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Original Paper

Key Influencing Factors Affecting the Student Academic Performance and Student Satisfactions Ratings: Evidence from Undergraduate Students in China

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Abstract

This paper has developed a sound and practical method to evaluate the key teaching quality including the student academic performance and student satisfaction ratings. The method makes use of the existing data already readily available in a Chinese university, focusing on the identification of key influencing factors affecting the student academic performance and student satisfactions ratings. The data analyses have shown the university student academic performance is significantly affected student gender, age, previous academic performance, settlements and occupations of parents. There is significant difference in the student ratings for different genders and academic positions of teaching staff. The student performance and satisfaction ratings also significantly vary in different years of intakes and different Schools/programs. The student's university academic performance can be accurately predicted using artificial neural networks with a prediction error of about 7%. This approach can help the university to improve the student academic performance and student satisfactions.

Keywords

higher education quality, internal quality evaluation, data analysis, hypothesis testing, ANOVA, artificial neural network

1. Introduction

Chinese higher education sector has experienced a series of reforms within last three decades, including decentralisation, introduction of market incentives, university merger, internationalisation and expansion of higher education (Li, 2010). The continuing reform of Chinese higher education has been largely driven by its national policy of domestic social-economic reform and open door policy over last three decades. In line with the worldwide trends, quality has become increasingly important in Chinese higher education. In particular, the extensive expansion of China's higher education since late 1990s has raised many concerns about the quality of Chinese higher education. Chinese higher education has now entered a stage of connotative development of quality improvement. The National Medium-and Long-Term Education Reform and Development Plan (2010-2020) (Chinese Ministry of Education, 2010) points out that improving quality is the core task of higher education development and the basic requirement for building a country with strong higher education. The Party leadership's proposals for formulating the 14th Five-Year Plan (2021-2025) for National Economic and Social Development and the Long-Range Objectives through the Year 2035 was adopted in October 2020. The document has clearly put forward the construction of a high-quality education system, which has become the main topic of China's education development (Zhang, 2022).

In order to improve the quality of higher education, it is necessary to evaluate higher education quality and identify the factors affecting the quality. However, there are different opinions about quality in the context of higher education. In this paper, the concept of quality is based on the ISO 9000 standard, defined as the "degree to which a set of inherent characteristics of an object fulfils requirements" of the customers and stakeholders (including students, their future employers and society) (ISO, 2015). The student academic performance clearly represents the requirements of students' future employers, whereas the student ratings of the teaching reflect the student satisfaction.

Evaluation of higher education quality may be carried out at various levels (e.g., institution, program or module level) and by different parties (either external or internal). Whilst external evaluation is useful for external quality assurance, the importance of internal quality evaluation is increasingly recognised since it can facilitate the quality control, quality assurance and also quality improvement (Li, 2010).

Student quality is a fundamental manifestation of the quality of higher education. For example, M. Frazer (Chen, 2004a) believes that the quality of higher education refers first to the quality of student development. The academic achievement of university/ college students is the most important benchmark to compare the quality of college students (Chen, 2004b). It is also the basic criteria for university/college to monitor the quality of teaching and learning and for employers to evaluate and select the students.

As the students are customers of higher education, their experience and satisfaction are also important part of higher education quality. Whilst the student satisfactions may cover a range of issues, this paper only considers the student satisfaction at module (subject) level.

This paper will focus on the quality evaluation and quality improvement at program and module levels and present an approach based on the existing data already available from a case study Chinese university. The quality evaluation will be centred on the student academic performance (i.e., the weighted average of all the modules studied over the 4 year duration of the program) and the student evaluation of each module. The paper will perform in-depth analyses and discussions of the important influencing factors affecting the student academic performance and the student satisfaction ratings, including student's personal, social economic background and educational factors.

2. Methodology

2.1 Data Sample

It is possible to collect a lot of data about the students and the teaching in a university, either existing or specially collected for the study. This paper has tried to make the best use of the existing data. A total of 1,085 undergraduate students (275 female and 810 male) were selected from the student intakes from year 2011 to 2013 from three undergraduate programs within three Schools (Education, Math and Electronics Information) of the case study University Q. Their examination results over four year studies, together with their national university entrance examination results, personal and socio-economic background information were collected. The entrance examination results included five core subjects: Chinese, English, Math, Comprehensive Science and Basic Ability. The student examination performance was determined using the weighted average marks for the entire four year duration of their studies.

