simultaneous effects of students' systems thinking (ST) skills and proactive personality (PP) on academic performance. The linkage between ST skills and PP has not been investigated adequately in the literature. The study aims to examine the ST skills and PP to predict the academic performance of engineering students and to find if there is a relationship between students' PP and the level of ST skills. Two established instruments, namely, ST skills instrument with seven dimensions and PP with one dimension, are administrated for data collection. A web-based cross-sectional survey using Qualtrics was used to collect the data using a sample of college engineering students. Different classification techniques were applied to perform the analysis and to compare the validity of results. This study provides implications and contributions to the engineering education body of knowledge. First, the study provides a better understanding of students' academic performance. This intent is to help educators, teachers, mentors, college authorities, and other involved parties to understand students' individual differences for a better training and guidance environment. Second, a closer look at the level of systemic thinking and PP of engineering students would help to understand engineering students' skillset.

Keywords: Systems thinking skills, proactive personality, academic performance, individual differences, engineering students, education.

1. Introduction and research background

Academic performance of college students, particularly those who are in a STEM engineering program, continues to receive attention in the education literature. For performance efficacy of students in academics, there exists a correlation among different factors pertaining to five different domains of personality traits, psychosocial contextual influences, motivational factors, students' approaches to learning, and self-regulatory learning strategies [1] – [7]. Many different instruments and measures are developed, utilized, and tested in the education literature. However, two potential predictors, namely, Systems Thinking (ST) skills and Proactive Personality (PP), have not been investigated adequately in the education literature. Research showed that systems thinking is correlated with personality characteristics [8] – [12]. Additionally, proactive personality can be correlated to several dimensions of systems thinking skills such as level of interaction, independence, change, systems worldview, and flexibility. Therefore, the proactive personality scale and ST skills measure are utilized in this study to investigate if there is a relationship between engineering students' PP and their level of ST skills and how this relationship might impact their academic performance. To build an effective future workforce, identifying potential factors that would affect students' academic performance is a necessity. ST skills and PP can be two of the potential factors that influence students' academic performance, which are vital for students' future involvement with different sectors, including industrial, academic, healthcare, and military.[13] - [16]. To the best of our knowledge, there is no prior study has been conducted to provide a detailed analysis on how academic performance might vary based on students' ST skills and PP. This study would address this gap.

Students' Academic Performance: In order to clarify which non-intellective factors are most useful in understanding academic performance, six research domains were considered including personality traits, motivational factors, self-regulatory learning strategies, students' approaches to learning, and contextual psychology. Table 1 below presents the different application domains, general themes, discussion, and findings of the six research domains.

Table 1. Current Themes of Academic Performance in the Education Literature

Contributor (year)	General themes	Description and Main Findings	Application Domain
Costa & McCrae (1992) [1]	Conceptualizing and assessing personality	In the longitudinal study, it is observed that personality traits are stable in adulthood and can be related to psychometric intelligence.	Personality traits
Tinto (1993) [2]	Integration challenge	Tinto's student integration theory is useful for analyzing student retention, and important relationships among students' initial and later academic goals and commitments have been identified by analyzing retention.	Psychosocial contextual influences
Phillips et al. (2003) [3]	Measuring motivation	The indirect effects of intention and perceived control of undergraduate students on their final grade of examination were investigated. Students' intentions had a relatively greater impact on their final grade.	Motivational factors
Boyle et al. (2003) [4]	Assessment method	It was found that different learning styles of Vermunt's 4-factor model correlated with students' academic performance from a sample of British college students. Additionally, deep strategies for promoting optimal learning and enhanced performance were used.	Students' approaches to learning
Pintrich (2004) [5]	Academic performance	Several measures and instruments of students' motivation and self-regulated learning in the college classroom were introduced, which potentially influence students' academic performance.	Self-regulatory learning strategies
Boekaerts & Corno (2005) [6]	Regulations by students	The messy world of classroom learning creates a situation in which different goals compete for students' attention. Students with well self-regulatory capacity and good work habits have better classroom learning.	Self-regulatory learning strategies
Poropat (2009) [7]	Conscientiousness	Correlations between Conscientiousness and academic performance were largely independent of intelligence upon studying, and academic performance was found to correlate significantly with Agreeableness, Conscientiousness, and Openness.	Personality traits

