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Bridging the gap: A comparative analysis of traditional and neural network regression methods for predicting university entrant performance in SUAST examination

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ABSTRACT. In developing countries like the Philippines, access to free and high-quality tertiary education is crucial for better job opportunities. The State University Aptitude and Scholarship Test (SUAST) is used as a college admission examination by Davao Oriental State University (DOrSU). However, the passing rate for SUAST was only 54% for the academic year 2018-2023, and non-passers were still accepted due to policy changes, which undermine the purpose of the examination. This study aimed to identify the factors that influence the performance of university entrants in the SUAST examination using a researcher-made survey questionnaire administered online, utilizing both multiple-layer perceptron neural network (MLPNN) and multiple linear regression analysis (MLR) methods. A sample size of 359 was recommended, and the study found that family income, senior high school general weighted average (SHSGWA), library entry, intrinsic goal, openness and intellect, and behavioral reaction were significant predictors of SUAST exam scores. MLPNN analysis further identified library access and resources, family income, and academic self-belief as the most important predictors of SUAST exam scores, and MLPNN outperformed MLR. This study provides recommendations for DepEd and HEI's to enhance the preparation and performance of students taking the SUAST exam, such as offering study materials and test-taking strategies, evaluating alternative admission tests, and reviewing the content validity of the questionnaire. The study also suggests looking at other indicators of student readiness for university, such as high school grades and extracurricular activities, and conducting future research on the impact of financial aid and scholarships on academic achievement and performance disparities between male and female students.

Keywords: *Academic performance, multiple linear regression, multi-layer perceptron neural network, predictive modeling, state university aptitude and scholarship test*

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INTRODUCTION

Access to free, inclusive, and high-quality tertiary education is critical in many developing countries, including the Philippines, for finding better job opportunities. Many local universities in the country offer free higher education for those students who would be able to qualify for all of the admission requirements. Ideally, one of those is the college admissions examination (CAE). College admission examinations are s tandardized tests that determine students' chances of pursuing a degree in an academic institution (Bai et., 2014). To gain admission to a university or any tertiary institution, students must adhereto the guidelines outlined in CHED Memorandum Order No. 105, series of 2017. This involves taking and successfully passing the college entrance examination set by the college admission office, which is aligned with specific standards. Davao Oriental State University, officially known as DOrSU, is the only tertiary education institution that offers inclusive and free higher education in the province of Davao Oriental. The university, as affirmed by Dr. Roy G. Ponce, the university president, is presently classified as a medium-sized institution. The enrollment for the academic year 2022-2023 in the first semester, verified by the DOrSU registrar, stands at 14,140 (see Figure 1). Similar to other state-owned universities nationwide, Davao Oriental State University (DOrSU) has instituted its own college entrance examination, the State University Aptitude and Scholarship Test (SUAST). The primary objective of SUAST is to assess and select new students for admission across the university's five campuses, while also qualifying them for various scholarship programs within the DOrSU Educational System. Beyond acting as a screening tool, SUAST assists students in identifying their academic strengths and potential fields of study. This measure is crucial in ensuring that only well-prepared and deserving students gain access to free higher education, acknowledging the university's limited capacity for providing such opportunities. During the academic year 2021-2022, amid the prevalent COVID-19 pandemic,

Davao Oriental State University grappled with the challenges of administering entrance exams to a large number of high school graduates. Faced with the difficulty of monitoring for cheating in remote testing, the university temporarily suspended the requirement for entrance exam results in the admission procedure. While some advocate for making this suspension permanent (Paris and Heiser, 2022; Letukas, 2016), concerns arise about the immediate consequences, including potential compromises to the quality of admitted learners and a nearly doubled student population from over 8,000 in 2017 to 14,000 in 2022, posing challenges to academic resources. Another issue pertains to the role of admission exams in upholding educational standards, as evidenced by a decline in interest in math and science among non-passers. Despite the acceptance of non-passers in recent academic years, the essence of the SUAST examination is questioned due to changes in admission policies. Furthermore, concerns about unethical behavior among students admitted without exams highlight the impact of admission exams on non-cognitive variables. The SUAST examination's 54% passing rate for the academic year 2018-2023, falling below expectations for inclusive tertiary education, raises questions about the potential discrimination against economically disadvantaged students. According to the of Kim and Hull (2015), critics argue that imposing entrance exams could disproportionately affect socio-economic status, potentially limiting access for financially challenged students.

To investigate the success rate of students in college entrance examination, numerous studies on significant predictors

ENROLLMENT DATA

1st Semester, 2022-2023

A. MAIN CAMPUS	I	II	III	IV	V	TOTAL
Graduate Program						
MAED - Educational Mgt.	28	11	0	0	0	39
MAED - Teaching English	8	42	0	0	0	50
MST - General Science	14	13	2	0	0	29
MST - Mathematics	12	17	7	0	0	36
MPA	0	1	0	0	0	1
MBA	12	23	0	0	0	35
MSES	14	11	0	0	0	25
Ed.D. - Educational Leadership Management	7	4	0	0	0	11
Ph.D. - Biology	5	2	0	0	0	7
Ph.D. - Environmental Science	4	3	0	0	0	7
Sub-Total	104	127	9	0	0	240
Degree Program						
Bachelor of Elementary Education	133	128	83	56	0	400
Bachelor of Early Childhood Education	41	70	36	28	0	175
Bachelor of Special Needs Education	45	36	27	30	0	138
Bachelor of Physical Education	46	44	39	55	0	184
BSED - Biological Science	0	0	0	2	0	2
BSED - English	45	98	46	47	0	236
BSED - Filipino	42	71	31	77	0	221
BSED - Mathematics	90	81	34	44	0	249
BSED - Science	26	64	41	43	0	174
BTLE - Home Economics	39	46	44	73	0	202
BTLE - Industrial Arts	40	56	24	98	0	218
BS Agriculture - Animal Science	67	40	18	7	0	132
BS Agriculture - Crop Science	78	0	0	0	0	78
BS Agriculture - Horticulture	0	60	24	16	0	100
BS Agribusiness Management	429	297	69	186	0	981
BS Biology	78	148	36	0	0	262
BS Biology - Animal Biology	0	0	0	24	0	24
BS Biology - Ecology	0	0	0	12	0	12
BS Development Communication	113	73	14	16	0	216
BS Environmental Science	135	90	44	67	0	336
BS Nursing	65	116	82	54	0	317
BS Business Administration	535	552	223	331	0	1641
BS Criminology	288	327	191	189	0	995
BS Hospitality Management	450	208	56	66	0	780
Bachelor in Industrial Technology Mgt.	401	139	41	121	0	702
BS Civil Engineering	138	173	121	129	9	570
BS Information Technology	263	160	82	94	0	599
BS Mathematics	76	38	21	36	0	171
BS Mathematics with RS	42	22	25	12	0	101
Sub-Total	3705	3137	1452	1913	9	10216
Sub-Total MAIN	**3809**	**3264**	**1461**	**1913**	**9**	**10456**
B. BAGANGA EXTENSION CAMPUS						
BS Agriculture - Crop Science	42	0	0	0	0	42
BS Agribusiness Management	81	0	0	0	0	81
BS Criminology	46	0	0	0	0	46
BS Environmental Science	69	0	0	0	0	69
BS Hospitality Management	49	0	0	0	0	49
BS Information Technology	41	0	0	0	0	41
BS Mathematics	46	0	0	0	0	46
Sub-Total BEC	**374**	**0**	**0**	**0**	**0**	**374**
C. BANAYBANAY EXTENSION CAMPUS						
Bachelor in Agricultural Tech.	0	71	0	32	0	103
BS Agriculture - Crop Science	81	0	0	0	0	81
BS Business Administration	188	125	32	52	0	397
BS Information Technology	115	50	0	4	0	169
BTLE Home Economics	46	86	43	57	0	232
Sub-Total BEC	**430**	**332**	**75**	**145**	**0**	**982**
D. CATEEL EXTENSION CAMPUS						
Bachelor in Agricultural Tech.	0	88	7	25	0	120
BS Agriculture - Animal Science	42	0	0	0	0	42
BEED	64	74	52	32	0	222
BS Agribusiness Mgt.	111	55	18	22	0	206
BS Business Administration	179	215	39	74	0	507
BS Criminology	86	112	40	0	0	238
Sub-Total CEC	**482**	**544**	**156**	**153**	**0**	**1335**
E. SAN ISIDRO EXTENSION CAMPUS						
Bachelor in Agricultural Tech.	0	63	19	38	0	120
BS Agriculture - Crop Science	44	0	0	0	0	44
BEED	40	58	33	33	0	164
BS Business Administration	148	130	41	96	0	415
BS Criminology	88	123	39	0	0	250
Sub-Total SIC	**320**	**374**	**132**	**167**	**0**	**993**
GRAND TOTAL	**5415**	**4514**	**1824**	**2378**	**9**	**14140**

Figure 1. DOrSU student population certified by the registrar.