Additionally, another set of data about the student ratings of teaching staff are collected from three Schools (Education, Math and Physics) and the data cover 1343 modules taught over 4 years from 2013/14 to 2016/17.

2.2 Data Analysis

Several kinds of data analyses are performed, including exploratory, confirmative and modelling. The exploratory data analyses mainly include descriptive statistics and correlation analysis, whilst the confirmative data analyses are statistical hypothesis testing, e.g., t-test and ANOVA.

The purpose of these analyses is to identify the main influencing factors affecting the student performance and student satisfaction. These understanding will help the university to identify suitable ways to enhance the student learning and the quality of its programs and teaching.

The correlation analysis calculates Pearson correlation coefficients to measure the linear relationships among the five university entrance examination subjects, the University Entrance Examination Total Marks (UEETM) and the University Weighted Average Marks (UWAM). The correlation analysis can show deep insight into the relationships between subjects and overall academic performance. This understanding also helps to evaluate and model the academic performance and the correlated variables are further used as the input in the ANN modelling.

The factors affecting the student performance are based on the available data and can be broadly grouped into the following categories:

Personal: student gender, age and previous academic performance (university entrance examination marks, fresh vs former High School Graduate (HSG));

Social-economic factors: rural vs urban, high school area and parents' occupations;

Educational: year of intake, different university schools/programmes;

Based on the exploratory analysis of the data and literature review, the following hypotheses have been identified in Table 1, concerning the factors affecting the student's UEETM and UWAM for each student over the whole duration of 4 years studies.

Table 1. Hypotheses Concerning the Factors Affecting the Student UEETM and the Student's University UWAM

Influencing factors		Hypotheses
Personal	Gender	H1A: The UEETM is equal for male and female students.
		H1B: The UWAM is equal for male and female students.
	Age	H2A: The UEETM is equal for students at different ages.
		H2B: The UWAM is equal for students at different ages.
	Fresh vs former HSG	H3A: The UEETM is equal for fresh and former HSG students.
		H3B: The UWAM is equal for fresh and former HSG students.
Social-economic	Rural vs urban	H4A: The UEETM is equal for students from rural and urban areas.
		H4B: The UWAM is equal for students from rural and urban areas.
	High school areas	H5A: The UEETM is equal for students from high schools in different areas.
		H5B: The UWAM is equal for students from high schools in different areas.
	Parents' occupation	H6A: The father's occupations have no significant influence on the UEETM.
		H6B: The father's occupations have no significant influence on the UWAM.
		H7A: The mother's occupations have no significant influence on the UEETM.
		H7B: The mother's occupations have no significant influence on the UWAM.
Educational	Year of intake	H8A: The UEETM is equal for students from different years of intake.
		H8B: The UWAM is equal for students from different years of intake.
	School/program	H9A: The UEETM is equal for students from different school/programs.
		H9B: The UWAM is equal for students from different school/programs.

The student rating of each module and teaching staff is important for the university to evaluate its teaching quality from students' perspective. Table 2 lists the hypotheses to be tested concerning factors affecting the student ratings.

Table 2. Hypothesis Concerning the Student Rating of Each Module and Teaching Staff

Hypothesis
H10: The mean student ratings are equal for male and female teaching staff.
H11: The mean student ratings are equal for staff with different academic positions.
H12: The mean student ratings are equal for different years of intake.
H13: The mean student ratings are equal for different school/programs.

Note. These hypotheses in Tables 1 and 2 are tested using either two sample t-test or ANOVA, with a significance level of 0.05.

2.3 Data Modelling Using Artificial Neural Networks

Data modelling has also been used to study the relationships between various influencing factors and the student academic performance. Since the model is rather complex with nonlinear relationships, traditional statistical models (e.g., linear or nonlinear regression) are unlikely suitable. Artificial Neural Networks (ANNs) have been used for modelling very complex relationships. Cybenko (1989) and Funahasi (1989) have demonstrated that ANNs can uniformly approximate arbitrary continuous mapping, although the proofs were centred on the existence of such ANNs. The ANNs have found successful applications in signal processing, quality engineering and education (Yang, 1994; Kardan, 2013; Bahadir, 2016; Hu, 2017).