Systems Thinking (ST) in Education: Complex system problems are marked by increasing complexity, excessive information, ambiguity, emergence, and high levels of uncertainty [17], [18], [30]. In order to deal with problems exhibiting these characteristics, it requires a focus on the non-technological, inherently social, organizational, and political knowledge [17], [18], [30]. Although a plethora of accepted approaches and techniques available in the literature, ST is often proposed as a potential solution to managing complex system problems. Checkland, one of the pioneers of systems theory, described ST as the thought process, which demonstrates the ability to think and speak through holistic language for understanding and dealing with complex systems problems [19]. The current literature is replete with studies related to the application of ST in the education setting [14], [20] – [33]. For example, Sweeny and Sterman [20] developed a list of ST characteristics to assess students' capability to comprehend the dynamic behavior of the complex problem. In another study, Assaraf and Orion [21] investigated the ST capability for the junior high school level students pertaining to earth system education. Similarly, Frank [5] tested the cognitive aptitude and ST of a group of engineers by an instrument called 'capacity for engineering systems thinking.' Interested readers are referred to the works of Bloom and others [20] – [33] (See Table 2).

Table 2: Current Themes of ST in the Education Literature

Contributor (year)	General themes	Description and Main Findings	Application Domain
Bloom (1956) [22]	Development of a taxonomy system for categorizing the outcome of student learning	Six levels of taxonomy using knowledge, comprehension, application, analysis, synthesis, and evaluation are used by different approaches among students that can help students to be critical thinkers.	Education
Churchman, Ackoff, & Arnoff, (1957) [23]	Replacement models are used for replacement of correct timing of replacement analysis	Cost minimization under conditions of known life and effectiveness, and the probability distribution of effective live of machines	Education
Flood & Jackson (1991) [24]	Total system intervention for the practical facing of critical system thinking	A powerful and fruitful interactive manner can be used in the system of system and individual methodologies in working and everyday life.	Education
Richmond (1993) [25]	Dynamic system	By analyzing the multidimensional nature of thinking skills, time that can be required by people for understanding environmental problems can be reduced.	Education
Sweeny & Sterman (2000) [20]	Development of a list of ST characteristics to evaluate students' capability	For improving the system thinking skills, inventory can provide the means for testing the effectiveness of training and decision aids.	Education
Frank (2000) [14]	Differentiation between "system thinking" and "engineering system thinking"	Based on suggested thirty system thinking laws, a curriculum for engineering system thinking can be developed.	Engineering education
Assaraf & Orion (2005) [21]	Examination of the ST skills among the junior high school level students	Individual students' cognitive ability and their involvement in learning are found to be the two most important factors.	Education
Cabrera et al. (2008) [26]	Thinking in a system	Different rules can be applied to existing evaluation knowledge with transformative results.	Education
Cooper (2013) [27]	Learning technology standards	In order to deal with environmental complexity, facets of interoperability such as organizational, syntactic, and semantic can be used.	Education
Scherer & Tiemann (2014) [28]	Analyze the impact of task interactivity and grade level on thinking skill of an individual	Scientific problem solving can be regarded as a multidimensional construct, task interactivity can be used for problem-solving, and there exists development in the analytical component of problem-solving across grades, which suggests that psychological theories of problem-solving skills can be transferred to complex problem-solving skills.	Education
Holt et al. (2015) [29]	Determination of the factors contributed most to improve the critical thinking skills of the university students	More student-centered classes can have greater improvement, and more research is needed for research alignment and assessment in student learning.	Education
Jaradat (2015) [30]	Development of an instrument purposefully designed for the system of system domain	Complex system governance development needs the effectiveness and identification of developmental areas for enhancing practitioner capabilities are presented.	system of system
NSF (2017) [31]	Engineering formation	Preparation and submission of a proposal using RIEF proposal guidelines.	Education
Clarck et al. (2017) [32]	Learning of system thinking	Active integration of environmental dashboards into lessons for students' content related system thinking skills and content retention.	Education
Priyaadharshini et al. (2018) [33]	Higher-order engineering education	The cloud-based flipped classroom can be used for higher-order competency skills, such as problem-solving, critical thinking, and creative thinking.	Education

Proactive Personality (PP): Some literature indicate that psychological factors such as personality can influence college-aged students in different capacities. For example, Prayoonsri et al. [34] found that classroom environment, psychological characteristics, intellectual characteristics, and family characteristics affect the higher-order thinking of students. However, no study has concentrated on testing the impact of PP on the students' academic performance, and this study aims to evaluate whether or not PP benefits or suppresses the students' academic performance. Table 3 presents some common themes pertaining to PP in the current literature.