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affecting how well students succeed in the SUAST examination have recently been conducted in different countries. The success rate of students in college entrance examinations is influenced by various factors, including socioeconomic status (SES), academic performance, and psychological factors (Hess and McAvoy, 2018; Strayhorn, 2018). SES has been identified as a robust predictor of exam performance, with students from higher SES backgrounds generally outperforming their counterparts from lower SES backgrounds, attributed to factors such as access to test preparation tools and higher-quality educational opportunities (Hess and McAvoy, 2018; Strayhorn, 2018). Academic factors, including high school GPA and course rigor, are crucial predictors of exam success (Huang and Anderson, 2020; Langdon, 2021; Patel and Patel, 2019). Students with higher grades and those who undertake challenging courses, such as Advanced Placement or International Baccalaureate, tend to perform better on college entrance exams (Huang and Anderson, 2020; Patel and Patel, 2019). Additionally, psychological factors like exam anxiety, personality traits (such as conscientiousness and emotional stability), and motivation play significant roles in predicting students' success in these exams (Pekrun et al., 2009; Schoeps et al., 2018; Stricker, 2019). Individuals with high levels of exam anxiety tend to score lower (Pekrun et al., 2009), while students with positive personality traits and higher motivation levels perform better on college entrance exams (Schoeps et al., 2018; Stricker, 2019). Understanding and addressing these contributing factors can enhance students' performance in admission examinations, as demonstrated by several published studies.

Educational studies use various statistical and research methods (Valverde-Berrocoso et al., 2020). One of the simplest and easy-to-understand modeling methods is multiple regression. Utilizing Multiple Linear Regression (MLR) in educational assessments offers valuable insights into predicting complex outcomes like college entrance exam scores by considering multiple predictors simultaneously, but its limitations in capturing non-linear associations prompt the introduction of Multi-Layer Perceptron Neural Network (MLPNN) (Hyman, 2017; Koenig et al., 2008; Shamseldin et al., 2007; Cakir et al., 2014). MLPNN, known for excelling in modeling complex non-linear relationships, proves suitable for understanding intricate interactions influencing college entrance exam scores. Despite MLPNN's strengths, its weaknesses, such as the need for substantial data for training and the risk of overfitting, are acknowledged. The combined use of MLR and MLPNN aims to offer a nuanced understanding of factors influencing university entrant performance in the SUAST Examination, leveraging the complementary strengths of both methodologies (Hyman, 2017; Koenig et al., 2008; Shamseldin et al., 2007; Cakir et al., 2014). In this study, the focus is on identifying factors significantly affecting students' SUAST examination performance by comparing predictive models generated by MLR and MLPNN. The research objectives include creating mathematical models, identifying significant predictors, and comparing the efficacy of MLR and MLPNN in explaining student performance in the SUAST entrance examination, aiming to provide a comprehensive analysis of the factors influencing student outcomes.

METHODOLOGY

Research design

Research design is a blueprint or plan specifically created to answer the research questions and control variance (Dulock, 2003). This study was conducted through a descriptive-correlational quantitative approach using multi-layer perceptron neural network approaches (MLPNN), multiple linear regression analysis (MLR), and Pearson R correlation as the main statistical techniques for analyzing the data. These statistical techniques were used to predict SUAST examination scores by exploring the inputs, such as possible influential factors, underlying the SUAST result as the response or output. Secondly, to create a mathematical model that would describe and predict the SUAST examination based on traditional regression and advanced neural network approaches. After that, models will identify the significant predictors that impact the success of students in the SUAST examination. Lastly, to compare the models generated by MLR and MLPNN, determine the best-fitted model that can accurately explain student performance in the SUAST entrance examination. The aid of statistical software was used to assist in the generation of results.

Research instrument

A researcher-made survey questionnaire was utilized, which consisted of four (4) portions. The first part was designed to identify the socio-demographic profile of the respondents in terms of gender, age, ethnicity, marital status, and, most importantly, the estimated State University Aptitude and Scholarship test (SUAST) exam score. The second portion asked for socioeconomic indicators such as family income, size, and parental education. Subsequently, the third part was utilized to determine the academic indicators of the respondents by asking them to provide some valuable information, such as estimated senior high general weighted average (SHSGWA), monthly library entry, and national career assessment examination (NCAE) or national achievement test (NAT) results, if applicable. The last part was utilized for evaluating external factors, and these factors were emotional and psychological constructs such as health anxiety level, personality traits, and student motivation.

The researcher adapted structured questions used to measure the following constructs: for instance, to measure the examination anxiety level, an Examination Anxiety Scale developed by Abbasi and Ghosh (2020), the big five factor markers developed by Goldberg (1992 for student personality, and the Motivation to Learn Questionnaire (MLOQ) developed by Fowler (2018) for student motivation were incorporated into the overall structure of the researcher-made questionnaire. A pilot study was conducted to facilitate the validation of the research questionnaire. A reliability test using Cronbach's test and construct validity through factor analysis were done to ensure the internal consistency and reliability of the questionnaire before administering it to the target group.

Sampling procedures

For this study, the sample size was determined using Cochran's Formula (1977) for a finite population, with a confidence interval of 95%, a margin of error of 5%, and a population proportion of 50%. Based on these parameters, a sample size of 359 was recommended. The 359 samples from the five strata were then randomly selected using stratified random sampling. The overall population of target students of the Davao Oriental State University for the study, as shown in Table 1, was 5,618, with students from AY: 2019-2020 (4th Year Students) and AY: 2022-2023 (1st Year Students) included since the SUAST examination was administered during these academic years.

To ensure the representativeness of the sample, the researcher divided the population into five strata that corresponded to the five senior high school academic strands or tracks, namely Science and Technology, Engineering and Mathematics (STEM), General Academic Strand (GAS), Accountancy and Business Management (ABM), Humanities and Social Sciences (HUMSS), and Technical-Vocational Livelihood Education (TVL). At least 359 samples were then drawn randomly from the five strata using a stratified random sampling procedure based on population proportion.

Table 1. Number of student for the DOrSU main campus.

Year	Program	Exam Takers
2019 – 2020 (1st Sem)	BSIT	94
	BSCE	129
	BITM	121
	BSM	48
	BS BIO	36
	BS ENVI SCI	67
	BSA	23
	BSAM	186
	BSDC	16
	BSN	54
	BSC	189
	BSBA	331
	BSHM	66
	BSED MATH	44
	BSED SCIENCE	45
	BEED	56
	BTLE	171
	BSED ENG	47
	BSNED	30
	BPED	55
	BSED FILIPINO	77
	BSCED	28
		Sub-Total: 1,913
2022-2023 (1st Sem)	BSIT	263
	BSCE	138
	BITM	401
	BSM	118
	BS BIO	78
	BS ENVI SCI	135
	BSA	145
	BSAM	429
	BSDC	113
	BSN	65
	BSC	288
	BSBA	535
	BSHM	450
	BSED MATH	90
	BSED SCIENCE	26
	BEED	133
	BTLE	79
	BSED ENG	45
	BSNED	45
	BPED	46
	BSED FILIPINO	42
	BECED	41
		Sub-Total: 3,705
		Total: 5,618

To facilitate the selection process, the researcher used an electronic random generator. Overall, the sample selection process was conducted in a manner that was both systematic and rigorous, ensuring that the sample was representative of the target population.

Data and collection

In this study, the questionnaires were distributed through online engagement. The researcher administered a Google form that directly asked close-ended questions to the respondents through online interactions. The survey questionnaire was created by the researcher and encapsulated in Google Forms. This questionnaire was sent to the students of Davao Oriental State via a Google Form link, and messaging platforms such as Facebook Messenger, Gmail, and Telegram were utilized for passing the survey form. After the data was completely retrieved, it was then encoded in Excel and subjected to pre-processing steps such as data cleaning, data visualization, and data imputation for missing data. Data collection ran for a week. The study then measured the results conclusively through statistical means to finalize the results.

Data analysis

Figure 2 below shows the flow of the overall analysis. First, the data will be subjected to imputation if there are missing values, cleaning, normalization, transformation, and validation (pre-processing). Data associated with the influential factors (demographics, socio-economic, academic, and psychological factors) can be classified as input parameters, and data from the SUAST examination scores (350-item test) will be the output. Next, Pearson R correlation, a statistical tool, will be utilized to determine if there is a linear relationship between the influential factors and the SUAST examination scores. If the linear relationship among dependent and independent variables is established, then the data will be subjected to a test for linear regression assumptions. These are the tests for linearity, normality, independence of observation, homoscedasticity, and the presence of outliers.