The architecture of ANN which was modelled earlier by Authors (2018) was adopted in this study and it is characterised with one input layer, two hidden layers and one output layer. The detailed design and performance studies can be found in (Authors, 2018). The input layer has 11 input variables, including student gender, location, fresh or former HSG, high school area, parents' occupations, and the entrance exam results including Chinese, English, Maths, Comprehensive Science and Basic Ability. The output is the student academic performance CGPA, based on the standardized Cumulative Grade Point Average (CGPA) for the entire four year duration of their studies. Similar to (Authors, 2018), Levenberg-Marquardt algorithm was used as the backpropagation training rule. The ANN performance is further evaluated through ANN prediction errors.

3. Results and Discussions

3.1 Correlation Analysis

The correlation analysis of university entrance exam subject marks, UEETM and UWAM is shown in Table 3.

Table 3. Correlation Analysis of University Entrance Exam Subject Marks, UEETM and UWAM

	Chinese	Math	English	Comprehensive Science	Basic Ability	UEETM	UWAM
Chinese	1						
Math	-0.186	1					
English	0.140	0.070	1				
Comprehensive Science	-0.265	0.031	-0.281	1			
Basic Ability	0.099	0.101	-0.140	-0.011	1		
UEETM	0.160	0.441	0.346	0.540	0.082	1	
UWAM	0.111	0.012	0.255	0.068	0.142	0.230	1

Table 3 shows the UEETM has a strong correlation with English, Math and Comprehensive Science, whereas the UWAM has strong correlation with English and UEETM. It is interesting to note that Comprehensive Science has a strong negative correlation with Chinese and English, also between Math and Chinese. This is likely due to the conflicts in student's interests and/or study time allocations. It is also important to note Math and Comprehensive Science have very weak correlation with the UWAM.

3.2 Testing of Hypothesis Concerning the Influencing Factors on the Student Academic Performance

3.2.1 Student Gender's Influences on Academic Performance

The t-test results of both the UEETM and the UWAM based on students' gender are shown in Table 4.

Table 4. Hypothesis Testing Concerning the Influence of Student Gender on UEETM (H1A) and UWAM (H1B)

Hypothesis	H1A		H1B	
Variable	Female	Male	Female	Male
Mean	547.1	538.4	81.1	75.5
Variance	321.9	318.9	17.4	20.8
Observations	810	275	810	275
df	1083		1083	
t Stat	6.98		18.82	
p-value	**0.000**		**0.000**	

In Table 4, the p-values in both cases are far less than 0.05, indicating a significant difference in both the UEETM and the UWAM performance of male and female students, where female students score better than male students. Some researchers believe that this is due to that girls' non-intellectual factors are better than boys', girls have stronger desires and motivations to get better grades than boys, thus investing more time and working harder to learn (Wang, 2005). Some studies also believe that the current university teaching model is still based on the teacher's step-by-step systematic teaching, and the use of students' participation and inquiry-based learning methods is not high. The examinations also tend to focus on the memory of system knowledge, requiring little creative application of knowledge (Ge, 2005). There are also obvious differences in the way of learning between male and female students. Girls are better than boys in class notes and recall, whilst boys are better than girls in practical application of knowledge. Therefore, female students often tend to achieve better academic achievement.

3.2.2 Student Age's Influences on Academic Performance

The t-test results of both the UEETM and the UWAM based on students' age are shown in Table 5. The results show a significant difference between the UWAM for two age groups of students, where younger student group score better than older student group. However, the differences in the UEETM are not significant.