Table 3: Current Themes of Proactive Personality and Related Topics in the Literature

Contributor (year)	General themes	Description and Main Findings	Application Domain
Bateman & Crant (1993) [35]	Proactive personality	The proactive personality was introduced as a dispassion construct toward proactive behavior as the first study in the literature. The proactive personality scale defines the extent that individuals take action to influence their environments (i.e., inclination toward affecting environmental change).	Proactive personality
Crant (1995) [15]	Proactive personality and performance	It is found that Specific personality measures can have incremental validity to big five factors, and additional evidence for criterion validity is observed by using a sample of different real estate agents.	Proactive personality
Seibert et al. (1999) [16]	proactive personality and career success	Hierarchical regression analysis is performed depending upon variables such as demographics, human capital, motivational, organizational, and industry, which suggests variance in proactive personality for both objective and subjective career success.	Proactive personality
Crant (2000) [36]	Proactive behavior general	Proactive behavior is exhibited by individuals, exists in an array of domains, is essential for linking many personal and organizational processes and outcomes, and it can be constrained or prompted via managing context.	Proactive behavior
Frese & Fay (2001) [37]	Personal initiative review	Interview measure of personal initiative is measured for construct validity, which uses nomological variables and the influence of motivational parameters.	Personal initiative
Griffin et al. (2007) [38]	Proactive performance	Positive correlation among self-reported proactivity and two other external factors is observed.	Proactive behavior
Raunch & Frese (2007) [39]	Personal initiative and entrepreneurship	Different reasons for the current rebirth of personality effects in entrepreneurship are presented, and early dominance and eventual decline of personality research in entrepreneurship are discussed.	Personal initiative
Grant & Ashford (2008) [40]	Proactive behavior	Integrative theory for general dynamic proactivity is discussed, which fits with current trends in order to emphasize the increasing importance of organizational life.	Proactive behavior
Fuller & Marler (2009) [41]	A meta-analysis of proactive personality	A time-lagged study report is analyzed for discussing practical implications and potential limitations of the present study and also giving direction to future research.	Proactive personality
Parker et al. (2010) [42]	"Can do, reason to, energized to" model	Similarities, differences, and interrelationships among multiple proactive behavior types are analyzed using factor analyses.	Proactive behavior
Fuller et al. (2012) [43]	Bridge-building	It can be suggested that supervisors with proactive personalities are more prone to value and reward subordinate proactive behavior in comparison to passive supervisors, and proactive behavior did not result in a negative consequence.	Proactive behavior
Li et al. (2014) [44]	Latent change score approach	Important practical implications for organizations and employees can be attained in addition to nuanced interplays between an agentic person and work characteristics with an analysis of the relationship between proactive personality and work characteristics.	Personal initiative
Spitzmuller et al. (2015) [45]	The usefulness of proactive personality	There exists a unique job variance in overall job performance and task performance even after controlling big personality traits and mental ability in general.	Proactive personality
Plomp et al. (2016) [46]	Career competencies	It can be stated that proactive employees can enhance their well-being both through proactive job redesign and development of career-related skills and abilities after doing structural equation modeling analyses for supporting the double mediation model.	Proactive personality

2. Methodology

The instruments used in the study will be presented, followed by the dataset description, dataset preprocessing, and introduction of three machine-learning methods for data analysis. In this study, three different machine learning models are developed to illustrate the relationship between engineering students' ST skills and PP based on their academic performance. Discriminant Function Analysis (DFA), decision tree, and Artificial Neural Network (ANN) using SPSS software version 26.0 are employed to classify students based on their Cumulative Grade-Point

Average (CGPA) and current Semester Grade-Point Average (SGPA). The latter will be described in the data collection section.