Preferably, if all the assumptions are met, then the data will be utilized for predictive modeling using stepwise multiple linear regression (SMLR) analysis to answer objective 1. On the other hand, if one assumption is not met, then the data will be subjected to data preprocessing procedures until it satisfies all the given assumptions for the MLR analysis. Additionally, the data will be subjected to a test for artificial neural network assumptions. These are the identification of a suitable model network or architecture; well-represented input with real value; prediction ability; and competitive algorithms. Finally, if the basic assumptions for neural networks are met, then multi-layer perceptron neural network (MLPNN) approaches will be used in order to answer objective 1 and also to derivemodels that best describe howwell the students perform inthe SUAST examination in rlation to its influential factors as input parameters. Additionally, it also predicts the SUAST examination scores relative to the influential factors stated in the study.

For the MLPNN process, the feed forward-backpropagation algorithm was used to train a multi-layer perceptron neural network (MLPNN) with an architecture composed of 16 input predictors such as family income, family size, senior high school grades, and more, two hidden layers, and a single output layer. The MLPNN design included 4 to 20 hidden nodes, and the activation function utilized on both hidden layers was the hyperbolic tangent sigmoid function. 70% of the available data was used to train the model, with the remaining 30% used for testing and validation. This approach helps to ensure that the model is not overfitting to the training data and can generalize well to new data.

This method ensures that the model is not overfitting to the training data and that it can generalize effectively to fresh data.

Significant factors were identified in both the MLR and MLPNN models to answer objective 2. Moreover, there will be a comparison between the MLR and MLPNN models to answer objective 3. By using MLR to build certain prediction models, the researcher could use the MSE and R^2 measures and the Q-Q plot technique to evaluate the goodness of fit of the regression model (Yang et al., 2018). Moreover, in the study of Djeddou et al., (2021), the root mean square error (RMSE), mean absolute error (MAE), R-square (R^2), and index of agreement (d) were applied and calculated to evaluate the performance of the models. Meanwhile, coefficient of determination (R^2) and mean-square error (MSE) will be the criteria for determining the appropriate model in this study to answer objective 3.

Research ethics

This study's ethical concerns were carefully planned and implemented to ensure that the research was done in a way that protected the study participants' rights and well-being. The researcher specifically secured free prior and informed consent (FPIC) from all respondents, which implies that participants were fully informed about the nature of the study and gave their voluntary assent to participate. Furthermore, the researcher included those respondents who elected

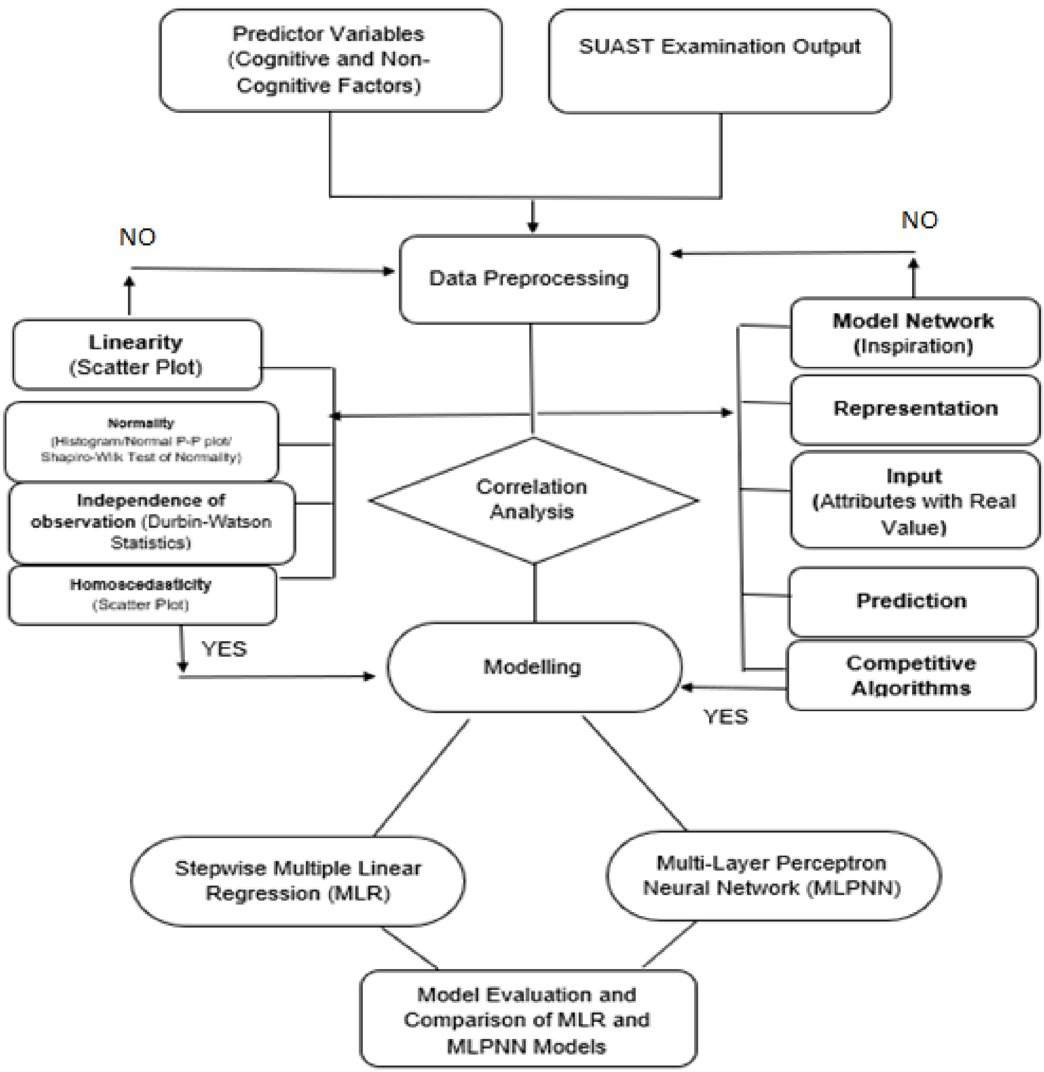

Figure 2. Flow chart of the analysis.

not to reply to the survey's questions in order to respect their right to privacy and autonomy. The researcher also sought to explain the significance of the study to participants but ultimately accepted their option to respond or not respond to the survey questions.

Several precautions were taken to guarantee that the study followed ethical procedures and that the respondents' privacy was respected. The study was done in a lawful and responsible manner by obtaining FPIC and respecting the rights of participants.

RESULTS AND DISCUSSION

Multiple Linear Regression Analysis

Multiple regression analysis was used to investigate the predictive ability of family income, family size, SHSGWA, library entry, examination anxiety factor, personality factors, and student motivation. This analysis was also used to address objective 1. Traditional criteria such as R^2 and MSE were used to assess the goodness of fit of regression models. R-squared (R^2) reflects the fraction of the variation in the dependent variable that is explained by the model's independent variables. R^2 values vary from 0 to 1, with higher values suggesting a better fit between the model and the data. The MSE metric was used to determine how close a prediction regression line is to a set of actual dependent variable values. A lower MSE value indicates thatthe model is better suited.

As a variable selection process for models 1-6, the "stepwise" approach was utilized, which entails adding or deleting variables from the model one at a time depending on statistical criteria. The variable with the highest correlation coefficient, or the lowest p-value, is the first to be included in the model. The model is then updated with the next variable with the highest correlation coefficient or lowest p-value, and so on until no more variables can be included. Following that,family income is included to the model as the first predictor, with SUAST test results acting as the anticipated dependent variable, designating this model as model 1.

For the final model, model 6's unstandardized beta coefficients, t-value, MSE, and R^2 are also shown in Table 2. Six (6) constructs are found to have a statistically significant contribution to model 6's prediction power ($p<0.05$). The factors with substantial predictive potential in explaining SUAST test results are family income ($t = 14.89$, $p<.05$), library entry ($t=10.71$, $p<.05$), SHSGWA ($t=4.44$, $p<.05$), behavioral reaction ($t=-6.57$, $p<.05$), intrinsic goal ($t=2.96$, $p<.05$), and openness and intelligence ($t = 2.88$, $p<.05$). In comparison to the hypothesized regression model, the MSE value is .003, and the R^2 is .878.