Table 5. Hypothesis Testing Concerning the Influence of Student Age on the UEETM (H2A) and the UWAM (H2B)

Hypothesis	H2A		H2B	
Variable	Age L	Age H	Age L	Age H
Mean	544.0	545.8	80.3	79.1
Variance	372.9	295.8	23.8	23.9
Observations	542	542	542	542
df	1082		1082	
t Stat	-1.56		4.07	
p-value	0.119		**0.000**	

3.2.3 Influence of Fresh or Former HSG on Academic Performance

Table 6 shows the t-test results of the differences in both UEETM and UWAM based on whether or not the student is a former or fresh High School Graduate (HSG). Whilst the differences in the UEETM are not significant, there is a significant difference in the UWAM for the two student cohorts, where fresh HSG students score significantly higher than former HSG students. A study by Fu et al. (2022) has confirmed this point of view: the Grade Point Average (GPA) of different types of students from highest to lowest are: rural fresh HSG students, urban fresh HSG students, urban former HSG students, and rural former HSG students.

Table 6. Hypothesis Testing Concerning the Influence of Fresh or Former HSG on UEETM (H3A) and UWAM (H3B)

Hypothesis	H3A		H3B	
Variable	Former HSG	Fresh HSG	Former HSG	Fresh HSG
Mean	543.8	545.4	78.2	80.3
Variance	277.0	358.8	24.6	22.8
Observations	315	770	315	770
p-value	0.214		0.000	

3.2.4 Settlement's Influences on Academic Performance

The t-test results of the differences in both the UEETM and the UWAM based on rural and urban settlements are presented in Table 7.

Table 7. Hypothesis Testing Concerning the Influence of Location on UEETM (H4A) and UWAM (H4B)

Hypothesis	H4A		H4B	
Variable	Rural	Urban	Rural	Urban
Mean	545.3	543.7	79.8	79.2
Variance	331.7	346.1	23.3	26.9
Observations	824	261	824	261
df	1083		1083	
t Stat	1.18		1.65	
p-value (two tail)	0.237		0.099	
p-value (one tail)	0.119		**0.049**	

As shown in Table 7, the differences in the UEETM of rural and urban areas are not statistically significant. But the one-tailed t-test of UWAM has a p-value marginally smaller than 0.05 (two-tailed test with p-value of 0.099), indicating the UWAM of the rural students is significantly higher than that of the urban students. This result is similar to that reported in (Chu, 2011): the college students with higher income levels from cities have lower academic performance than the students from rural areas with lower family incomes. Coleman (1966) pointed out that family background is the most important factor affecting academic achievement, and its influence runs through the whole process of students' studies, and the influence has an accumulating effect. Under China's urban-rural dual system, there is a big gap between urban family conditions and rural family conditions. Different levels of capital provided to the children by families with different backgrounds have an impact on college students' input to learning (Liu, 2015), which affects academic performance. Generally, college students from county towns, townships and rural areas have significantly higher learning input than college students from provincial capital cities (Li, 2022). In addition, the psychological quality of students is affected by the family environment and conditions. The students with poor economic conditions tend to have more positive learning attitudes and stronger learning motivation. Rural college students are more diligent and hard-working than urban students, with good psychological qualities such as hard working and perseverance. These good learning qualities are an important factor for college students to achieve excellent results.

3.2.5 Student High School Areas' Influences on Academic Performance

In order to test if there is a significant difference between the student performances from different high school areas, ANOVA has been carried out of both the UEETM and UWAM in 17 different high school areas, with the results shown in Tables 8A/8B. The results have shown no significant differences in both UEETM and UWAM due to different high school areas.

Table 8A. ANOVA of the UEETM in Different High School Areas (H5A)

Source of Variation	SS	df	MS	F	P-value	F crit
Between Groups	4620.125	16	288.7578	0.859455	0.61712	1.652984
Within Groups	358824.1	1068	335.9776			
Total	363444.2	1084				

Table 8B. ANOVA of the UWAM in Different High School Areas (H5B)

Source of Variation	SS	df	MS	F	P-value	F crit
Between Groups	468.4369	16	29.27731	1.353055	0.157541	1.652984
Within Groups	23109.3	1068	21.63792			
Total	23577.74	1084				

3.2.6 Student Parent's Occupation on Academic Performance

Table 9 combines the two ANOVA tables for testing the differences in both the UEETM and the UWAM due to the different occupations of fathers and mothers. The results have shown the differences in the UEETM due to parents are not significant. But both parents have significant influences on the UWAM, with mothers (p-value of 0.016) having more significant influences than fathers (p-value 0.082). There are 6 categories of occupations for a parent: unspecified (0), unemployed (1), farmers (2), self-employed or factory workers (3), professional (teachers or engineers or doctors) (4) and officers or managers (5). The differences in the UEETM are not significant for either fathers' or mothers' occupations, but the differences in the UWAM are significant for mothers' occupational influence. The fathers' occupational influences on the UWAM are not significant at a significance level of 0.05, but significant at a significance level of 0.10.