Instruments: Two established instruments, namely ST skills instrument with seven dimensions and 39 questions (coefficient alpha 0.92) [17], [18], [30] and PP with one dimension, which consists of seventeen questions (coefficient alpha 0.88) [15], [16], [35], [36] are administrated for data collection. The ST instrument shown in Table 4 was developed using mixed quantitative and qualitative research approaches based on the grounded theory coding method [17], [18], [30], and all of the related scale development analyses were conducted to ensure the construct validity of the instrument. The instrument consists of seven dimensions, namely interaction, independence, change, uncertainty, complexity, systems worldview, and flexibility, as shown in Table 4. Based on these dimensions, the ST skills of an individual are evaluated.

Table 4: Seven Dimensions of Systems Thinking (ST) Skills Instrument [17]

Less Systemic (Reductionist)	Dimension	More Systemic (Holistic)
Simplicity (S): Avoid uncertainty, work on linear problems, prefer the best solution, and prefer small-scale problems.	***Level of Complexity***: Comfort with multidimensional problems and limited system understanding.	**Complexity (C)**: Expect uncertainty, work on multidimensional problems, prefer a working solution, and explore the surrounding environment.
Autonomy (A): Preserve local autonomy, a trend more toward an independent decision and local performance level.	***Level of Independence***: Balance between local-level autonomy versus system integration.	**Integration (G)**: Preserve global integration, a trend more toward dependent decisions and global performance.
Isolation (N): Inclined to local interaction, follow a detailed plan, prefer to work individually, enjoy working in small systems, and interested more in cause-effect solution.	***Level of Interaction***: Interconnectedness in coordination and communication among multiple systems.	**Interconnectivity (I)**: Inclined to global interactions, follow a general plan, work within a team, and interested less in identifiable cause-effect relationships
Resistance to Change (V): Prefer taking few perspectives into consideration, over-specify requirements, focus more on internal forces, like short-range plans, tend to settle things, and work best in a stable environment.	***Level of Change***: Comfort with rapidly shifting systems and situations.	**Tolerant of Change (Y)**: Prefer taking multiple perspectives into consideration, underspecify requirements, focus more on external forces, like long-range plans, keep options open, and work best in a changing environment.
Stability (T): Prepare detailed plans beforehand, focus on the details, uncomfortable with uncertainty, believe the work environment is under control, and enjoy objectivity and technical problems.	***Level of Uncertainty***: Acceptance of unpredictable situations with limited control.	**Emergence (E)**: React to situations as they occur, focus on the whole, comfortable with uncertainty, believe the work environment is difficult to control and enjoy non-technical problems.
Reductionism (R): Focus on particulars and prefer analyzing the parts for better performance.	***Systems Worldview***: Understanding system behavior at the whole versus part level.	**Holism (H)**: Focus on the whole, interested more in the big picture, and interested in concepts and abstract meaning of ideas.
Rigidity (D): Prefer not to change, like determined plans, not open to new ideas, and motivated by routine.	***Level of Flexibility***: Accommodation of change or modifications in systems or approaches.	**Flexibility (F)**: Accommodating to change, like a flexible plan, open to new ideas, and unmotivated by routine.