Family income (B =.234), SHSGWA (B =.993), library entry (B =.255), intrinsic goal (B =.011), and openness and intellect (B =.255) all have a positive linear correlation with the dependent variable (SUAST exam scores), with the exception of behavioral reaction (B = -.021). The model also demonstrates that a one-unit increase in family income results in a.234 increase in the SUAST exam score based on a specific scale; similar findings may apply to the other components except for behavioral reaction. In behavioral reaction, a one-unit increase in behavioral reaction translates into a 0.021 drop in the SUAST exam score. Typically, the final regression model is: Y (SUAST exam score)=-.782 +.234 (family income)+.255 (library entry)+.021 (behavioral reaction) +.933 (SHSGWA) +.011 (intrinsic goal) +.013 (openness and intellect).

There is some research on the relationship between family income and academic success. For example, the income achievement gap has been growing over time, implying that students from better-income homes are more likely than their counterparts from lower-income families to attain higher levels of academic performance (Reardon et al., 2019). This disparity has been ascribed to a variety of reasons, including disparities in educational resource availability, social support, and parental participation. Duncan and Murnane (2011) discovered that family income is highly related to a variety of cognitive and non-cognitive qualities that are critical for academic attainment. The authors discovered that students from high-income families have more vocabulary, math abilities, and

Table 2 Hypothesized stepwise regression coefficient and percent of variance in SUAST examination raw score explained by constructs for model 1-6.

Models	Constructs	SUAST score	Standard error	t-value	MSE	R^2
Model 1	(Constant)	.442*	.043	10.21	.005	.404
	Family Income	.455*	.010	43.72		
Model 2	(Constant)	.713*	.044	16.33	.004	.652
	Family Income	.320*	.014	22.39		
	Library Entry	.309*	.025	12.25		
Model 3	(Constant)	.966*	.052	18.51	.003	.669
	Family Income	.273*	.015	18.63		
	Library Entry	.280*	.024	11.68		
	Behavioral Reaction	-.025*	.003	-7.85		
Model 4	(Constant)	-.852*	.413	-2.06	.003	.874
	Family Income	.248*	.016	15.99		
	Library Entry	.259*	.024	10.79		
	Behavioral Reaction	-.025*	.003	-7.94		
	SHSGWA	.996*	.225	4.43	.003	.876
Model 5	(Constant)	-.727*	.413	-1.76		
	Family Income	.238*	.016	15.07		
	Library Entry	.252*	.024	10.50		
	Behavioral Reaction	-.022*	.003	-6.60		
	SHSGWA	.933*	.224	4.16	.003	.878
	Intrinsic Goal	.011*	.004	2.73		
Model 6	(Constant)	-.782*	.410	-1.91		
	Family Income	.234*	.016	14.89		
	Library Entry	.255*	.024	10.77		
	Behavioral Reaction	-.021*	.003	-6.57		
	SHSGWA	.993*	.224	4.44		
	Intrinsic Goal	.011*	.004	2.96		
	Openness and Intellect	.013*	.005	2.88		

**Significant at 0.05 probability level* general knowledge, as well as superior social skills and self-control, than their low-income peers. Also, Farkas et al., (2021) discovered a favorable association between library use and academic achievement among college students. The authors stated that using libraries might improve students' academic performance by offering access to educational materials, social support, and academic counseling.

Also, several studies have revealed a negative relationship between test anxiety and academic success (Putwain et al., 2010). Test anxiety has also been shown in studies to have a detrimental influence on students' psychological well-being and academic self-efficacy (Katz and Assor, 2007). Students who are anxious about tests may feel physiological symptoms s uch as elevated heart rate, perspiration, and muscular tension, which can impair their ability to concentrate and perform well on exams. Furthermore, studies have proposed that test anxiety is impacted by a number of factors, including the individual's cognitive capacity, personality qualities, and the situation in which the exam is being administered (Putwain et al., 2010). As a result, treatments aimed at lowering test anxiety and enhancing academic achievement should be personalized to the individual and take these diverse aspects into consideration.

High school GPA is also a substantial predictor of academic achievement in college, according to research (Kuncel et al., 2005). Furthermore, one study discovered that high school grades and test scores are the best indicators of college achievement (Rojstaczer and Healy, 2012). This emphasizes the significance of utilizing a high school GPA or GWA to predict academic achievement in higher education. Furthermore, research has demonstrated that academic achievement correlates favorably with intellect and cognitive capacity (Deary et al., 2007). These findings imply that children with superior cognitive capacities may be better able to study and do well in school, resulting in higher GPAs and test scores.

Previous studies have found a favorable association between intrinsic goal orientation and academic achievement. For example, intrinsic goal orientation has been found to predict academic success among university students (Van Yperen et al., 2014). Students with a high level of intrinsic goal orientation were more likely to participate in academic tasks, which led to greater academic accomplishment (Elliot et al., 2011).

Many researchers have also found a correlation between personality qualities like openness and intelligence and academic success (Poropat, 2009; Zaidman-Zait and Roth, 2015). Furthermore, intelligence has been shown to be a strong predictor of academic accomplishment (Gignac and Bates, 2017). Personality qualities, coupled with cognitive ability, can play an important role in predicting academic achievement. Understanding the importance of these variables in predicting academic success can thus aid in the development of effective interventions and methods for students to improve their academic performance.

Residual analysis

Residual analysis is significant in multiple linear regression analysis since it helps to evaluate the appropriateness of the model and discover any data concerns. According to Kutner et al., (2005), "residual plots are essential for examining the assumptions of normality, constant variance, and error independence". Neglecting residual analysis might result in incorrect findings and forecasts (Fox, 1991).

Figure 3 depicts the distribution of the regression-standardized residual required to test the error normality assumption. The residuals are normally distributed, asseen by the histogram's bell-

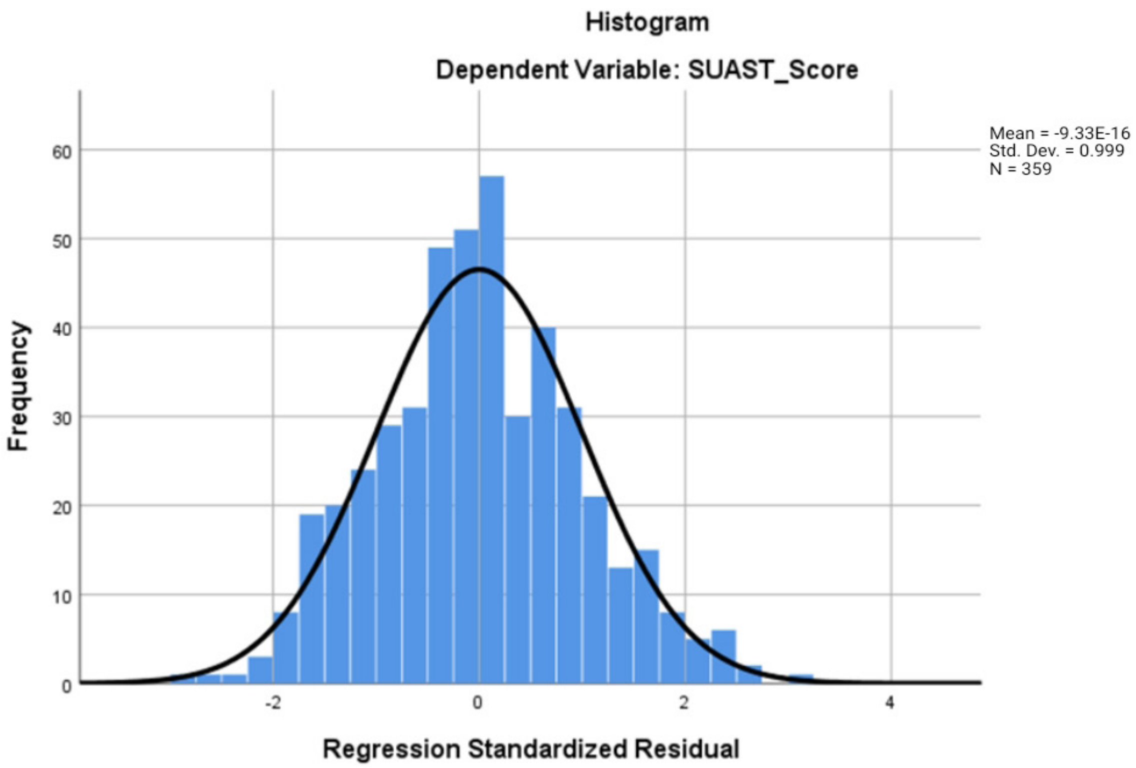

Figure 3. Distribution of regression standardized residual.