Table 9. ANOVA of the UEETM and UWAM due to Occupational Influences of Fathers (H6A/H6B) and Mothers (H7A/H7B)

		UEETM		UWAM	
Programme	df	F	p-value	F	p-value
Father	(5,1079)	1.474	0.196	1.963	0.082
Mother	(5,1079)	1.504	0.186	2.808	0.016

We believe that the relationship between parental occupation and student academic performance is influenced by the mediating factor of learning involvement (Crook, 1995; Ermisch, 2010; Marks, 2008). Nord (1998) found that the higher the father's level of learning involvement with the child, the better the child's academic performance is. Fathers with lower levels of education are usually less involved in student learning. Similarly, the occupation type of Chinese mothers has a great influence on children's academic performance. It can be explained that there is always a tradition of "male outside, female inside" in China. In many families, mothers and children have more contact when their children grow up. In China, Pang (2013) and Li (2020) and other studies have found that the level of education of mothers has a more significant impact on students' academic performance than their fathers.

Close examination reveals the differences in the UWAM are significantly caused by category 4 occupation (professionals including teachers, engineers and doctors), the further ANOVA of the other 5 categories shows no significant differences in the UWAM. The students with a professional mother have performed significantly lower than the other group of students. The students with a professional father have also performed lower than the other group of students, although only significant at a significant level of 0.10.

The significant differences are likely due to that professional parents are often very busy and have therefore less contact with their children.

3.2.7 Different Intake's Influences on Academic Performance

Table 10 shows the ANOVA results of both the UEETM and the UWAM in different years of intakes. The comparison has been made for each of three School/Programs, Education, Mathematics and Electronics Information. The ANOVA results have shown that there are significant differences (p-value=0.000) in the UEETM for all three School/Programs. However, for the UWAM, only Mathematics has significant difference in the performances of three years' intakes.

Table 10. ANOVA of the UEETM (H8A) and the UWAM (H8B) in Different Intakes

		UEETM		UWAM	
School/Program	df	F	p-value	F	p-value
Education	(2,325)	91.521	0.000	1.092	0.337
Mathematics	(2,315)	102.609	0.000	5.944	0.003
Electronics Info.	(2,436)	559.989	0.000	2.117	0.122

3.2.8 Different School/Program's Influences on Academic Performance

Table 11a combines two ANOVA tables to test the differences in both the UEETM and UWAM for different School/Programs. The ANOVA results have shown significant differences in both the UEETM and the UWAM among the three School/Programs. Table 11b shows that the UEETMs for Education and Mathematics programs are significantly higher than the Electronics Information Program and that in the UWAM, Education School/Program scores significantly higher than other two Schools/Programs.

Table 11. ANOVA of the UEETM (H9A) and the UWAM (H9B) in Different School/Programs

a) Combined ANOVA tables

		UEETM		UWAM	
ANOVA of 3 different	df	F	p-value	F	p-value
School/Programs	(2,1082)	217.9361207	0.000	84.17819034	0.000

b) Performance statistics for each School/Program

		UEETM		UWAM	
Groups	Count	Average	Variance	Average	Variance
Edu	328	552.64	194.74	82.03	15.02
Math	318	553.37	220.14	79.94	23.84
Electronics	439	533.02	286.78	77.72	23.31

3.3 Testing of Hypotheses Concerning the Influencing Factors on Student Satisfaction Ratings

3.3.1 Teacher Gender's Influences on the Student Ratings

In Table 12, the two-sample t-Test performed has shown the mean ratings for male teaching staff are significantly higher than female teaching staff, but the significance varies amongst the three Schools. The difference in the ratings of male and female staff is only significant (t(206)=-3.35, p-value=0.000) in Math School/Program, but not in Education (t(331)=-0.75, p-value=0.452) and Physics (t(333)=-1.36, p-value=0.175).