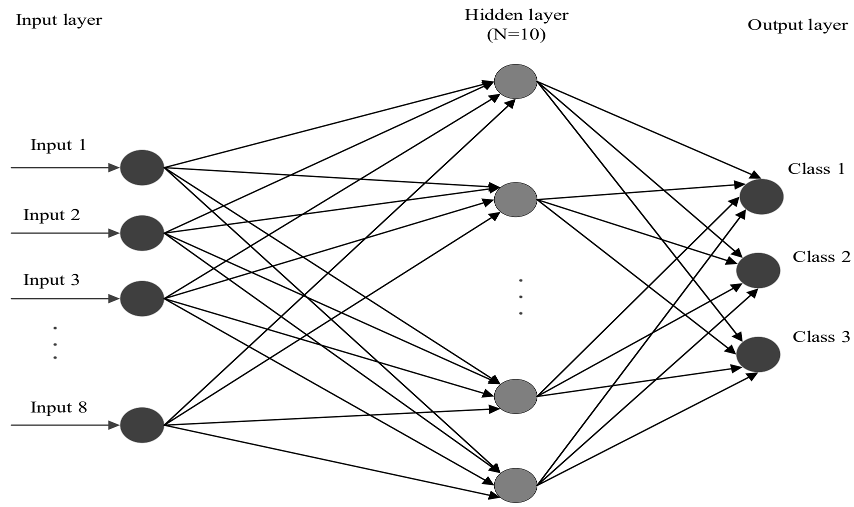
Data collection: Data acquired from 96 surveys were collected from students currently enrolled in a bachelor, master, or PhD degree at a large public University. Among 96 received surveys, 69 completed responses are included in data analysis. The questionnaire consisted of four main sections gathering data about ST skills instrument, PP, Big Five personality, and demographic questions, including CGPA, SGPA, gender, the field of study, and others. For ST skills, seven scores corresponding to seven dimensions of the ST skills instrument are calculated. Each ST dimension score was the average of questions in the corresponding dimension. The PP score was assessed based on the average of seventeen Likert-scale questions. We investigated both GPAs from the recently completed semester (called, SGPA) and cumulative GPA (CGPA). Participants were informed that their participation was entirely voluntary and anonymous. The percentage of male and female respondents was 49.3% and 50.7%, respectively. The proportion of graduate to undergraduate students was 47.8% to 52.2%. About 89.8% of students were full time while the rest were part-time. 8.6% of students were junior, 44.9% of students were senior, 14.5% of them enrolled in a master's degree, and 31.9% of students were pursuing an engineering doctoral degree. The average age of engineering students was 26.1 years, with *SD* of 6.6 years. The average CGPA of students was 3.57, with an *SD* of 0.43. The average SGPA of students was 3.51, with an *SD* of 0.84 years. The minimum CGPA and SGPA were 2.56 and 2.50, respectively. For CGPA and SGPA classification, values between 2.50 to 2.99 are assigned to class 1, values between 3.00 to 3.49 are assigned to class 2, and values equal and greater than 3.50 are assigned to class 3. In this study, CGPA and SGPA are the indicators of engineering students' performance.

Discriminant Function Analysis (DFA): is a statistical method that uses Bayes theorem and labels of training data to determine group membership of the dependent variable in such a way that these different classes have the lowest within-group variance and highest between-group variance. In DFA, predictor variables need to be independent of one another and normally distributed, and group membership needs to be mutually exclusive.

Decision Tree: Decision tree classification is a statistical procedure, which starts from the root and uses the most important predictor variable in each next level to classify input data. Decision tree uses a decision rule depends on the type of data (the threshold for numeric data and probability of classes for categorical data) to divide each internal node into two or more subtrees to maximize class purity based on information theory impurities such as Gini index, entropy, mean square error, and others.

Artificial Neural Network (ANN): Inspired by the human brain [44], ANN is an intelligent and robust method for processing information. ANN consists of a set of units called artificial neurons that are connected using weight vectors. An ANN has a structure that consists of three elements: an input layer, one or more hidden layers, and an output layer. Based on the designed network structure, artificial neurons are organized in these layers. ANN models are trained through iterative simulations and extract the hidden patterns and information via the "learning by example" approach. In the initial step, weight vectors are randomly set and can be adjusted during the training phase using a loss function. The loss function indicates how accurate are the predictions, and back-propagation algorithm distributes the error through the network. To better compare the results of different methods, other mathematical models, such as optimal control, simulation, and object-oriented modeling, can be used in conjunction with ANN [48] – [53]. In this study, different network structures are designed and applied to the dataset, in which the ANN with one hidden layer and ten neurons provided the best results. Figure 1 represents the designed ANN.