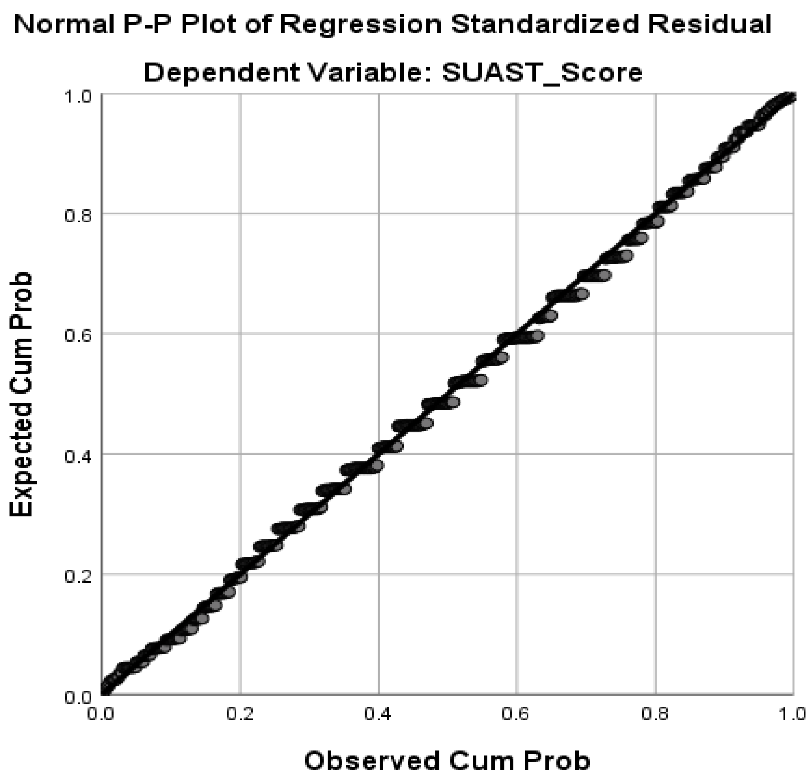

Figure 4. Normality probability plot of regression standardized residual.

shapedcurve. Because the histogram reveals a symmetrical distribution of residuals around a central value, the normality assumption is fulfilled. Furthermore, there are no severe outliers in the histogram, indicating that most observations do conform to the normal distribution assumption.

Moreover, the illustration in Figure 4 depicts the normality probability plot of the regression standardized residual, which is crucial for testing the linearity and normality assumptions of errors. The NPP has a linear pattern, showing that the residuals are distributed normally. The NPP points do not stray from a straight line, implying that the residuals are normally distributed. Furthermore, the NPP has no outliers, which might suggest the presence of severe residuals impacting the regression model. Furthermore, there is no curve in the NPP that shows a skewed distribution. Similarly, there is no flattened and pointed curve in the NPP, indicating a kurtotic distribution of residuals. Overall, the NPP points fall along a 45-degree straight line, indicating that residuals are normally distributed.

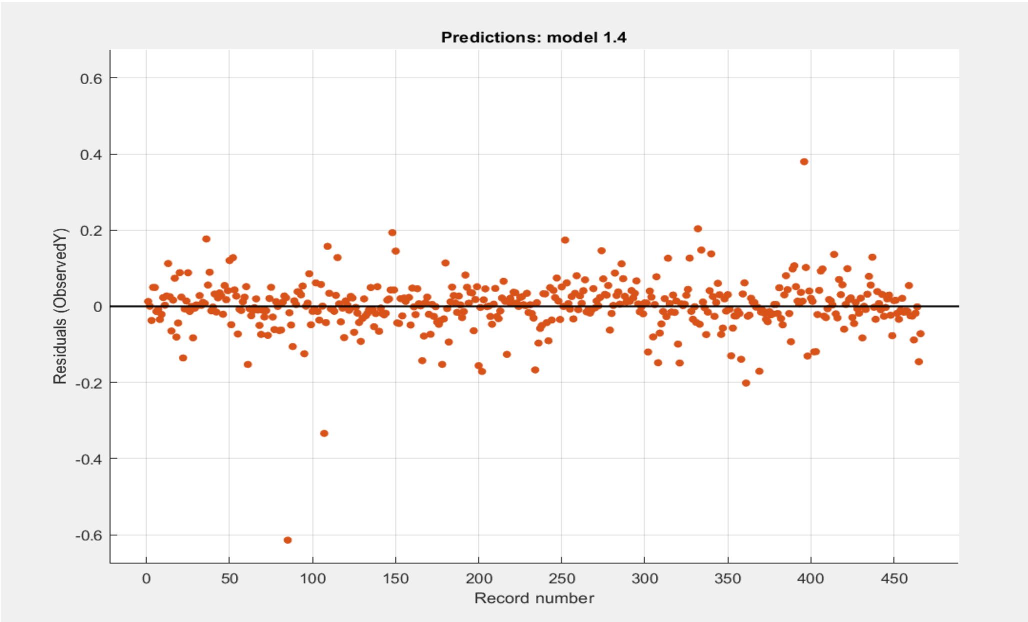

Figure 5. Residual plot for the hypothesized model.

Figure 5 shows the residual plot for the regression model, which is required to check for a random pattern of residuals around the zero line with no discernible pattern, outliers, or non-constant variance that may indicate whether or not the MLR model is valid. According to Figure 4.3, the residual plot displays a random pattern, indicating that the connection between the predictors and the response variable is linear. Furthermore, the residuals have a constant distribution across the anticipated value range, indicating that the homoscedasticity criterion is met. Outliers can be found among anticipated values that are far from the zero line. This might imply that the MLR model is missing a crucial characteristic of the data. Finally, the residuals are normally distributed around the zero line, indicating that the normality requirement is met.

The Multilayer Perceptron Neural Network (MLPNN) was employed in this investigation. Table 3 indicates that using MLPNN with varied input parameters might result in distinct models with different numbers of hidden nodes and performance in predicting the output parameter, which in this case is the SUAST test score. The best model for

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predicting the SUAST test score, according to the study, is the fc-16tansig model, which includes 16 hidden nodes and two hidden layers and is trained for 7 iterations. The coefficient of determination (R^2) for this model is 0.89598, while the mean square error is 0.002302. The fc-14 tansig model with 14 hidden nodes, on the other hand, fared the worst at iteration 8, with an R^2 of 0.69946 and a mean square error of 0.0036624.

Moreover, this study's input parameters include family income, family size, senior high school general weighted average, library entry, health anxiety level, personality attributes, and student motivation. These factors are most likely picked because they are known to have an effect on student academic achievement. For example, family income and size are frequently connected with educational success and achievement, but the general weighted average and library entrance may represent the student's academic preparation and habits. Meanwhile, health concerns, personality qualities, and student motivation may suggest psychological and emotional issues that may impair academic achievement.

MLPNN Modeling

Table 3. Derived MLPNN model performances for SUAST examination prediction.

		Derived models		
Models	**Hidden Nodes**	**Epoch**	**R^2**	**MSE**
fc-4tansig	4	6 iterations	0.84	0.0032
fc-6tansig	6	10 iterations	0.86	0.0075
fc-8tansig	8	9 iterations	0.84	0.0050
fc-10tansig	10	6 iterations	0.87	0.0022
fc-12tansig	12	7 iterations	0.87	0.0028
fc-14tansig	14	8 iterations	0.69	0.0037
fc-16tansig	16	7 iterations	0.89	0.0023
fc-18tansig	18	11 iterations	0.88	0.0034
fc-20tansig	20	9 iterations	0.77	0.0036

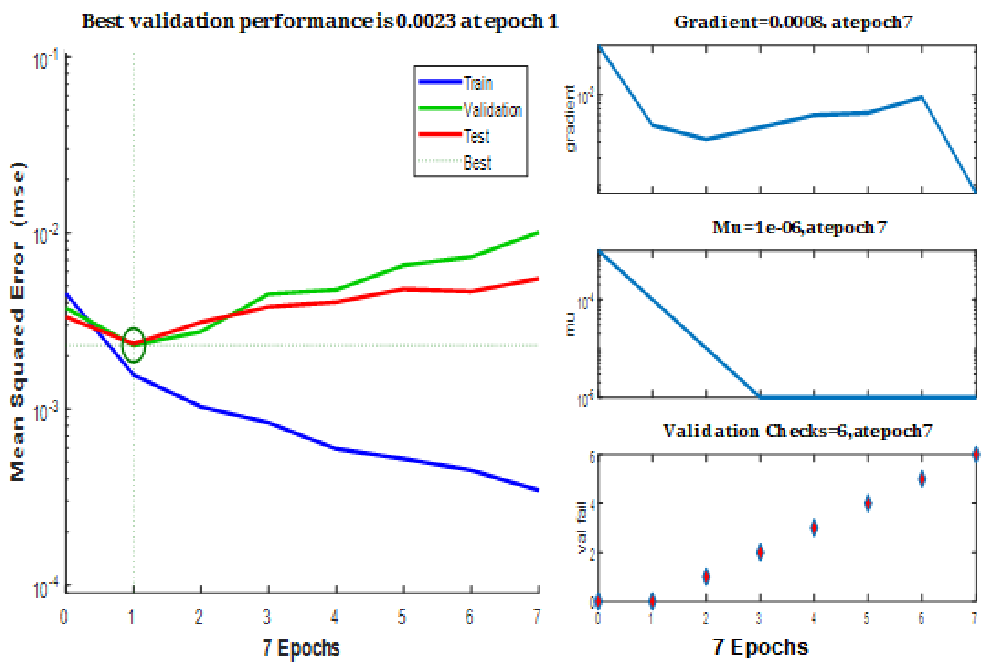

Figure 6. Performance of model fc-16 tansig.