Table 12. T-test of the Mean Student Ratings of the Lectures for Different Gender of Teaching Staff

Variable	Female	Male
Mean	94.84	95.04
Variance	1.630	1.069
Observations	493	850
df	865	
t Stat	-2.95	
p-value	**0.003**	

3.3.2 Teacher Academic Position's Influences on the Student Ratings

Hypothesis H11 is used to test if the mean average of the student ratings are equal for different academic positions. In the Education School, a two-sample t-Test indicates that the ratings for Teaching Assistants are significantly (t(13)=4.43, p-value=0.000) lower than Lecturers/Associate Professors/Professors. But the single factor ANOVA shows that the ratings are not significantly (F(2, 464)=0.41, p-value= 0.661) different amongst the Lecturers, Associate Professors and Professors.

In the Math School, there are significant (F(2,375)=4.13, p-value= 0.017) difference in the ratings of the Lecturers, Associate Professors and Professors, with the mean ratings of 94.9, 95.1 and 95.3, respectively. In Physics School, the evaluated staff also include teaching Technicians and Senior Technicians. The ANOVA has shown that there are significant (F(4,473)=4.13, p-value= 0.017) differences amongst the ratings of the five categories of teaching staff, with the decreasing rating means of 95.5, 95.2, 95.0, 94.8 and 94.7 for Professors, Technicians, Associate Professors, Senior Technicians and Lecturers, respectively.

3.3.3 Different Intake's Influences on the Student Ratings

Hypothesis H12 is used to test if the mean average of the student ratings of the lectures are equal for different intakes. The ANOVA has indicated that there are significant (F(3,1339)= 28.5, P-value=0.000) difference in the ratings of 4 year intakes, with the mean ratings of 94.84, 94.53, 95.05 and 95.41 for 2013/14, 2014/15. 2015/16 and 2016/17, respectively.

3.3.4 Different School's Influences on the Student Ratings

Table shows the ANOVA table for the testing of different school's influences on the student ratings. The ANOVA has shown that there are significant (F(2,1340)= 4.29, P-value=0.014) difference in the ratings of 3 Schools, with the mean ratings of 94.85, 95.05 and 95.03 for Education, Math and Physics, respectively.

Table 13. ANOVA Table for the Testing of the Mean Student Ratings for the Three Different Schools

Source of Variation	SS	df	MS	F	P-value	F crit
Between Groups	10.95459	2	5.477295	4.289398	0.013902	3.00244
Within Groups	1711.097	1340	1.276938			
Total	1722.052	1342				

According to the two-sample t-Test performed, the ratings for the Math/Physics Schools are significantly (t(842)=-2.76, p-value=0.006) higher than the Education School, but the differences between Math and Physics Schools are insignificant (t(845)=0.25, p-value=0.806).

3.4 ANN Modelling

Based on the ANN modelling approach by Authors (2018), the ANN model of the university academic performance is performed using Matlab software. The input layer consists of 11 variables about students' personal/social economic background (i.e., gender, location, fresh or former HSG, high school area, parents' occupations) and the entrance exam results including Chinese, English, Maths, Comprehensive Science and Basic Ability. Each of the two hidden layers has 30 hidden neurons and the single output neuron predicts the students' CGPA.

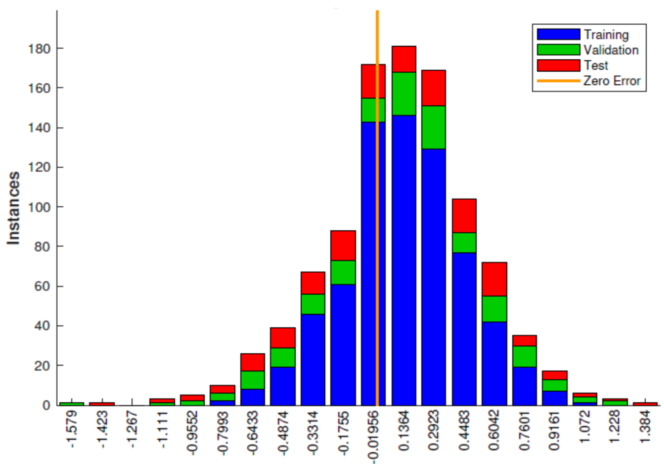

Figure 1. ANN Prediction Error Histogram

Data samples are randomly mixed and divided into three subsets for training, validation and test with a ratio of 0.7:0.15:0.15, respectively. Levenberg-Marquardt algorithm is used during the training and learning with a damping factor ζ of 0.001 and the training epoch of 1,500. The ANN training continues until the validation error failed to decrease for six iterations during the validation process. After training and validation runs, the ANN has achieve a performance with the MSE≈0.27 or 6.9%, demonstrating a good prediction performance, with the error histogram shown in Figure 1.