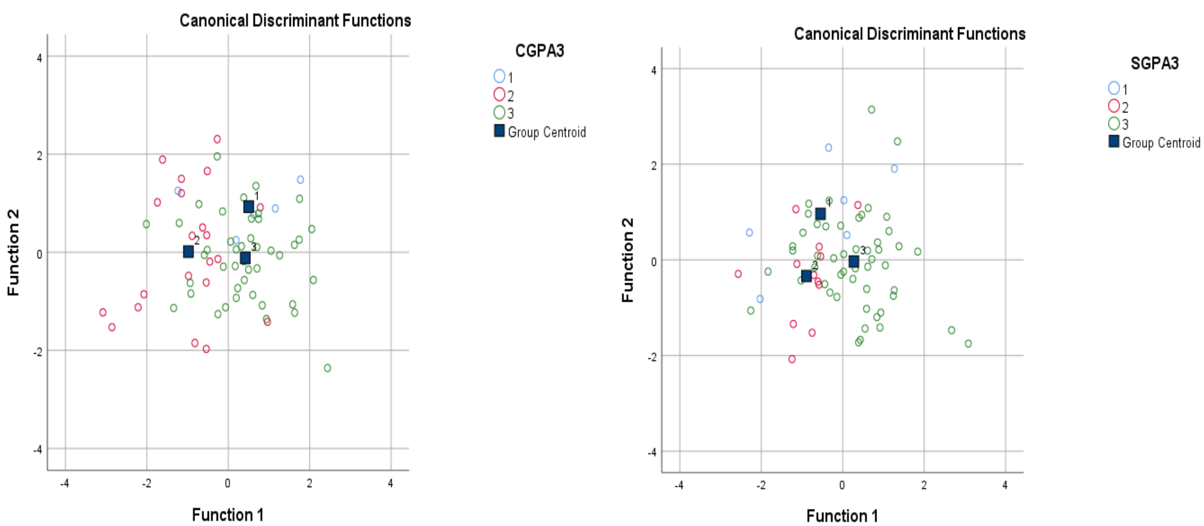
Figure 1: Designed ANN Network Structure



3. Result and Discussion

Three machine-learning methods are utilized to investigate the relationship between the study independent variables (that is, ST skills and proactive personality) and the dependent variable (that is, academic performance). ANN and similar predictive models have three advantages over traditional methods. 1)ANN has the capacity to model non-linear relationships between variables (not using/depending on the traditional linear correlational analysis to show the interdependency between variables), 2) the ability to make the model more generalizable to predict noisy, incomplete, or censored data, and 3) the ability to minimize the bias and restrictions generated from inputting data (the traditional methods have many restrictions for type and volatility of input data). As a result, in this study, ANN is selected as the main data analysis technique. In addition to ANN, two predictive models DFA and Decision Tree, are used to enhance the validity and reliability of the results. The intent is to predict students' academic performance based on their ST skills and proactive personality indicators. Since ANN and similar predictive models work well with categorical data, the study dependent variables (that is, CGPA and SGPA) were converted to categorical variables. It is common and meaningful to use categorical GPAs instead of continuous measures [54] – [56]. The academic performance of engineering students was classified into three equal distance classes of CGPA and SGPA values. Values between 2.50 to 2.99 are assigned to class 1, values between 3.00 to 3.49 are assigned to class 2, and values equal and greater than 3.50 belong to class 3. To show the prediction power of the ST skills and PP on the academic performance of engineering students, DFA, decision tree, and ANN analyses are performed using SPSS software version 26.0. Although it is recommended that a large sample size produces robust and valid results using ANN and similar predictive models, research also shows that small sample size data can produce meaningful and interpretable results [57] – [59]. DFA, decision tree, and ANN models are trained and tested using the dataset, and results for each model are discussed next. Two classification models (training and testing) based on each algorithm are developed to classify data based on two dependent variables, including CGPA and SGPA, separately. In order to evaluate the performance of the models, the dataset is split into training data (80%) and testing data (20%). This partitioning has been repeated twenty times to create twenty pairs of training and testing data. Figures 2a and 2b present the results of DFA for two dependent variables of CGAP and SGPA, respectively. In other words, students were classified into three academic performance classes based on their ST skills and PP skills. In Figure 2a and 2b, the green circles represent students who are classified into class three of academic performance (CGPA and SGPA >= 3.50), the red circles represent students who are classified into class two of academic performance (3.00 =< CGPA and SGPA < 3.50), the blue circles represent students who are classified into class one of academic performance (2.50 =< CGPA and SGPA < 3.00), and blue squares are the centers of each class. Figure 2 shows an acceptable classification visualization for CGPA and SGPA variables.

Figures 2. DFA Classification Result for a) CGPA (left) and b) SGPA (right)



Note: Students who are classified into [1:]class one, [2:]class two, and [3:]class three of academic performance based on their ST and PP.