Eisa and Al-Khalifa (2018) conducted a related study in which they explored the use of MLPNN in predicting academic success. They employed MLPNN to forecast university students' academic success based on demographic information and previous academic records. The study discovered that MLPNN could successfully predict students' academic achievement, with the maximum accuracy reached when demographic data and historical academic records were used as input parameters. This study emphasizes MLPNN's promise for predicting college admission test scores by utilizing numerous input factors. However, further research is required to evaluate the usefulness of these models in various scenarios and to investigate the feasibility of adding other input factors to improve prediction accuracy.

The finding presented in Figure 5 pertains to the model performance of model fc-16tansig, which is evaluated using mean square error (MSE) as the performance indicator. The figure shows that the lowest MSE value of 0.002302 is achieved at epoch 1. However, the MSE value increased from epoch 2 to epoch 7, which led to the termination of the modeling process due to the maximum fail (validation checking) being set to 6 only. The gradient value at epoch 7 is 0.000 81276, while the learning rate (Mu) is 1e-06 at epoch 7.

The increase in MSE from epoch 2 to epoch 7 suggests that the model may have started to overfit the data, resulting in poorer performance on the validation set. This finding underscores the importance of monitoring the performance of neural network models over time, as changes in the model's performance can provide insights into the model's suitability for the task at hand. Moreover, the low learning rate and gradient values suggest that the model may have reached a

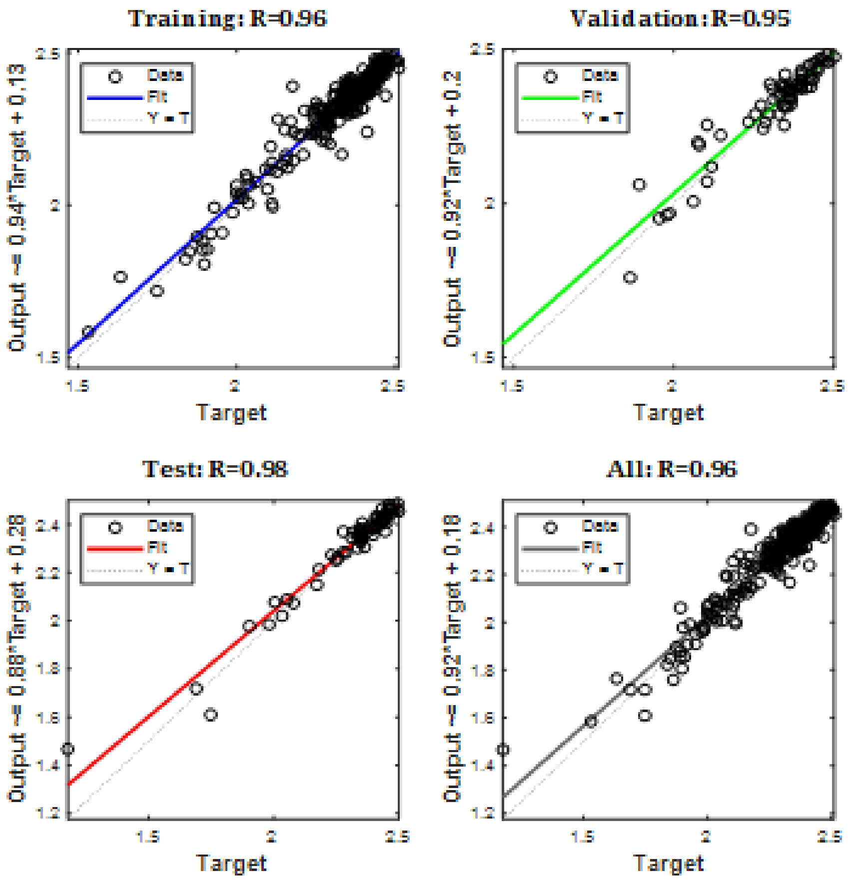

Figure 7. Pearson R of model fc-16 tansig.

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plateau in terms of its ability to learn from the data.

The regression values of the model fc-16tansig, which is used to predict the SUAST test score based on the input parameters, are shown in Figure 6. The plot reveals that the majority of the data points are near the 45-degree line, indicating a good match between the projected and actual values. Ideally, the regression value, represented as R in Figure 6, represents how closely related the dependent variable (SUAST test score) and the independent factors (input parameters) are. The model scored high R values of 0.96303 for training, 0.97749 for testing, and 0.94656 for validation in this scenario, indicating that it can reliably predict the SUAST exam score based on the input parameters.

One recent study sought to create a model that may predict college students' academic success based on variables such as age, gender, high school grade, and university admission exam score. In terms of forecasting academic achievement, MLPNN models with several hidden layers outperformed models with a single hidden layer (Fazeli et al., 2020). Furthermore, these results indicated that the model fc-16tansig using the Levenberg-Marquardt training method and 16 hidden nodes in two hidden layers is a strong model for predicting SUAST test scores. However, more validation and testing may be required to determine the model's generalizability to diverse groups or circumstances.

Significant predictors

For multiple linear regression analysis (MLR), Model 6 in Table 3 reveals that the significant predictors with substantial predictive potential in explaining SUAST test results are family income ($t = 14.90$, $p<.05$), library admission ($t = 10.71$, $p<.05$), SHSGWA ($t = 4.44$, $p<.05$), behavioral reaction ($t = -6.57$, $p<.05$), intrinsic goal ($t = 2.96$, $p<.05$), and openness and intelligence ($t = 2.88$, $p<.05$). The findings indicate that a range of factors influence academic success as judged by the SUAST exam. These predictors include socioeconomic status, library entry, intrinsic goal, behavioral reaction, and cognitive capacity. This implies that the current admission practices at DOrSU may benefit from a more holistic consideration of these factors in the screening process. Specifically, acknowledging the impact of socioeconomic status, library access, student motivation, prosocial behavior, and cognitive abilities could contribute to a more comprehensive and fair evaluation of potential students. Recognizing and integrating these predictors into the admission system could enhance its accuracy and inclusivity, aligning with DOrSU's mission to establish a quality student population. Implementing such improvements may not only refine the selection process but also promote a more equitable and effective approach to identifying students prepared for the challenges of higher education.

Independent variable importance (IVI) was utilized in the Multi-layer Perceptron Neural Network Approach (MLPNN) to evaluate the relevance of each independent variable in predicting the dependent variable. The weights assigned to each independent variable in the MLPNN model are used to calculate the IVI. Some studies may regard a variable with an IVI value greater than a specific threshold, such as 0.5 or 0.7, as significant, while others may employ alternative thresholds or criteria. For example, Hosseini et al., (2021) considered a variable with an IVI value greater than 0.5 to be relevant for predicting visitors' hotel selection behavior using an artificial neural network.