Table 14. Summary of the Testing Results of the Hypotheses Concerning the Factors Affecting the Student Academic Performance

Influencing factors		Hypotheses	Decision
Personal	Gender	H1A: The UEETM is equal for male and female students.	Reject
		H1B: The UWAM is equal for male and female students.	Reject
	Age	H2A: The UEETM is equal for students at different ages.	Accept
		H2B: The UWAM is equal for students at different ages.	Reject
	Fresh vs former HSG	H3A: The UEETM is equal for fresh and former HSG students.	Accept
		H3B: The UWAM is equal for fresh and former HSG students.	Reject
Social-economic	Rural vs urban	H4A: The UEETM is equal for students from rural and urban areas.	Accept
		H4B: The UWAM is equal for students from rural and urban areas.	Reject
	High school areas	H5A: The UEETM is equal for students from high schools in different areas.	Accept
		H5B: The UWAM is equal for students from high schools in different areas.	Accept
	Parents' occupation	H6A: The father's occupations have no significant influence on the UEETM.	Accept
		H6B: The father's occupations have no significant influence on the UWAM.	Reject @α=0.10
		H7A: The mother's occupations have no significant influence on the UEETM.	Accept
		H7B: The mother's occupations have no significant influence on the UWAM.	Reject
Educational	Year of intake	H8A: The UEETM is equal for students from different years of intake.	Reject
		H8B: The UWAM is equal for students from different years of intake.	Note[1]
	School/program	H9A: The UEETM is equal for students from different school/programs.	Reject
		H9B: The UWAM is equal for students from different school/programs.	Reject

Note. Reject for Mathematics Program, Accept for Education and Electronics Information Programs.

Table 15. Summary of the Testing Results of the Hypotheses Concerning the Student Rating of Each Module and Teaching Staff

Hypothesis	Decision
H10: The mean student ratings are equal for male and female teaching staff.	Reject
H11: The mean student ratings are equal for staff with different academic positions.	Reject
H12: The mean student ratings are equal for different years of intake.	Reject
H13: The mean student ratings are equal for different school/programs.	Reject

4. Conclusion

This paper has developed a practical approach to evaluate the quality of university teaching and learning using the existing data which are already readily available. It aims to identify the important influencing factors affecting the student academic performance and the student satisfaction rating of teaching staff and modules. The study has considered student's personal, social economic background and educational factors. The relationship between the key factors and student academic performance has been further modelled with Artificial Neural Networks (ANNs).

The findings of the data analyses and hypothesis testing are summarised in Tables 14 and 15, which present the overall patterns of the relationships between the various influencing factors and the learning and teaching quality in terms of academic performance and student satisfaction ratings. The following can be concluded from these results:

1) The university student academic performance is significantly affected student gender, age, previous academic performance, settlements and occupations of parents (particularly mother's occupation).

2) Male, older, urban, former HSG students and those with professional parent(s) tend to have significantly lower performance than their counterparts.

3) The student academic performance significantly varies in different years of intakes and different Schools/programs.

4) Based on the case study of University Q, there is significant difference in the student ratings for different genders and academic positions of teaching staff.

5) The student satisfaction ratings also significantly vary in different years of intakes and different Schools/programs.

6) The student's university academic performance can be quite accurately predicted using ANN with a prediction error of about 7%.

These findings are based on the limited data samples from three schools of the case study university. Similar studies (including data analyses and modelling) can be extended to more schools and more universities. These types of findings can be used to evaluate, diagnose and predict the quality of the learning and teaching. They will also help the university to identify suitable practices and resources to enhance and improve the student academic performance and student satisfactions, contributing to the continual improvement of higher education quality.

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