Table 5 presents the results of the three machine-learning methods; "Testing Accuracy" represents the average of models' performance on the twenty iterations of testing data. The general interpretation of these analyses indicates that the three machine learning methods can predict the academic performance of engineering students with reasonable to good accuracy based on the ST skills and PP scores, which indicates a significant relationship between the academic performance of engineering students and their ST skills and PP scores. Given different factors from six different domains of personality traits, psychosocial contextual influences, motivational factors, students' approaches to learning, and self-regulatory learning strategies have a potential impact on students' academic performance. The findings of this study introduce two important factors that can influence students' academic performance, namely, ST skills and PP. According to the analyses, engineering students in class three have relatively higher ST skills scores than students in the other two classes while they scored relatively less on the PP scale than the other two classes.

Table 5: Accuracy Results of Three Classification Models.

Model	Testing Prediction Accuracy	
	CGPA	**SGPA**
Discriminant Function Analysis (DFA)	63.8%	71%
Decision Tree	73.3%	76.5%
Artificial Neural Network (ANN)	79.4%	85.4%

4. Conclusion

This study was conducted to analyze the impact of ST skills and PP on engineering students' academic performance based on CGPA and SGPA. The study findings found that ST skills and PP might be significant predictors of students' academic performance. According to the literature [1] – [7], there exist five different domains that influence students' academic performance, and two selected factors of the current study, proactive personality and systems thinking skills, belong to the most important domains. Additionally, it is common to select a few correlated factors from some of the five domains [1] – [7], which is similar to the current study approach. Past research showed that systems thinking is correlated with personality characteristics [8] – [12]. In addition, proactive personality can be correlated to several dimensions of systems thinking skills such as level of interaction, independence, change, systems worldview, and flexibility. Thus, the proactive personality scale and systems thinking skills measure are utilized to investigate if there is a relationship between engineering students' proactive personality and level of systems thinking skills with their academic performance. Since the study is a pilot testing of a larger study, future research will shed more light on the validity and reliability of the current study findings. In this study, however, we have used three different machine learning methods to indicate appropriate comparative validity for the study findings. Since all three machine learning methods produced consistent results, there is a high possibility that both ST skills and proactive personality predict the academic performance of engineering students. Additionally, we designed training and testing for each machine learning method to create cross-validation for the study findings.

All in all, the researchers endeavored to conduct a sound study despite study limitations such as small sample size and selection of study factors. Future research will concentrate on rectifying the limitations of the current study. The study concludes that:

- Systems thinking skills and proactive personality might be essential predictors of engineering students' academic performance.
- Students who are classified into three classes have relatively different systems thinking skills and proactive personality compared to each other.
- Students in class three (CGPA and SGPA >= 3.50) have relatively higher systems thinking skills than the other two classes, indicating they are more comfortable in dealing with complex systems problems where complexity, uncertainty, and interaction are the main characteristics.

- Students in class one (2.50 =< CGPA and SGPA < 3.00) have relatively higher proactive personality scores than the other two classes, meaning they have more inclination toward affecting classroom environment change.
- The three machine learning methods have consistent prediction accuracy results, which shows the validity and reliability of classification results. Additionally, the prediction accuracy results of SGPA classification were greater than the CGPA classification.

The relatively small sample size is one of the study limitations. To enhance the study results, in the future, more emphasis should be placed on gathering a large sample size. In this study, we believe that small sample size is relatively normal in pilot testing studies. Future studies can focus on including participants from various majors of engineering studies and delve into how other factors, such as the Big five personality instrument, motivation, self-efficacy, time management, and demographic characteristics, in conjunction with ST skills and PP, might influence the academic performance of engineering students. All the mentioned measures and scales, including the Big five personality instrument, motivation, self-efficacy, time management, and demographic characteristics, as well as the current study variables, which are part of the comprehensive theoretical model of a bigger study, will be used for future data collection and analysis. Moreover, it would be beneficial to compare the predictive validity of ST skills and PP to other well-known predictors of academic performance. Future studies would also include the type of training needed to enhance students' level of systems skills based on their skillset. The type of ST training sessions needed to improve students' performance is another area of investigation.

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