According to Figure 7 and Table 4, library entry has the highest IVI value of.199, showing that it is the most important predictor of SUAST exam score when compared to other factors. Furthermore, the model considers family income (IVI =.162) and self-efficacy (IVI

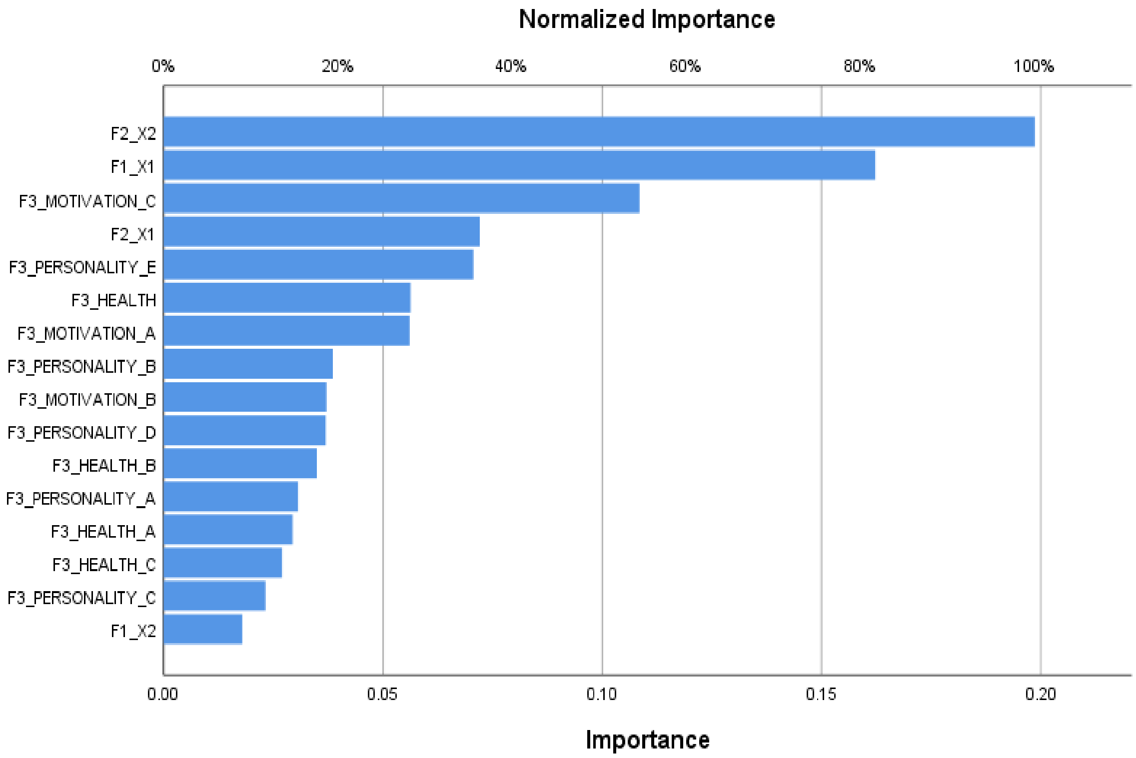

Figure 8. Graphical presentation of the normalized importance.

Table 4. Independent variable importance in MLPNN.

Construct	Importance	Normalized Importance (%)
Family Income (F1_X1)	**.162**	**81.7**
Family Size (F1_X2)	.018	9.0
SHSGWA (F2_X1)	.072	36.3
Library Entry (F2_X2)	**.199**	**100.0**
BODILY_SYMPTOMS (F3_HEALTH_A)	.029	14.8
COGNITIVE(F3_HEALTH_B)	.035	17.6
EMOTIONAL_REACTION (F3_HEALTH_C)	.027	13.6
BEHAVIORAL REACTION (F3_HEALTH_D)	.056	28.3
NEUROTICISM (F3_PERSONALITY_A)	.031	15.4
EXTRAVERSION (F3_PERSONALITY_B)	.039	19.4
OPENNESS/INTELLECT (F3_PERSONALITY_C)	.023	11.7
AGREEABLENESS (F3_PERSONALITY_D)	.037	18.6
CONSCIENTIOUSNESS (F3_PERSONALITY_E)	.071	35.6
INTRINSIC (F3_MOTIVATION_A)	.056	28.2
EXTRINSIC (F3_MOTIVATION_B)	.037	18.7
SELF_EFFICACY (F3_MOTIVATION_C)	**.108**	**54.6**

such as senior high grades. This would necessitate revising admission criteria to reflect a more comprehensive evaluation of potential students. Adjusting the weightage assigned to different criteria based on their Independent Variable Importance (IVI) values and MLR findings is proposed, giving greater influence to factors like library entry, identified as crucial predictors. Additionally, a reconsideration of admission quotas, incorporating flexibility based on relevant predictors, is advised for a balanced representation of students. The introduction of support programs for students with identified challenges, such as lower family income, and awareness campaigns to educate applicants about the importance of various predictors are crucial changes. Furthermore, ongoing evaluation and refinement of the admission policy, integrating new insights and research findings, are recommended to ensure continued relevance and fairness over time. These initiatives collectively aim to transform the admission policy of DOrSU,fostering a more inclusive and equitable approach aligned with the university's mission of admitting a quality and diverse student population.

Model comparison

Table 5 compares the MLR and MLPNN techniques' performance using R^2 and MSE as assessment criteria. Among the MLR models, Model 7 (MLR 06) gets the greatest R^2 value of 0.878 and the lowest mean-square error of 0.003. This shows that, utilizing the input parameters, the MLR technique is able to capture a considerable percentage of the variability in the output parameter (SUAST test score) using the series of input parameters (family income, family size, senior high school general weighted average, library entry, health anxiety level, personality traits, and student motivation).

Model 7 (fc-16tansig) scores the best among the MLPNN models, with an R^2 value of 0.89 and a reduced MSE of 0.00. This demonstrates that the MLPNN technique is able to capture

Table 5. Derived MLR and MLPNN models with R^2 and MSE of each model.

Models		Analysis	R^2	MSE
1	MLR_00	MLR	.88	.003
2	MLR_01		.40	.005
3	MLR_02		.65	.004
4	MLR_03		.67	.003
5	MLR_04		.87	.003
6	MLR_05		.88	.003
7	MLR_06		.88	.003
1	fc-4tansig	MLPNN	0.843	0.003
2	fc-6tansig		0.863	0.007
3	fc-8tansig		0.846	0.005
4	fc-10tansig		0.869	0.002
5	fc-12tansig		0.873	0.003
6	fc-14tansig		0.699	0.004
7	fc-16tansig		0.896	0.002
8	fc-18tansig		0.884	0.003
9	fc-20tansig		0.770	0.004

a greater degree of nonlinearity and interactions among the input parameters, resulting in improved prediction accuracy. The findings indicate that the MLPNN technique may outperform the MLR approach in predicting complicated connections between many input characteristics. It is crucial to note, however, that the performance of MLPNN models can be heavily influenced by the architecture and training technique utilized, as well as the quality and representativeness of the data used.

The research by Wu and Tsai (2016) is one significant piece of literature that supports the use of MLPNN in predicting academic success. They used an MLPNN model to predict college students' academic success based on multiple input factors such as high school GPA, aptitude test scores, and demographic information. Their findings demonstrated that the MLPNN strategy beat the MLR approach and gave useful insights into the non-linear correlations between the input parameters.

Conversely, MLPNN surpasses MLR in predicting university applicants' success in the SUAST test, according to the result. This is due to MLPNN's capacity to identify non-linear09 trends in data and its model flexibility. MLR, on the other hand, is a strong statistical technique forlinear trend datasets and is still beneficial in finding significant predictors of the SUAST test and in classification tasks. This conclusion is consistent with earlier research that examined MLPNN and MLR performance in various fields. For instance, Li et al., (2020) examined the efficacy of MLPNN and MLR in forecasting soil moisture content. MLPNN outperformed MLR in forecasting soil moisture content because of its capacity to capture non-linear correlations between input and output variables, according to the research. Similarly, Zhong (2021) examined MLPNN and MLR performance in forecasting urban road traffic congestion. The study discovered that MLPNN outperformed MLR interms of prediction accuracy.

Overall, this conclusion implies that MLPNN is an effective tool for predicting outcomes in non-linear datasets, but MLR is better at discovering important predictors in linear datasets. Both strategies may be used by researchers and practitioners to obtain a better grasp of the data and create more accurate predictions.

CONCLUSIONS

This study analyzed the key factors that influence the performance of university entrants in the State University Aptitude and Scholarship Test (SUAST) examination. The study used a descriptive-correlational quantitative approach, utilizing both Multi-Layer Perceptron Neural Network (MLPNN) and Multiple Linear Regression Analysis (MLR). The MLR analysis revealed that family income, SHSGWA, library entry, intrinsic goal, openness, and intellect were significant predictors of SUAST exam scores. Also, the regression equation generated using MLR was Y (SUAST exam score) =-.782 +.234 (family income) + .255 (library entry) -.021 (behavioral reaction) +.933 (SHSGWA)+ .011 (intrinsic goal) + .013 (openness and intellect).

Moreover, the MLPNN analysis identified library access and resources, family income, and academic self-belief as the most important predictors of the SUAST exam score, while family size, on the other hand, has the least important value in the model. The study revealed that MLPNN slightly outperforms MLR in predicting university entrants' performance in the SUAST test. The study also highlighted the importance of addressing students' behavioral, emotional, cognitive, and bodily reactions during exams. The study recommends DepEd and HEI's focus more on providing students with study materials and test-taking tactics, employing alternative methods to assess student readiness, and focusing future research on the influence of financial aid and scholarships on academic achievement as well as performance discrepancies between male and female students and their distinct personality characteristics and levels of motivation on academic success. Alternative entry examinations, such as competency-based or performance-based exams, should also be investigated. Performing a content validity analysis on the SUAST exam can ensure that it measures what it is intended to measure.

Additionally, providing students with study materials and test-taking strategies, such as mock exams and study guides, may also be beneficial. It is also important to consider other indicators of student readiness for university beyond entrance exam results, such as high school grades,extracurricular activities, and letters of recomendation, to provide a more comprehensive picture of their preparation. Finally, future research may focus on the influence of financial aid and scholarships on academic achievement and examine performance discrepancies between male and female students and how their distinct personality characteristics and levels of motivation may impact academic success.

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REFERENCES

Abbasi, N., and Ghosh, S. (2020). Construction and standardization of examination anxiety scale foradolescent students. *International Journal of Assessment Toolsin Education,* 7(4), 522-534.

Bai, C. E., Chi, W., and Qian, X. (2014). Do college entrance examination scores predict undergraduate GPAs? A tale of two universities. *China Economic Review,* 30, 632-647.

Çakır, Y., Kırcı, M., and Güneş, E. O. (2014, August). Yield prediction of wheat in south-east region of Turkey by using artificial neural networks. *In 2014 The Third International Conference on Agro-Geoinformatics (pp. 1-4). IEEE.*

Cochran, W. G. (1977). Sampling techniques. john wiley & sons.

Deary, I. J., Strand, S., Smith, P., and Fernandes, C. (2007). *Intelligence and educational achievement.* Intelligence, 35(1), 13-21.

Djeddou, M., Zhao, X., Hameed, I. A., and Rahmani, A. (2021, August). Hybrid Improved Empirical Mode Decomposition and Artificial Neural Network Model for the Prediction of Critical Heat Flux (CHF). In International Conference on Nuclear Engineering (Vol. 85253, p. V002 T07A026). *American Society of Mechanical Engineers.*

Dulock, M. V. (2003). Research Design. The SAGE Handbook of Human Resource Management (pp. 269-285). *Sage Foundation*

Duncan, G. J., and Murnane, R. J. (Eds.). (2011). Whither opportunity?: Rising inequality, schools, andchildren's life chances. *Russell Sage Foundation.*

Eisa, A. A., and Al-Khalifa, H. S. (2018). Prediction of academic success for university students using multilayer perceptron neural network. *Journal of Information Science and Engineering,* 34(1), 205-215.

Elliot, A. J., and Harackiewicz, J. M. (1996). Approach and avoidance achievement goals and intrinsic motivation: A mediational analysis. *Journal of personality and social psychology,* 70(3), 461.

Farkas, D., Osterweil, S., and Greenberg, J. (2021). Library use and academic performance among college students. *Journal of Academic Librarianship*, 47(3), 102282.

Fazeli, S., Mirbagheri, A., and Naeini, M. R. (2020). A comparative study of artificial neural network models for predicting academic achievement. *Computers & Education*, 146, 103763.
Fowler, S. (2007). The motivation to learn online questionnaire (Doctoral dissertation, University of Georgia).
Fox, J. (2019). Regression diagnostics: An introduction. *Sage publications.*
Gignac, G. E., and Bates, T. C. (2017). Brain volume and intelligence: The moderating role of intelligence measurement quality. *Intelligence,* 64, 18-29.
Hess, R. K., and McAvoy, R. (2018). Socioeconomic status and college entrance exams: A review of the literature. *Educational Policy,* 32(5), 657-684.
Hosseini, M., Khezerloo, M., and Khojastehpour, M. (2021). An Analysis of Influential Factors on Tourists' Hotel Selection Using the Artificial Neural Network Approach. *Journal of Travel Research*, 60(2), 275-292.
Huang, G. H., and Anderson, R. E. (2020). The predictive validity of high school grades and test scores in college admissions. *Journal of College Admission,* 249, 26-34.
Hyman, J. (2017). ACT for all: The effect of mandatory college entrance exams on postsecondary attainment and choice. *Education Finance and Policy,* 12(3), 281-311.
Katz, I., and Assor, A. (2007). When choice motivates and when it does not. Educational Psychology Review, 19(4), 429-442.
Kim, K. H., and Hull, M. F. (2015). Effects of motivation, ACT/SAT, GPA, and SES on college choice for academically advanced students and other students. *World Journal of Educational Research (Online),* 2(2).
Koenig, K. A., Frey, M. C., & Detterman, D. K. (2008). ACT and general cognitive ability. *Intelligence,* 36(2), 153-160.
Kuncel, N. R., Credé, M., and Thomas, L. L. (2005). The validity of self-reported grade point averages, class ranks, and test scores: A meta-analysis and review of the literature. Review of educational research, 75(1), 63-82.
Kutner, M. H., Nachtsheim, C. J., Neter, J., and Li, W. (2005). Applied linear statistical models. *McGraw-hill.*
Langdon, C. K. (2021). College admissions and the predictive value of high school GPA: A systematic review. *Educational Research Review,* 34, 100386.
Letukas, L. (2016). College admissions testing: Current understanding and future implications. *Sociology Compass*, 10(1), 98-106.
Li, J., Zhang, C., Sun, Y., and Wang, Y. (2020). Comparison of MLPNN and MLR in forecasting soil moisture content. *Journal of Earth Science,* 31(5), 956-962.
Paris, J. and Heiser, R. (2022). An examination of the predictive validity of a measure of college admissions applicants' attributions of success and failure. *Journal of Postsecondary Student Success,* 1(4), 112-140.
Patel, N. V., and Patel, D. R. (2019). The predictive validity of Advanced Placement and International Baccalaureate examination scores for college admission test scores. *Journal of College Admission,* 244, 12-20.
Pekrun, R., Elliot, A. J., and Maier, M. A. (2009). Achievement goals and achievement emotions: Testing a model of their joint relations with academic performance. *Journal of educational Psychology,* 101(1), 115.
Poropat, A. E. (2009). A meta-analysis of the five-factor model of personality and academic performance. Psychological bulletin, 135(2), 322.
Putwain, D. W., Woods, K. A., and Symes, W. (2010). Personal and situational predictors of test anxiety of students in post-compulsory education. *British Journal of Educational Psychology,* 80(1), 137-160.
Reardon, S. F., Kalogrides, D., and Shores, K. (2019). The geography of racial/ ethnic test score gaps. *American Journal of Sociology,* 124(4), 1164-1221.

Reyes, J. D. C. (2019). Mathematical Performance of Freshman Students' vis-à-vis: Admission test Results. *International Journal of Humanities and Education Development* (IJHED), 1(3), 115-127.

Rojstaczer, S., and Healy, C. (2012). Where A is ordinary: The evolution of American college and university grading, 1940-2009. *Teachers College Record,* 114(7), 1-23.

Pontes-Neto, O. M., Silva, G. S., Feitosa, M. R., De Figueiredo, N. L., Fiorot Jr, J. A., Rocha, T. N., and Leite, J. P. (2008). Stroke awareness in Brazil: alarming results in a community-based study. Stroke, 39(2), 292-296.

Shamseldin, A. Y., O'connor, K. M., and Nasr, A. E. (2007). A comparative study of three neural network forecast combination methods for simulated river flows of different rainfall—runoff models. *Hydrological Sciences Journal,* 52(5), 896-916.

Strayhorn, T. L. (2018). College students' sense of belonging: A key to educational success for all students. *Routledge.*

Stricker, L. J. (2019). Motivation and test performance of college-bound students. *College Student Journal,* 53(2), 211-220.

Valverde-Berrocoso, J., Garrido-Arroyo, M. D. C., Burgos-Videla, C., and Morales-Cevallos, M. B. (2020). Trends in educational research about e-learning: A systematic literature review (2009–2018). *Sustainability,* 12(12), 5153.

Van Yperen, N. W., Blaga, M., and Postmes, T. (2014). A meta-analysis of self-reported achievement goals and nonself-report performance across three achievement domainsm (work, sports, and education). *PloS one*, 9(4), e93594.

Wu, T.-T., and Tsai, M.-J. (2016). Applying artificial neural networks for predicting academic achievement of college students. *Journal of Educational Technology & Society,* 19(3), 47-60

Yang, S. J., Lu, O. H., Huang, A. Y., Huang, J. C., Ogata, H., and Lin, A. J. (2018). Predicting students' academic performance using multiple linear regression and principal component analysis. *Journal of Information Processing,* 26, 170-176.

Zaidman-Zait, A., and Roth, R. (2015). The Big Five personality traits and academic achievement. *Journal of Research in Personality,* 56, 21-33.

Zhong, S., Zhang, K., Bagheri, M., Burken, J. G., Gu, A., Li, B., and Zhang, H. (2021). Machine learning: new ideas and tools in environmental science and engineering. *Environmental Science & Technology,* 55(19), 12741-12754.